

KARADENİZ TECHNICAL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

DEPARTMENT OF FOREST ENGINEERING

**MODELING BIOMASS AND CARBON STORAGE FOR ANATOLIAN BLACK
PINE (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe) – TURKISH RED
PINE (*Pinus brutia* Ten.) MIXED FORESTS IN TÜRKİYE USING
ARTIFICIAL NEURAL NETWORKS**

DOCTORAL THESIS

MOUSSA BEAU-GARS MBOHOU

NOVEMBER 2023
TRABZON



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Moussa Beau-Gars MBOHOU

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PREFACE

This thesis, entitled “Modelling biomass and carbon storage for Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe) – Turkish Red Pine (*Pinus brutia* Ten.) Mixed Forests in Türkiye Using Artificial Neural Networks”, was prepared at the Department of Forest Engineering, within the doctoral program of the Graduate School of Natural and Applied Sciences of Karadeniz Technical University in Türkiye. *ALLAH'a Şükür!*

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Moussa Beau-Gars MBOHOU
Trabzon 2023

THESIS ETHICS DECLARATION

I hereby declare that I have carried out this study entitled “Modelling Biomass and Carbon Storage for Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe) - Turkish Red Pine (*Pinus brutia* Ten.) Mixed Forests in Türkiye Using Artificial Neural Networks”, as a doctoral thesis, under the responsibility of my thesis supervisor, Prof. Dr. Mehmet MISIR, from start to finish, having myself collected the data/samples, performed/conducted the experiments/analyses in the appropriate laboratories, having sufficiently indicated the sources of provenance and references of other information in this thesis, having acted in accordance with scientific research ethics and ethical rules during the work process, and accepting all legal consequences in the event of discovery to the contrary.

10/11/2023

Moussa Beau-Gars MBOHOU

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SUMMARY

Doctoral Thesis

MODELING OF BIOMASS AND CARBON STORAGE FOR ANATOLIAN BLACK PINE (*Pinus nigra* Arnold subsp. *pallasiana* (Lomb.) Holmboe) – TURKISH RED PINE (*Pinus brutia* Ten.) MIXED FORESTS IN TÜRKİYE USING ARTIFICIAL NEURAL NETWORKS

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The Graduate School of Natural and Applied Sciences
Department of Forest Engineering
Supervisor: Prof. Dr. Mehmet MISIR
2023, 390 pages

This study was conducted in 21 FMDs of 13 DFM's across Türkiye. The aim was to develop prediction models for biomass and carbon storage in natural mixed stands of *Pinus nigra* and *Pinus brutia*. In addition to dendrometric measurements (diameter, height, age), 138 trees of *P. nigra* (68) and *P. brutia* (70), 138 stem sections, 138 branches and leaves, 92 litter, 46 deadwood, 46 herbaceous covers, 208 root cylinders, and 206 organic soil cylinders samples were utilized. Stand characteristics were analyzed through several key parameters (age, diameter, height, tree density, basal area, volume, and mixture ration). Biomass and carbon stocks were calculated for each aboveground pool (individual tree, stem, branches, leaves, bark, litter, deadwood, herbaceous cover) and belowground (roots and organic matter). The results indicated that the average biomass and carbon stock per single-tree were 162.56 kg and 80.72 kg for *P. nigra*, and 195.63 kg and 98.25 kg for *P. brutia* respectively. The stem accounted for 64-66% of an individual tree's biomass and 63-66% of its carbon stock, followed by branches, leaves, and bark. In the biomass of litter (17.4 t/ha), deadwood (2.33 t/ha), herbaceous cover (0.45 t/ha), roots at 0-90 cm (55.60 t/ha), and mass of soil organic matter (7560.9 t/ha), the carbon stock represented 44.5%, 47.7%, 46.1%, 48.1%, and 3.35% respectively. Using ANN and Regression analysis methods, several prediction models were developed for biomass and carbon storage. For each species, (i) top 10 non-linear regression models (Power) for each tree components and for individual tree, using only tree diameter ($D_{1.30}$), (ii) two MLR models and (iii) two MLP models for each individual tree, using $D_{1.30}$ and height (H), as well as (iv) two MLR models and two MLP models for stand level using five stand parameters, were developed. Compared to the MLR models, the MLP models demonstrated better performance for prediction of biomass and carbon storage. The spatial distribution and the potential biomass and carbon stored by all mixed stands of *P. nigra* and *P. brutia* were analyzed. The carbon stock capacity of these ecosystems represents about 3.31% (0.066 GtC) of the country's total forest ecosystem carbon stock capacity (Türkiye).

Keywords: Türkiye's Mixed Forests, *Pinus nigra* and *Pinus brutia*, Biomass and Carbon Storage, Artificial Neural Networks, Allometric Equations

ÖZET

Doktora Tezi

TÜRKİYE'DEKİ KARAÇAM (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe) - KIZILÇAM (*Pinus brutia* Ten.) KARIŞIK MEŞCERELERİNİN BİYOKÜTLE VE KARBON DEPOLAMANIN YAPAY SİNİR AĞLARI KULLANILARAK MODELLENMESİ

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Bu çalışma, Türkiye'deki 13 Orman İşletme Müdürlüğü'nde bulunan 21 Orman İşletme Şefliği'nde gerçekleştirilmiştir. Çalışmanın amacı Türkiye'de doğal olarak yayılış gösteren *Pinus nigra* ile *Pinus brutia* karışık meşcerelerinden biyokütle ve karbon depolama için tahmin modelleri geliştirmektir. Dendrometrik ölçümlere (çap, boy, yaş) ek olarak, 138 ağaç (*P. nigra* (68), *P. brutia* (70)), 138 gövde kesiti, 138 dal ve 138 yaprak, 92 ölü örtü, 46 ölü odun, 46 diri örtü, 208 kök silindiri ve 206 organik toprak silindiri örneği kullanılmıştır. Meşcere özellikleri (yaş, çap, boy, ağaç sayısı, göğüs yüzeyi, hacim ve karışım oranı) gibi birkaç temel parametre üzerinden analiz edilmiştir. Toprak üstü (tek ağaç, gövde, dal, yaprak, kabuk, ölü örtü, ölü odun, diri örtü) ve toprak altı (kök ve organik madde) bileşenler için biyokütle ve karbon depolama miktarları hesaplanmıştır. Bu çalışma sonucunda, tek ağacın biyokütlesi ve karbon depolama miktarı sırasıyla *P. nigra*'da 162,56 kg ve 80,72 kg, *P. brutia*'da ise 195,63 kg ve 98,25 kg olarak belirlenmiştir. Ağaç gövdesi, tek ağaç biyokütlesinin %64-66'sını, tek ağaç karbon depolama miktarının ise %63-66'sını oluşturmaktadır. Meşcere bileşenlerinin biyokütleleri ; ölü örtüde 17.4 t/ha, ölü odunda 2,33 t/ha, diri örtüde 0,45 t/ha, 0-90 cm derinliğindeki köklerde 55,60 t/ha ve toprakta kütlesi 7560,9 t/ha olduğu ve bu biyokütlelerin karbon oranları ise sırasıyla %44,5, %47,7, %46,1, %48,1 ve %3,35 olarak tespit edilmiştir. YSA ve Regresyon Analizi Yöntemlerinin kullanılarak biyokütle ve karbon depolama için çeşitli tahmin modelleri geliştirilmiştir. Her bir tür için, (i) her bir ağaç bileşeni ve her bir tek ağaç için sadece ağaç çapı ($D_{1.30}$) kullanılarak en iyi 10 doğrusal olmayan regresyon modeli (Power), (ii) her bir tek ağaç için $D_{1.30}$ ve yükseklik (H) kullanılarak iki MLR modeli ve (iii) iki MLP modeli ve ayrıca (iv) ekosistemin beş parametresi (D_m , H_m , N, CC, SI) kullanılarak meşcere seviyesi için iki MLR modeli ve iki MLP modeli geliştirilmiştir. MLR modelleri ile karşılaştırıldığında, MLP modelleri tahmin için daha iyi performans göstermiştir. *P. nigra* ve *P. brutia*'nın tüm karışık meşcerelerinin mekansal dağılımı, potansiyel biyokütlesi ve depoladığı karbon analiz edilmiştir. Bu meşcerelerin için Türkiye'nin toplam (1.99 GtC) orman ekosistemi karbon depolama kapasitenin %3.31'ini (0.0659 GtC) temsil ettiği görülmüştür.

Anahtar Kelimeler : Türkiye'de Karışık Meşcereleri, *Pinus nigra* - *Pinus brutia*, Biyokütle ve Karbon Depolama, Allometrik Denklemler, Yapay Sinir Ağları

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SYMBOLS AND ABBREVIATIONS

AFOLU	: Agriculture, Forestry and Other Land Uses
ANN	: Artificial Neural Networks
AR	: Assessment Report
BECF	: Biomass Expansion and Carbon Factor
BEF	: Biomass Expansion Factor
CBD	: Convention on Biological Diversity
CCFM	: Canadian Council of Forest Ministers
CDM	: Clean Development Mechanism
CF	: Carbon Factor
CO ₂	: Carbon Dioxide
COP	: Conference of the Parties
DBH	: Diameter at Breast Height (D _{1.30})
DECCW	: Department of Environment, Climate Change and Water
DFM	: Directorate of Forest Management
ETFOP	: Principles and Procedures for the Regulation of Ecosystem-Based Forest Functional Management
FAO	: Food Agricultural Organization
FAOSTAT	: Food and Agriculture Organization Corporate Statistical Database
FAT/TOD	: Foresters Association of Turkish/Türkiye Ormancılar Derneği
FRA	: Forest Resources Assessment
GHG	: Greenhouse Gases
GPGLULUCF	: Good Practice Guidance for Land-Use, Land Use Change and Forestry
IRAD	: Agricultural Research Institute for Development
IPCC	: Intergovernmental Panel on Climate Change
IPPU	: Industrial Processes and Product Use
IRD	: Institute of Research for Development
IUCN	: International Union for Conservation of Nature
MINRESI	: Ministry of Scientific Research and Innovation
MLP	: Multi-Layer Perceptron
MLR	: Multiple Linear Regression

MRA	: Multiple Regression Analysis
NARX	: Nonlinear Auto-Regressive with eXogenous inputs
NASA	: National Aeronautics and Space Administration
NIR	: National Inventory Report
NOAA	: National Oceanic and Atmospheric Administration
OECD	: Organization for Economic Co-operation and Development
OGM/GDF	: General Directorate of Forestry
R ²	: Coefficient of Determination (Correlation)
RCP	: Representative Concentration Pathways
RDF	: Regional Directorate of Forestry
RF	: Radiative Forcing
RMSE	: Root Mean Square Error
SE or Se	: Standard Error
SOC	: Soil Organic Carbon
SOM	: Soil Organic Matter
SSE	: Sum Square Error
TÜBİTAK	: Türkiye Bilimsel ve Teknolojik Araştırma Kurumu / Scientific and Technological Research Council of Türkiye
TÜİK	: Türkiye İstatistik Kurumu (Statistical Institute of Türkiye)
U.S. DOE	: United States Department of Energy
UN	: United Nations
UNCCD	: United Nation Convention to Combat Desertification
UNEP	: United Nations Environment Program
UNFCCC	: United Nations Framework Convention on Climate Change
UN-REDD	: United Nations Collaborative Program on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries
USA	: United State of America
US-EPA	: United States Environmental Protection Agency
WMO	: World Meteorology Organization
WRI	: World Resources Institute
ÇkÇz	: Çk is Karaçam (<i>Pinus nigra</i>) and Çz is Kızılçam (<i>Pinus brutia</i>) local names

1. GENERAL INFORMATION

1.1. Introduction and Literature Review

The emergence of crucial global concerns regarding the adverse impacts of climate change dates back to the discussions held in preparation for the Stockholm Conference in 1972 (Kiss and Sicault, UN 1972). Building on this momentum, the World Climate Conference of 1979 convened under the guidance of the World Meteorological Organization (WMO) to delve into the scientific dimensions of climate change (WMO, 1979). As the climate system undergoes accelerated transformations due to the absorption of greenhouse gases released by human activities, researchers worldwide are compelled to unravel carbon dynamics, seeking to mitigate the risks associated with ongoing environmental and climatic changes (IPCC, 2021; Abbass et al., 2022). In 1983, the United Nations (UN) established the World Commission on Environment and Development (WCED), a 23-member body led by Gro Harlem Brundtland (Norway). This commission aimed to orchestrate international dialogues and formulate a multidisciplinary cooperative framework to address environmental concerns. This endeavor culminated in the adoption of the Vienna Convention on the Protection of the Ozone Layer on March 22, 1985. This convention sought to advance the reduction of substances depleting the ozone layer. Subsequently, the Montreal Protocol emerged in 1987-89, garnering support from 197 parties, with the objective of progressively reducing and ultimately eliminating ozone-depleting substances, including hydrochlorofluorocarbons. The year 1988 marked a significant milestone with the establishment of the Intergovernmental Panel on Climate Change (IPCC) by the United Nations Environment Program (UNEP) and the WMO. This initiative was formulated to deliver comprehensive assessments of the scientific, technical, and socio-economic insights into climate change. The IPCC's mandate encompassed exploring the causes of climate change, its potential impacts, and devising strategies for mitigation and adaptation. In essence, climate change has emerged as a paramount global challenge over the past few decades, exerting profound impacts on professional (Fosso and Karahalil, 2021), societal and economic stability, as well as the equilibrium of Earth's ecological systems. It encompasses persistent and aberrant alterations in weather patterns and temperature within the global land-ocean system (IPCC, 1997).

1.1.1. Environmental Challenges and Global Warming

The global demographic evolution, illustrated by recent data, reveals that the world population growth rate has dropped from 1.5% to about 0.6% between 1992 and 2022. However, this slight decrease does not mask the rapid expansion of the global population. In 2023, the world's population reached 8.045 billion persons. Projections suggest a possible increase in population even between 9.7 and 10 billion by 2050 (UNFPA, 2023). This demographic growth is also observed in Türkiye, where the population has grown from 78.7 million in 2015 to 84.7 million in 2021 and about 85.280 million in 2022. With an estimated growth rate of around 13.5% (in 2015) to 12.7% (in 2021), the Turkish population is projected to reach 97 million by 2050 (TÜİK, 2023). The Food and Agriculture Organization of the United Nations (FAO) was already warning the world of the urgency of meeting the vital needs of more than 7.9 billion people in 2022. In the face of this demographic growth, humanity is confronted with a series of major challenges (Fang et al., 2018). Among these, the increase in frequency and intensity of extreme climate events such as heatwaves, marine heatwaves, heavy rainfall, intense tropical cyclones, agricultural and ecological droughts, as well as the gradual melting of Arctic ice caps, stands out. These developments result in economic losses and growing uncertainties, causing significant damages in several countries around the world, including the United States (\$1.7 trillion), China (\$799 billion), Japan (\$735 billion), Italy (\$212 billion), and others (USWITCH cited by Cossardeaux, 2022). Climate changes increase the risk of forest fires in Mediterranean regions (Mısır et al., 2021) and influence nutrient cycles, such as carbon flux (Lasslop, 2019). These elements provide substantial evidence of a direct relationship between the amplification of many changes in the climate system and the increase in global warming (IPCC AR6, 2022).

In Türkiye, for instance, extreme events and regular weather disturbances, including heatwaves, floods (27%), and landslides (4%), have been recorded over the last 30 years. Precipitation has decreased by 15% in 1999 and 7% in 2000. The country's agricultural production is threatened by drought, erosion, and variations in precipitation patterns. In the forest sector, approximately 74,493 and 64,812 forest fires affected Türkiye during 1937-2003 and 1991-2000, leading to the disappearance of 1,556,150 and 300,752 hectares of forest areas respectively (Öztürk, 2002; Mısır et al., 2021; Celik et al., 2022; Türkiye Orman Derneği, 2022). Over the past 20 years (2002-2021), forest fires in Türkiye have resulted in the burning of 310,484 hectares of forest area.

In 2021, more than 139,500 hectares of forest were destroyed by 2,793 fires. In 2020, only 20,971 hectares were burnt in 3,399 fires. Thus, the combined average for these two years (2020 and 2021) is 80,237 hectares burned in 3,096 fires produced, an increase of 37% and 10 times over the previous 18 years (Kavgacı et al., 2023). Soil losses due to land use practices result in changes in forest carbon values (Hacısalıhoğlu et al., 2017; Mısır et al., 2007). Furthermore, during the period from October 1, 2022 to January 3, 2023, precipitation in Turkey fell by 31% (Meteoroloji Genel Müdürlüğü, 2023). The terrestrial biosphere, as a vital reservoir of life, is not immune to these climatic upheavals. Net Primary Productivity (NPP) of vegetation and agricultural yields weaken and experience unexpected seasonal variations under the influence of temperature, precipitation, solar radiation, droughts, and soil water reserves (FAO, 2014). This situation is further exacerbated when temperatures exceed or fall below the optimal range (Berthelot et al., 2002). According to the United Nations, at the Conference of the Parties (COP27) in Egypt (2022), global agricultural growth slowed due to climate change. For example, Africa is the most affected region, experiencing a loss of 34% in agricultural productivity growth since 1961 (Trisos et al., 2022; WMO, 2023). High temperatures and disruptions in precipitation are affecting the carbon cycle by disturbing plant growth seasons and the amount of soil water available for tree biomass production (Woo and Seo., 2022; Jdaidi, 2016).

Climate change is leading to significant and irreversible biodiversity losses, affecting both animal and plant species, especially those vulnerable species with low adaptive capacity, exposed to diseases, various mutations, and human-induced disturbances, leading to erosion (Otto, 2018; Başkent, 2019). About 31.7% of the 22,036 tropical vascular plant species are threatened with extinction due to climate change (IRD, 2019). Human activities such as deforestation, land use changes (1.5 GtC/year), fossil fuel combustion, and cement production (U.S. DOE, 2008; IPCC, 2013) influence the global carbon cycle and its flux. Land degradation is intensifying, and deforestation is becoming recurrent with increasing rates and significant carbon emissions (3.2 GtCO₂eq/year) (Grinand et al., 2013; Smith et al., 2014; Watson et al., 2005). In the context of plants, most physiological processes, including photosynthesis, have an optimal temperature range beyond which their efficiency decreases (Johnson et al., 2013 in cited in the Canadian Council of Forest Ministers, 2009). The responses of primary productivity to rising temperatures are complex and vary based on species, tree age, leaf type (needles vs. leaves), and constraints imposed by water and nutrient deficiencies, as well as pathogenic attacks (TOD, 2022).

Climate change is closely linked to additional amounts of greenhouse gases, of which the most significant is CO₂, associated with anthropogenic production activities to meet the growing needs of the global population (IPCC, 2022). In light of the intricate web of consequences posed by climate change, it becomes imperative to delve deeply into the key drivers of this phenomenon. One of the most critical factors contributing to the alteration of our planet's climate is the increased concentration of greenhouse gases.

1.1.2. Greenhouse Gases Concentrations in the Global Atmosphere

The world's scientists are increasingly unanimous on the theory that anthropogenic greenhouse gases (CO₂, CH₄, H₂O, O₃, CO, fluorinated compounds, etc.) are the main cause of the abnormal variations in global average temperatures responsible for the current climate change. The main greenhouse gases of anthropogenic origin recognized as dangerous are the subject of careful global monitoring by the international community, particularly the National Oceanic and Atmospheric Administration (NOAA, 2021; Jancovici, 2003). Figure 1 shows the main greenhouse gases covered by the Montreal (1987) and Kyoto Protocols (1995).

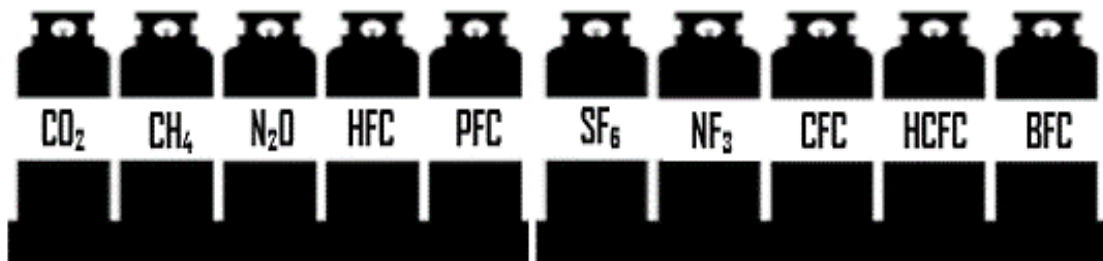


Figure 1. Top 10 of greenhouse gases in the world

All the main anthropogenic GHGs (Figure 1) occupy less than 0.1% of the atmospheric volume. They include Carbon Dioxide (CO₂), Methane (CH₄), Nitrous Oxide (N₂O), Hydrofluorocarbons (HFCs), Perfluorocarbons (PFCs), Sulfur Hexafluoride (SF₆), Trifluoronitrogens (NF₃), and Ozone-Depleting Substances such as Chlorofluorocarbons (CFCs), Hydro-chlorofluorocarbons (HCFCs), and Bromo-fluorocarbons (BFCs). CO₂, CH₄, and N₂O represent 96% (in CO₂ equivalent) of the seven main greenhouse gases (GHG) considered in the Kyoto Protocol (IPCC, 1990; US-EPA, 2023; NOAA, 2023).

Widely present in the atmosphere, CO₂ represents more than 76% of global anthropogenic emissions followed by Methane (16%), Nitrous Oxides (6%), and fluorinated compounds (2%). CO₂ is the main GHG and is particularly the subject of wide international debate. In 2021, CO₂ concentrations in the atmosphere reached 414 ppm, followed by those of Methane (1860 ppb), N₂O (340 ppb), HFC (230 ppt), and others (PFC, SF₆, and NF₃) with low levels (NOAA, 2023). A recent analysis shows that global anthropogenic emissions and CO₂ concentrations have been increasing during the last decades (US-EPA, 2023; NOAA, 2023), as shown in Figure 2.

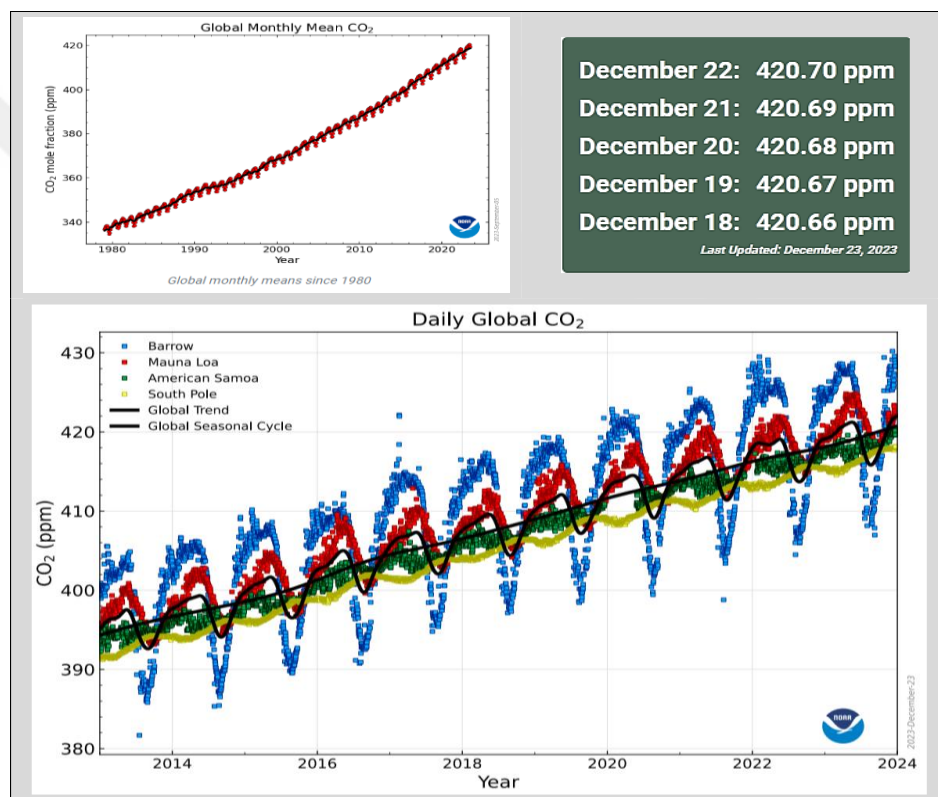


Figure 2. Changes in annual CO₂ concentrations in the atmosphere

The graph of Figure 2 displays the daily average CO₂ from four GML Atmospheric Baseline observatories: South Pole, Antarctica (yellow), American Samoa (green), Mauna Loa, Hawaii (red), and Barrow, Alaska (blue). The concentration of CO₂ in the atmosphere has constantly increased considerably over the past five decades. Indeed, this rapid increase in the concentration of CO₂ is an alarm that worries nature defenders. Indeed, it has gone from 277 ppm in 1750 (Joos and Spahni, 2008) to 414.7 ppm in 2022 with growth rates varying between 1.8 and 3.0 (2.18 in 2022).

According to NOAA (2023), the CO₂ concentration reached 419.51 ppm in June 2023, 420.66 pp in Decembre 2023, and could reach 450 in 2050. Today, more than 1 million kilograms of CO₂ are emitted into the atmosphere every second. In equivalent quantity, the carbon emitted into the atmosphere rose from 36.8 GtCO₂eq/year in 2019 (Planetoscope, 2019). Carbon (C) is the basic component of Carbon Dioxide (CO₂). IPCC (AR6, 2022) estimates that the remaining carbon budget to keep global temperatures below its climate targets (Kyoto Protocol) has decreased by 21 GtC (77 GtCO₂). Unfortunately, we are still far from achieving the zero-emission goal by 2050 (US-EPA, 2020; NOAA, 2023). According to four global scenarios of IPCC (2007), the proportions of carbon could reach significant values over the next 80 years, as shown in Table 1 (Demir et al., 2013).

Table 1. Representative Concentration Pathways

	RCP 8.5	RCP 6.0	RCP 4.5	RCP3-PD
RF	>8.5	6.0	4.5	3.0
Period	2100	After 2100	After 2100	Before 2100
Variation	Increase	Stabilization before goal	Stabilization before goal	Peak and drop at 3.0
Concentration of CO₂ (ppm)	1370	850	650	Peak and drop at 490
Emission GHG (Kyoto Protocol)	The increase continues until 2100	All in the last quarter of the century	The fall from the mid-century	All in the last quarter of the century
ppm: parts per million (1ppm= 1mg/kg)			RF: Radiative Forcing (w/m ²)	

According to Table 1, if no measures are taken today to reduce the emissions of greenhouse gases into the atmosphere, especially the increasing levels of CO₂, in order to mitigate global warming, humanity will witness an increase from 560 ppm to 1370 ppm by the end of the century (2100). This would lead to a radiative forcing exceeding 8.5 W/m² (RCP 8.5). Such a scenario would exacerbate shifts in energy flux and result in a more significant temperature rise, ranging between 2°C and 6°C (IPCC, 2007). The additional volumes of anthropogenic CO₂ already present in the atmosphere contribute to the radiative forcing that impacts the redistribution of solar energy. Building on this analysis, it is imperative to delve deeper into our understanding of global mechanisms and the effects of greenhouse gases.

1.1.3. Global Energy Distribution and the Greenhouse Gases Effect Mechanism

Due to its extended atmospheric lifetime, CO₂ influences the global energy flux by modifying radiative forcing (Forster et al., 2007; Sitch et al., 2007; Myhre et al., 2013). The atmospheric lifetimes of Methane (CH₄) and Nitrous Oxide (N₂O) are relatively short (12 years and 120 years, respectively), whereas that of CO₂ is considerably longer (approximately 100 years), accompanied by a notably high Global Warming Potential (GWP = 1). CO₂ is a stable molecule (CO₂eq = relative GWP x 0.2727). The prolonged lifespan of CO₂ has already contributed to a 41% increase in radiative forcing within the atmosphere since 1990. For every annual increment of 1.9 ppm in atmospheric CO₂ concentration, the radiative forcing (CO₂) experiences a 20% impact (Houghton et al., 1990). CO₂ accounts for approximately 82% of the amplification in radiative forcing. This process profoundly affects the quantum of radiation traversing the atmosphere, thus altering the energy flux from the sun to the atmosphere (Forster et al., 2007), ultimately leading to the greenhouse effect. According to various researchers, there exists a dynamic interchange of energy, a radiative equilibrium, between the sun and the Earth-atmosphere system that fundamentally shapes the planet's climate (Houghton et al., 1990; Houghton, 2002; Hugh et al., 2003; IPCC, 2014; Merle et al., 2013; Trenberth & Fasullo, 2012). Figure 3 illustrates energy exchanges within the Earth-atmosphere system.

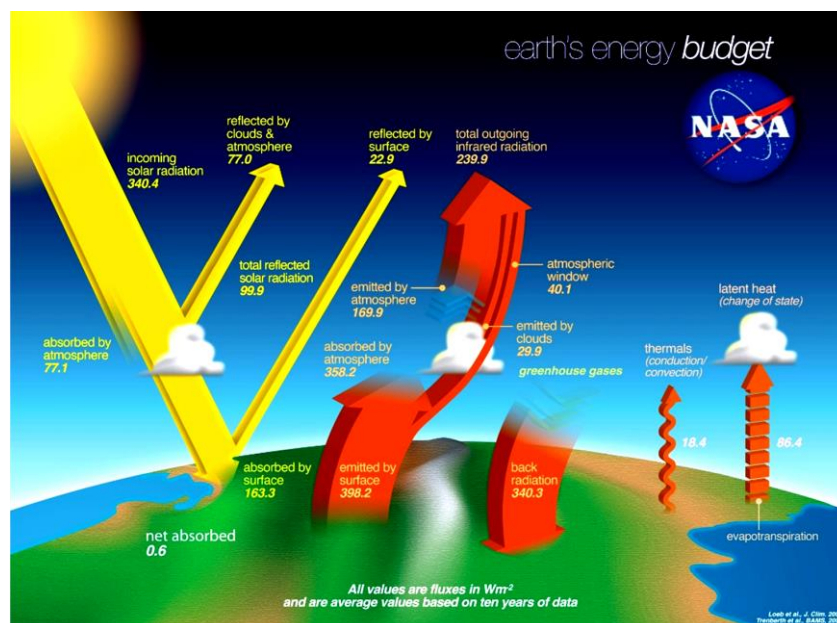


Figure 3. Global energy flows in the earth-atmosphere climate system

In Figure 3, the dispersion of solar energy is uneven across the atmosphere (including clouds, aerosols, and dust) and the Earth's surface. Employing the albedo process, the solar energy that reaches the Earth is reflected back into space. The incident rays not reflected back are absorbed, with 20.7% by the atmosphere and 51% by the land surface. Within the Earth system (comprising land, oceans, glaciers, and biota), approximately 54% (184 w/m^2) of the total emitted solar energy (340.4 w/m^2) is received, subsequently around 12% (23 w/m^2) is rerouted back to the atmosphere. However, a substantial 88% (161 W/m^2) of the absorbed energy is stored within the Earth's surface, contributing to its warming. The additional energy is returned to the atmosphere in accordance with the principles of thermodynamics, from hot (Earth) to cold (atmosphere). A good part of this energy emitted in the form of infrared radiation (84%, 333 w.m^{-2}) is trapped in the lower atmosphere by greenhouse gases (CO_2 , CH_4 , N_2O , etc.) and returned to Earth (Trenberth & Fasullo, 2012 & 2013; Anderson et al., 2016; Houghton et al., 1990; Forster et al., 2007; Fleming, 1999). This process opposes the cooling of the Earth's surface and is responsible for the abnormal rise in global average temperature compared to that of thermal equilibrium ($+15^\circ\text{C}$) (WMO, 2016 & 2023; Akin., 2006). Over the past 100 years, the Earth's average temperature has increased drastically (Rhode, 2022; Mersmann, 2023). Figure 4 shows the graphs of global average temperature evolution since 1850-60.

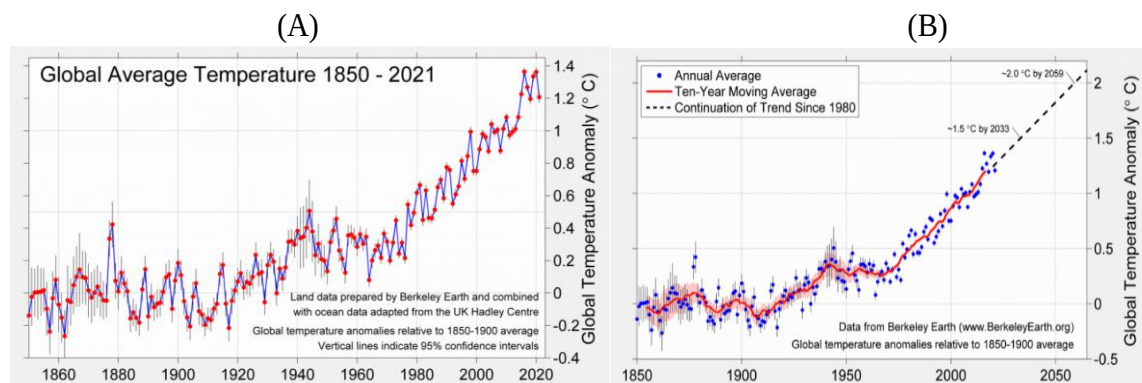


Figure 4. Global average temperature evolution diagram in the world

From the Figure 4, the Earth's global average temperature increased from 0.19°C (pre-industrial reference period) to 1.29°C (2.17°F) as shown in Chart (A) between 1850 and 2021. The overall scenario shows that this temperature is expected to continue increasing, possibly exceeding 2°C around 2060 (B) (Rohde, 2022).

In all CO₂ emission scenarios considered, IPCC (2021) estimates that the temperature at the Earth's surface will continue to increase at least until the middle of this century. Global warming of 1.5°C and 2°C will be exceeded in the 21st century. For the particular case of Türkiye, the country has experienced significant temperature variations over the last five decades. Figure 5 illustrate the state of temperature between 1971-2022 (Turkish State Meteorological Service, 2023).

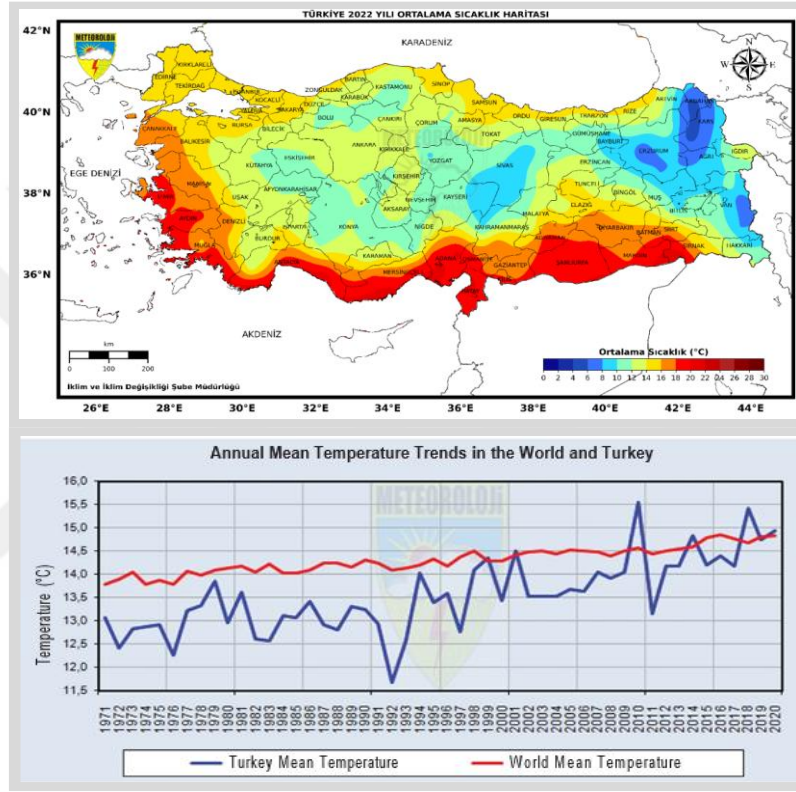


Figure 5. Annual mean temperature variations and anomalies in Türkiye

According to Turkish State Meteorological Service (2021-2023), the Türkiye's Annual Mean Temperature in reached 14.9 °C in 2020, with 1.4°C higher than the 1981-2010 average. In 2022, the Türkiye's Mean Temperature was 14.5°C with 0.6°C above the 1991-2020 mean value (13.9°C). The extreme limits often recorded oscillate around -31.5°C and 46.7°C. In 2020, the extreme levels were observed in Erzurum with -31.9°C in February, and the highest temperature was recorded in Cizre with 47.3 °C in July. The highest temperature ever recorded in Türkiye was reported at 49.1°C (2021) in the locality of Cirze, a district of Şırnak in Southeastern Anatolia. The average annual temperature would therefore have increased by 1°C (1991-2020).

In 2022, the lowest temperature reached -34.4°C (January) in Özalp (Van), and the highest temperature reached 47.9°C (August) in Silopi (Şırnak). The anomalies around 20.9°C , indicating September as the hottest month in the last 52 years. The country should expect several phenomena related to climate change (MGM, 2023). The scenario studied in Türkiye for the period 2013-2040 shows typical growth trends of 2°C to 3°C in the North-West and South-West during the summer and 1°C to 1.5°C during the winter. For the period 2040-2070, we expect a temperature increase of 1°C on average in all seasons according to the previous period. On the other hand, the temperature will increase by 2°C to 3°C in summer in the eastern regions and by 1.5°C to 2°C in other regions of the country (Demir et al., 2013). According to the worst-case scenario, the country can expect a temperature rise of around 7°C (1370 ppm) by 2100. It is therefore imperative to take urgent measures to mitigate atmospheric CO_2 concentrations and also to adapt to climate change in all production sectors that are sources of CO_2 emissions.

1.1.4. Key Players and Origins of Human-Induced CO_2 Emissions

The production sectors sources of carbon emissions have been clearly highlighted in Figure 6 produced by Hannah Ritchie (2020) using data from the World Resources Institute (WRI) and Climate Watch Data (C.W.D.) published in OurWorldinData (2020).

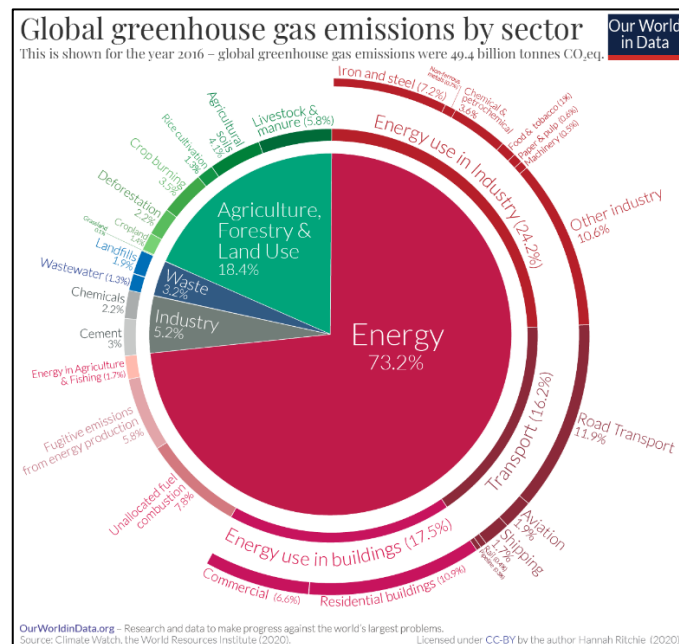


Figure 6. Key-players and sectors of anthropogenic greenhouse gases sources

In the Figure 6, the main sectors and global sources of carbon emissions (CO_2) are related to energy (73.2%), industry (5.2%), waste and pollution (3.2%), and Agriculture, Forestry and Other Land Uses (AFOLU) with 18.4%. Each year, approximately 40 million tons of CO_2 are emitted into space (IPCC, 2014). The net change in forestry is the outcome of the contrast between losses and gains in forested areas. Net emissions of carbon dioxide from changes in forestry cover (positive emissions), constituting 2.2% of the total, result from deforestation (In C.W.D. of W.R.I., 2020; cited by OurWorldinData.org, 2021; Ritchie, 2020). From 1970 to 2010, carbon emissions increased from $420 \pm 35 \text{ GtCO}_2\text{eq}$ (1970) to $1300 \pm 110 \text{ GtCO}_2\text{eq}$ in 2010. CO_2 emissions in the AFOLU sector increased by 8%, particularly between $7.5 \text{ MtCO}_2\text{eq}$ (1990) and $8.1 \text{ MtCO}_2\text{eq}$ (2000). The biggest polluters in the world and account for more than 85% of the net increase in carbon emissions are China, United States, India and European Union (27). In 2020, China holds the record for CO_2 emissions with 9.9 million tons of CO_2eq , representing 30% of global emissions (Gaudiaut, 2021). Türkiye is the 18th emitter of CO_2 in the world with more than 476.34 million tons of CO_2eq until 2020 representing 1% of global emissions (C.W.D, 2022). The 5 main emission sectors of national greenhouse gas (CO_2 , NH_4 , NO_2 , F-Gases) are presented in Figure 7 (TÜİK, 2023).

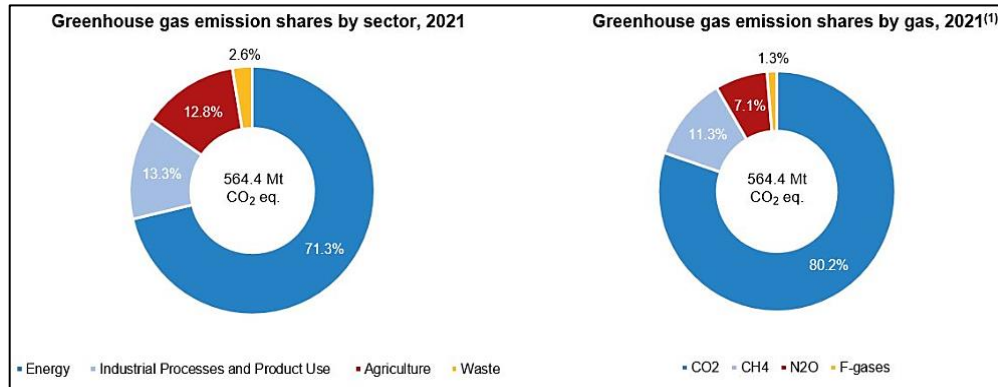


Figure 7. Carbon dioxide (CO_2) emissions by production sector in Türkiye

In Türkiye, total greenhouse gas emissions are estimated at $564.4 \text{ MtCO}_2\text{eq}$ in 2021, which increased by 7.7% more than in 2020 and a growth of 157.1% compared to 1990. According to Figure 7, the Energy sector represents 71.3% of the country's greenhouse gas emissions in 2021 following by the Industrial Processes and Product Use (IPPU) sector (13.3%), Agriculture sector (12.8%) and Waste sector (2.6%).

The Carbon Dioxide is the most emitted greenhouse gases in Türkiye (80.2%), following by Methane (11.3%), Nitrogen Monoxide (7.1%) and Fluoro-gases (1.3%) in 2021. In the Energy sector (402.5 MtCO₂e) in 2021, the emission increase of 9.8% in 2021 compared to 2020, and of 188.4% compared to the pre-industrial period (1990). Emissions from Industrial Processes and Product Use (IPPU) sector represent 75.1 MtCO₂eq in 2021, with an increase of 10.6% compared to 2020, and 228.7% compared to the reference period (1990). The Agricultural sector represents 72.1 MtCO₂e and indicate a decrease trend of -1.5% compared to 2020 and an increase to 56.5% compared to 1990. In the Waste sector that contributed about 14.7 Mt CO₂eq to national emissions in 2021, the trend shown a decrease of -9.9% compared to 2020 and an increase of 32.6% compared to 1990 (TÜİK, 2023). The LULUCF sector represents a special case in the distribution of CO₂ emissions.

1.1.5. Carbon Dioxide Emissions in Land Use, Land-Use Change, and Forestry

Indeed, between 1750 and 2011, LULUCF was the world's third-largest source of atmospheric CO₂ emissions (GIEC, 2014). Beyond the natural mechanism (respiration), several researchers believe that the anthropogenic mechanisms of CO₂ emissions in this sub-sector are mainly deforestation, exploitation and degradation of forest soils (Ferretti-Gallon et al., 2014), combustion and decomposition of biomass (Watson et al., 2019). The global emission rate has been estimated at 12% (2000 to 2009). Forest cover losses have been estimated at over 420 million hectares since 1990. Since the 1700s, the area of forests has increased from 52% of the earth's surface to 48% (1900) and 38% (2018), according to Wallach and Aboulazm (2022). The Food and Agriculture Organization of the United Nations (FAO) estimated that the flux of net emissions from the Forest and Other Land Uses (FOLU) subsector to the atmosphere has decreased from 3.9 GtCO₂eq/year in 1991-2000 to 3.2 GtCO₂eq/year in 2001-2010 (FAOSTAT, 2013). Between 1990 and 2010, the net flux of carbon from LULC change was 12.5% of the human carbon emissions (Houghton et al., 2012). Recently, global emissions fell from 3.2 GtCO₂ in 2010 to 1.36 GtCO₂eq in 2019, i.e., a drop of 1.84 GtCO₂eq/year (Smith et al., 2014; Karsenty, 2020). In Türkiye, emissions from the LULUCF sub-sector are due to industrial logging in forests, forest fires, exploitation of non-timber forest products, urbanization, tourism, logging mining and agriculture, roads and agro-pastoral overgrazing (FAOSTAT, 2022).

The browsing of young shoots by animals limits the natural regeneration of forest cover leading to the progressive aging of the forest. Topping and limbing for animal fodder, soil compaction and declining water reserves also limit the regeneration and growth of standing trees (FAO, 2016; NIR Türkiye, 2022). Despite this, the sub-sector contributes only about 1.7% to the country's total emissions. Without the LULUCF sub-sector, the country's CO₂ emissions would amount to 506.1 MtCO₂eq. By integrating the LULUCF sub-sector, national emissions amount to 422.1 MtCO₂eq. The forests would therefore have sequestered 84 MtCO₂eq emitted by Türkiye in 2019 (NIR Türkiye, 2022; Sun and Liu, 2020). The LULUCF sub-sector plays a much greater role in mitigation and adaptation through the sequestration of atmospheric CO₂ and its storage in the aboveground and belowground biomass of forest ecosystems (TOB, 2023). LULUCF is the subject of particular attention in the national strategy (GDF, 2018) and international commitments to combat climate change.

1.1.6. International Actions to Combat Climate Change

a. Intergovernmental Panel on Climate Change and Assessment Reports

The Intergovernmental Panel on Climate Change (IPCC) is an international organization responsible for assessing the extent, causes and consequences of ongoing climate change. It is established by the United Nation in 1988. The work carried out over the years by the Intergovernmental Panel on Climate Change (IPCC) has been reported and referenced in six main documents known as Assessment Reports (AR), that provide a baseline of interdisciplinary and reliable information on climate change (UNFCCC, 2006).

In AR1 (1990), the IPCC outlines the greenhouse effect caused by human activity that has led to warming of land surfaces and oceans, seriously threatening lives and ecological systems (IPCC, 1990). In 1995, AR2 examined the economic and social aspects of climate change including the scientific and technical aspects of environmental science, impact, reduction and adaptation to climate change (IPCC, 1995). In AR3 (2001), the consequences of climate change and its devastating regional effects were discussed. In AR4 (2007), the topic of fossil fuels and land use as important factors in the contribution to climate change was studied (IPCC, 2007). In AR5 (2014), IPCC reported on climate change adaptation and mitigation measures, stressing that increasing GHGs will affect climate components, increase the global average temperature, and leads to irreversible changes in the long term.

Most recently published in 2022, the 6th Evaluation Report (AR6) outlines the new foundations for a good physical understanding of the climate system and climate change (IPCC, 2022). This report reaffirms that changes in the climate system exist at the level of the earth and in each region of the world. In summary, human activities remain the main source of climate influence and have yet to determine climate change in the face of which the expectations of the United Nations Framework Convention on Climate Change (UNFCCC) are accurate.

b. United Nations Framework Convention on Climate Change

At the end of international consultations by the Brundtland Commission, the report entitled "Our Common Future" was published in 1987. This report evokes for the first time the notion of sustainable development as being "development which meets the needs of the present without compromising the ability of future generations to meet theirs". The Brundtland report was used as a basis for reflection at the Earth Climate Summit, held in Rio de Janeiro, Brazil, from June 3 to 14, 1992. During this United Nations Conference on Climate Change (1992), 189 countries and 120 Heads of State and Government resolved to bring about structural changes in United Nations climate policy, declaring that the environment and development are inseparable and must be discussed fairly. This international commitment on climate has led to the signing of important documents such as (i) the Rio Declaration, (ii) the Forest Principles, (iii) Agenda 21, and (iv) three important conventions, namely (a) Convention on Biological Diversity (CBD), (b) Convention to Combat Desertification (UNCCD) and (c) United Nations Framework Convention on Climate Change (UNFCCC). The UNFCCC is the main convention and the first major environmental contract on global warming, concluded between the United Nations Secretariat and member countries and governments. The main objective of the UNFCCC is "The stabilization of GHG concentrations at a level that prevents dangerous human interference with the climate system". The UNFCCC aims to reduce, minimize the effects, promote carbon pools and maintain at a precise level the emissions of greenhouse gases in the atmosphere. Such a level should be reached in sufficient time to allow ecosystems to adapt naturally to abnormal climate variations, and to guarantee economic development and food security.

Members' commitment is based on the principle that industrialized countries that emit more greenhouse gases should take more responsibility. This principle of "Common but Differentiated Responsibilities and Relative to Capacities" foresees a serious contribution of developed countries to this global effort, through financing and the transfer of technology to developing countries. The member countries have been divided into three groups:

(1) Annex I countries are the 42 countries and the European Union (EU) divided into two groups: Group 1 made up of the former members of the Organization for Economic Cooperation and Development (OECD, 1961), including Türkiye (July 12, 1962) and the European Union, and Group 2 made up of countries in the process of moving to a market economy. Annex I countries are required to limit their greenhouse gas emissions, protect and increase their carbon pools, report on their policies and the measures taking to prevent climate change.

(2) Annex II countries are the 23 countries and the EU that must take the necessary measures to transmit, facilitate and finance access to technologies in developing countries, in line with environmental objectives.

(3) Non-Annex Countries are the 154 countries encouraged to reduce their greenhouse gas emissions, collaborate on research and technology transfer, and protect their carbon sinks. However, they are not subject to any special obligations.

Türkiye has been a signatory to the Montreal Protocol since December 19, 1991 as a developing country, and contributes to its implementation. Since 1995, the country has celebrated the International Day for the Protection of the Ozone Layer held every September 16. Türkiye has been a signatory member of the United Nations Framework Convention on Climate Change since 2014. It is the only Annex I country that does not have a transition economy. It is recognized by the Lisbon European Council in accordance with resolutions 26/CP.7 of Marrakesh, as being part of a particular situation due to its different position. Türkiye was therefore removed from the list of countries in Annex II at the Conference of the Parties held in Marrakech (2001). Its economy is thus recognized as a transition economy and the country must benefit from funding in accordance with resolution 1/CP.16 of the Conference of Parties in Cancun (2010). Taking into account decisions 2/CP.17 in Durban (2011) and 1/CP.18 in Doha (2012), Türkiye is also encouraged to continue negotiations on the modalities of its support in its efforts to reduce carbon emissions, promote technology development and transfer, financing and capacity building.

By making climate change a national priority, Türkiye officially plans to reduce its greenhouse gas emissions by 21% by 2030, in favour of developing alternative sources of renewable energy such as biomass, in accordance with the guidelines of the Kyoto Protocol.

c. Kyoto Protocol

The Kyoto Protocol was an international treaty that extended the United Nations Framework Convention on Climate Change (UNFCCC) by committing state parties to reduce greenhouse gas emissions, based on scientific consensus that global warming is occurring and that man-made CO₂ emissions are causing it (UNFCCC, 1998). To implement the ambitious objectives of the UNFCCC, the Kyoto Protocol was adopted at the third Conference of the Parties (COP3) held on December 11, 1997 in Kyoto (Japan). It came into force in 2005 and today has 191 members. The Protocol is a binding contract that regulates the general principles of precaution, of differentiated responsibility, and of the right to development of the members, the strategies of action and the obligations of the contracting parties. The primary goal is to reduce total global GHG emissions to minus 5.2% from 1990 emissions, representing approximately 29% of global GHG emissions. The Kyoto Protocol obliges 37 industrialized countries to reduce their carbon emissions, more than 70% of which result from industrial transformations. The main areas of implementation of the protocol are based on (i) mitigation of greenhouse gases, (ii) adaptation and resilience to climate change, (iii) reduction of vulnerability, (iv) carbon market, (v) support for developing countries, (vi) the global report on collective progress, and (vii) a transparency framework to report regularly on national GHG emissions. For this purpose, the protocol has set up three flexible mechanisms: (a) A Carbon Market (CM) or Emission Permits (EP), (b) a Joint Implementation Mechanism (JI), and (c) a Clean Development Mechanism (CDM). These mechanisms allow for the application of carbon credits or emission credits based on investment projects, particularly in developing countries. The Clean Development Mechanism (CDM) is a pioneer in investment and environmental credit within the framework of collaboration and the carbon market. It provides a standardized instrument for offsetting carbon emissions such as Certified Emission Reduction Units (CRUs). In other words, the CDM allows a country (Part Annex II) to implement an emissions reduction project for a better cost/efficiency ratio. This is a carbon selling and buying system where established projects can earn salable Certified Emission Reduction (CER) credits.

Each credit is equivalent to 1 ton of CO₂. Türkiye signed the Kyoto Protocol on June 4, 2008, and ratified it on February 5, 2009. In reality, Türkiye has no quantified commitment to reduce or limit greenhouse gas emissions under the Kyoto Protocol. The reason is that it was not yet a party to the UNFCCC in 1997 when the Kyoto Protocol was adopted. This did not allow it to be listed in Annex B to the Protocol, or the quantified obligations to reduce or limit greenhouse gas emissions are defined (MFA, 2023). Despite this status, the country must periodically update, publish and submit its annual inventory report on the sources of emissions and absorptions (reservoirs) from all sectors emitting greenhouse gases not covered by the Montreal Protocol in accordance with the contractual principles of the Paris Agreement as per the application of articles 4 and 12 of the convention.

d. Paris Climate Agreement

The Paris Climate Agreement was adopted on October 5, 2015, during the 21st Conference of the Parties to the Convention (COP21) held in Paris (Jenik, 2021). It was signed by 196 members on April 22, 2016, in New York (USA) and entered into force on November 4, 2016. The Paris Climate Agreement brought nations into a common cause to combat climate change. The agreement aims to limit the temperature rise to -2°C compared to the pre-industrial level by reducing global carbon emissions. The imminent goal of the Paris Agreement is to limit the rise in the earth's average temperature to 1.5°C. The recent COP27 held from November 6 to November 18, 2022, in Sharm el-Sheikh (Egypt) is a compliant extension of the Paris Agreement (CMA 4). The parties reaffirmed their commitment to limit the increase in global temperature to 1.5°C above pre-industrial levels. Although water is recognized and mentioned for the first time in a COP document, underlining the crucial role it plays in adapting to climate change, COP27 invited the members of the convention to strengthen their efforts through “rapid, deep and sustained reduction of global greenhouse gas emissions by 43% by 2030 compared to 2019 levels. The Kyoto Protocol and the Paris Agreement promote an international mitigation and adaptation strategy. This strategy is based on identifying natural carbon reservoirs, developing sustainable natural CO₂ sensors, and estimating carbon stock in these reservoirs. Forest ecosystems are the main natural reservoirs of carbon. Research has highlighted the flow, values, budgets and natural reservoirs of carbon in nature (Ciais et al., 2021; US-EPA, 2020).

1.1.7. Main Carbon Sinks and Reservoirs in the Global Natural System

Atmospheric carbon dioxide (CO_2) is the fourth most abundant element in the universe (NASA Earth Observatory, 2011). In its recent AR6 assessment report, IPCC (2022) estimate that the carbon is present in four large reservoirs in nature, as shown in Figure 8 (Next page). The basic component of carbon dioxide is carbon. All life on Earth is based on carbon. Carbon is part of the essential molecules, such as DNA and proteins, that make up our bodies, and constitutes the fats and carbohydrates in our diet. The air we breathe contains carbon in the form of carbon dioxide. It is also stored in the ocean, rocks, fossil fuels and plants. The flow of carbon between each of these places is explained by the carbon cycle (Britannica, 2023). For example, carbon moves in and out of the atmosphere and living organisms on a continuous basis (National Geographic, 2023).

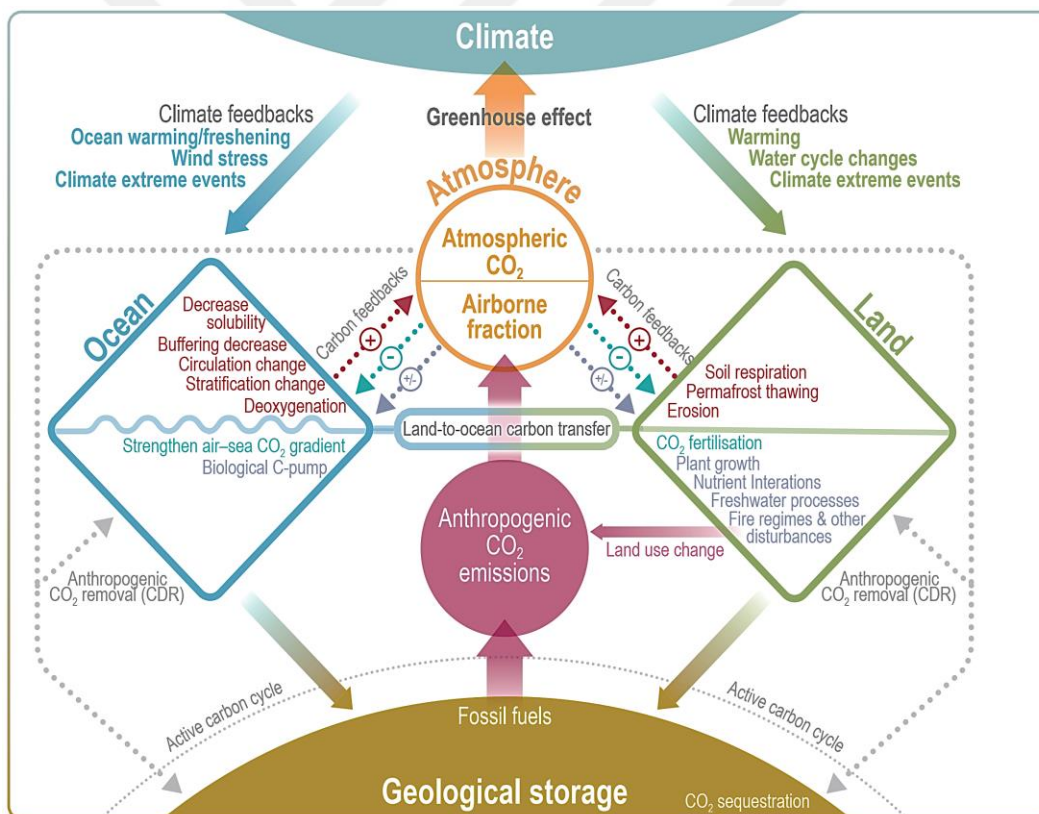


Figure 8. Main carbon sinks/reservoirs and their natural connections

Carbon is present in nature in organic and inorganic forms. These two states allow this molecule to move between the environments and constituents of nature (Lal, 2008; Le Quéré et al., 2014; Le Quéré et al., 2018).

According to several studies, carbon circulates in four major natural reservoirs, namely (i) Atmosphere, (ii) Hydrosphere (Oceans), Shallow Lithosphere (geological crust), and (iii) Biosphere (ecosphere), as show in diagram of Figure 8 proposed by (IPCC, 2022; NASA Earth Observatory, 2011; Berner et al., 1997; Britannica, 2023; Raupach et al., 2014). In the diagram of Figure 8, the arrows represent the processes of moving carbon from one sink to another. The Atmosphere receives carbon (CO_2) from the Lithosphere (volcanism, fossil fuels combustion, cement manufacturing, etc.) and the Biosphere (respiration/oxidation, agriculture, land uses, and deforestation). It releases CO_2 to the Biosphere (photosynthesis), to the Hydrosphere (absorption), and to the Lithosphere (alteration of limestone and silicates). The Lithosphere accumulates carbon release by the Hydrosphere (precipitation of CaCO_3) and by the Biosphere (burial of organic matter). The Biosphere also releases carbon to the Hydrosphere (respiration/oxidation). Globally, Figure 9 illustrates the carbon cycle, carbon stocks, sources, fluxes and their values between the different reservoirs/sinks.

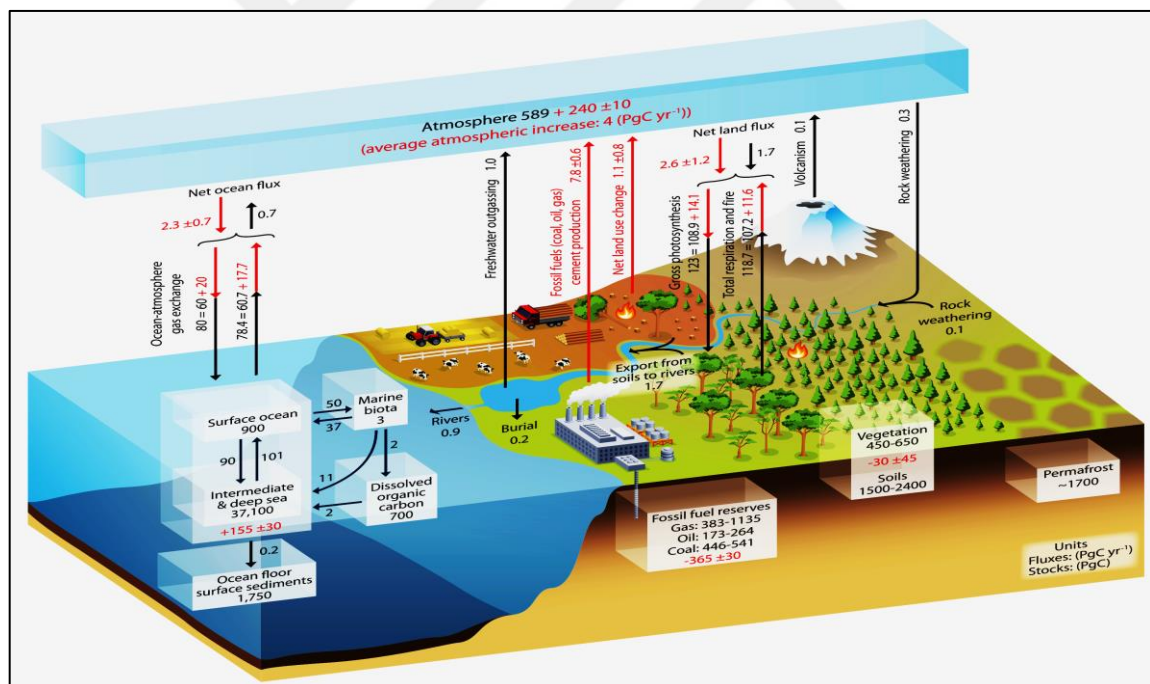


Figure 9. Representation of the global carbon cycle among the major reservoirs in the nature, where carbon fluxes are recorded (1PgC=1015 gC)

The Figure 9 indicate the simplified representation of Global Carbon Cycle showing the sinks of carbon stocks (PgC), annual flows values, carbon sources, paths, natural flows (black arrows) and human activities (red arrows) in GtC/year (Ciais et al., 2013).

For example, we note phenomena or processes of CO₂ absorption such as gross photosynthesis (108.9 PgC/year) or CO₂ emission such as ocean degassing (60 PgC/year). The mass of carbon in reservoirs and in exchange flows is represented by the black arrows and associated numbers and is attributed to preindustrial estimates (1750). The annual flows attributed to human activities for post-industrial periods (after 1750) are represented by the red arrows and associated numbers and are considered sources of carbon cycle disturbances. These flows (red arrows) represent the growth rate of CO₂ emitted from fossil fuels and cement, net land use change, and average atmospheric CO₂ increase. The terrestrial and oceanic net flows represented by the red arrows constitute carbon sinks/reservoirs. Several studies have been able to establish the difference between a Carbon Sinks and a Carbon Reservoirs (IPCC, 2003, 2013 and 2019; Bonan, 2008; Britannica, 2023; Le Quéré et al., 2009).

Indeed, a Carbon Sink refers to a natural or artificial system or process that absorbs and stores carbon dioxide (CO₂) from the atmosphere (Wikipedia, 2020), thereby reducing the concentration of CO₂ in the air. This can include ecosystems such as forests, oceans, peatlands, and soils that capture carbon from the atmosphere through photosynthesis and store it as biomass or organic matter. Carbon sinks contribute to reducing greenhouse gas emissions and play a crucial role in mitigating climate change. Forests are generally carbon sinks, absorbing more carbon than they release (National Geographic, 2023). On the other hand, a Carbon Reservoir refers to a reserve or stock of carbon stored over the long term. This can include geological formations such as coal, oil and natural gas deposits, as well as biological carbon reserves such as soils rich in organic matter and peatlands.

Carbon reservoirs are accumulations of carbon that can be released into the atmosphere by processes such as fossil fuel combustion or organic matter degradation. It should be noted that the terms Carbon Sink and Carbon Reservoir are often used interchangeably, but they refer to slightly different concepts (Baugh, 2023). The main difference between the two terms is that carbon sinks are processes that remove carbon from the atmosphere and store it in a reservoir, while carbon reservoirs are simply places where carbon is stored. Carbon sinks are more dynamic and involve active processes of capturing and storing carbon from the atmosphere, while carbon reservoirs refer to more passive stocks of carbon that can be released or sequestered over long periods. All movements of carbon between the sinks or reservoirs showed in Figure 9 constitute the Global Carbon Cycle (Lal, 2008; Friedlingstein et al., 2022; IPCC, 2003, 2013 and 2019).

The Carbon Cycle is defined as the spatio-temporal amplitude and residence time of carbon exchange between the Earth system and other spheres through photosynthesis and autotrophic/heterotrophic respiration (Six et al., 2002; Houghton and al., 2009; Houghton and al., 2005; Baugh, 2023). According to IPCC (2013), there are two cycles of carbon in the nature: the long cycle and the short cycle.

- The Long Carbon Cycle consists of carbon stored in rocks and sediments. The cycle lasts hundreds or even millions of years. CO₂ from the atmosphere is stored in sedimentary rocks through the weathering of silicates, hydrocarbons and other processes. The geological layers store more than 905 GtC of carbon with a flux of 9 to 10 GtC/year towards the atmosphere (Ciais et al., 2013). Exchanges with other short-cycle environments are only possible through volcanic CO₂ emissions, chemical weathering, erosion, and the formation of sediments in the seabed and other wetlands (Findlay, 2013; Dodds et al., 2010; Friedlingstein et al., 2022).

- The Short Carbon Cycle consists of carbon present in the atmosphere, ocean and surface ocean sediments, and on land in vegetation, soil, and freshwater, which moves quickly between reservoirs. This field undergoes large flows and relatively “rapid” reversals (Ciais et al., 2013; Ciais et al., 2021; Baugh, 2023).

CO₂ from the atmosphere is absorbed partly by water and partly by organic matter, i.e. plants, during the short cycle, which lasts around 4-5 years. The CO₂ is released when these plants decompose and returns to the atmosphere (Britannica, 2023; Selin, 2023). The oceans are the largest natural reservoir of carbon in the world. They store about 45,000 GtC including 700 GtC organic, with annual fluxes of 80 GtC/year with the atmosphere (Dodds et al., 2010). In the terrestrial biosphere or ecosystem, plants store about 500 GtC while soils and permafrost store between 1700-2000 GtC and just under 1700 GtC respectively. The annual carbon flux between the atmosphere and the biosphere is estimated at 130 GtC/year (Friedlingstein et al., 2022). It is in the terrestrial biosphere that the forest ecosystems in which the studied carbon is contained in plant mass and soils are located (Selin, 2023; Britannica, 2023).

1.1.8. Forest Ecosystem Dynamic in Climate change

a. Dynamics of Carbon Cycle and Natural Flow in Forest Ecosystems

Understanding the bio-geophysical, biogeochemical and biogeographical processes that drive this carbon cycle was facilitated by Bonan (2008) in “Forest and Climate Change: Forcings, Feedbacks and the Climate Benefits of Forests”, as shown in Figure 10.

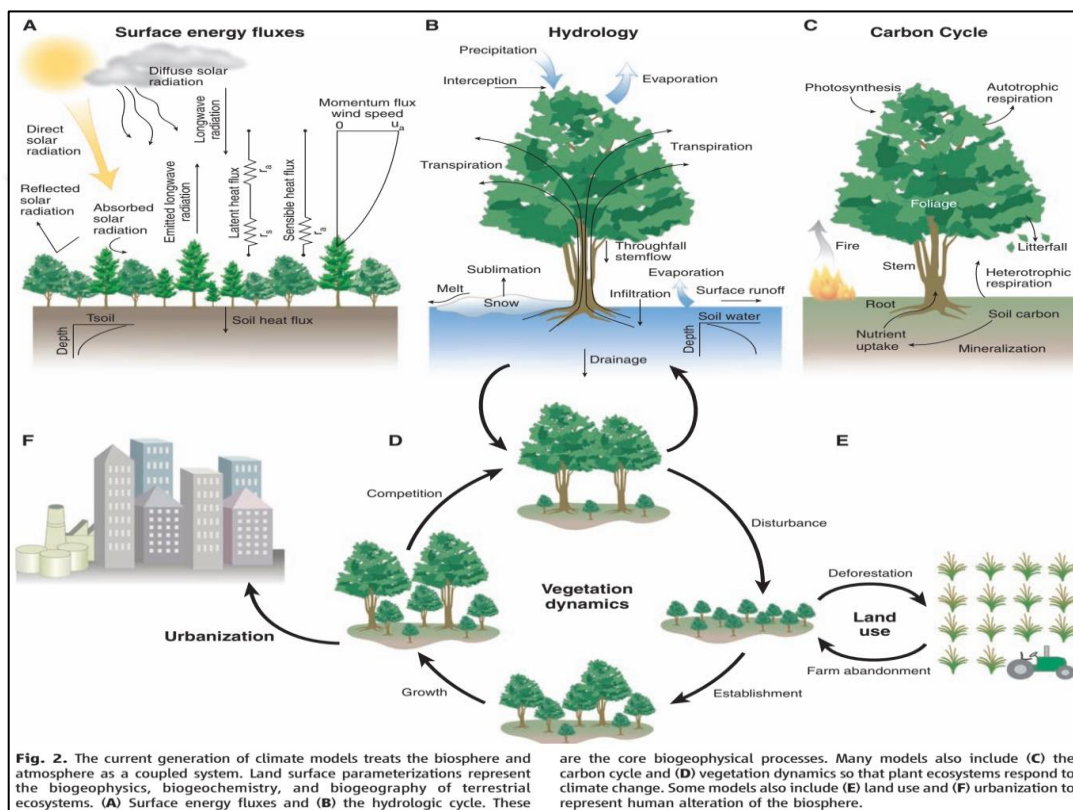


Figure 10. Carbon cycle in forest dynamics (Bonan, 2008)

In Figure 10, biomass formation movement and accumulation of carbon in the coupled biosphere-atmosphere system, determine the cycling and flux of carbon in forest ecosystems. Bonan’s approach (2008) emphasizes the importance of forests in the carbon cycle, highlighting their ability to capture, store and release carbon, as well as their essential role in mitigating climate change. Indeed, in forest dynamics, many nutrients are subject to the exchange process and to biophysical and biogeochemical factors that mediate the flux of carbon between the terrestrial ecosystem and the atmosphere. Photosynthesis and respiration are the two main carbon accumulation and loss processes in forest ecosystems as shown by the follow relationships (Figure 11).

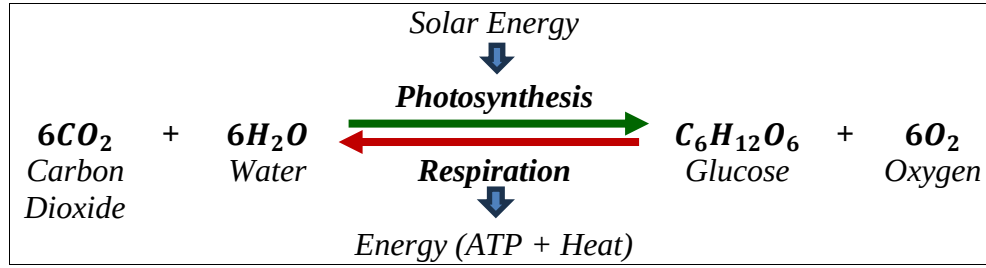


Figure 11. Photosynthesis and respiration equations in forest ecosystems

The Figure 11 shows that the Photosynthesis is the most important biogeochemical process in the forest carbon cycle, by which Autotrophic Organisms (trees) fix atmospheric CO_2 and water molecules (H_2O) in the presence of light, to produce organic compounds (C_nH_{2n}) which constitutes Gross Primary Production (GPP) or biomass, usable during respiration by the ecosystem (Mackenzie, 2004). According to Bar-On et al. (2018), the overall biomass of the biosphere contains approximately 550 GtC and mainly terrestrial plants represented 450 GtC. As shown by several studies, the carbon flows contained in biomass are the result of several biogeochemical processes. The production of biomass (Köhl, 2017) can help to substitute the fuel production because it is also the alternative source of fuel combustion (Koruba et al., 2017). Forest production is a part of changes in biomass and carbon storage (Köhl et al., 2015). A summary of some of these processes is presented in Table 2 (Next page).

Table 2. Biogeochemical process in the carbon flux and biomass accumulation

Biosphere or Terrestrial (Forest Ecosystems) Dynamics of Biomass/Carbon Production			
	Key driver	Definition	Expression
C flow	Ecosystem Respiration (ER)	Efflux of carbon from autotrophic and heterotrophic respiration	$\text{ER} = \text{R}_a + \text{R}_h$
	Gross Primary Production (GPP)	Total carbon fixed by the autotrophs during photosynthesis	$\text{GPP} = \text{Total C}$
	Net Primary Production (NPP)	Potential biomass/C available in the ecosystem after autotrophic metabolism	$\text{NPP} = \text{GPP} - \text{P}_a$
	Net Biome Production (NBP)	NEE with non-respiratory carbon loss and heterotrophic carbon gain (or) GPP with total ER and anthropogenic carbon flux	$\text{NBP} = \text{NEE} - \text{C}_{\text{efflux}} - \text{C}_{\text{influx}}$ or $\text{NBP} = \text{GPP} - \text{ER} - \text{A}_{\text{lulc}}$
	Net Ecosystem Exchange (NEE)	Net exchange of carbon between ecosystem and atmosphere	$\text{NEE} = \text{NPP} - \text{R}_h$
	Net Ecosystem Production (NEP)	Net carbon flux to or from an ecosystem	$\text{NEP} = \text{GPP} - \text{ER}$ or $\text{NEP} = \text{GPP} - \text{ER} - \text{A}_{\text{lulc}}$
R_a : Autotrophic Respiration; R_{ab} : Belowground Autotrophic Respiration; R_h : Heterotrophic Respiration.; A_{lulc} : Anthropogenic Land Use and Land Use Change. (Hari and al., 2022)			

In Table 2, the Total Carbon fixed represents Gross Primary Production (GPP). According to Kindermann et al. (2008), global forest cover accounted for 80% of all plant biomass on Earth and 75% of terrestrial gross primary production (Beer, 2010). In contrast, Ecosystem Respiration (ER) is the Total Efflux from Autotrophic (plants) and Heterotrophic (microorganisms) Respiration. CO₂, converted to carbon by the main biogeochemical process (photosynthesis), is stored in aboveground and belowground biomass, and in soil organic matter in the forest ecosystem (IPCC, 2003). Moreover, compared with the atmosphere, forests store more carbon in their biomass and soils. The quantification of these carbon stocks over the decades has revealed the importance and value of extensive forest ecosystems worldwide (IPCC, 2006, FAO, 2010; FAO, 2015).

b. Extent, Goal, Value and Importance of World's Forest Ecosystems

According to the World Resources Institute (WRI), forests are terrestrial ecosystems dominated by trees, covers at least 10% of the ground surface and an area of at least 0.5 hectares (FAO, 1999; Matthews et al., 2000; European Union, 2020). Forests cover diverse regions around the world. 31% of the Earth's total forest is found in Asia, 21% in South America, 17% in Africa, 17% in North and Central America, 9% in Europe and 5% in Oceania (FAO 2010). The Figure 12 presents an overview of the distribution of the global forest cover (Pan et al., 2013).

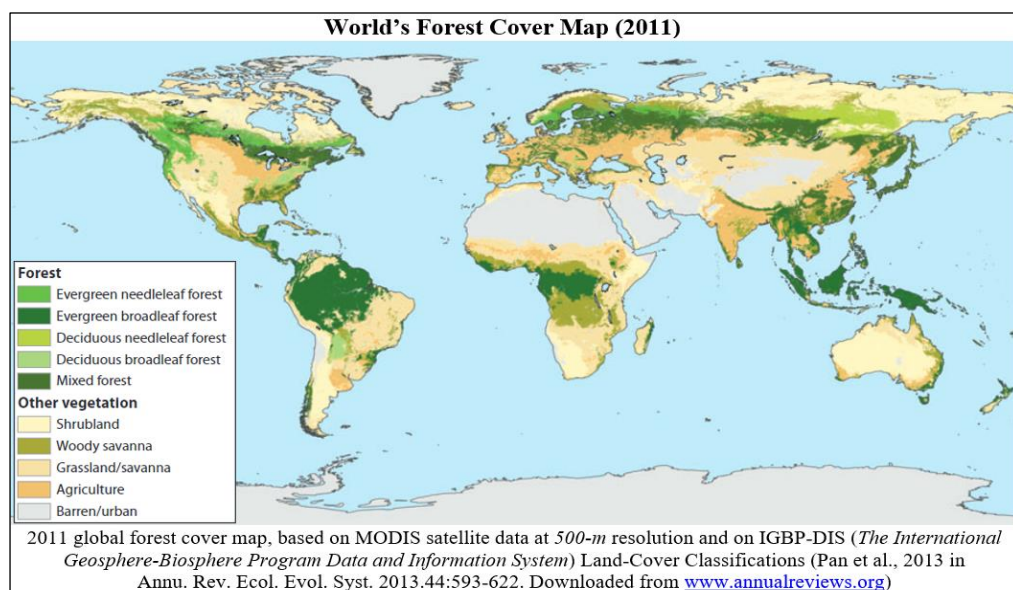


Figure 12. Overview of the map of world's forest ecosystems

According to recent data of FAO (2021), the main world's forests are constituted of 45% of tropical forests, 27% of boreal forests, 16% of temperate forests and 11% of subtropical forests (Figure 12). In the Global Forest Resources Assessment Report (FRA, 1990-2020), Food and Agriculture Organization (FAO, 2021) estimates that the total area of global forests is about 4.06 billion hectares (ha) in 2020 compared to 1990 (4.236 billion ha) and representing 31% of the total surface area of the earth. The most of the world's forests are located in the Russian Federation (815 million hectares), followed by Brazil (497 million hectares), Canada (347 million hectares), the United States of America (310 million hectares), China (220 million hectares) and the rest of the world (1870 million hectares). These five countries represent more than half (63%) of the world's primary forests. The one-third (34%) of primary forests consisting of native tree species and not having undergone significant human activities or ecological disturbances. Natural and Planted forests represent 93% and 7% (294 million hectares) of the world's forest area in 2020, respectively (FAO, 2021). Other wooded land was estimated at 977 million hectares in 2020, and represents 7% of the total land area (about a quarter of the world's forest area).

In Türkiye, forest ecosystems (closed and degraded) play important ecological (48.5%), economic (42.3%) and socio-cultural (9.2%) roles (Tolunay, 2013). The Global Forest Goals Report 2021 shared by United Nations Department of Economic and Social Affairs (UN-DESA, 2021), indicated that forest ecosystems are a reservoir of disease, and their conservation protects humans from infection. The destruction of forest landscapes generally gives rise to 75% of emerging infectious diseases, mainly zoonoses. Many essential health products, from masks to cleaning supplies, and ethanol for sanitizers (etc.), are supplied by forests. In developing and developed countries, herbal or plant-based medicines account for 80% and 25% respectively. Forests are home to most of the planet's terrestrial biodiversity, including ecosystems, species, and genetic diversity. Trees are the foundation of forest ecosystems, and many tree species are also important components of wooded and agricultural landscapes. Forests provide habitats for about 80% of amphibian species, 75% of bird species, and 68% of mammal species. About 60% of all vascular plants are found in tropical forests. However, the genetic diversity of trees is threatened and eroded by loss of tree forest stands, unsustainable harvesting practices, overgrazing, climate change, fires and invasive species. Forests have significant economic value, representing more than USD 1,520 billion in global GDP and providing jobs for 33 million people (FAO, 2021).

Forests ecosystems (sustainably managed) plays a central role in natural mitigation and adaptation to climate change. The diagram in Figure 13 presents some important roles that forests play in global climate change.

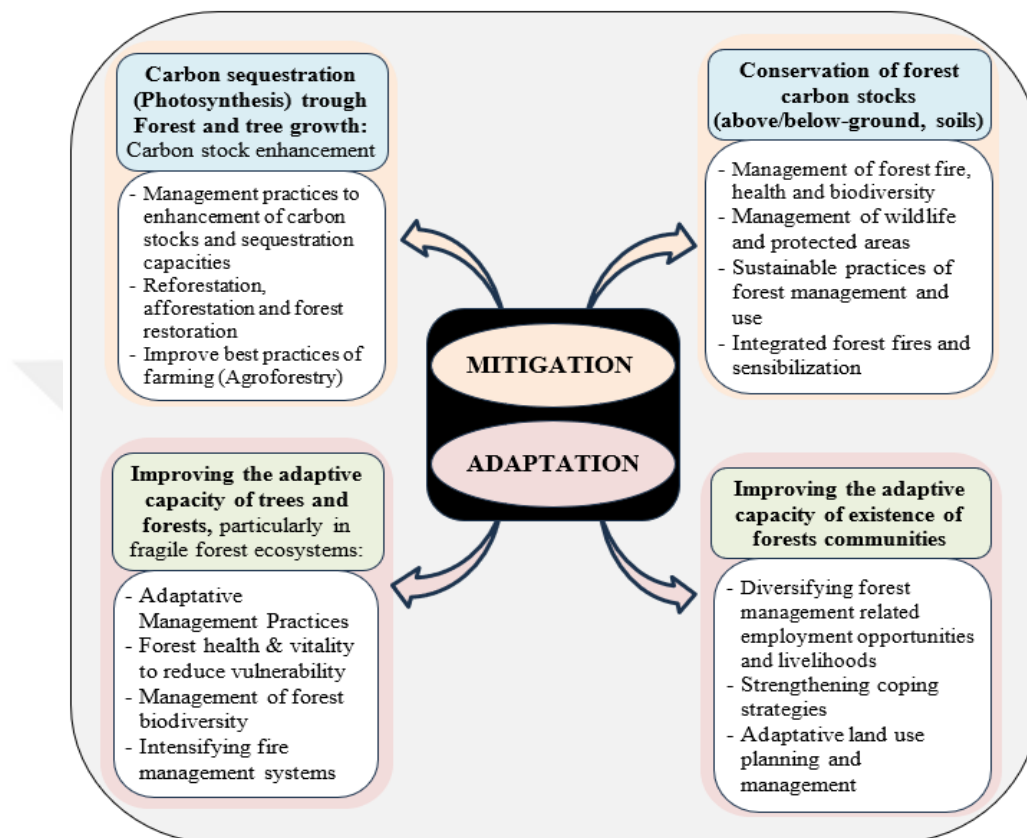


Figure 13. Mitigation and Adaptation playing by forests in global climate change

As shown in Figure 13, forests play an important role in climate change through the provision of ecosystem services such as protection of fragile ecosystems, oxygen production, carbon sequestration and storage. Excluding sedimentary rocks, about 67% of the carbon held in terrestrial ecosystems and 75% of this carbon held by vegetation worldwide are held in forests. According to UN-DESA (2021), forest ecosystems represent the largest terrestrial carbon sink and sequestering about two billion tons of CO₂/year. In 2020, the total carbon stock in forests was estimated at 662 Gt, with an average of 163 t/ha. Approximately 45% of the forest carbon stock in 2020 was in living biomass, 45% in soil organic matter, and 10% in dead wood and litter (FAO, 2021). Although the global forest carbon stock decreased between 1990 and 2020, the forest carbon stock per hectare increased, probably in part due to improved forest management.

The distribution of carbon in these forest types has been estimated from gross primary production, net primary production (NPP), respiration and the carbon cycle. Ameray et al. (2021) estimated that there are three forest management strategies widely and according to each of different forest types (tropical, temperate and boreal). These forests have significant carbon sequestration and storage capacity, such as indicated in Figure 14.

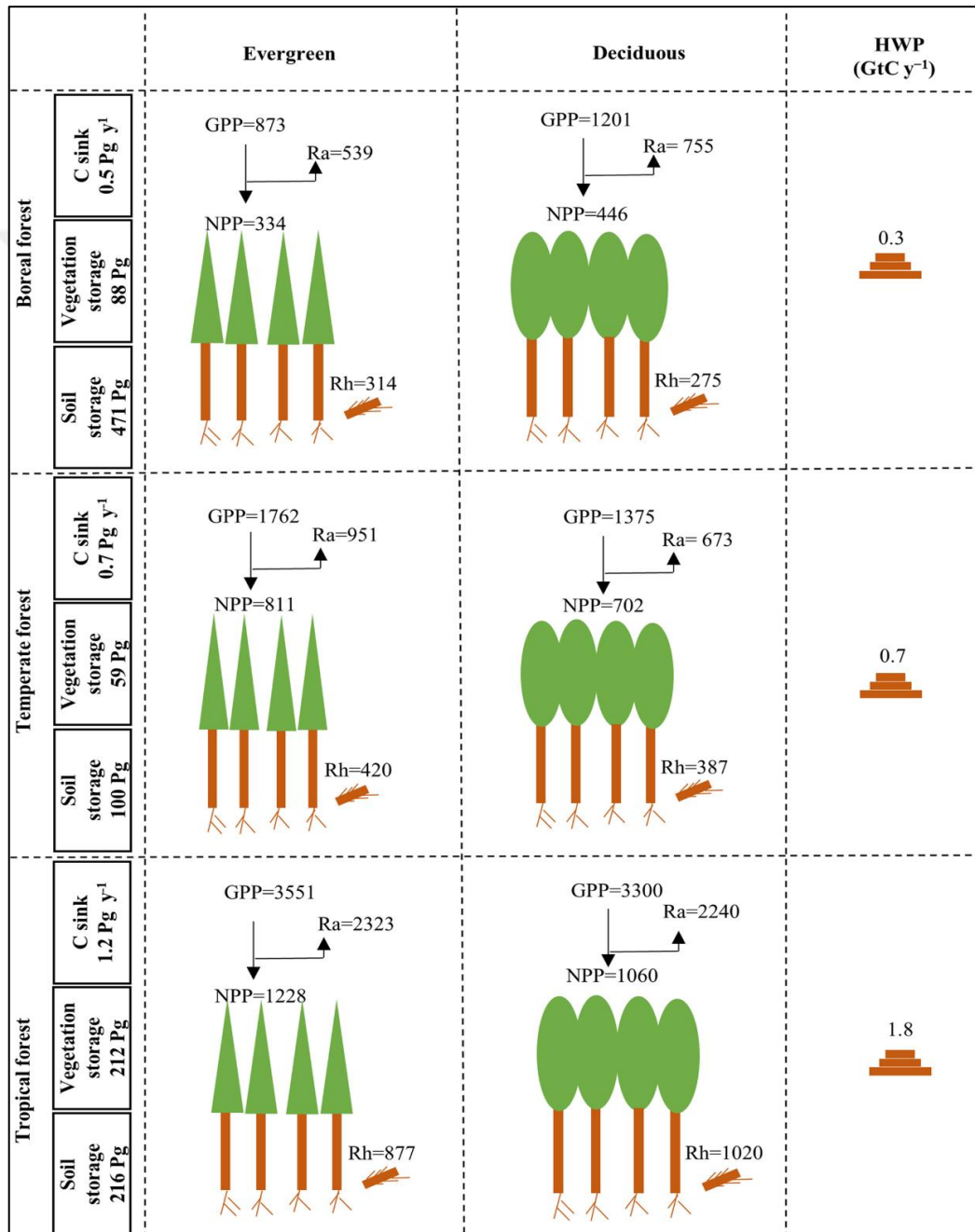


Figure 14. Harvested wood production, carbon sequestration and storage capacities of boreal, temperate and tropical forest ecosystems (Ameray et al., 2021)

According to Figure 14, boreal evergreen forests exhibit GPP, NPP, Ra, and Rh values of 873 g/m²/year, 334 g/m²/year, 539 g m²/year, and 314 g/m²/year, respectively. Tropical forests, with GPP exceeding 3000 g/m²/year, demonstrate a higher carbon sequestration capacity despite elevated Ra and Rh values (>2000 g/m²/year). Ameray et al (2021) indicates that temperate evergreen and deciduous forests have lower NPP but contribute significantly to carbon sequestration (Li et al, 2010). Boreal forests, with a total C sink of 0.50 Pg/year, store 88 Pg of carbon in biomass, surpassing temperate forests but falling short of tropical forests. Several studies have documented the importance of tropical forests in carbon sequestration with their significant biomass (Panzou et al., 2016). However, deforestation in tropical forests may release significant carbon into the atmosphere (1–2 Pg/year). Forest management strategies affect the net removal of carbon dioxide and contribute to climate change mitigation, particularly. Net emissions from land use, land-use change and forestry were 4.1 GtCO₂ per year, or about 10% of total anthropogenic CO₂ emissions, between 2011 and 2020. However, the land sink (mainly forests) was considerably larger than emissions from land-use change, sequestering 11.4 GtCO₂ per year, or about 29% of annual anthropogenic CO₂ emissions in 2011-2020. The carbon sequestered by forest ecosystems is stored in aboveground and belowground biomass pools, as well as in dead wood, litter, living plant matter and soil organic matter (FAO, 2021).

c. Principal Carbon Pools in Forest Ecosystems

According to IPCC (2006), there are six (06) categories of land use in the biosphere (terrestrial ecosystems), namely (i) forest land, (ii) croplands, (iii) grasslands, (iv) wetlands, (v) settlements and (vi) other types of land. The differentiation of forest ecosystems is the basis of their distribution and depends not only on animals and plants (biomass) but also on several other parameters, as altitude, density, productivity, time, dendrometric, climatic, edaphic, geographical and floristic data that influence this distribution (Ehbrecht et al., 2021). The carbon stored in forest ecosystems in organic form is distributed in different pools as can be distinguished in Figure 15 (Tree generated in this study, with Microsoft).

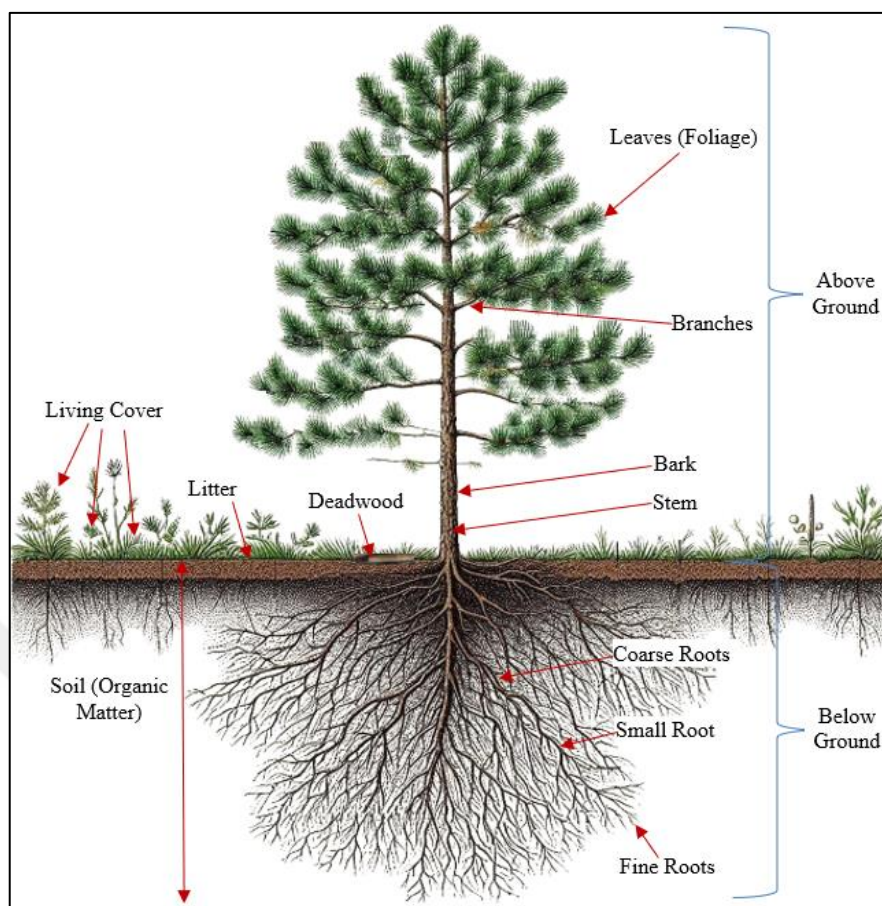


Figure 15. Biomass and carbon pools in a forest ecosystem

According to the Good Practice Guidance for Land Use, Land Uses and Forestry (LULUCF/IPCC, 2003-2006), the distribution of forest biomass can be found in the aboveground and belowground compartments (Figure 15). The further clarification on carbon pools terminology in these compartments are presented in Table 3.

Table 3. Terminology of biomass and carbon pools in forest ecosystems

Above-Ground	Living Trees	Stem, branches, foliage/leaves, bark, seeds, and stumps
	Living Cover	Herbaceous and other woody plants
	Dead Cover (Litter)	Branches, foliage/leaves, seeds, cones, etc., all kinds of debris and dead wood remains less than 2.5 cm in diameter
	Dead Wood	Dead trees standing or overturned, branches (>2.5 cm) Standing dead: least 12.7 cm diameter and root mass. Downed dead: diameter ≥ 7.5 cm includes stumps and roots
Below-Ground	Roots	Capillary or fine roots (0-2 mm); small roots (2-5 mm); coarse roots (5 mm>)
Soil		Soil Organic and/or Mineral Matters

In view of Figure 15 and Table 3, Carbon is distributed in both aboveground and belowground biomass. The distribution of carbon in aboveground biomass is influenced by temperature, precipitation, age and frequency of stands, latitude, soil characteristics and physiographic factors (land structure, slope, elevation, aspect). In belowground biomass (organic matter), carbon accumulation is influenced by the species and types of vegetation (coniferous or deciduous, shrubs, grasslands, etc.), the age of the species, the nutrients in the soil and the soil texture (Cairns et al., 1997). Soil organic carbon (SOC) is the largest carbon pool in the terrestrial diet which stores 54% carbon. SOC is transferred to the atmosphere and organic biota through soil carbon flux which is influenced by soil pH and nitrogen content (FAO, 2010; Hari and Tyagi, 2022). In these different forest carbon pools, global estimates of carbon stocks have been advanced by FAO (2021) for the period 1990-2020. The graph in Figure 16 illustrates the carbon stock distribution in forest pools.

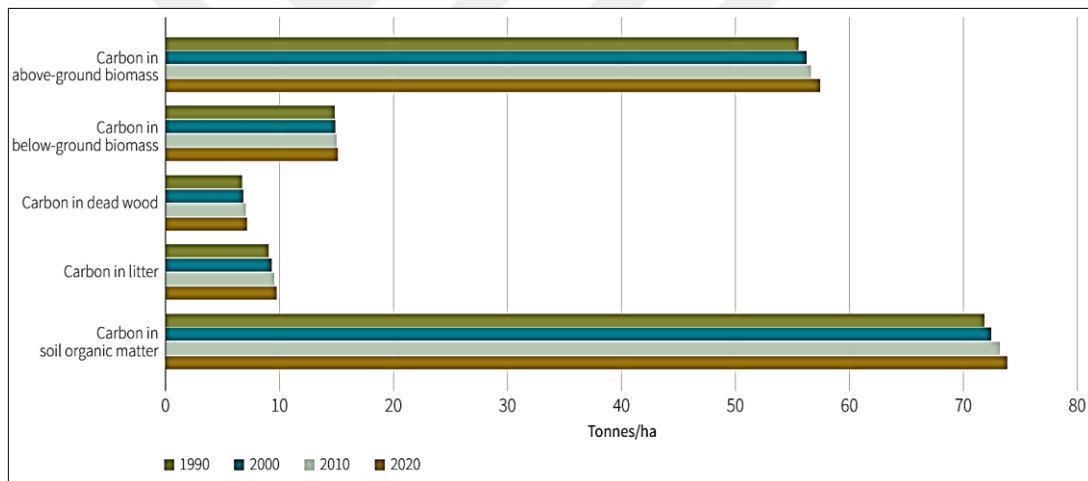


Figure 16. Global forest carbon stocks allocation by pools for 1990-2020 period

In the view of Figure 15, the mass of soil organic matter stores more carbon than all other carbon pools in forest ecosystems. Estimates are around 70-73 t/ha. Then, the aboveground biomass stores the second important part of forest carbon (about 60 t/ha), followed by belowground biomass (about 16 t/ha), litter (about 9-10 t/ha) and finally dead wood (about 6-8 t/ha). At the global, level, tropical dry forests store more than 14 GtC and lose approximately 0.58% annually. Tropical moist forests store more than 295 GtC and lose 0.45% by year. Mangroves retain 77.3 GtC and lose 0.13% by year. Temperate broadleaf forests store 133 GtC with an annual loss of 0.35%. Boreal forests store 283 GtC with an annual loss of 0.18% (FAO, 2021).

Temperate coniferous forests that retain more than 66 GtC lose about 0.28%/year. Boreal forests, tropical forests and temperate forests are estimated to sequester respectively 0.5 GtC/year, 1.19 GtC/year and 0.72 GtC/year (Pan et al., 2011 cited by Grafton et al., 2021; Ali et al., 2022). Beyond being a large habitat for several thousand animal and plant species, the forests of Türkiye constitute an immense natural carbon reservoir in the temperate regions. In these forest ecosystems, carbon storage varies significantly on several factors including tree species, diameter (1.30m), age, height, climatic conditions, soil properties, topography, and forest management strategy (Tolunay, 2011; Sun et al., 2019).

1.1.9. Extent, Value and Importance of Türkiye's Forest Ecosystems

Türkiye belongs to the domain of temperate forests. Its total forest area has increased from 20.199 million hectares in 1973 to 22.343 million hectares in 2015 and 23.245 million hectares in 2023 (TRT Haber, 2023), currently represents 29.8% of the national territory (78,3562 million hectares). Türkiye is among the top 10 countries that achieved an average annual net gain of 0.53% in forest area between 2010-2020 (FAO, 2021). Over the past four decades (1973-2015), Türkiye's total forest wealth has increased by about 48%. An expansion of 177,000 hectares of forests was recorded in the country in 2021 (OGM, 2021). Figure 17 shows a 2020 approximate forest cover map of Türkiye.

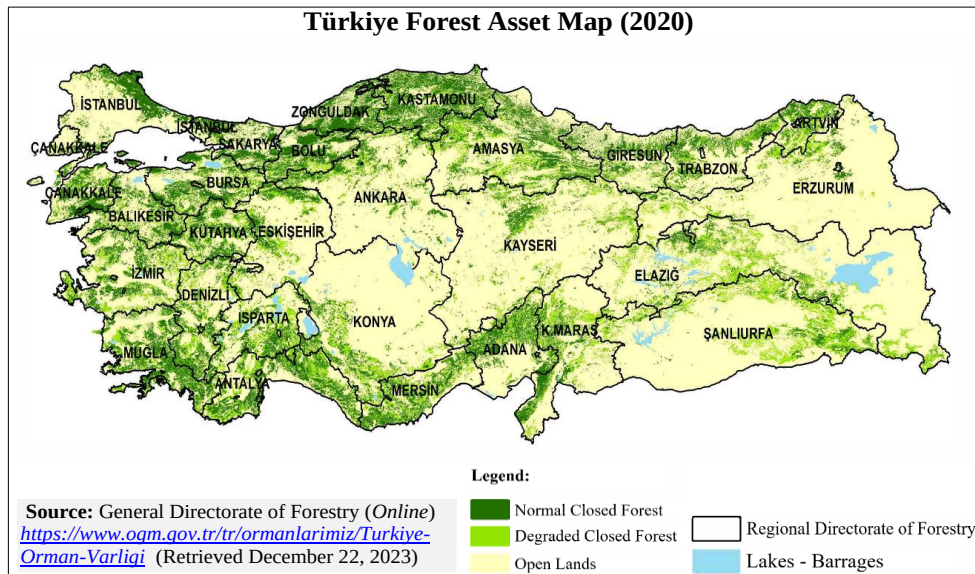


Figure 17. Map illustrating the forest cover of Türkiye

Between 2015 and 2020, the average yearly forest increase was 119.2 thousand hectares. Although the country has no primary forests, regenerated natural forests cover more than 21.5 million hectares in 2020 (Figure 17). Even-aged or same-age forests account for 12.79 million hectares of closed forest and 9.66 million hectares of degraded forest (OGM, 2021; TOD, 2022; FRA Türkiye Report, 2020). Country's Forests are primarily composed of conifers (48%) and deciduous trees or broadleaved forest land area (32%). Mixed (coniferous-broadleaved) forest land account for 20% (4,831 million hectares). More than 184 tree species are present in Türkiye. The primarily and important (socio-cultural, economic and ecological) tree species are made up of 29.42% pure and mixed stands of oaks (*Quercus spp.*), 22.74% Calabrian or Red pines (*Pinus brutia*), 18.31% Anatolian Black Pines (*Pinus nigra*), 8.19% beeches (*Fagus orientalis* and *Fagus sylvatica*), 6.15% Scots pines (*Pinus sylvestris*) and many other species (15.19%).

The study of the forest structure has already been addressed in several research works. For example, Yavuz et al. (2010) determined the parameters of *Pinus sylvestris* (Scots pine) mixed forests. The stand parameters are indispensable to describing the structure of forests. In other term, they contribute to the knowledge of the forests as well as their nature, physical, biometric, and dendrometric characteristics. Even-aged forests account for 12.79 million hectares of closed forests and 9.66 million ha of degraded forests. On the other hand, uneven-aged forests (1%) represent 292.4 thousand ha of normal closed forests, and 8.39 million ha of degraded forests. Uneven-aged forests account for 1% of total forest area, which is divided into normal closed forests (292.4 thousand hectares) and degraded forests (8.39 million hectares). Pure forests represent 8.38 million ha in normal non-degraded forests and 5.23 million in degraded forests. Mixed forests, on the other hand, cover 4.9 million hectares of normal forests and 4.43 million hectares of degraded forests. Normally closed forests account for 13.26 million hectares (58%) of the total, whereas degraded forests account for 9.7 million hectares (42%). According to national forecasts, 23.5 million hectares of forest will be developed by the end of 2023 (OGM, 2021; TOD, 2022).

Türkiye's forests play an important social (3%), economic (50%) and ecological (47%) functional roles for the country (Köse et al., 2002). Over the last 5 years (2017-2021), the industrial production of wood has increased by 78.7% (27.74 million m³) and that of firewood by 25.9% (4.12 million m³), i.e., a total national of 31.85 million m³ (69.5%) of wood production. More than 18.27 million m³ of wood was extracted from normal and degraded forests (9.7 million ha) (Türkiye Orman Derneği, 2022).

The annual increment of normal productive high forests represents 95,2% and 3,7% for degraded high productive coppices forests. Current increment of normal productive high forest represents 45,63 million m³ (95,8%) and the part of degraded high forests is 1,97 million m³ (4,2%) in 2021. Industrial production of wood has increased from 15.52 million m³ (2017) to 27.74 million m³ in 2021, i.e., 78% of production. The production of firewood used as an energy source increased from 3.27 million to 4.12 million m³ during the same period, i.e., 25.9% of production. The forest growing stock estimated to 1702 million m³ in 2021 (OGM, 2021). The growing stocks of conifers and broadleaved forests are respectively more than 1173 million m³ and about 5,49 million m³. It is therefore obvious to note that Türkiye has an important forest resource. This is why forest management is at the heart of the national climate change strategy in Türkiye.

1.1.10. Türkiye's Forest Management Strategy related to Carbon Control

Türkiye has implemented a meticulous national forest management strategy under the guidance of the document Principles and Procedures for the Regulation of Ecosystem-Based Forest Functional Management (ETFOP), outlined in Directive No. 299 (2017). The primary goal of this regulatory framework is to ensure sustainable management of the country's forest ecosystems. This strategy places significant emphasis on the ecological importance of forests, particularly their role in climate regulation and mitigation, achieved notably through carbon sequestration and storage. ETFOP advocates for thorough assessments of forest biomass and carbon stocks across all stands, as specified in Section 5.4.5 of Directive 299 (2017). Moreover, the directive establishes fundamental principles and methodologies for evaluating forests' carbon footprints, referencing the Good Practice Guide for the Land Use, Land Use Change and Forestry (GPG-LULUCF) sector, developed by the Intergovernmental Panel on Climate Change (IPCC, 2003-2006). Türkiye's national Forest Management Strategy aligns with these international obligations to maintain ecological equilibrium, underscoring its commitment to combat climate change through effective control of carbon storage capacities (Mısır et al., 2018; Seringil, 2018).

1.1.11. Carbon Storage Capacity of Forest Ecosystems in Türkiye

According to estimates from several studies, temperate forests sequester 0.72 GtC/year (Pan et al., 2011 cited by Grafton et al., 2021).

Coniferous forests in this temperate region store approximately 66 GtC and lose nearly 0.28% each year (Pan et al., 2011; Houghton et al., 2009; Liu et al., 2012; Köhl et al., 2015). According to estimates from 1960 to 1995, Türkiye's Forest ecosystems absorbed between 70 million tons (1960) and 79.5 million (1995) tons of atmospheric CO₂. These forests can store up to 875 million tons of carbon, with 63.1% in plant biomass and 36.9% in forest soil biomass (Asan, 1995). According to a recent Report on the State of Forests in Türkiye 2021, the country's forest ecosystems store 1.99 GtC and produce over 43.37 MtO₂ (OGM, 2021). In northern Türkiye, carbon stored in living biomass increased from 293,900 tC (1997) to 327,200 tC (2013) (Mısır, 2013). The soil profiles in coniferous (751 samples) and in deciduous (191 samples) stands in Türkiye store on average 77.1 MgC/ha and 80.4 MgC/ha, respectively. Forest dead cover stores 7.8 MgC/ha of pure conifers, 3.1 MgC/ha of deciduous trees, 7.2 MgC/ha of mixed conifers, 7.0 MgC/ha of mixed coniferous and deciduous trees, and 6.4 MgC/ha of mixed deciduous trees (Tolunay and Çömez, 2008).

The aboveground biomass (with litter) in *Fagus orientalis* stands in Northern Türkiye (Trabzon), accounted for 70% of the stored carbon (Mısır et al., 2018). Based on soil profiles at depths of 0-15 cm and 15-30 cm, the root biomass capacity of pure and mixed stands of Scots pine (*Pinus sylvestris*) is 9328 kg/ha and 18720 kg/ha, respectively (Yavuz et al., 2010). Similar studies have been conducted in other forest stands such as *Picea orientalis* stands (Mısır et al., 2010) and *Pinus strobus* stands (Peichl and Arain, 2007), in addition to the same species as studied by Tolunay (2009). The rate of carbon sequestration in Çaykara Managed Forest Unit is 1.37 MgC/year/ha by living biomass due to increases in forest area and growing stock (tree) over the past 40 years (1971-2010) in Türkiye (Karahalil et al., 2018). In Türkiye, the distribution of carbon stocks is fundamentally influenced by different types of forest stands.

Çömez (2012) estimated that terrestrial biomass (above-ground) and tree roots stored approximately 1.279 tC/m³, and this varied across several types of Scots pine (*Pinus sylvestris* L.) stands in the mountainous region of Sünderken (Eskişehir). The variations were based on their developmental stage and degree of crown closure. Pure and mixed forests of *Pinus sylvestris* in Türkiye could store between 28 t/ha and 120 t/ha respectively (Yavuz et al., 2010). In the essay titled "Best practices and policies addressing forest in response to climate change", Mısır et al. (2018) indicate that the forests of Türkiye, considered as a terrestrial reservoir, play an important part in the global carbon cycle by absorbing 2.908 PgC/year between 2004 and 2013.

Mısır et al. (2012) assessed the biomass and carbon of the roots (Fine, Small, and Coarse) in research on *Abies normaniana* stands in the Black Sea Region (Türkiye) to be 39628 kg/ha and 9365 kg/ha, respectively. According to the authors (Misir et al., 2018), the total carbon store in country's forest ecosystems in 2015, was roughly 2649 TgC, with living biomass accounting for 92.20% of that total. Several authors believed that incorporating studies on spatiotemporal changes in biomass and forest carbon stocks into management methods enabled an adequate valuation of ecosystem functions and sustainable forest management in Türkiye, particularly in light of climate change (Fosso, 2021; Karahalil et al., 2018; Vatandaşlar et al., 2019). The Türkiye Forest Sector Strategic Plan 2019-2023 anticipates an increase in national forest areas (OGM, 2019). This will increase carbon sink capacity by increasing forest productivity. Several other studies have demonstrated the forest's importance in mitigating climate change in Türkiye, Europe, and around the world by sequestering and storing carbon in forest biomass (Misir et al., 2013; Misir et al., 2011). According to the Ministry of Agriculture and Forestry of Türkiye, the carbon storage capacity of all forest soils in Türkiye is 55.68 t/ha in the 0-30 cm depth range, accounting for 38.33%, alongside 33.39% (49.77 t/ha) for pasture and 26.94% (35.96 t/ha) for agricultural lands (Çem, 2018).

In summary, In the LULUCF sector, TÜİK (2021) estimates show that Türkiye's forests and processed wood products captured 75.31 million and 11 million tons of CO₂ equivalent respectively, between 1990-2019. Only 2 million tons of CO₂ equivalent emissions were released. Thus, the net carbon capture of the LULUCF sector is 84 million tons of CO₂ equivalent. This represents an increase of 47 percent from 1990. Forest ecosystems therefore constitute the main natural drivers of CO₂ sequestration in Türkiye, through sustainable land use, forest management, afforestation and restoration studies, and land rehabilitation. In addition to the guide proposed by the FAO (2010), IPCC (2006) proposed methodological recommendations for the evaluation and calculation of the variation of carbon stocks according to their emission sources and their storage sink.

1.1.12. Forest Biomass Carbon Stock Estimation Methods in Türkiye

Carbon in an ecological system, is typically measured using either direct (destructive) or indirect (non-destructive) methods, or a combination of the two.

The goal of each method is to precisely quantify the carbon contained in the living and/or belowground biomass of the sampling ecosystem, as well as soil organic matter. Globally, several classic and modern methods for monitoring carbon changes, flux and stock have evolved or used in the world (Petrokofsky et al., 2012; Birdsey et al., 2013; Kurz et al., 2016; Kadioğulları and Karahalil, 2013; Pearson et al., 2007). The most well-known are the Turbulence Covariance Method (Launiainen et al., 2005; Lognoul, 2014), Dynamic Chamber Method (Duthoit et al., 2020), Integrated Models (Foley et al., 1996), Allometric Equation and Remote Sensing (Vashum and Jayakumar, 2012). In the literature, we find Harvest Method (destructive), Carbon Flux Measurements (gain and loss, stock-difference), Satellite or Remote Sensing (aerial data), and the Modeling Approach particularly for Above-Ground Biomass and Carbon (Güner and Güner, 2021), and also Cut and Dug-up (destructive) method and/ allometric equations for belowground (roots biomass and Carbon) (U.S. Forest Projects, 2015; Uykun, 2018; Woodall et al., 2011). For example, Işık (2013) experimented with different methods (conversion factor and allometric equations) for estimating biomass in the forest ecosystems of Kapıkaya Planning Unit (Türkiye). The approaches recommended by the United Nations Framework Convention of Climate Change (UFCCC) in Good Practice Guidance of Land Use, Land-Use Change and Forestry (GPG-LULUCF) are also Direct Method or Higher-Method (field inventories) and Indirect methods (Coefficients and Expansion Factors), Allometric Equations, and Remote Sensing Methods (IPCC, 2003-2006; FRA/FAO, 2010). From this LULUCF guide, the methods currently used in Türkiye have been regulated and documented in the ETFOP national strategy for the study of biomass and carbon in forest ecosystems.

a. LULUCF/AFOLU and FRA 2010 Carbon Estimation Methods

Türkiye, like all Kyoto Protocol signatory countries, primarily uses the IPCC-recommended Guide to Good Practice of Land Use, Land Use Change, and Forestry (GPG-LULUCF/AFOLU) in the preparation of the annual national report on the inventory of changes in biomass and carbon stocks in forest ecosystems. This guide proposes three methodical approaches for estimating biomass and carbon stocks and variations in forest ecosystems (Peter et al., 2014; IPCC, 2003 & 2006; Indur et al., 2014).

➤ Method 1 or Tier 1 Approach (Default or Indirect Method)

Method 1 is an indirect method that uses global default data based on the Coefficients of Conversion and Expansion Factors (C/EF) defined from global data sources for coniferous and deciduous forests separately, as indicated in Table 4.

Table 4. Terminology of biomass and carbon coefficient in LULUCF/AFOLU

LULUCF (2003)		AFOLU (2006)	
Symbols	Indication	Symbols	Indication
WD	Wood Density (t/m ³)	BCEF₁	Wood Density (t/m ³)
BEF₁	The increase in stem biomass resulting from the annual net volume increase (including bark) is calculated as the above ground biomass expansion factor (dimensionless)	BCEFs	The increase in stem biomass resulting from the annual net volume increase (including bark) is calculated as the above ground biomass expansion factor (dimensionless)
BEF₂	Available mass of stem biomass above ground biomass expansion factor (dimensionless)	BCEF_r	Available mass of stem biomass above ground biomass expansion factor (dimensionless)
R	Root to shoot ratio (dimensionless)	R	Root to shoot ratio (dimensionless)
FBL	The part of the biomass decomposing in the forest (dimensionless)	CF	Carbon factor (0.51 for the coniferous, 0.48 for the leaves)
CF	Carbon factor (0.50)		

Method 1 (IPCC Tier 1 Approach) is based on the use of dendrometric information obtained from forest inventories. The most important of which are Diameter at Breast Height (D_{1.30}) and in rare cases, the tree Height (H). These inventories are conducted to determine the commercial value of the stem wood rather than the biomass of the ecosystem (Tolunay, 2019; Mısıır et al., 2017). The tree diameter collected during field inventories is used in the application to calculate the commercial volume of each tree. The predefined allometric equation specific to each species are also used to estimate individual tree stem volume or biomass. Using the wood density or conversion coefficients and expansion factors (BEF, BECF, CF) of GPG-LULUCF/AFOLU or FRA 2010 (FAO, 2010), the resulting volume table is converted into biomass and then into carbon stock. In 2010, the Food Agricultural Organization (2010) established the default conversion/expansion coefficients/factors recorded in the Forest Resources Assessment Guide (FRA 2010), which each country can use in the event of the absence or insufficiency of national data. Table 5 defines the terminology used in the FRA 2010 guide's default parameters for deciduous and coniferous forests using in Türkiye.

Table 5. Parameter terminology of the FRA 2010 method (FAO, 2010)

Carbon Pools	Forest Types	Calculation Methods and Coefficients	
		Productive Forests	Degraded Forests
Above-Ground Biomass (AGB)	Coniferous	SV x 0,496 x 1,22	SV x 0,496 x 1,22
	Deciduous	SV x 0,638 x 1,24	SV x 0,638 x 1,24
Below-Ground Biomass (BGB)	Coniferous	AGB x 0,29	AGB x 0,40
	Deciduous	AGB x 0,24	AGB x 0,46
Above-Ground Carbon (AGC)	Coniferous	AGB x 0,51	AGB x 0,5
	Deciduous	AGB x 0,48	AGB x 0,4
Below-Ground Carbon (BGC)	Coniferous	BGB x 0,51	BGB x 0,51
	Deciduous	BGB x 0,48	BGB x 0,48
Dead Woods Carbon (DWC)	Coniferous	AGC x 0,01	AGC x 0,01
	Deciduous	AGC x 0,01	AGC x 0,01
Dead Cover Carbon (DCC)	Coniferous	A ₁ x 22	A ₃ x 6
	Deciduous	A ₂ x 13	A ₄ x 2
Soil Organic Carbon (SOC)		(A ₁ + A ₂) x 34	(A ₃ + A ₄) x 34
Ecosystem Total Carbon (ETC)		AGC + BGC + DWC + DCC	
SV = Stem Volume (m ³); A ₁ : Coniferous and Productive Forest Area; A ₂ : Deciduous and Productive Forest Zone; A ₃ : Coniferous and Degraded Forest Zone; A ₄ : Leafly and Degraded Forest Area			

The biomass and carbon stock of belowground pools (roots) and litter are calculated using factors and ratios in Indirect Approach (Tier 1). Method 1 was used to create Türkiye's first national carbon report (2006). This indirect approach has been used in several works in Türkiye (Tolunay and Çömez, 2008; Yavuz et al., 2013; Tolunay, 2012 and 2019; OGM, 2019; Durkaya ve ark., 2018; Varol ve ark., 2018; Ünsal, 2007; Çömez, 2011).

➤ IPCC Tier 2 Approach or Method 2 (Indirect Method)

IPCC Tier 2 Approach is similar to Method 1 (Tiers 1 Approach) but the distinction is due to Method 2 is based on the coefficient (conversion/expansion factors and coefficients) developed by the country from the national data and use at the national level. In this context, it is important to remember that the first factors, as shown in Table 6, were developed in Türkiye by Assan (1995; 1999; 2002). The limitations of the Asan method were quickly identified in light of the FRA 2010 method, which emerged over time (Asan, 2011).

In accordance with the Procedures and Principles for the Regulation of Ecosystem-Based Forest Functional Management Plans (ETFOP), several authors proposed new coefficients and factors (Varol, 2018; Mısır et al., 2017; Tolunay, 2013; Asan, 1995).

Table 6. Terminology of coefficients and factors of Asan method (1995)

Asan Calculation Methods Method (1995)		
Pools	Type of Tree Species	Calculation Methods
Above-Ground Biomass (AGB)	Deciduous Forests	$SV \times 0,640 \times 1,25$
	Coniferous Forests	$SV \times 0,473 \times 1,20$
Below-Ground Biomass (BGB)	Deciduous Forests	$AGB \times 0,15$
	Coniferous Forests	$AGB \times 0,20$
Dead and Living Covers Biomass (DLCB)		$(AGB + BGB) \times 0,40$
Total Biomass (TB)		$AGB + BGB + DLCB$
Total Carbon in TB (TCTB)		$TB \times 0,45$
Soil Organic Carbon (SOC)		$TB \times 0,45 \times 0,58$
Total Carbon (TC)		$TCTB + SOC$

In the works entitled “Coefficients that can be used in the calculation of plant mass and carbon amounts from Increment and Forest Wealth in Türkiye” and “Biomass factors used to calculate carbon storage of Turkish forest”, Tolunay (2019) proposed new coefficient for Türkiye’s Forests. Table 7 (next page) shows the coefficients proposed for biomass and carbon estimation in deciduous and coniferous forests in Türkiye.

Table 7 shows some of the conversion coefficients developed in Türkiye over the last few decades. The use of these coefficients (Tier 2 Approach) in the assessment of carbon stocks in forest biomass has been regulated by ETFOP (Türkiye NIR, 2021; OGM/ETFOP in Directive No 299, 2017; Mısır et al., 2017; Gültekin et al., 2019; Gültekin et al., 2017).

According to ETFOP based on Tier 2, which is based on factors and coefficients for estimating biomass and its conversion into carbon (Tier 2 Approach) showing in Table 8 Next page), the indirect method facilitates the derivation of biomass and global equivalent carbon stock. This is achieved by using the cumulative values of above-ground biomass, below-ground biomass, dead wood and soil organic matter, in conjunction with conversion and expansion factors. The total biomass and equivalent carbon stock of the ecosystem is obtained by summing the totals of all individual pools (above/below ground) (Yolasığmaz et al., 2016).

Table 7. Terminology of biomass and carbon coefficients (conversion, expansion) proposed in ETFOP and others researchers in Türkiye

Elements	Group of Species	BCE _{F1} (t/m ³)	BCE _{Fs} (t/m ³)	BCE _{Fr} (t/m ³)	BCE _{Fleaf} (t/m ³)	BCE _{Fbranch} (t/m ³)	BE _{F1}	BE _{F2}	CF	WD
Türkiye's National Forest Management Strategy Document (ETFOP)										
ETFOP	Coniferous	0.541	0.563	0.612	/	/	1.212	1.262	0.51	0.446
	Deciduous	0.709	0.717	0.797	/	/	1.310	1.326	0.48	0.541
Proposed by Several Authors										
Tolunay, 2019	Coniferous	0.518	0.533	0.580	/	/	1.208	1.265	0.51	0.40
	Deciduous	0.691	0.657	0.730	/	/	1.293	1.335	0.48	0.52
Mısır et al., 2017	Coniferous	0.548	0.570	0.620	0.031	0.070	/	/	/	/
	Deciduous	0.712	0.729	0.810	0.043	0.128	/	/	/	/
Tolunay, 2013	Coniferous	0.541	0.563	0.612	0.028	0.067	/	/	/	/
	Deciduous	0.709	0.717	0.797	0.039	0,128	/	/	/	/
Çömez, 2010	<i>Pinus</i>	0.545	/	/	/	/	1.279	/	/	/
	<i>Sylvestris</i>									
Atmaca, 2008	<i>Pinus</i>	0.510	/	/	/	/	1.198	/	/	/
	<i>Sylvestris</i>									
Uğurlu 1976	<i>Pinus</i>	0.529	/	/	/	/	1.242	/	/	0.426
	<i>Sylvestris</i>									
Ünsal, 2007	<i>Pinus</i>	0.645	/	/	/	/	1.349	/	/	/
	<i>brutia</i>									
Çakıl, 2008	<i>Pinus nigra</i>	0.503	/	/	/	/	1.071	/	/	0.470

The terminology of ETFOP (national) coefficients is presented in Table 8.

Table 8. Terminology of the ETFOP method for calculating forest carbon

ETFOP Carbon Pools	Forest Types	Calculation Methods and Coefficients	
		Productive Forests	Degraded Forests
Aboveground Biomass (AGB)	Coniferous	SV x 0,446 x 1,212	SV x 0,446 x 1,212
	Deciduous	SV x 0,541 x 1,31	SV x 0,541 x 1,31
Belowground Biomass (BGB)	Coniferous	AGB x 0,29	AGB x 0,40
	Deciduous	AGB x 0,24	AGB x 0,46
Aboveground Carbon (AGC)	Coniferous	AGB x 0,51	AGB x 0,51
	Deciduous	AGB x 0,48	AGB x 0,48
Belowground Carbon (BGC)	Coniferous	BGB x 0,51	BGB x 0,51
	Deciduous	BGB x 0,48	BGB x 0,48
Dead Woods Carbon (DWC)	Coniferous	AGC x 0,01 x 0,47	AGB x 0,01 x 0,47
	Deciduous	AGC x 0,01 x 0,47	AGB x 0,01 x 0,47
Dead Cover Carbon (DCC)	Coniferous	A x 7,46	A x 1,86
	Deciduous	A x 3,75	A x 0,93
Soil Organic Carbon (SOC)	Coniferous	A x 76,56	A x 19,14
	Deciduous	A x 84,82	A x 21,20
Total Carbon (ETC)		AGC + BGC + DWC + DCC + SOC	
Indications		SV = Stem Volume (m3); A: Sample Area	

Globally, using method 1(Tier 1) and 2 (Tier 2) improved by the GPG-LULUCF/AFOLU, 2003-2006; FRA 2010 (FAO, 2010) and ETFOP (IPCC, 2003-2006; OGM, 2014; Tolunay, 2013 and 2019), whose principle of application is the same, several research works have been carried out in Türkiye on a limited number of trees species such as the *Pinus brutia* (Ten.) or Turkish pine (Aydın et al., 2017), *Pinus sylvestris* or Scots pine (Tolunay, 2009; Tüfekçioğlu et al., 2010; Demir, 1992; Çömez, 2011), *Pinus nigra* Arnold subsp. *Pallasiana* (Lamb.) Holmboe or Anatolian Black Pine (Özkan, 2003; Sevgi, 2003). Other studies have also been carried out for the *Fagus orientalis* (Mısır et al., 2013; Yener, 2006; Özhan, 1977).

➤ IPCC Tier 3 Approach or Method 3 (Direct Method)

Method 3 (Tier 3 Approach) is a higher-tier and complex method recommended in GPG-LULUCF (IPCC, 2003 & 2006). It is a complex approach based on the direct fieldworks and reflects national conditions (Amon et al., 2021; Federici and Grassi, non-dated). This approach is intricate, highly accurate, enabling the direct collection of comprehensive and explanatory data in the fieldworks. While it carries potential harm to the biota and proves costly for operators, it affords the incorporation of ecological, climatic, and edaphic (soil) attributes, particularly numerous species-related variables, including single-tree attributes (species, height, diameter, age, quality), community characteristics (stand type, density, influence), growth environment factors (site index, canopy consistency, diverse development stages, various age classes), topographic properties (elevation, slope, aspect), geographic data (altitude, coordinates), and silvicultural practices (IPCC, 2006).

Moreover, this pragmatic approach is rooted in a meticulous inventory, facilitating the estimation of net primary production (NPP) as well as belowground and aboveground biomass within the studied ecosystem (Yavuz et al., 2010; Başkent and Makineci, 2021). This method aligns with the aspiration for precise national forest carbon stock estimates and serves as a robust benchmark, validating other quantification methods through its consideration of terrestrial ecosystem-influencing factors (Misir et al., 2018). Despite localized biased sampling errors arising from disparities in inventory timing, plot locations, measurement inaccuracies, and imprecise estimation patterns, the comprehensive (direct) method sets the standard for extending indirect approaches from the local scale to the national, regional, or even global level (Hari and Tyagi, 2022).

In Türkiye, a few studies on pure and mixed stands consisting of a few tree species (*Pinus brutia*, *Pinus nigra*, *Pinus sylvestris*, *Quercus*, *Abies nordmanniana*, etc.) have been carried out using the Tier 3 Approach (Yavuz et al., 2010; Mısır, 2012; Mısır et al., 2018; Çömez, 2012; Öztürk, 2022; Sakıcı et al., 2016; Gültekin et al., 2019; Güner and Güner, 2021). These studies devoted great material, human and financial resources to collecting data in the field and realize laboratory works. Globally, several of these studies also resorted to Remote Sensing methods (Kanja et al., 2019; Karahalil et al., 2018; Aksoy, 2021), regression (allometric models) and artificial intelligence such as Artificial Neural Networks (Sakıcı et al., 2018; Seki, 2023) to analyze forest biomass and carbon storage. Their work indicated considerable improvements over those using indirect methods (Varol et al., 2018).

b. State of Biomass and Carbon Storage Modeling in Türkiye

- Regression Method used in Biomass and Carbon Modelling

Regression is one of the methods used to model the statistic or mathematical relationship between two or more independent and one or more dependent variables through linear and/or non-linear equations. In forestry, several studies used regression methods to developing allometric equations (models), capable of explaining precisely the influence relationships between dependent (volume, biomass or carbon) and independent (diameter, height, volume and others stand parameters) dendrometric, biometric and other variables types. Some examples of these biomass prediction models are illustrated in Table 9 (next page). Several other works have also documented linear and non-linear regression models for biomass and carbon storage of some trees and stands in Türkiye (Aydın and Can, 2017; Karagöz and Akbulut, 2016; Demir and Kaya, 2014). Many biomass prediction models are developed based on the diameter at breast height ($D_{1.30}$) considered alone or sometimes with the height (H) of the trees as independent variable(s). Several other studies have established carbon prediction relationships for certain tree species based on diameter and/or height. The world compilation of tree allometric is showing by GlobAllomeTree (Henry et al., 2013) and Fantallometrik (Trotta et al., 2013). In Türkiye, this is the case of the studies presented in Table 10 (next page), with C is total tree carbon stock (kg/ha or t/ha); D is tree diameter (cm) at 1.30 m.

Table 9. Illustration of biomass models of some tree species in Türkiye

Species	Name	Models	References
<i>Pinus sylvestris</i>	Scots Pine	$Y = 6.8334237 + 0.6652d^2$	Atmaca, 2008
<i>Pinus sylvestris</i>	Scots Pine	$Y = 0.445 + V^{1.011}$	Çömez, 2011
<i>Pinus sylvestris</i>	Scots Pine	$Y = -6.358 + 0.139D^2$	Aydın, 1996
<i>Pinus sylvestris</i>	Scots Pine	$Y = 31.071 - 4.202D + 0.57D^2$	Ülker, 2010
<i>Pinus sylvestris</i>	Scots Pine	$Y = 0.0347(HD^2)^{0.8974}$	Tolunay, 2012
<i>Fagus orientalis</i>	Oriental beech	$Y = 0.212D^{2.277}$	Bulut, 2012
<i>Fagus orientalis</i>	Oriental beech	$Y = 0.51592 + D^{2.677403}$	Erkut, 2013
<i>Fagus orientalis</i>	Oriental beech	$Y = 41.483(1.073)^D$	Mısır et al., 2013
<i>Abies normaniana</i>	Caucasian fir	$Y = 0.042861 + 0.04161D^2$	Karabürk, 2011
<i>Abies normaniana</i>	Caucasian fir	$Y = 107.197 - 13.702D + 0.665D^2$	Mısır et al., 2012
<i>Cedrus libani</i>	Lebanese cedar	$Y = -31.0516 + 0.303619D^2$	Ülküdür, 2010
<i>Pinus brutia</i>	Turkish pine	$\ln Y = 6.564528 + 1.50280256 \ln D$	Ünsal, 2007
<i>Pinus nigra</i>	Black Pine	$Y = 5.927536 + 1.155611^D$	Güner et al., 2014
<i>Pinus nigra</i>	Black Pine	$Y = -103.221 - 9.773876D + 0.10335D^2$	Çakıl, 2008
<i>Pinus nigra</i>	Black pine	$Y = 0.112D^{2.343}$	Sakıcı et al., 2016
<i>Pinus nigra</i>	Black pine	$Y = -113.505 + 0.247D^2 + 0.493DH$	Sakıcı et al., 2016

In Table 9, Y represent the total tree biomass (kg/ha or t/ha); D is Diameter at Breast Height (cm); H is the tree height; V is the Total Tree Volume (m³).

Table 10. Carbon equation developed for some species in Türkiye

Species	Name (Local)	Models	References
<i>Abies nordmanniana</i>	Caucasian fir	$C = 0.0109D^{2.092}$	Mısır et al., 2012
<i>Fagus orientalis</i>	Oriental beech	$C = 0.025672D^{2.775}$	Mısır et al., 2011
<i>Picea orientalis</i>	Caucasian spruce	$C = 0.33D^{2.43}$	Mısır et al., 2011
<i>Pinus sylvestris</i>	Scots pine	$C = -28,36 + 0.413D^2$	Yavuz et al., 2010
<i>Quercus sp.</i>	Oaks	$C = 31.071 - 4.202D + 0.57D^2$	Ülker, 2010
<i>Pinus nigra</i>	Black Pine	$C = 0.054D^{2.362}$	Sakıcı et al., 2016
<i>Pinus nigra</i>	Black Pine	$C = 1.2 + 0.172D - 0.001D^2$	Sakıcı et al., 2016
<i>Pinus nigra</i>	Black Pine	$C = 82.385 - 10.501D + 0.275D^2 + 0.298DH$	Sakıcı et al., 2016

In Table 9, C represent the Carbon Storage in a tree (kg/ha or t/ha); D is tree Diameter at Breast Height (cm); H is the tree height.

Carbon models, similar to biomass models (Table 10), rely on the same modeling principle and independent variables, such as tree diameter ($D_{1.30}$). While these models are practical and accessible through statistical software, like SPSS, SAS, MatLab, and Statistica, their reliability depends on meeting certain statistical assumptions. These assumptions include normal distribution of model error, homogeneity of error variances, no correlation between errors (Autocorrelation), and no correlation (Flores et al., 2012). To address these limitations, the Artificial Neural Network (ANN) Method has emerged as a recommended alternative for statistical analysis, embraced by researchers for its improved performance.

- Artificial Neural Networks method used in modelling

The Artificial Neural Networks (ANNs) method is a statistical technique that goes beyond the conventional (linear and non-linear) regression models. Its models are based on artificial intelligence. The ANN is a set of mathematical or computational systems, algorithms, and, most importantly, a modeling strategy that was carefully modeled after biological neural networks (nervous system), which have a propensity to naturally store and make available experimental knowledge. ANNs are tools for modeling non-linear statistical data. It is a fresh, practical, reliable, effective, precise, and clever tool for modeling data, especially for biometricians. The ANN method operating scheme's architecture is comparable to a biological neuron system found in humans. Backpropagation (BP) Artificial Neural Networks are a data analysis technique that, in contrast to conventional approaches, transduce imputed information and process intricate imperfect and nonlinear data using Multi-Layer Perceptron. The advantages in ANNs are the distribution free, underlying process don not need to be defined/known, easily handless nonlinear data, effectively handle very complex problem, not problem in collinearity among predictors, using multisource data (Brososke et al., 2014). According to Chiarello et al. (2019) which conducted a comprehensive review on the application of Artificial Neural Networks (ANN) in forest biometrics and modeling by analyzing 1140 articles published between 2007-2018 (in English and Portuguese), 35% of the studies focused on merchantable tree volume analysis, and 63% of the research being conducted by Brazilian researchers. Moreover, 78% of the studies utilized the Multi-Layer Perceptron (MLP) architecture, and 28% employed the Statistica Software for their analyses. The use of the ANN and/or in the modeling of biological processes has been widely documented, particularly in the field of forestry.

This analysis technique based on deep learning makes it possible to assess single and multiple regression models. In using ANN method, many studies on stem taper, tree height, Stem volume and tree height-diameter, were realized in many countries (Socha et al., 2020; Nunes and Görgens, 2016; Fonweban et al., 2011). In Poland, for example, Cywicka et al. (2022) have modeled the variation in the bark thickness of 144 Scots pines (*Pinus sylvestris* L.) and 750 common oaks (*Quercus robur* L.) using recurrent neural networks and taking into account influencing factors such as tree age, origin, geographical location, site conditions (temperature, water availability), and compared it with Stem Taper Curves Adjusted to predict double bark thickness. Schikowski et al. (2018) modeled the shape and volume of the *Acacia negra* stem using machine learning. Analyzing the accuracy of Machine Learning (ML) techniques against a volumetric model and a conic function allowed the authors to conclude that ML models have proven to be suitable as an alternative to traditional modeling applications in forest measurement. De Azevedo et al. (2020) used the Artificial Neural Network to model stem multi-volumes of 460 *Eucalyptus* stems with great interest and accuracy, concluding that this approach is more appropriate. Nunes and Gorgens (2016) evaluated the performance of the ANN with Random Forest Regression, despite the fact that the stems of tropical forest trees are very asymmetrical, making it impossible for conical equations to predict their diameter at any height of the stem. The authors came to the conclusion that the neural network method, which acts on local effects, produced favorable results. In the work of Dos Santos et al. (2018) in Brazil, the leaf area of 140 leaves of *Ormosia paraensis* Ducke was successfully modeled using 100 MLP-ANNs trained with the Backpropagation algorithm. In China, Tuan et al. (2019) used ANNs and non-linear regression to build predictive models of the relationship between height and diameter of *Pinus koraiensis* trees in the Mengjiagang forests.

In Türkiye, Bolat (2021) recently used ANN and regression analysis (single and multiple) to obtain predictive models (generalized height-diameter, segmented taper, tree volume, stand growth, diameter distribution and single-tree diameter increment) of 300 trees sampled in 180 plots studied in pure stands of Anatolian Black Pine (*Pinus nigra*) in the Ankara Regional Forest District. Concluding that Artificial Neural Network models have no over-fitting problems and can have strong generalization capabilities, Bolat (2021) also revealed the usefulness of this intelligent approach by modeling the bole volume of 89 Scots pine (*Pinus sylvestris* L.), 96 red pines (*Pinus brutia* Ten.), 107 cilicica firs (*Abies cilicica* Carr.) and 67 cedars of Lebanon (*Cedrus libani* A. Rich.).

With this in mind, Yousefpoor et al. (2017) highlighted the robustness, practicality, efficiency, reliability and accuracy of ANN models in predicting tree volume, thanks to the experiment they conducted on 108 experimental plots of pure stands of black pine (*Pinus nigra* subsp. *pallasiana* (Lamb) Holmboe) in the Yenice forest management unit (Türkiye). Ercanlı et al. (2018) observed the significance in the predicting of Leaf Area Index (LAI) and found more interest in the ANN method. Seki (2023) used regression approaches and Artificial Neural Networks (ANN) to study stem taper prediction models from individual diameters of Scots pine (*Pinus sylvestris*) in northwest Türkiye. Vahedi et al. (2016) compared the two methods (ANN and allometric Equations) when studying the prediction of aerial biomass in mixed beech forests in Iran. Özçelik et al. (2013) also tested them on the prediction of Crimean Jupiter tree height in the southwestern region of Türkiye. Just as Seki et al. (2022) recently showed on *Pinus nigra* (Crimean pine), Diamantopoulou (2005) already indicated that ANN was an alternative tool for estimating the volume of *Pinus brutia* bark compared with regression models.

ANN is the approach that consistently provides the most accurate estimate of bark thickness at a specific stem height when using the Artificial Neural Network technique. Günlü et al. (2019) estimated the stand parameters from the textural properties of the WorldView-2 satellite image in Türkiye by using the Multilayer Perceptron (MLP) and Radial Basis Function (RBF) architectures of the Artificial Neural Network and the technique of Multiple Regression methods. The models developed using the WorldView-2 satellite image and based on ANN (MLP and RBF) were effective, advantageous, and superior for estimating the parameters of a stand, the authors concluded. Using an Artificial Neural Network technique, Sakıcı and Ozdemir (2018) determined the individual stem shapes of 278 Kazdag Fir (*Abies nordmanniana* subsp. *equi-trojani*) and 238 Oriental Beech (*Fagus orientalis*) trees in mixed stands (Türkiye). The authors reported that ANN models were more successful in estimating stem taper for both tree species after analyzing 45 ANN models and 4 stem equations created from diameter at breast height, tree height, diameter at stump height, and diameter at intervals (1 m section) on tree stem. The use of Tier 3 Approach (destructive sampling method) in even-aged forest stands allowed the author to develop three regression-type stem taper models and an ANN model. The best results were obtained with the Kozak taper model, which accounted for 99% of the total variance in stem diameter predictions.

Özkal et al. (2021) recently studied the comparison of traditional regression models with Artificial Neural Network models in a study of the mathematical relationship between height and diameter of trees in uneven-aged stands of *Abies nordmanniana* subsp. *equi-trojani* in the Bolu (Kökez) region in Türkiye. In a comparative study of the Artificial Neural Network (ANN) method and Multiple Regression Analysis (MRA) carried out on the prediction of log skidding time in the Black Sea region of Türkiye, Çalışkan and Sevim (2018) claimed that the results of the comparison indicate that the ANN Multi-Layer Perceptron (MLP) and Cascade Forward-Backward Propagation (CFBP) models better predict total time during skidding operations than the MRA model. Che et al. (2022) used the parametric method in combination with two modeling algorithms from the Artificial Neural Network (Levenberg-Marquardt and resilient back-propagation) in order to propose robust, reliable, and practical models for predicting the height of stems of Taurus cedar (*Cedrus libani* A. Rich) in plantations located in the western Mediterranean Region in Türkiye. After careful consideration, the authors conclude that the resilient back-propagation algorithm is a trustworthy addition to existing modeling methodologies because it produced more precise predictions of tree stem height. The authors revealed that the prediction was efficient with the power model in the Artificial Neural Network feed-forward backpropagation algorithm. But some studies suggest that there are other, more practical methods than ANNs. In a study of land area modelling based on stand parameters (age, number of trees per hectare, mean diameter and productivity index) using mixed-effects modelling, ANN and support vector machine methods, Che et al. (2019) concluded that the support vector machine method was more efficient.

Using Landsat 8 satellite images in a study by Sakıcı and Günlü (2018), stand parameters were estimated in Artificial Neural Networks to explain the variability in mean diameter, number of trees per hectare, height at 1.30 m, stand volume, was explained at 59, 61, 63, 65%, respectively. The effect of linear and nonlinear crown variables on the accuracy of the compatible volume and taper equation model was studied for 173 Turkish Red Pine (*Pinus brutia*) trees (Özçelik et al., 2014). The results showed a significant improvement in model performance with the incorporation of these variables. Nonlinear regression models were less accurate than the neural network models tested for bark diameter and stem volume predictions. Levenberg-Marquardt neural network models were the most accurate in terms of prediction and are therefore recommended for modeling bark diameter and volume prediction (Özçelik et al., 2014).

In a Review on recent applications of ANNs in forest resource management published in an American Association for Artificial Intelligence (AAAI Technical Report), Peng and Wen (1999) indicated that ANNs have been widely used in modeling over the last 10 years, particularly in the analysis of data from various sources such as Forest Growth and Dynamics, Spatial Data and GIS (Satellite Image Processing), Plant Disease Dynamics and Insect Pest Management, Climate change and others. When using ANN modeling approaches, several ANN algorithms are employed by users. The most common are Multi-Layer Perceptron (Soarse et al., 2013; Dos Santos et al., 2018; Şenyurt and Ercanlı, 2019; Tuan et al., 2019; Çalışkan and Sevim, 2022), Radial Basic Function (Şenyurt and Ercanlı, 2019), Bayesian Regularization (Bolat, 2021; Cywicka et al., 2022), Levenberg-Marquardt (Cywicka et al., 2022), Scaled Conjugate Gradient (Cywicka et al., 2022). Some authors have focused on Activation Function types (Baheti, 2023) such as Sigmoid Function (Ercanlı and Kaya, 2019), Logistic Function (Sakıcı et al., 2018), Hyperbolic Tangent Function (Sakıcı et al., 2018; Ercanlı and Kaya, 2019), Linear Function (Sakıcı et al., 2018; Ercanlı and Kaya, 2019; Puig-Arnavat et al., 2013), Network Pruning and Tree Pruning (Kalaierasi et al., 2011), Resilient Propagation (Karatepe et al., 2022), and others.

- Remote Sensing Method to Model and Map Biomass and Carbon Stocks

Remote sensing techniques enable the determination of parameters, biomass and carbon quantities in forest areas. For instance, LANDSAT 7 ETM and/or Landsat 8 OLI and Sentinel-2 satellite images and/or LIDAR data have been used to estimate the biomass and carbon storage capacity of forest ecosystems in Türkiye (Misir et al., 2011; Bulut, 2012; Costa, 2016; Kanja et al., 2019; Bulut et al., 2022; Ercanlı et al., 2017; Turgut et al., 2022) and worldwide. Linear and non-linear regression methods and techniques based on ANN allow the development of allometric models for the prediction of volume, biomass, and forest carbon storage (Potter et al., 2011). These models can include Geographic Information Systems (Ravindranath and Ostwald, 2008). The data produced with these models can be related to satellite image strips (Lidar, Landsat, Spot, etc.) to determine the stand parameters (Kanja et al., 2019), the tree or stand biomass and/or carbon distribution at the scale of the unit area, forest stand, and/or the forest ecosystem scale.

In Türkiye several studies have been carried out to estimate or model the biomass and/or carbon in forest ecosystems using remote sensing data (Bulut, 2012; Gülsunar et al., 2011; Kanja et al., 2019; Karahalil et al., 2018). The Table 11 presents some relationships that have been established in Türkiye (Mısır, 2012; Mısır et al., 2011).

Table 11. Some carbon allometric using slope, aspect, and image bands

Bands	Models	R²
1	$C = 325.461 - 2.187(Band1)$	0.456
	$C = 592.070 - 2.407(Band1) - 1.094(Slope)$	0.503
2	$C = 928.835 - 10.264(Band2) + 0.033(Band2)^2$	0.688
	$C = 684.482 - 0.074(Aspect) - 0.171(Slope) - 4.057(Band2)$	0.676
	$C = 657.51 - 3.027(Band3) - 0.008(Band3)^2$	0.420
3	$C = 714.306 - 4.207(Band3) - 0.003(Band3)^2$	0.548
	$C = 736.221 + 0.055(Aspect) - 4.567(Band3) - 0.362(Slope)$	0.649
Indications R ² = Coefficient of Correlation		

The Remote Sensing method is an excellent approach recommended by the GPG-LULUCF Guide (IPCC, 2006). This method enables the extrapolation of above-ground biomass estimates to the local scale and over large areas where reference data may be lacking, using inventory data collected in the field (Ferraz et al., 2014). In this technique, slope values, field aspect, and reflected band values are calculated and used as variables or parameters of equations (Table 11). These variables can be integrated into the models of established equations, and the quantities of carbon can be differentiated on thematic maps. Gopal and Woodcock (1996) demonstrated the usefulness of this combination in analyzing changes in forest cover in the Lake Tahoe Basin in California (USA). Despite the efforts made by researchers and decision-makers involved in the quantification processes of biomass and forest carbon by indirect and/or direct methods, it is worth highlighting all the issues that motivate our curiosity through this research.

1.2. Research Problem

Türkiye has significant forest potential, estimated at over 23 million hectares (2021), and more than 184 tree species. Indeed, in the conifer class, Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.)) or Karaçam (Çk) and Turkish Red Pine (*Pinus brutia* Ten.) or Kızılçam (Çz) account for a significant share of forest resources and are the main forest species of great economic and ecological importance in Türkiye. Overall, these forest ecosystems store around 2 GtC, more than 60% of which is in living biomass and around 40% in forest soils. This potential is currently thought to be underestimated, given the methods used to estimate it. We can agree with Misir et al (2007) that the current understanding of carbon stocks is largely insufficient in Türkiye, particularly for the mixed species of *Pinus nigra* and *Pinus brutia* found in various natural ecosystems, taking into account the different structural and climatic variations (Mediterranean, Anatolian, Marmara, Aegean, and Black Sea) that characterize them. By assessing the actual storage capacities of these ecosystems using suitable models, this would help the country towards more accurate estimates in the context of competition on the future international carbon market.

Unfortunately, there is very little reliable data on the biomass and carbon content of mixed stands involving these two important tree species. More specifically, these forest stand types (*Pinus nigra* - *Pinus brutia*) have not yet been widely studied at national level, taking into account their different types in existing forest ecosystems and in the country. As a result, there are no reliable generalized data or models for estimating the biomass and carbon of individual trees across their different growing ecosystems in Türkiye. There are very few studies of this kind, although some have been carried out in specific localities.

A review of the literature on biomass and carbon stock modelling of these types of mixed natural stands (*Pinus brutia* - *Pinus brutia*) reveals that very few similar studies have been documented. However, almost all of them have been documented. There are no large-scale studies, at national level, on their actual carbon sequestration and storage capacities. Very few studies of mixed stands have been carried out in limited localities (Çelik, 2006 cited by Tolunay et al., 2008; Yavuz et al., 2010). The volume and annual growth tables are based on data from Forest Inventory Reports for trees with a diameter greater than or equal to 8 cm (Tolunay, 2019; Asan, 1995 & 2002; Tolunay, 2012; Mısır et al., 2017). This does not directly include all diameter classes (young) in the biomass estimation (Özçelik et al., 2016).

Apart from the stem wood removed from the ecosystem, a significant part of debris (foliage, bark, branches, roots) is left behind. It can thus be seen that inventories are not carried out to directly determine forest biomass (Yildiz, 2004; Tolunay, 2019). It is also important to note that several shortcomings exist in the processes and tools for quantifying forest biomass and carbon in Türkiye, leading to inaccuracies and inconsistencies in the data. Despite the updates made at the national level, the indirect methods based on coefficients and conversion factors (BEF, BECF, CF, WD) have also shown their limits in terms of consistency and accuracy even if they are non-destructive (Hari and Tyagi, 2022; Misir et al., 2017; Tolunay et al., 2018). With these indirect methods, the real capacity of forest biomass and carbon is underestimated. For example, between the indirect methods of the GPG-LULUCF, FRA 2010 and ETFOP and Asan (1999), there are major differences that justify our concern about the quality of the data they produce.

Durkaya et al. (2018) compared these three methods in a study carried out in the Forest Management Unit (2011-2030) of Bartın (73,227.20 ha) in Türkiye. The authors report that the differences varied between 135.7 t/ha with the Asan method (1995 & 2002), 119.4 t/ha with FRA 2010 (FAO, 2010) and 142 t/ha with ETFOP (LULUCF/Tier 2). Losses in quantity of biomass and forest carbon are 4.5% (Asan, 1995 & 2002) and 16% (FRA 2010) compared to ETFOP. Using coefficient and factor methods (AFOLU and FRA 2010), Misir et al. (2017) also compared biomass and carbon data determined from the data of National Forest Inventory Report (NIR Türkiye, 2015). The authors showed that with the same data, the FRA 2010 method (FAO, 2010) estimates that forest ecosystems store 1.5 GtC and 2.6 GtC with the AFOLU method (IPCC, 2006). An inconsistency of 42.3% was recorded between the carbon data obtained from the two methods.

The indirect methods as a whole and the data resulting from these techniques are therefore inconsistent, less accurate, unreliable, insufficient, incomplete and affected by considerable inaccuracies. These estimation methods lead to multiple unavoidable uncertainties (Kenzo et al., 2020; Hari and Tyagi, 2022). They cannot allow the development of robust and efficient allometric models (Hari and Tyagi, 2022) like the complex method (Tier 3 Approach) of LULUCF (IPCC, 2003). Although modeling by regression technique using data from indirect methods makes it possible to arrive at satisfactory statistical results, several researchers believe that the imprecision of the data on forest carbon is linked to the imperfections of the models (Kenzo et al., 2009; Kuyah et al., 2012).

Considering mixed stands in conifers, it was found that there are no reliable allometric models (volume, biomass and carbon) for *Pinus nigra* and *Pinus brutia* considered individually in their natural environment in mixed status in Türkiye. In Türkiye, the few studies found on natural mixed stands of *Pinus brutia* dominated by *Pinus nigra* have been carried out in limited region, less representative localities (Öztürk, 2022). The statistical models that currently exist for some species of conifer trees are mostly developed with data from indirect methods. However, their effectiveness is questioned. Data on biomass and carbon sinks are not harmonized to express, on a national level, the real capacities of a given forest species to store carbon. This situation calls into question the quality of the information consolidated in the national inventory reports prepared by the country to fulfill its obligations under the Kyoto Protocol (Serengil, 2018). In this context, method 3 (Tiers 3 Approach) of the GPG-LULUCF/AFOLU is rarely used in the country, yet it makes it possible to generate reliable, detailed and accurate data collected in the field. This complex information can also be used to produce reliable data and robust and efficient statistical models (Çömez, 2012; Mısıır, 2012; Öztürk, 2022; Öztürk and Yılmaz, 2019; Sakıcı et al., 2016) unlike the models derived from data obtained with indirect methods with more uncertainty (Varol et al., 2018; Hari and Tyagi, 2022; Yolaşığmaz et al. 2017).

Modeling the prediction of volume, biomass quantity and carbon storage for Karaçam and Kızılçam species in mixed stands, must (1) take into account all the forest ecosystems that support this type of stands, (2) consider the (a) single-tree species in its growing environment, (b) structure of the forest, (c) different development stages, (d) topographic characteristics and those of the soil, (e) dendrometric data, (f) age classes, (g) climate factors and (h) silvicultural practices that all have an impact on the variation of carbon stocks in the forest. Satellite images (Lidar, Spot, Landsat, etc.) are essential in a complex method to establish the actual spatial distribution of biomass and carbon stocks according to the areas occupied. It is in this context that the present research was set up as part of a doctoral thesis integrated within the TÜBİTAK Project 118O311 of Karadeniz Technical University (Türkiye). This thesis aims to develop robust, efficient and practical predictive models for volumes, biomass and carbon storage in natural mixed forest stands of Anatolian Black Pine or Karaçam (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.)) mixed with Turkish Red Pine or Kızılçam (*Pinus brutia* Ten.) across forest ecosystems in Türkiye. We have therefore formulated scientific hypotheses to which we have provided practical answers within the framework of this work.

1.3. Research Hypothesis

As part of the research problem raised in this work, some hypotheses have been formulated as follows:

- In Türkiye, the natural mixed forest stands of Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana* Lamb.) - Turkish Red Pine (*Pinus brutia* Ten.) presents distinctive features that could contribute to understanding their current situation.
- In Türkiye, the biomass of each aboveground component (trees, leaves, bark, dead wood, litter, herbaceous plant cover) and belowground component (roots and soil organic matter) of *Pinus nigra-Pinus brutia* natural mixed forest stands of stores a significant amount of organic carbon.
- In Türkiye, modeling biomass and carbon storage in mixed natural forest stands of *Pinus nigra-Pinus brutia* using predictors such as diameter at breast height, height, and stand parameters highlights significant mathematical relationships between these structural variables and the quantities of biomass and carbon stored within the components of these specific ecosystems.
- In Türkiye, the total quantities of biomass and carbon stocks estimated in the entirety of mixed natural forest ecosystems of *Pinus nigra-Pinus brutia* are unevenly distributed between the aboveground and belowground components.
- The mapping of biomass and carbon in the mixed natural forest ecosystems of *Pinus nigra-Pinus brutia* reveals their geographical distribution through their preferred zones.

1.4. Research Objectives

The objective of this study is to contribute to the enhancement of scientific knowledge on capacities of forest ecosystems to combat climate change in the context of Türkiye, by developing and proposing robust, reliable and accurate mathematical models that can help to predict biomass and carbon storage capacities of natural mixed forest composed of Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe) with Turkish Red Pine (*Pinus brutia*) across Türkiye. More specifically, this research aims to:

- Characterize the natural mixed forest stands of Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe) and Turkish Red Pine (*Pinus brutia*) in Türkiye.
- Determine the quantity of biomass and carbon stock in each component of both aboveground (trees, leaves, bark, dead wood, litter, herbaceous plant cover) and belowground (roots and soil organic matter) reservoirs in mixed natural forest stands of *Pinus nigra* and *Pinus brutia* in Türkiye.
- Develop allometric equations and demonstrate the existence and types of mathematical relationships that exist between the structural variables (diameter at 1.30 m, tree heights, and stand parameters) and the observable variability in biomass accumulation and carbon storage by trees and mixed natural forest stands of *Pinus nigra* (68 trees) and *Pinus brutia* (70 trees) in Türkiye.
- Estimate the total biomass and carbon storage capacity in the aboveground and belowground components of natural mixed forest ecosystems of *Pinus nigra* and *Pinus brutia* in Türkiye.
- Mapping the biomass quantities and carbon stocks in the mixed natural forest ecosystems of *Pinus nigra* and *Pinus brutia* and demonstrating their geographical distribution through their preferred zones in Türkiye.

2. RESEARCH METHODOLOGY

2.1. Material

2.1.1. Geographical and Administrative Presentation of the Study Areas

Türkiye is a transcontinental country located at the intersection of three phytogeographical regions namely Euro-Siberian, Mediterranean and Irano-Turanian. It is situated between 38.9637° North Latitude and 35.2433° East Longitude. Türkiye covers an area of 783,562 km² with approximately 8333 km of coastline and 2753 km of border. The highest mountain in the country is Mount Ararat (5137 m). Most part (97%) of the country is located in Asia (Anatolia) and almost 3% of the country is part of the European continent, west of the Bosphorus. The country is surrounded by two seas, in particular by the Black Sea to the North, the Mediterranean Sea to the West and to the South (seas of Thrace, Aegean, Crete to the West, Marmara to the North-West, and the Levantine basin to the south). The country is approximately 1.3% water and 98.7% land. Türkiye has 81 provinces divided into 7 major administrative regions.

Türkiye's forest area is estimated at 23.245 million ha (29.8% of the territory) including 56% of normal productive high forests, 38% of degraded high forests, 2% of productive coppice forests and 4% of degraded coppice forests (OGM, 2023). Türkiye's Forest Policy is guided by Law No. 6831 of August 31, 1956 (Bakir, 2015) whose implementation is ensured by the Ministry of Agriculture and Forestry through the General Directorate of Forestry (GDF). Within the GDF, there are 30 Regional Directorate of Forestry (RDF), 277 Directorate of Forest Management (DFM) and nearly 2147 Department of Forest Management (DFO) distributed in the 7 major administrative regions of the country (OGM, 2023). This study was conducted in 5 of the 7 major administrative regions of Türkiye, particularly in the Directorates of Forest Managements (DFM) and Directorates of Forest Operations (DFO), hosting the natural mixed stands of *Pinus nigra* and *Pinus brutia* (Ten.) in Türkiye. Table 12 shows the areas of interest of the present study, their estimated size (km² and ha) and the geographical coordinates.

Table 12. Administrative, size and geographical information of study zones

Regions and Area (km ²)	Regional Directorate of Forestry and Area (ha)	Directorate of Forest Management			Department of Forest Operation	
		Name and Area (ha)	Year	Geo-positioning	Name	Estimated Area (ha)
Central Anatolian (162,305)	Ankara (791,676)	Nallıhan (72,146.1)	1943	X: 359718.8 Y: 4449785.1	Andiz	17 258.9
	Eskişehir (637,836)	Mihalıççık (67,954.5)	1990	X: 359718.8 Y: 4449785.1	Kartal	19 386.3
Marmara (62,067)	Balıkesir (632,405)	Edremit (60,796.1)	1955	X: 501345.9 Y: 4382677.1	Çınarlıhan	4 992.2
					Burhaniye	6 562.8
	Bursa (771,364)	Orhaneli (69,395)	1943	X: 644008.5 Y: 4438712.8	Harmancık	13 434
					Karabayır	7 622.2
					Meyran	13 791.1
Çanakkale (582,666)	Bayramiç (60,531.4)	1944	X: 466840.3 Y: 4406799.1	Evciler	6 208.6	
Black Sea (131,218)	Bolu (637,973)	Göynük (72,262)	1958	X: 312022.2 Y: 4474225.9	Hacıosman	7 804.4
					Dedeler	8 570.4
					Ilıca	10 739
					Himmetoğlu	11 555.1
	Sinop/Kastamonu (369,466)	Gerze (42,629)	2016	X: 682816.4 Y: 4630268.5	Dikmen	12 112.7
Aegean (83,251)	Denizli (812,168)	Denizli (58,300)	1943	X: 684448.2 Y: 4183712.1	Denizli	147 127.1
					Kocabaş	11 602.1
	Kütahya (646,552)	Gediz (53,957)	1955	X: 706924.3 Y: 4318756.7	Karadona	10 389.5
		Tavşanlı (83,676)	1944	X: 714442.2 Y: 4380246.5	Alabarda	9 295.0
		Emet (63,974)	1958	X: 694765.8 Y: 4356940.5	Emet	9 045.0
Mediterranean (110,176)	Isparta (739,165)	Gölkisar (60,923.7)	1966	X: 722968.1 Y: 4114580.2	Gölova	26 073.4
		Burdur (69,401.4)	1943	X: 260822.4 Y: 4177946.2	Aziziye	15 313.8
5	10	13			21	

Source : <https://www.ogm.gov.tr/tr/kurulusumuz/orman-bolge-mudurlukleri> (07.07.2023)

In Table 12, the data mentioned in the "Region" column represent the names of the major administrative regions and their estimated areas in km². The second column represents the names of the Regional Directorates of Forestry with their forest area including normal and degraded forests (in ha). Column 3 presents the Directorates of Forest Management (DFM) with the areas of normal forests (degraded forests excluded). Column 4 presents the years of creation of DFMs and column 6 indicates the coordinates of DFOs.

Finally, column 7 presents the operational forest units in which experimental plots and data were collected (OFE). Figure 18 shows the localization of DFM where the experimental samples were established and data were collected.

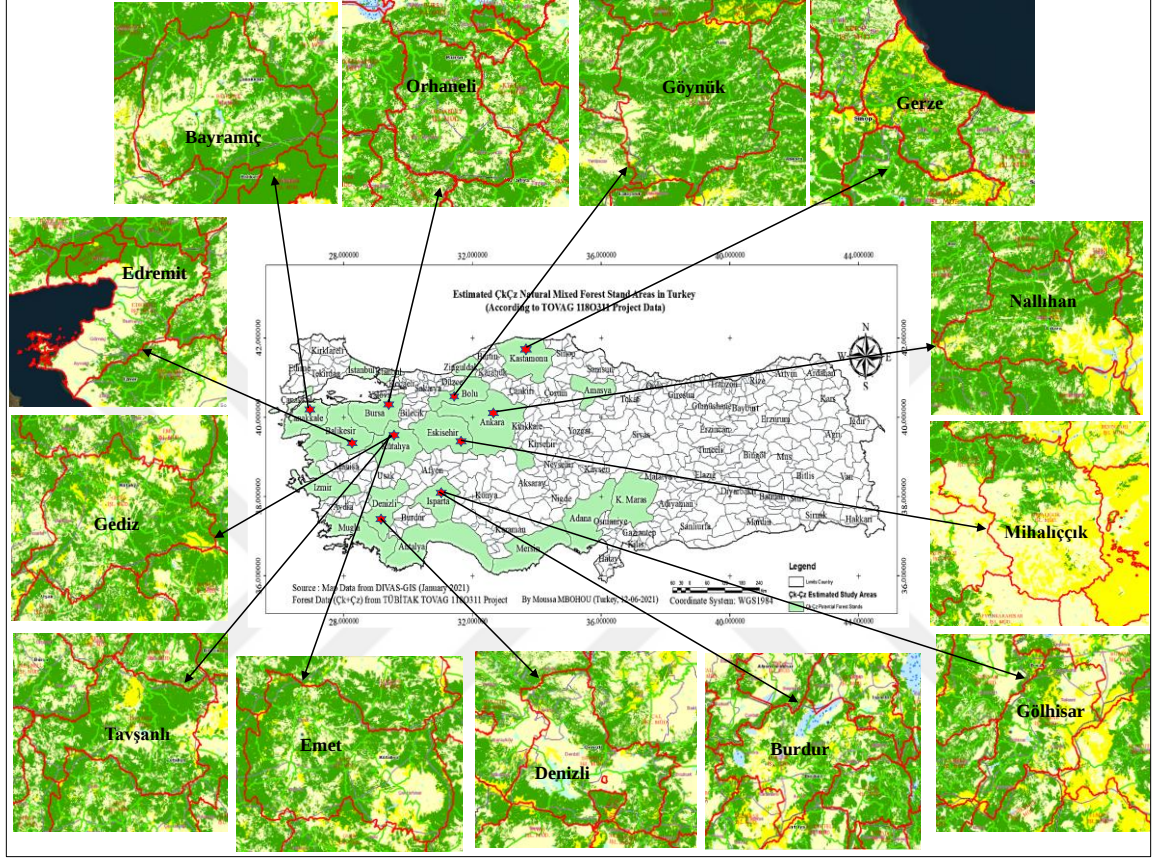


Figure 18. Map of study areas that indicates the Directorate of Forest Management and particularly the Directorate of Forest Operations where the data were collected

According to the map showing in Figure 18, the study focused on natural mixed stands of *Pinus brutia* dominated by *Pinus nigra* located in 13 Directorates of Forest Management (DFM) across 10 Regional Directorates of Forestry (RDF). In Türkiye, mixed stands make up 1/3 of the forests lands and are mostly productive forests (Çatal et al., 2017). Conifer stands make up 48% of forest land, with 7,440,845 ha in normal productive forest and 3,636,080 ha in degraded forest (OGM, 2022). The forests examined in this study consist mainly of conifer stands. According to the forest management plans analyzed in the context of TÜBİTAK Project 118O311, the forest data concerning mixed forest stands of *Pinus nigra* with *Pinus Brutia* indicated their presence in 21 RDFs, 113 FMDs, and about 350 DFOs, with an estimated total area of 79,207.444 hectares (0.34%).

Several studies have analyzed the distribution and ecological preference of natural species in Türkiye (Acar et al., 2018). Particularly, two tree species (*Pinus nigra* and *Pinus brutia*) were the focus of this biomass and carbon storage study project, considering them in their natural mixed environment, which involves their specific morphological, ecological, and geographical conditions. Both species belong to the class Pinopsida, division Coniferophyta, order Pinales, family Pinacea, genus *Pinus*, species *Pinus nigra* and *Pinus brutia*, and several varieties (*pallasiana*, Ten, etc.). For these both species, several research works have already contributed to knowledge. The most studies concern particularly the silviculture (Karadağ, 2022 cited by TOD, 2022; Ertaş ve Çalışkan, 2022), seed transfer (Atalay, 1977), flora (Öztürk et al., 2002), dendroecology, origin, genetic diversity and variation (Gülcü and Ücler, 2008; Alptekin, 1986), systematics (Yilmaz, 2022), edaphic properties and characteristics (Sevgi et al., 2011; Akburak et al., 2013), nutritional cycle (Sevgi and Tecimen, 2022), dendrochronology (Carus et al., 2011; Sevgi and Akkemik, 2007), visual characteristics and composition (Acar et al., 2018), distribution and ecological attributes (Sarıkaya ve Avcı, 2011; Atalay et al., 1998; Atalay and Efe, 2012; Kavgacı et al., 2013; Enescu et al., 2016), fertility (Çerçioğlu and Birir, 2018; Gülcü and Bilir, 2000), productivity (Oğuzoğlu and Özkan, 2015), ecological suitability (Acar et al., 2018), climate conditions (Deligöz et al., 2021), and others. Only a few aspects of these knowledges have been addressed in this study.

2.1.2. Geo-Ecological Characteristics of Study Areas and Tree Species

Locally called Karaçam (Çk) and Kızılçam (Çz), Anatolian Black Pine (*Pinus nigra* Arnold. subsp. *pallasiana* Lamb. Holmboe) and Turkish Red Pine (*Pinus brutia* Ten.) respectively are native species found widely in Türkiye's Black Sea, Central Anatolia, Mediterranean, Marmara and Aegean regions. They are rare in the eastern part of the country. *Pinus nigra* and *Pinus brutia* represent more than 4.2 million ha (19.8%) and 5.6 million ha (25%) of national forests areas respectively. The ecogeographical characteristics of each region are particular to understand the distribution of mixed stands of *Pinus brutia* dominated by *Pinus nigra* in the different forest ecosystems in which our work was carried out in Türkiye. These two main species grow naturally in several regions in Türkiye. The work of Atalay and Efe (2012) estimated the approximate distribution of these species in their preferred region in Türkiye, as shown by the diagrams in Figure 19.

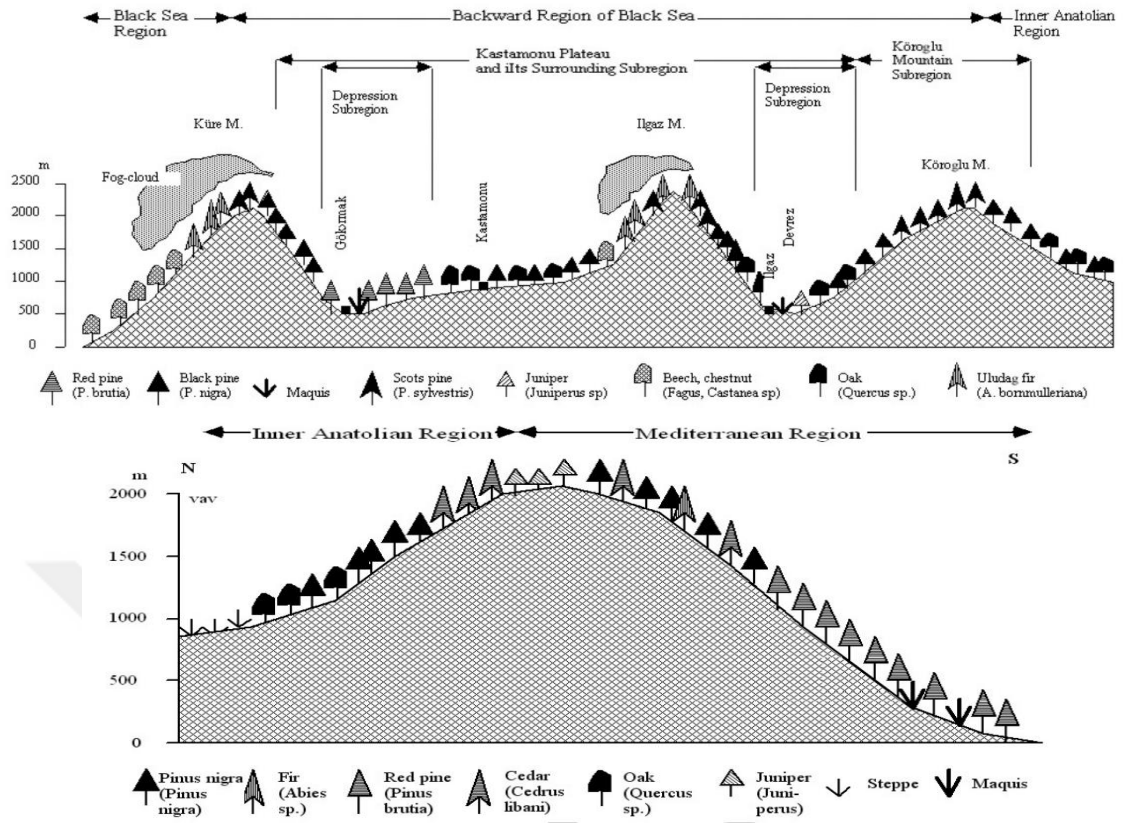


Figure 19. Approximate ecogeographical distribution of Anatolian Black Pine (*Pinus nigra*) and Turkish Red Pine (*Pinus brutia*) in Türkiye

Pinus nigra Arnold subsp. *pallasiana* (Lamb.) Holmboe var. *pallasiana*, also known as Anatolian Black Pine, is a subspecies of the European black pine that grows naturally in the southern, western, and northern Anatolian Mountains of Türkiye as a mid-elevation species (Figure 19). Although three varieties of Anatolian Black Pine are recognized, namely var. *pallasiana*, var. *fastigiata* Businsky with pyramidal form, and var. *seneriana* (Saatcioglu) Yalt (Gülsoy et al., 2014).

a. Geo-ecological characteristics in the Black Sea Region (Karadeniz)

The Karadeniz Region (Eastern, Central, and Western) is situated in the northern part of Türkiye and covers 18% of the national territory (1400 km East-West and 100-200 km North-South). It comprises a coastal zone (north central and western) and an interior zone. In the coastal zone, *Pinus nigra* stands are established in the Çitdere basin on the mountainside between 1150-1600 m altitude, where the species grows naturally on weathered rocks and deep serpentines.

These stands are also observable in the coastal belt between Zonguldak and Çatalzeytin and Doğanyurt, between 400-600 m altitude, and on the slopes of the Küre mountains, where they mix with other species such as *Pinus nigra*, which is part of our study zone (Kastamonu-Sinop). The inner Black Sea area is situated between the northern slopes of the Canik Mountains, the southern Küre Mountains, and the high southern slopes of Köroğlu. The region extends from the contact zone with the eastern part of the Marmara Region to the east of Niksar, north of the Erbaa-Niksar depression zone, and south of the Canik mountains. It serves as a transition zone between the Black Sea region and the Central Anatolia region. In the inner area of the Black Sea region, natural stands of Anatolian Black Pine (*Pinus nigra*) are observed from valley slopes (500-800 m) to tectonic corridors (1400-1900 m). Stands of Turkish Red Pine (*Pinus brutia* Ten.) are observable in the lower part of the corridor and valleys where they mix with *Pinus nigra*. The Kastamonu plateau and the northern slopes of the Kaz, Alaçam, and Ilgaz mountains are areas with high productive density of *Pinus nigra* (1200-1500 m).

Pure stands are also observed near Mudurnu-Göynük, in the Kibriscik plateau (800-1000 m), in the depression zone of Ladik and Suluova, Mengen, and Eskipazar. Under these suitable natural conditions, *Pinus nigra* can reach 35 to 50 m in height, a diameter of 220 cm to 310 cm, and can be over 300 years old. It is established at altitudes ranging from 400m to 2100 m. Biomass productivity increases on limestone, silt, and sandstone soils up to 1400 m altitude and begins to decrease due to lower temperature. In this region, Turkish pine (*Pinus brutia*) can reach 25 m in height and 60 cm in diameter up to 150 m in diameter. These bibliographic resources helped to synthesize essential information about the geo-ecological and geoclimatic characteristics of the study areas, as well as the specific characteristics of the species studied within the scope of this research.

b. Geo-ecological characteristics in the Marmara Region

The Marmara region comprises the Biga peninsula (West) and the watersheds of the rivers that flow into the Sea of Marmara. It extends from the mountains of Demirci, Simav, and Murat (South) to the Uludag-Domaniç mountain range in the Southeast, whose altitude increases from north to south between the mountains of Simav (1801 m), Akdağ (2009 m), Eğrigöz (2181 m), Murat (2312 m), and Domaniç (2543 m). *Pinus nigra* stands are observed on the slopes of the Kaz and Alaçam mountains between 1000-1400 m altitude.

c. Geo-ecological characteristics in the Aegean Region

The Aegean region covers the western part of Anatolia (West) and extends to the eastern Aegean plateau. It is located between the eastern limits of the Marmara region, which is covered with natural forests of *Picea orientalis*, and the northern limit of the mountains south of Taurus, which is covered with forests of *Cedrus*. The orobiomes cover the coasts of the rivers Gediz, Büyük Menderes, and Küçük Menderes. In the mountain areas, stands of *Pinus brutia* dominated by *Pinus nigra* can be observed gradually from the south (800 m) to the north (1000 m) of the mountains. The latter evolves up to 2000 m on the sides of the mountains (Simav, Boz, Aydın, and the north of the Mentese mountains). Between the northern and southern slopes of these mountains, *Pinus nigra* can be observed from 400-500 m altitude and 500-800 m altitude, respectively. From the mountains of Murat, stands of *Pinus nigra* are observable from 500-600 m on the northern slopes, at 800-1000 m altitude on the southern slopes up to 2000 m in the eastern part of the Aegean region. These settlements can also be observed on the mountains of Yılanlı, Boz, Aydın, and Muğla.

d. Geo-ecological characteristics in the Mediterranean Region

The Mediterranean region extends from the Köycegiz district (West), the Boz and Honaz mountains, the Dazkiri district, and the southern slopes of the Sultan mountains (northwest) to the orobiomes of the high and middle Taurus mountains (North) and the Nur Mountains (East). It is mainly covered with coniferous forests, especially *Pinus nigra*, which can be observed between the eastern part of the Gulf of Iskenderun (East) to the southwest of the Taurus Mountain range. It can also be found in the south of the Mentese mountains, northern Gulf (Antalya), Taseli plateau, and catchment area of the Seyhan and Ceyhan rivers. Mixed stands are observable on the southern slopes of Taurus between 600-700 m altitude (*Pinus nigra*, *Pinus brutia*, *Fagus orientalis*) and 1000-2400 m altitude (*Pinus nigra*, *Abies cilicica*, *Cedrus libani*, *Juniperus* sp., etc.). They can be found in the basin of Göksu, the locality of Abanoz, on the mountains of Dedegöl (Beysehir), around Lake Eğirdir, in the north of Sütçüler, and in the zone of depression in Gölhisar (700-800 m). In karstic land, *Pinus* seeds germinate easily in limestone cracks where plant roots follow seeping water. Stands mixed with *Pinus brutia* are observed in this environment.

e. Geo-ecological characteristics in the Central Anatolia Region

Anatolia is the main continental region of Türkiye and is made up of the regions of Eastern, Central, Southeast Anatolia, and the interior parts of Thrace. The region is bordered to the west by the Murat-Sandikli Mountain ranges, from the southern high slopes of northern Anatolia, to the east by the mountain ranges of the Uzun and Tahtali plateau, by the eastern part of Kütahya, and the northern slopes of the Taurus Mountains (south). The region also includes the Konya basins in southern inner Anatolia. The vegetation in the Anatolian regions is composed of herbaceous plants and shrubs. *Pinus nigra* can be found in shrub form with low productivity. Well-productive stands of *Pinus nigra* can be found on the Yazılıkaya Plateau and on the slopes of the Sündiken Mountains (Northwest). The steppes dominate the inner zone. Stands with good productivity are observable on the northern slopes of the Sultan Mountains and southern Sündiken Mountains at varying altitudes between 800-1500 m. The study area is located in the north of inner Anatolia and is surrounded by mountain ranges south of the Bolu region. In short, the geographical distribution of stands of *Pinus nigra* in general, and of stands mixed with *Pinus brutia* in particular, varies considerably depending on ecological conditions such as exposure, parental material such as soils, and topography such as altitude. Additionally, the floristic composition, density, productivity, harvest, site index, and above all, the geographical variation of these stands depends on the regional climatic conditions to which they are subjected.

2.1.3. Geo-climatical Characteristics of the Study Areas

a. Climate and Seasons Types in Study Areas

In Türkiye, several ecoregions have been documented by previous studies that took into account their different climatic characteristics and distribution of ecosystems. There are 4 main types of climates, namely (i) the continental climate (Eastern, Central, and Western Anatolia), (ii) the Mediterranean climate, (iii) the Black Sea climate, and (iv) the Marmara climate (Bozkurt et al., 2012; Tekin et al., 2021). The main classes and subclasses of climates established by the General Directorate of Meteorology (Meteoroloji Genel Müdürlüğü) in Türkiye according to the Köppen classification are illustrated on the map in Figure 20 (GDM, 2022).

Köppen İklim Sınıflandırmasına Göre Türkiye İklimi

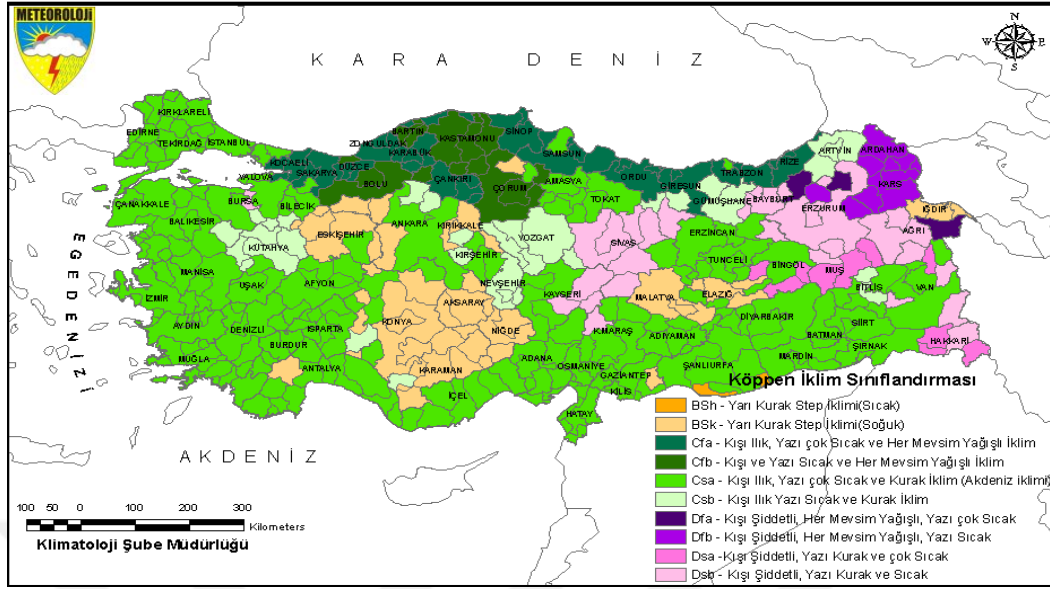


Figure 20. Climate classification map of Türkiye according to Köppen

According to Figure 20, the principal types of climate in Türkiye form three main climatic classes, namely (a) the arid climate (Central Anatolia, Central Black Sea, Inner Western Taurus, and the Middle and Upper parts of the Euphrates in the Southeast and Eastern Anatolia), (b) the mild and humid winter climate in the mid-latitudes (Coastal regions of the Central Taurus Mountains and Southeastern Anatolia), and (c) the Continental climate with humid mid-latitudes and cold winters (Eastern Anatolia, southeastern mountain regions, central Anatolia, inner Black Sea mountainous areas, and the Taurus Mountains). All climatic classes in the country experience an annual regime of four (4) seasons.

(i) Spring season: it runs from March 21 to June 22. It is the season between winter and summer. The trees are blooming and the air temperature is starting to rise. Heavy rains and the melting of ice formed by winter snow raise the level of waterways (lakes, ponds, streams, dams, etc.).

(ii) Summer season: it begins on June 22 and ends on September 23. This is the hottest season and conducive to field work in the forest (research, exploitation, silviculture, inventories, etc.).

(iii) Autumn season: it runs from September 23 to December 22. It is the transition between summer and winter. The days are shorter and the nights are longer. The number of cool days increases and heralds the winter season.

(iv) Winter season: begins on December 22 and ends on March 21. It is the cold season during which the air temperature drops and exceeds the freezing threshold. It is in these seasons that the forest ecosystems evolve in Türkiye.

b. Climatic Characteristics of Study Zones by Region

➤ Climatic characteristics in Black Sea (Karadeniz) Region

The Black Sea climate influences the Karadeniz region. In the coastal zone, which consists of mountains (slopes), the study area (Kastamonu-Sinop) experiences a humid, cool, and cold climate, forming orobiomes. The inner part of the Black Sea region is a transition zone (zono-ecotone), and the study area (Bolu) is therefore influenced by both the humid climate of the Black Sea Region and the semi-arid climate of the Central Anatolia Region. The Black Sea region receives precipitation throughout the year without a real dry season. The General Directorate of Meteorology (GDM) analyzed data (2022) showing that the whole region has an average annual precipitation of 842.6 mm. Specifically for the study areas, Bolu (1929-2021) has 551.2 mm, Kastamonu (1930-2021) has 482.8 mm, and Sinop (1936-2021) has 689.3 mm of precipitation annually. The annual average temperature for the whole region is 13.0°C, with Sinop (1936-2021) having 14.3°C, Kastamonu (1930-2021) having 9.9°C, and Bolu (1929-2021) having 10.4°C. July is the hottest month (22.2°C), and January is the coolest month (4.2°C). The average daily sunshine duration is 5.4 hours in Bolu (1930-2021), 5.8 hours in Kastamonu (1930-2021), and 5.4 hours in Sinop (1936-2021). The average annual air humidity in the region is above 70%, and Bolu (1929-2021) has an average of 131.1 rainy days annually, Kastamonu (1930-2021) has 124.1 rainy days annually, and Sinop has an average of 135.4 rainy days annually. Note that Sinop is included here because the data was collected in Gerze (Forest Operation Enterprise Unit), which belonged to Kastamonu before 2016, according to the current forest management plan.

➤ Climatic Characteristics in Marmara Region

The Marmara Region is a climate transition zone between the Black Sea climate, the continental climate and the Mediterranean climate. Thus, the study areas such as Balıkesir (Edremit), Bursa (Orhaneli) and Çanakkale (Bayramiç) are influenced by very abundant rainfall during the winter seasons.

But the region receives little rainfall (11.7%) and is dry during the summer seasons. Annual rainfall ranges from 500 to 1000 mm with an annual average of 595 mm in the region, 599.4 mm in Balıkesir (1999-2021), 709.5 mm in Bursa (1928-2021) and 625.5 mm in Çanakkale (1929-2021). The annual average temperature varies between 14-16°C in the region, and stands at 14.6°C in Bursa (1928-2021), 14.8°C in Balıkesir (1999-2021) and 15.2°C in Çanakkale (1929-2021). The average daily sunshine duration is 6.8 hours in Balıkesir (1999-2021), 6.2 hours in Bursa (1928-2021) and 7.2 hours in Çanakkale (1929-2021). The average annual air humidity in the region is above 70% and the average annual number of rainy days is 120.5 in Bursa (1928-2021) and 87.6 in Çanakkale (1929-2021).

➤ Climatic Characteristics in Aegean Region

The Aegean Region is influenced by a transitional climate. Summers are hot and dry while winters are mild and rainy although snowfall and frost are somewhat rare. The study areas like Denizli (Denizli) and Kütahya (Gediz, Tavşanlı and Emet) are part of the continental climate influenced by the Mediterranean part to the south (Denizli) and Western Anatolian to the north (Kütahya). In the Aegean region, the temperature varies from 8.7 °C (minimum) to 44.6°C. The high average temperatures for the hottest months range from 27-28°C and 17-18°C for the cold periods. The annual average temperature varies between 8-10°C in the region. The data analyzed by the GDM (2022) for the period 1957-2021 show that this annual average temperature is 16.2°C in Denizli and 10.8°C in Kütahya. Annual rainfall ranges from 600 to 1000 mm and stands at 563.6 mm in Kütahya (1929-2021) and 568.7 mm in Denizli (1957-2021). The average daily sunshine duration is 7.3 hours in Denizli (1957-2021) and 6.2 hours in Bursa (1928-2021) and 6.1 hours in Kütahya (1929-2021). The average annual air humidity in the region is above 50% and the average annual number of rainy days is 91 in Denizli (1957-2021).

➤ Climatic Characteristics in Mediterranean Region

The Mediterranean region, specifically the study areas in Isparta (Gölhisar and Burdur), are influenced by a Mediterranean-type climate observed from the Aegean Sea to the south of Marmara. Winters are mild and rainy, while summers are hot and dry. Frost and snowfall are rare in the coastal belt. However, in the heights of Taurus, winters are snowy and cold.

The average annual temperature is around 16.3°C, with extremes indicating 26.8°C for the hottest month (July) and 6.4°C for the coldest month (January). Winter is wetter, and the summer season accounts for 5.7% of annual precipitation. On average, the annual relative humidity is 63.3%. According to data analyzed by the GDM (2022) for the period 1929-2021, the study area (Isparta) has an average temperature of 12.3°C and an average annual precipitation of 568.4 mm, which is lower than that of the region (725.9 mm). The average daily sunshine duration is 7.1 hours in Isparta (1929-2021), and the annual average number of rainy days is 103.4 (1929-2021).

➤ Climatic Characteristics in Central Anatolian Region

The study area (Ankara-Nallıhan) is located in the northern area of the Anatolia Region, which extends to the southern western limits of the Black Sea (Bolu) region. As a result, it experiences a semi-arid continental climate characterized by steppe vegetation, cold and snowy winters, rainy springs, and dry and hot summers. Observations from the period 1927-2021, as reported by GDM (2022), show that January is the coldest month with an annual average low of 3.2°C, while July-August is the hottest period with an average of 30.3-30.5°C (Ankara). The study area's average annual temperature is around 12°C. Spring sees abundant rainfall, with annual averages around 392 mm, while summer accounts for 14.7% of total precipitation. The average annual relative humidity is 64%, with an average daily sunshine duration of 6.8 hours and an average annual rainy day of 103 (1927-2021).

➤ Summary of General Information of Study Areas

The Climate Classification in Türkiye were evaluating according to Holdridge Life Zones (Tekin et al., 2021). In the light of the information provided in Section 2.1.3. on the various study regions, Table 13 (next page) summarizes the main climatic and vegetation characteristics of the areas explored in this study.

Considering the data in Table 13, we can see that, in the 5 regions explored through the 21 Directorates of Forest Enterprise in Türkiye, forest ecosystems consisting of natural mixed stands of *Pinus nigra* - *Pinus brutia* are subject to varied climatic regimes. This explains their wide adaptability to all types of soil, despite the problems of disease, forest fires and so on.

Table 13. Summary of climatic information on study area

Observations		Study Areas and Climatic Characteristics (<i>Average Data</i>)					Türkiye
		Marmara	Karadeniz	Aegean	Mediterranean	Central Anatolian	7
RDF	10	Balıkesir Bursa Çanakkale	Bolu Kastamonu	Denizli Kütahya	Isparta	Ankara Eskişehir	30
DFM	13	Edremit Orhaneli Bayramiç	Göynük Gerze	Denizli Gediz Tavşanlı Emet	Göhlisar Burdur	Nallıhan Mihalıççık	277
DFE	21	Çınarlıhan Burhaniye Harmancık Karabayır Meyran Evciler	Hacıosman Dedeler Ilıca Himmetoğlu Dikmen	Denizli Kocabaş Karadona Muratdağı Alabarda Emet	Gölova Aziziye	Andiz Kartal	2147
Vegetation Type (<i>Even-age</i>)		Coniferous	Coniferous	Coniferous	Coniferous	Coniferous	48%
Dominated Tree Species (Mixed)		A. Black Pine (<i>Pinus nigra</i> Arnold subsp. <i>pallasiana</i> (Lamb.) Holmboe) and Turkish Red Pine (<i>Pinus brutia</i> Ten.)					0.35%
Altitude	m	371-1204	525-814	583-1345	289-1393	972-1040	1141
Rainfall	mm	599-626	480-700	560-568.7	568.4-725.9	392	618.9
	Day	87-121	124-135.4	91	103.4	103	1.041
Humidity	%	70	70	50	63.3	64	63.5
Sunshine	Hours	6-8	5.4-5.8	6-7.3	7.1	6.8	6.7
T °C	°C	14-16	9.9-14.3	10-16.2	12.3-16.3	12	13.3
	Coolest	7.9	4.2	8.7	6.4	3.2	2.3
	Hottest	24-27	22.2	27-28	26.8	30.3-30.5	24.5
Climate	Type	Transition zone	Humid, cool, and cold climate	Transitional climate	Mediterranean-type climate	semi-arid continental climate	Various
Winter		From	December	22	to	March	21
Spring		From	March	21	to	June	22
Summer		From	June	22	to	September	23
Autumn		From	September	23	to	December	22
Sources	TÜBİTAK TOVAG Project 118O311 (KTÜ, 2018); Orman Genel Müdürlüğü (OGM, 2021); Turkish Meteorological Service Reports (2022 and 2023)						

In ecosystems formed by pine species such as *Pinus nigra* subsp. *pallasiana* (Lamb.) Holmboe (Anatolian Black Pine) with *Pinus brutia* Ten. (Turkish Red Pine), forest fires are the main source of disturbance (TOD, 2023). These managed forests have a higher growth rate than pure forests, which is favorable for high yield and consequently, significant biomass formation and carbon storage (Noormets et al., 2015). Due to the lack of applied natural regeneration, these tree species retain their general and particular characteristics, but these mixing ratios are deviated from their adaptation for management purposes or simply transformed into pure forests (Genç et al., 2008; Sevgi et al., 2022).

In the context of these different growth environment, many indicators were used to understand the evolution of *Pinus brutia* and *Pinus nigra* mixed stands in Türkiye. For example, Carus and Çatal (2011) observed through the annual rings that diameter increments occurred every 5 years in the stem sections of *Pinus brutia* and *Pinus nigra* species. They estimated that changes in diameter increment were influenced by tree species, age, section height (length), and bilateral and trilateral interactions.

2.1.4. Most Characteristics of *Pinus nigra* and *Pinus brutia* Tree Species

a. *Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe

Pinus nigra Arnold subsp. *pallasiana* (Lamb.) Holmboe var. *pallasiana*, also known as Anatolian Black Pine, is a significant coniferous subspecies of the European black pine that grows naturally in the southern, western, and northern Anatolian Mountains of Türkiye as a mid-elevation species. Although three varieties of Anatolian Black Pine are recognized, namely var. *pallasiana*, var. *fastigiata* Businsky with pyramidal form, and var. *seneriana* (Saatcioglu) Yalt (Gülsoy et al., 2014; Farjon, 2010; Farjon et al., 2014). The images in Figure 21 illustrate the morphological presentation (stem, bark, foliage, cones) of *P. nigra*.



Figure 21. Illustration of the stem, bark, foliage and cone of *Pinus nigra*

It is an evergreen tree that can reach up to 20-40 m in height, forming a conical crown with young trees and an umbrella with old trees (OGM, 2022). *Pinus nigra* is a perennial species with a lifespan of up to 300-400 years. The tree's bark is dark grayish-brown and has deep longitudinal cracks that are typically seen in older trees. The foliage consists of finely toothed thorns (needles) in pairs, straight or curved in posture, which measure between 8-15 to 19 cm long and 1-2 mm in diameter. The reproductive organs are internal in *P. nigra* with the male organ having a yellow color and the female inflorescences having a reddish color. The symmetrical cones are 4-9 cm long and 2-4 cm wide, with a yellow-brown appearance. The cones mature in autumn of their second year and open to the ground in their third year. Each cone carries between 30-40 gray-colored seeds measuring 5-8 mm long, whose wings also measure between 19-26 mm long. Although *Pinus nigra* can grow to high altitudes (2200 m), their optimum altitude range varies between 400-2100 m. *Pinus nigra* subspecies *pallasiana* is prevalent in Türkiye as a specimen. The growth and development abilities of *Pinus nigra* are notable for their light-demanding and shade-tolerant nature, allowing them to withstand wind and grow in both dry and wet habitats with tolerance to temperature fluctuations. *Pinus nigra* is highly susceptible to pathogens that can alter its morphology, such as *Thaumetopea pityocampa*, *Gibberella circinata*, *Dothistroma pini*, *Sphaeropsis sapinea*, among others, which can destroy the foliage (needles). However, *Pinus nigra* can coexist with *Pinus brutia* and other species such as *Pinus sylvestris* and *Pinus halepensis*.

b. *Pinus brutia* Ten. Tree Species

Pinus brutia Ten is native species of the Eastern Mediterranean and is one of the most common conifers in Europe, particularly in Türkiye (Farjon, 2010). The first description of *Pinus brutia* was given by Michele Tenore (1780-1861) in 1811. In Turkish, it is locally called “Kızılcām”. The English names that are most widely used are “Calabrian pine” and “Turkish Red Pine.” The name of the species comes from the Italian province of Calabria, which was Brutia in the Roman era. Figure 22 illustrates the stem, bark, foliage and cone of *P. brutia*. Systematically, Turkish Red Pine (*Pinus brutia* Ten), a member of the Pinaceae family, is a significant tree that can grow up to 20-25 m in height and 60 cm in diameter. However, some Turkish Red Pine stands consist of tall and straight trees.



Figure 22. Illustration of the stem, bark, foliage and cone of *Pinus brutia*

Pinus brutia can grow on a variety of soils and at varying altitudes (400-1550 m). Like *Pinus nigra*, the bark of young trees is gray and smooth, while it appears dark reddish and deeply fissured in older trees. The foliage consists of thick, hard, dark green needles that measure between 10-16 cm. The spherically-shaped cone is light brown and shiny (OGM, 2022). In Türkiye, most mixed forests are naturally established and considered functional mixes due to their natural adaptation in the ecosystems that support them (Sun and Uğurlu, 1980). This provides advantages in forest structure and resistance against abiotic and biotic pests.

c. Summary of Characteristics of the Studied Tree Species

Table 14 shows the summary of characteristic data for the two conifer tree species.

Table 14. Summary table of data on the two conifer species studied

Characteristics	Tree Species	
	<i>Pinus nigra</i> Arnold subsp. <i>pallasiana</i> (Lamb.) Holmboe	<i>Pinus brutia</i> Ten.
English name	Anatolian Black (or Crimean) Pine	Turkish Red Pine
Local Name	Karaçam (Çk)	Kızılçam (Çz)
Year	1785 (Reisen Mariazell)	1811 (Michele Tenor)
Reign	Plantae	Plantae
Sub-Reign	Tracheobionta	Tracheobionta
Division	Coniferophyta	Coniferophyta
Class	Pinopsida	Pinopsida
Order	Pinales	Pinales
Family	Pinaceae	Pinaceae
Genre	Pinus	Pinus
Specie	<i>Pinus nigra</i> J.F. Arnold	<i>Pinus brutia</i>
Vegetation	Magnophanerophyta	Magnophanerophyta
Distribution	Large	Large
Diameter	50-150 cm	50 and 60 cm
Stem Height	20-40 m	20-25 m
Bark	Dark grayish-brown to black	Gray and smooth
Foliage / Needles	8-19 cm in length; 1-2 mm diameter	10-16 cm in length;
Cone Size	4-9 cm long and 2-4 cm wide	6 to 11 cm in length
Distribution	Large	Large
Altitude	200-2100	200-1500
Soil	Wet, deep, hard, sandy, loam...	
Root Type	Great capacity for adaptation (soils); Tap Roots (deep soils) and central roots (shallow, hard soil, poor soil, calcareous) ...	
Sources	General Directorate of Forestry (2021); www.tel-botanica.org (2022) Farjon, 2010; Farjon et al. 2014	

2.2. Research Methods

2.2.1. Secondary sources of information

In the context of this work, historical data, also known as secondary data or existing data, consists of all useful information related to our research subject that we have collected from documentary sources and scientific works available in literature. Sources of information used for this research include books, articles, reports, newspapers, course materials, conference proceedings, forums, development plans, etc.

The libraries (both physical and digital) of universities such as Karadeniz Technical University and others, national (Türkiye) and international (UN, NASA, FAO, IPCC, UN-REDD, GlobAllomeTree, iForest, EPA, NOAA, UN, etc.) scientific organizations, websites, journals, forest management plans, meteorological, environmental, cartographic and statistical services constitute the main sources of secondary information. The information collected from these sources allowed us to become familiar with the scientific environment surrounding our subject, select the areas of intervention, analyze the general and specific context of forest management and climate change, understand approaches to forest biomass and carbon studies in climate change mitigation strategies, and refine the methodology by which we planned field, laboratory, analytical and production work.

a. Acquisition, selection and Use of Existing Data

The available data on forest stand types used in our study were extracted from the TÜBİTAK 118O311 project databases compiled (Excel and GIS) from data provided by the General Directorate of Forestry (GDF). The GDF is a public service under the Ministry of Agriculture and Forestry of the Republic of Türkiye (established in 1924) whose main mission is the sustainable management of the country's agricultural and forestry resources. All other information relating to forest management and the current situation of target stands was obtained from the various forestry operations directorates (DFO). This enabled us to select and map managed forest units that potentially contained natural mixed stands of Anatolian Black Pine (*Pinus nigra*) or Karaçam (Çk), and Turkish Red Pine (*Pinus brutia*) or Kızılçam (Çz). Overall, 5 regions (Black Sea, Marmara, Aegean, Mediterranean, and Central Anatolia) were concerned in the country's 7 major administrative regions.

b. Research Methodology

After exploiting existing literary sources, all of the working methods that we have sequenced are shown in Figure 23.

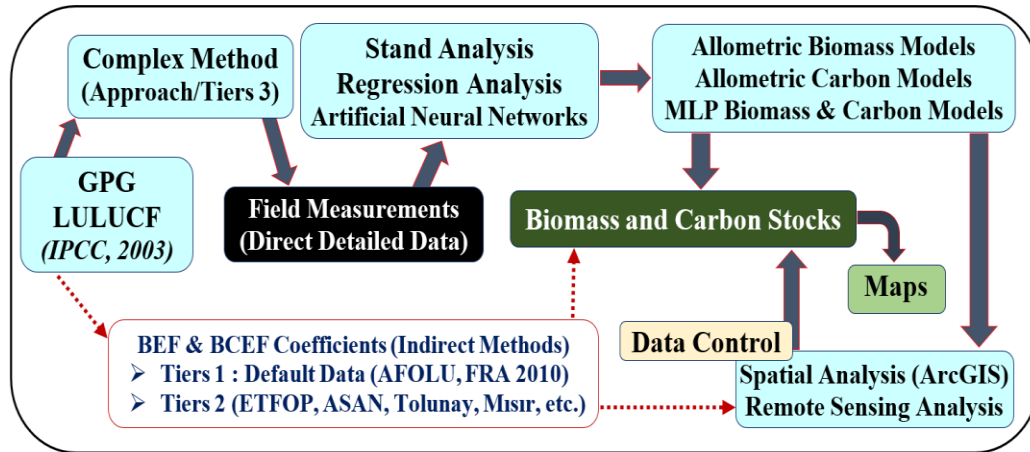


Figure 23. Diagram illustrating the research methodology process

In Figure 23, the main (thick) arrows represent the path and evolution of the methodologic process and main working methods that were followed in the framework of this study to achieve the research objectives. After choosing the IPCC methodology (2003-2006) described in the GPG-LULUCF, the complex method (Tier 3 Approach) was adopted. Dendrometric, biometric, geographic, edaphic, and environmental data were collected directly in the field and from literature. After processing, the information was subjected to in-depth statistical analysis leading to the development of biomass and carbon prediction models for mixed natural stands of *Pinus nigra* and *Pinus brutia*, displayed on a thematic map across all forest ecosystems concerned in Türkiye.

The field data collection method adopted in this study is the third approach (Method/Tiers 3) of the Good Practice Guidance for Land Use, Land-Use Change and Forestry (GPG-LULUCF) developed by the Intergovernmental Panel on Climate Change (IPCC, 2002-2006) at the request of the United Nations Framework Convention on Climate Change (UNFCCC). This Tier 3 Approach is a complex, demanding, detailed, practical, and effective method (Yavuz et al., 2010; Mısır et al., 2018; Sakıcı et al., 2016). The GPG-LULUCF is a technical-operational framework that helps countries produce inventories that are transparent, documented, consistent over time, complete, comparable, efficient in the use of resources, neither overestimated nor underestimated as much as possible, subject to quality control and assurance, and in which uncertainties are minimized as much as possible. The GPG-LULUCF distinguishes 5 natural biomass and carbon storage pools in forest ecosystems (IPCC, 2003).

The aboveground biomass is distributed in the living trees (stem, branches, foliage, bark, seeds, fruits), the living cover (herbaceous plants), the dead cover (branches, foliage, seeds, fruits, and any other debris with a diameter of less than 2.5 cm) and dead wood (debris with a diameter of more than 2.5 cm, dead standing or fallen trees). Belowground biomass is distributed in soil organic matter and in coarse (>5 mm), small (2-5 mm) and fine (0-2 mm) roots (Mısıır et al., 2018; Sakıcı et al., 2016). Data collection therefore consisted of a (direct) proximity approach on the observation units, and an actual estimate of biometric, dendrometric and environmental variables in the experimental plots (Çömez, 2012; Yavuz et al., 2010; Mısıır, 2012; FAO, 2012).

2.2.1.1. Planning and main stages of fieldworks

Figure 24 shows the main steps of fieldworks implementation (data collection).

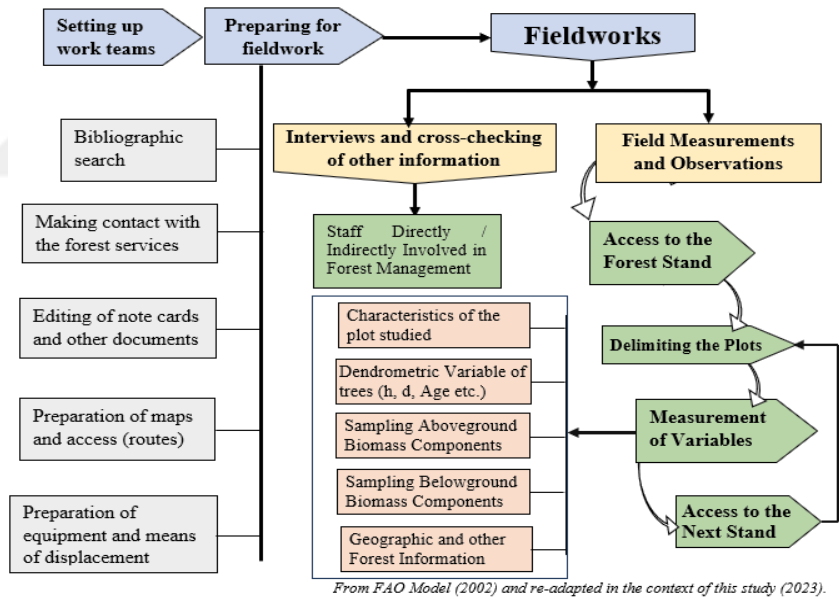


Figure 24. Diagram illustrating the main steps of fieldworks implementation

According to Figure 24, the data collection work was planned at the Forest Management Laboratory of the Faculty of Forest Engineering of Karadeniz Technical University in Türkiye. The work lasted for 3 consecutive years, during each summer season. The map data of each managed forest unit helped to identify potential stands to be surveyed beforehand, to know and plan the optimal measures in the face of geographical constraints (roads, topography, agricultural areas, housing, waterways, valleys, steep slopes, etc.).

The teams mainly consisted of professional foresters such as academics (Professors, Doctoral students, Masters and Bachelor students) and forestry staff (Engineers, Technicians, Firefighters, Drivers, Surveyors, Loggers, Temporary workers). The working materials were gathered (university and forest services) according to the methods involving their use. Significant means of transport and survival were mobilized. The work progressed according to the permissions for access to the forest and the availability of the forest services to host us and accompany us in the data collection.

2.2.1.2. Sampling and Criteria

In Türkiye, the document on the Procedures and Principles of Ecosystem-Based Functional Forest Management (ETFOP) specifies all the important parameters to be taken into account when describing a forest stand. Figure 25 shows an example of the basic forestry information compiled in the current management plan, on the basis of which the pre-selection of target stands was carried out.

	A	B	C	D	E	F	G	H	I	J	K	L
1	BOLGE ADI	ISLETME ADI	SEFLİK ADI	BLM NO	MES TIP	PYİL	MESCERE	BONİTET	YAS SIN	EGİM	ALAN	DURUM
2352	BOLU	GÖYNÜK	ILICA	5	ÇkÇzbc3	2019	ÇkÇzbc3	5	3	11	9,6	Çk+Çz
2353	BOLU	GÖYNÜK	ILICA	248	ÇkÇzbc2-1	2019	ÇkÇzbc2	5	4	28	1,8	Çk+Çz
2354	BOLU	GÖYNÜK	ILICA	8	ÇkÇzbc2-2	2019	ÇkÇzbc2	5	7	27	13,2	Çk+Çz
2355	BOLU	GÖYNÜK	ILICA	9	ÇkÇzbc2	2019	ÇkÇzbc2	5	6	29	7,1	Çk+Çz
2356	BOLU	GÖYNÜK	ILICA	13	ÇkÇzbc2	2019	ÇkÇzbc2	5	5	39	9,0	Çk+Çz
2357	BOLU	GÖYNÜK	ILICA	15	ÇkÇzbc2	2019	ÇkÇzbc2	5	3	21	3,7	Çk+Çz
2358	BOLU	GÖYNÜK	ILICA	15	ÇkÇzbc3	2019	ÇkÇzbc3	5	4	41	11,9	Çk+Çz
2359	BOLU	GÖYNÜK	ILICA	28	ÇkÇzbc2	2019	ÇkÇzbc2	4	6	24	13,7	Çk+Çz
2360	BOLU	GÖYNÜK	ILICA	49	ÇkÇzbc2-1	2019	ÇkÇzbc2	3	3	42	16,9	Çk+Çz
2361	BOLU	GÖYNÜK	ILICA	22	ÇkÇzbc3	2019	ÇkÇzbc3	5	6	19	17,0	Çk+Çz
2362	BOLU	GÖYNÜK	ILICA	164	ÇkÇzbc2	2019	ÇkÇzbc2	5	3	26	17,4	Çk+Çz
2363	BOLU	GÖYNÜK	ILICA	25	ÇkÇzbc2	2019	ÇkÇzbc2	4	6	15	13,2	Çk+Çz
2364	BOLU	GÖYNÜK	ILICA	25	ÇkÇzcd2	2019	ÇkÇzcd2	4	7	22	6,7	Çk+Çz
2365	BOLU	GÖYNÜK	ILICA	219	ÇkÇzbc2	2019	ÇkÇzbc2	5	3	21	27,1	Çk+Çz
2366	BOLU	GÖYNÜK	ILICA	32	ÇkÇzbc3	2019	ÇkÇzbc3	4	4	17	3,1	Çk+Çz

Figure 25. Example of information considered in choosing stands and planning

Based on the preliminary data available and secured in Excel spreadsheets (Figure 25), the target mixed stand types (Karaçam-Kızıldağ or ÇkÇz) were selected on the basis of a number of criteria, as shown in Table 15. According to Table 5, all the criteria follow the prescriptions of Procedures and Principles for Ecosystem-based Functional Forest Management Plans (PPREFFM/ETFOP) in Republic of Türkiye (Directive No 299, 2017). In the particular case of the Site Index (Bonitet), 5 classes are generally determined in Türkiye as shown in a study by Çatal et al (2017) entitled “Determination of Free-to-Grow Stages for Natural mixed Brutian pine (*Pinus brutia* Ten.) - Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.) Holmboe) stands”.

Table 15. The main criteria using to select stands

Criteria	Details	Source
Stand Type and Status	Mixed and undisturbed natural forest stands	
Site Index (Bonitet)	Good (I and II); Medium (III); Poor (IV and V)	
Age Class (6)	1-20; 21-40; 41-60; 61-80; 81-100 and 101 ⁺	
Clown Closure	1 (11-40%); 2 (41-70%) and 3 (71-100%)	ETFOP Directive No 299 (2017)
Size of Sample Plots	Depend of Clown Closure Degree: 1 (800 m ² or r=15.96 m); 2 (600 m ² or r=13.82 m) and 3 (400 m ² or r=11.28 m)	
Development Stage (Reference at 1,30 m)	a (1-7.9 cm); b (8-19.9 cm); c (20-35,9 cm); d (36-51.9 cm); e (52 cm)	

The 5 classes are classified as Very Well (I), Good (II), Medium (III), Poor (IV) and Very Poor (V). But in the context of this study, these classes were grouped in Good (I & II), Medium (III) and Poor (IV and V). The development stages of forest stand adopted in Türkiye can be seen in Figure 26 (Yılmaz, 2020).

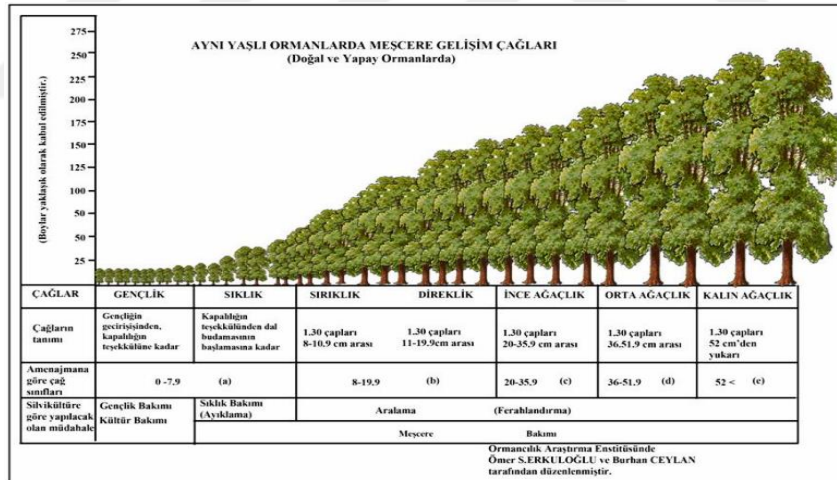


Figure 26. Stand development stages in even-aged forests in Türkiye

According to Figure 26, the main categories of development stage are named (i) young (**a**: 0-7.9 cm) that include thicket, reproduction and culture stage, (ii) sapling and pole stage or stem exclusion stage (**b**: 8-19.9 cm), (iii) thin wooded or small tree stage or understory reinitiation stage (**c**: 20-35.0 cm), medium stage (**d**: 36-51.9 cm), and (iv) thick or old growth stage (**e**: 52+ cm) woodlands (ETFOP Statement No 298, 2014; Genç et al., 2012 cited by Bayar et Genç 2013).

As a result, the stand selection method used a non-probabilistic (empirical) logic based on pre-established criteria, judgment, and identification, which resulted in sampling by reasoned choice (Dufour, 2020).

2.2.2. Field Activities and Data Collection

a. Locating and Accessibility in the Sampling Areas

The use of cartographic data (maps) and the support of forest service made it possible to locate forest stands on the ground. Connection with areas of interest was made possible thanks to vehicle travel and walking (on foot), GPS tracking and, above all, the expertise of the staff of the various host forest services. Despite certain limits in certain places, direct and careful observation as well as in situ evaluation of the current and apparent state of the stands and the immediate environment (type of stand, natural or planted species, level of disturbance, treatment, development stage, canopy, growing environment, density and dendrometric parameters) in turn helped with practical decisions. The sample plots were defined once arriving in the area of interest.

b. Delimitation of the Experimental Plots and Tree Inventory

A methodical practice that lays the fieldwork for data collection in the forest is the demarcation of an experimental plot. The experimental plots in each type of interest stand were delimited in accordance with Section 5.4.1. of the Procedures and Principles of Regulation of Functional Development Based on Ecosystems (ETFOP) relating to unit plots in Turkish forest inventories (ETFOP Tebliğ N° 299, 2017) (Figure 27).

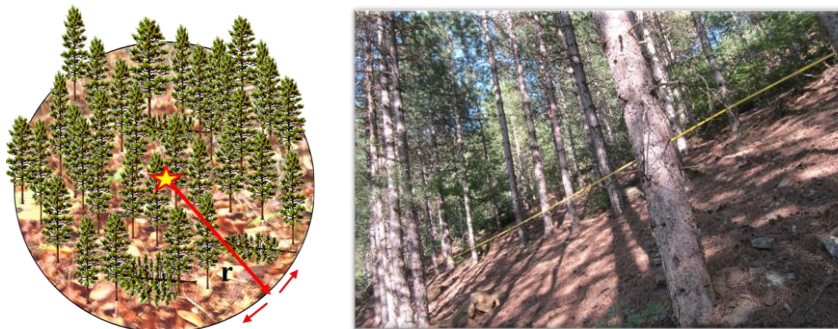


Figure 27. Illustration of the delimiting of a sampling unit plot

Figure 27 shows that circular-shaped experimental plots were established in the study areas for information gathering. Plot areas varied between 400 m², 600 m² and 800 m² depending on the size of the ambient canopy, 3, 2 and 1 respectively. In each experimental plot, all trees and their diameter at breast height ($D_{1.30}$) were inventoried, sample trees (4, 6 or 8) were selected and their height, age and bark thickness were estimated, one tree of each species was felled in the plot, geographical data (GPS) and other identification information were recorded in pre-established inventory books.

c. Tree Inventory Work in Experimental Plots

In the sampling plot, all the trees (living or dead) of the two studied species (Çk and Çz) were systematically counted. Figure 28 illustrates the inventory work in the plot.



Figure 28. Image illustrating the tree inventory works in an experimental plot

In Figure 28, the inventory consisted of counting each tree in the survey plot. A correspondence number was assigned to each tree in order to synchronize it with all the corresponding dendrometric information. ETFOP Tebliğ N° 299 (Section 5.4.1.) prescribes within the framework of forest inventories at the national level, the consideration of trees whose Diameter at Breast Height (DBH or $D_{1.30}$) is greater than or equal to 7.9 cm (GMO, 2017). But, in the context of this study, which aims to quantify the actual biomass and carbon equivalent stocks of each ecosystem concerned, all the diameters ($D_{1.30}$) of each tree species considered in each development stage were measured.

d. Measurement of Tree Diameters at 1.30 m ($D_{1.30}$)

The Diameter at Breast Height (DBH or $D_{1.30}$) of all trees sampled (Cf. Figure 27) in each plot was measured according to the international standard (FAO, 2002; IPCC, 2003), as shown in Figure 29.

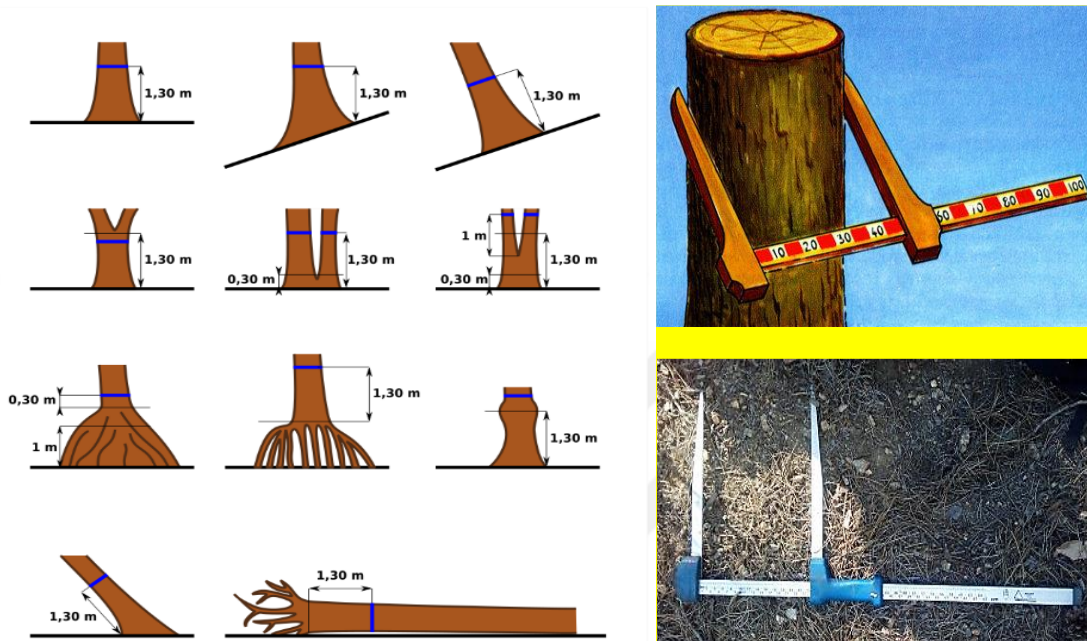


Figure 29. Illustration of Diameter at Breast Height ($D_{1.30}$) measurement

According to Figure 29, the measurement of the DBH on the bark consisted of fixing the arms of the Forest Compass to the stem, in particular at 1.30 cm from the ground ($D_{1.30}$), and noting the value of the diameter (cm) on the inventory sheet. Diameter has not been measured in the case of young plantations in which the height of the young plants (shrubs and/or sub-shrubs) are less than 1.30 m.

e. Measurement of Tree Height (h_i)

Tree Height (H) was measured using the Forestor Vertex III dendrometer (Pauwels, 2001; Gaudin et al., 2014). It is a device that emits ultrasound that travels from the transponder to the dendrometer. The photos in Figure 30 illustrate the device utilization.

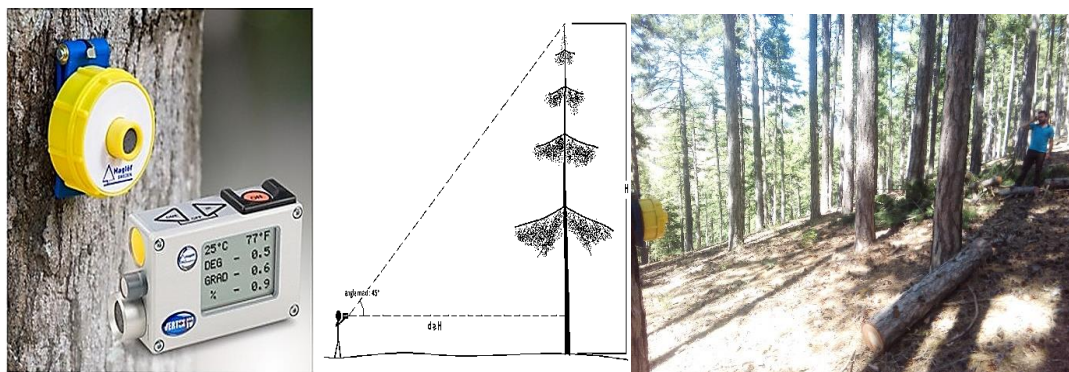


Figure 30. Tree height (H) measurement operation with the Vertex III Dendrometer

Indeed, the measurement of the height of the trees was carried out by one or two operators. After switching on the Vertex, connecting with the transponder, and calibrating the device (activation), the transponder is then fixed on the tree at 1.30 m from the ground (Figure 30). The operator stands approximately at the height of the tree. Then, he aims the transponder, which emits ultrasound, allowing the operator to mark the first value and finally aim for the top of the treetop for the second value. The reading on the telescope screen therefore makes it possible to read several pieces of information and, in particular, to note the height of the surveyed tree. This height is therefore communicated to the meter reader and transcribed on the collection sheet (Sweden, 2005; Pauwel, 2001).

f. Measurement of Tree Bark Thickness

Measurement of the bark thickness of each tree was performed using the Swedish Bark Gauge Meter (Stängle et al., 2018), shown in Figure 31.



Figure 31. Image of Swedish Bark Gauge Meter (SBGM)

Indeed, the SBGM is graduated in millimeters (0–50 mm) on its aluminum tube (Figure 31).

When the operator fixes the flattened end on the tree, he then inflicts a pressure that allows the axial blade, which has a sharp end and is housed in the aluminum tube, to be introduced through the bark of the tree and reach the underlying wood. In contact with the wood, the sleeve around the axis is offset on the surface of the blade and transmits resistance. It is at this level that the value of the level on the outer tube has been raised. This value is multiplied by 2 to give the value of the bark of the tree.

g. Estimation of the Tree Age by Increment Borer

The age of the standing trees was estimated through the heartwood extracted using the Swedish Increment Borer (Grissino-Mayer, 2003), as illustrated by the images in Figure 32.



Figure 32. Sampling and estimation of tree age from tree

In Figure 32, the operator fixes on the shaft (D_{1.30}) the sharp end of the steel rod (bit) provided with a screw thread. It turns and drives the steel tube perpendicular to the inner axis of the shaft to reach the heart (Figure 32). Then the extractor rod is inserted into the auger to hold the core in place. This carrot from the stem is extracted, and the rings are counted. The first 10 rings are measured in millimeter (mm). The total number of rings represents the age of the tree at that height (Grissino-Mayer, 2003).

h. Estimation of Tree Age on the Tree Profile

The wood transversal sections taken from the trees cut during the survey were subjected to the first measurements in the laboratory (Günel, 1981) as shown in the images in Figure 33.



Figure 33. Counting of growth rings and measurement of diameters of wood sections

As shown in Figure 33, the growth spines of certain trees were counted on cross sections taken at several height ranges on the stem. This exercise made it possible to extract the exact age, as well as the exact values of the over- and sub-shell diameter.

i. Sampling of Aboveground Biomass Components

Figure 34 illustrates the operations of tree and tree component extraction in the fieldwork.

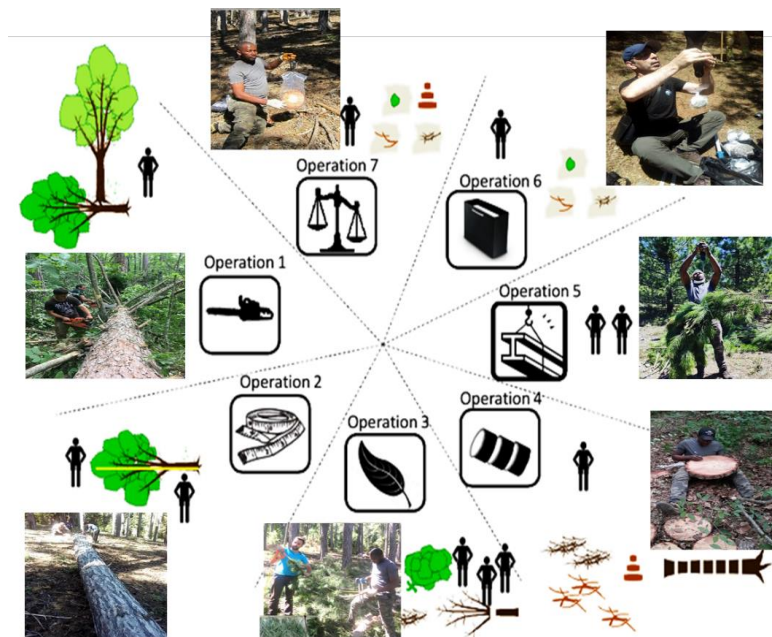


Figure 34. Different aboveground biomass sampling operations in the field

The stages of sampling the components of the aboveground biomass concern the operations that lead to the obtaining of the samples of trees, branches, and foliage, the weighing, and the packaging, as shown in Figure 34 (Adapted from FAO, 2012). According to Figure 34, several operations were carried out as part of the aboveground biomass sampling.

j. Felling of Trees and Removing the Branches and Sections

Figure 35 (next page) illustrates the felling of sample trees and removing of branches from stem. In the field works, an average tree of each species, especially those that present an ideal state of health in terms of average height, rectitude (right), quality, and without any anomalies (deformation, rot, impact, etc.), was cut at 30 cm from the ground.



Figure 35. Tree felling, branch cleaning and removal wood sections samples

In Figure 35, all the branches were separated from the stem. For some trees, sections (discs) of 3 to 7 cm thick were taken from the lower end of the stem (30 cm), then at 1.30 m ($D_{1.30}$), and finally every 2 m from the stem to the top of the tree. These sections allowed us to analyze the profile and estimate the age of several trees. A single intermediate section was used for the analysis of biomass and tree carbon ration.

k. Age and Diameter Estimation on the Wood Sections in Field

The age estimation (rings) and diameter measurement on each wood section taken from the tree stem at different heights were realized as shown in the images in Figure 36.



Figure 36. Counting growth rings on sampled wood sections

As the images in Figure 36 show, the growth rings of each section drawn from the stem of each fallen tree were carefully counted (Günel, 1981). This count helps to determine the actual age of the tree based on its age at 30 cm above the ground. It also makes it possible to estimate the different ages of formation for each section diameter (Mısıır, 2017).

l. Measurement and Sampling of Branches, Foliage (Leaves)

All cut branches on each sample tree were systematically measured, as shown in the images in Figure 37.



Figure 37. Illustration of the measurements on the tree branches in field works

Using the caliper and tape measure (Figure 37), the height (h_i) and big end diameter (d_i) of each branch of the tree were measured (Mısır et al., 2018).

m. Sampling of Tree Branch and Leaves (Needles or Foliage)

Among the branches that were cut from the felled tree, a branch sample was taken and carefully separated from its foliage, as shown in Figure 38.



Figure 38. Separation of foliage from sampled branch

In Figure 38, the sample represents the average branch chosen by simple visual analysis (approximately). On each branch, the foliage was carefully separated from the wood, and together with the branch, they were kept quickly, tightly, and separately in a plastic bag to prevent moisture loss.

n. Sampling of Dead Wood

Dead wood is considered to be all dead plants present in the survey plot whose diameter is greater than or equal to 2 cm (Figure 39).



Figure 39. Dead wood samples collected in the experimental plot

According to Figure 39, all deadwoods were taken in the small plot (1m x 1m) established in the inventory plot.

o. Sampling of Litter and Living Herbaceous Cover

Figure 40 illustrates the sampling of the live herbaceous and litter covers.

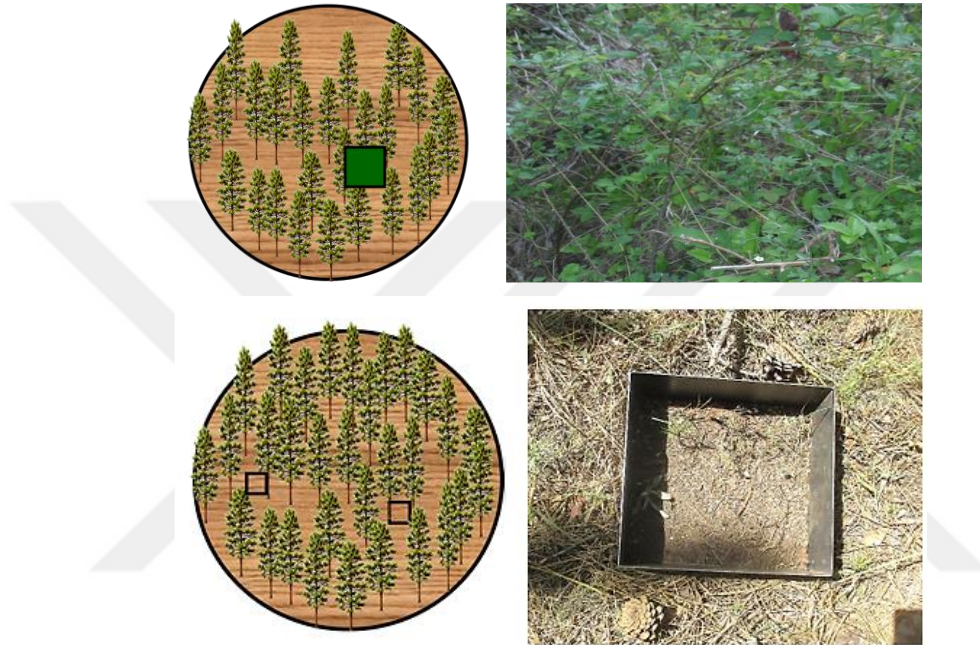


Figure 40. Sampling of living herbaceous and litter cover in the sample plot

According to Figure 40, the living plant cover was taken from the sampling unit. A small plot of 1 m² was delimited (1m x 1m) using a meter tape. All living herbs have been collected systematically. Also, as superficial dead vegetation (litter), the dead cover was sampled in each experimental plot (Seringil, 2018). The quadrat was launched randomly in two separate places within the experimental plot in order to collect dead plant matter (litter). For this category, we used the terms “land surface” to indicate all three components of above-ground biomass, namely litter, dead wood and cover.

p. Sampling of Belowground Biomass: Roots

The roots samples were taken using the cylinder present in Figure 41.



Figure 41. Collection of root samples from the experimental unit plot

According to Figure 41, root samples were taken using a 30 cm high and 6.4 cm diameter root cylinder. Root samples were taken at 0-30 cm, 30-60 cm and 60-90 cm depths.

q. Sampling of the Soil Organic Matter

In the same soil excavation that was carried out to collect the root samples, soil organic matter samples were taken as shown in Figure 42.



Figure 42. Soil organic matter sampling in the experimental unit plot

According to Figure 42, soil organic matter samples were taken at different profiles (0-10 cm, 10-30 cm, 30-50 cm, 50-80 cm and 80-100 cm) using the cylindrical tube of 10 cm (length) and 8 cm (diameter) (Misir et al., 2018).

r. Sample Conditioning, Weighting and Codification

In summary, the main types of stands that have been studied at different development stages are ÇkÇza, ÇkÇzab, ÇkÇzb, ÇkÇzbc, ÇkÇzc, ÇkÇzcd and ÇkÇzd. In fact, 47 experimental plots were established in 20 forestry companies spread across 13 forestry operations directions in Türkiye. In the 47 plots, dendrometric measurements were performed (diameter, height, age, and bark thickness) and samples were collected. Thus, 138 wood sections, 138 branches and 138 leaf samples were collected. For terrestrial biomass, 94 samples of litter (dead cover), 40 samples from dead timber, 47 samples of live herbaceous vegetation and 47 soil profiles (0-30 m, 30-60 m and/or 60-90 m) were collected from the field. The main information is stored in the booklets (Cf. Annex 1, 2 and 3). All samples collected in the field were packaged in suitable packaging. Some were weighed before packing, in order to collect their fresh weight. The pictures in Figure 43 illustrate the activities of weighing, packaging and transportation of samples.



Figure 43. Weighing, conditioning and transportation of collected samples

The transported samples (Figure 43) were subsequently processed in the Forest Management Laboratory and also the Forest Yield and Carbon Analysis Laboratory of the Department of Forestry Engineering of the Karadeniz Technical University.

2.2.3. Laboratory Works

In the context of the present study, the laboratory work consisted of a set of meticulous and delicate activities, such as pre-drying (aeration), checking, cleaning, separation, weighing, drying (oven), re-weighing (dry mass), crushing, packaging, analysis, and securing information (Mısır et al., 2018; Yavuz et al., 2010).

a. Drying of Samples by Aeration

The samples brought back from the forest were placed and secured in the ventilated premises of the forest management and the forest yield, Biomass and carbon analysis laboratories of Karadeniz Technical University. After verifying the consistency of the information, the samples were subjected to a first drying process which consisted in exposing them to the open air, as shown in Figure 44.



Figure 44. Illustration of samples exposure for drying by aeration

Indeed, all samples were exposed to the open air for a few days for pre-drying by aeration (Figure 44) in order to reduce humidity and especially to avoid disintegration (rot) of the plant material.

b. Conditioning of Stem Wood Sections

Figure 45 shown the measurements operations on the stem wood sections.



Figure 45. Separating the bark on the wood sections before over-drying

Indeed, on the stem sections which were taken for carbon analysis, the diameter and thickness were measured (Figure 45). Then the bark was separated from the wood. These samples have been prepared for oven-drying.

c. Washing, Extraction and Drying the Roots

The roots were delicately treated to obtain their dry mass according to their size and depth (Figure 46).



Figure 46. Washing and extraction of roots in samples of soils

In fact, all the roots collected from the soil forests were immersed in water for 12 to 24 hours, in order to facilitate their separation from impurities (Figure 46). Their release made it possible to extract all the roots whatever their size, as shown in Figure 47.



Figure 47. Image showing root extraction and air drying

After separating the roots from their impurities, all samples were exposed to pre-drying by aeration, for 2 to 5 days on average (Figure 47). Then, the roots were sorted according to their depth (0-30; 30-60 and 60-90 cm) and especially their size, namely: Coarse (>5 cm), Small (2-5 cm) and Fine (<2 cm). After sorting, the samples were placed in the oven-drying.

d. Processing Soil Samples for Organic Matter

Soil samples taken at different depths were also subject to special treatment (Fig. 48).



Figure 48. Soil samples cleaned and for drying in the oven

Indeed, the soil samples intended for the analysis of carbon in the soil organic matter were cleaned of their impurities after pre-drying (Fig. 48), and prepared for the oven-drying.

e. Weighing and Oven-drying of Samples

After drying in the air (aeration), all the samples were weighed before and after their second drying in the oven (Figure 49).



Figure 49. Weighing of samples before and after oven-drying

In Figure 49, weighing allowed to obtain the fresh weight and dry mass values of each sample. The accuracy of the device was 0.01 g.

f. Drying of Samples in the Oven

All samples were dried in the BINDER oven at different temperatures (Figure 50).



Figure 50. Drying of samples in the oven (BINDER)

The BINDER drying oven (Model ED 23) is an electrical chamber for drying and sterilization with natural forced convection and an adjustable air damper. It has a controller with a timer function, chrome-plated shelves, and a class 2 adjustable safety thermostat with a visual blade. The drying temperature range capacities vary between 5°C (41°F) and 300°C (572°F) (www.blinder-word.com).

In the case of this study, the different respective temperatures to which the samples were subjected are presented in Table 16.

Table 16. Temperature and time conditions used for drying samples in the oven

Oven-drying Conditions using in Laboratory			
Components	Temperature	Hours	Reference
Stem Section	65±3°C	96	Yıldız (2022) Yavuz et al. (2010) Mısır et al. (2018) TÜBİTAK Project 118O311 / 1001 BF-01 (2016)
Bark	65±3°C	96	
Branch	65±3°C	96	
Foliage	65±3°C	48	
Litter	65±3°C	48	
Deadwood	65±3°C	48	
Living Cover	65±3°C	48	
Coarse	65±3°C	48	
Roots	Small	24	
	Fine	24	
Soil Organic Matter	105±3°C	12	Gülçür (1974), Brady, N.C. (1990), Ngo ve diğ. (2013)

g. Conditioning and Grinding of Samples

To submit all samples to carbon analysis, grinding is an essential operation. It consists of crushing and powdering the particles of the considered sample (Figure 51).



Figure 51. Grinding works to obtain the powdered material

After weighing the samples at the exit from the drying oven, they were conditioned into smaller particles for crushing using a crusher. The powder obtained was used for the elemental analysis of carbon.

h. Combustion and Process of CNHS-O Elemental Analyzer

• COSTECH CNHS-O Elemental Analyzer Device and Consumables

The COSTECH Elemental Analyzer is highly recommended in the scientific community for analyzing elementary components (CHNS-O) in all combustible material (Michael, 2008; Bird et al., 2017; VanderWulp, 2023). It provides a means for the rapid determination of Carbon, Hydrogen, Nitrogen and Sulphur in organic matter and other types of materials (Micheal, 2008). COSTECH Elemental Analyzer equipment was used in this study to determine the C-N combination of each sample. Figure 52 shows an overview of the installation of the main device of COSTECH Elemental Analyzer in Forest Yield, Biomass and Carbon Analysis Laboratory of Karadeniz Technical University (Türkiye).



Figure 52. COSTECH elemental Analyzer System in laboratory

The COSTECH device (Figure 52) analyzed the ratio of carbon, hydrogen, nitrogen and sulfur contained in a given mass by the dry combustion method. It determines the carbon concentration contained in all the samples by subjecting them to very high temperatures. Particularly, it is an automated combustion analyzer used to determine total carbon and nitrogen content in plant and soil samples (Michigan State University - KBS LTER, 2004; Bird et al., 2017). The main consumables used in carbon ratio analysis are Tin and Silver (Aluminum) capsules, Quartz tubes, Reagents, Reference standards, Oxidation and Reduction catalysts and Copper wires.

i. Carbon Sampling and Analysis Process in COSTECH Analyzer

The COSTECH Analysis System represents an evolution in the technique of elemental analysis based on flash combustion, chromatographical separation, and multidetector techniques. The ignition of the furnaces was started 1.5 hours before the start of the analysis, the time necessary for the ovens to go from room temperature to operating temperature. In the Forest Yield, Biomass and Carbon Analysis Laboratory, the analysis was divided into 3 modules:

(i) Module 1: The first module involved preparing powder samples and subjecting them to high temperature combustion using the ECS 4010 system. Three (3) replicates of 0.6–1.0 mg powder samples were prepared and packaged in capsules. The samples were then measured on a microbalance with a precision of 0.001g and deposited in the well autosampler. In the analysis process, the system was calibrated as illustrated in Figure 53.

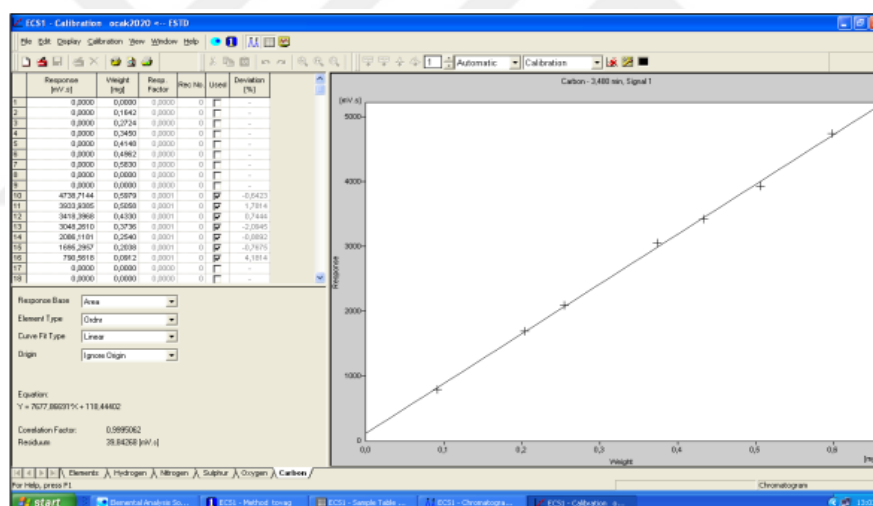


Figure 53. Calibration view of COSTECH software

According to Figure 53, the CN configuration (combination) corresponding to the search objectives was calibrated in the software. The samples were automatically fed into the combustion column and subjected to combustion at temperatures up to 1030°C using an inert helium-carrying gas. The combustion gases were then supplied to a gas chromatography separation column and a thermal conductivity detector. The system uses the micro-mode operation of a unique pneumatic system to select the combustion oxygen volume. The ashes and residues were eliminated by the tubes of the quartz reactors, extracted, and cleaned.

Chromatograms can be modified in various ways. It is possible to modify the chromatogram by entering global parameters or interactively by directly modifying the baseline on the graph.

(ii) Module 2: The second module is the detector system for measuring the combustion (pyrolysis) products. Figure 54 shows the internal architecture of the COSTECH Analyzer system.



Figure 54. Combustion and detection process in the COSTECH Analyzer

Module 3: The last module is the instrument control, data acquisition, and report generation software. The control interface of software, called Chromatogram, as well as the different views of the chromatogram evolution control, are presented in Figure 55.

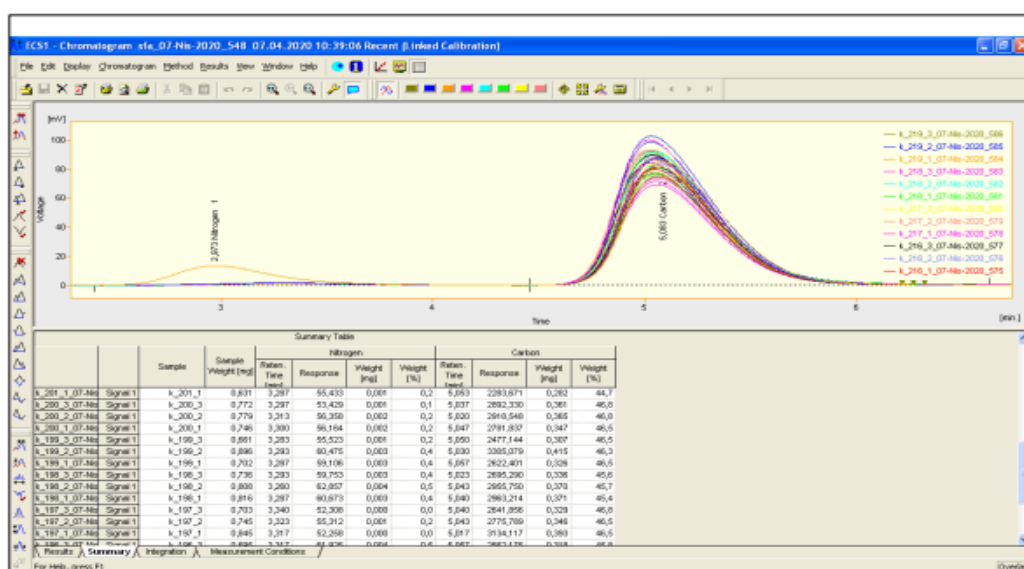


Figure 55. Panel and control chart of analysis process

This is a multi-channel interface that connects the ECS to a computer. This software was used to enter information on each sample, calibrate the system, and generate reports and statistics through the chromatograph interface (Software). During the analysis, the data was directly transferred to the computer program in which the preparations and the launching of the analyses were carried out. The percentage of carbon (%C) was determined in sampling. The time required for the analysis of a sample has been estimated between 4–30 minutes. Indeed, at the exit of the analyzer, the carbon value obtained represents that of the sample weighed at the entrance (0.5-0.99 g) of the COSTECH Elemental Analyzer. From these first data, the carbon ratio of the sample brought back from the forest, whose dry mass had already been obtained, was determined. Starting from this value, the carbon data at the scale of the experimental plot and the forest stand were determined. The combustion products, i.e. CO₂, H₂O, N₂ and SO₂, are separated and quantified by a high resolution TCD detector.

2.2.4. Data Analysis

a. Analysis of Forest Stand Parameters

❖ Calculation of Stand Age (A_s)

Age is a descriptive and classification criterion that can be very representative or not, depending on the nature of the forest (Gaudin, 1996). Stand age (A_s) is a parameter that affects carbon sequestration and storage by forest ecosystems in a given period. Its determination is crucial in the analysis of forest stands. To determine the age of the forest stand, several scientists recommend the arithmetic mean approach (Kalipsız, 1984; Pretzsch, 2009; Yavuz et al., 2010; Frivold and Frank, 2002; Ruiz-Peinado et al., 2021). In temperate regions of the northern hemisphere, where old natural mixed stands (Çk-Çz) are also found, this approach does not constitute a problem. However, there can probably be significant age differences within species. A_s in the case of this study, the age of the stand of each species (A_{i_k}) was calculated, and the arithmetic mean ages of the whole stand (A_s) was determined using the following relationships (Yavuz et al., 2010).

- Average Stand Age for k -specie with n -trees: ($\bar{A}_k$)

$$\bar{A}_k = \frac{\sum_{i=1}^n A_{i_k}}{n_k} = \frac{A_{1_k} + A_{2_k} + A_{3_k} + \dots + A_{n_k}}{n_k} \quad (1)$$

- Stand Age of mixed stand (A_s):

$$A_s = \frac{\sum_{k=1}^t \bar{A}_k}{t} = \frac{\bar{A}_1 + \bar{A}_2 + \bar{A}_3 + \dots + \bar{A}_t}{t} \quad (2)$$

Where A_s = Stand Age of all mixed stand (year); $\bar{A}_i$ = Average Age of n -tree of k -specie (year); n_k = Number of Trees of k -specie; A_{i_k} = Age of individual i -tree of k -specie (year); t = number of species in mixed stand; (i, n and $k \in \{1, 2, 3, \dots\}$).

❖ Calculation of Stand Arithmetic (D_q) and Quadratic (D_q) Mean Diameters

Arithmetic Mean Diameter (D_m) and Quadratic Mean Diameter (D_q) are two crucial measures for assessing the structure of these stands. According to Kendall and Buckland (1967), referred to by Curtis and Marshall (2000), Quadratic Mean Diameter (D_q) is the measure of average tree diameter (Curtis, 1968) conventionally used in forestry rather than arithmetic mean diameter (Ruiz-Peinado et al., 2021). It can also be assimilated as the average diameter per tree basal area. There are several approaches to determining the D_m and D_q of a stand. Arithmetic Mean Diameter (D_m) is a central measure of tree size in a stand. It is calculated by summing individual tree diameters (D_i) for each k -specie, then dividing this sum by the total number of trees. D_m gives an indication of the average tree size in a stand, enabling foresters to estimate productivity and carrying capacity. For k -species with n_k -trees, the Arithmetic Mean Diameter (D_{m_k}) formula is expressed as follows:

$$D_{m_k} = \frac{1}{n_k} \sum_{i=1}^{n_k} D_{i_k} = \frac{1}{n_k} \sum_{i=1}^{n_k} (D_{1_k} + D_{2_k} + \dots + D_{n_k}) \rightarrow D_m = \frac{1}{t} \sum_{k=1}^t D_{m_k} \quad (3)$$

Where i, n and $k \in \{1, 2, 3, \dots\}$; D_m = arithmetic mean diameter of mixed stand (cm); D_{m_k} = arithmetic mean diameter (cm) of k -specie; D_{i_k} = diameter of the individual i -tree of k -species (cm); t = number of specie in mixed stand, n_k = total number of trees of k -specie.

Species diversity interacts dynamically in the complex forest ecosystems of mixed conifer stands. By providing important information on tree structure and growth, these parameters are essential to characterize stand in forest management. The Quadratic Mean Diameter (D_q) measures the dispersion of diameters within a stand. According to Curtis and Marshall (2000), the term Mean Stand Diameter, commonly used in silviculture, actually refers to the Quadratic Mean Diameter rather than the Arithmetic Mean of Diameters. To calculate D_q , the square root of the average of the squared diameters is used (Ruiz-Peinado et al., 2021). The D_{qk} of each k -specie and D_q of mixed stand were calculated according to follows relationships:

$$D_{qk} = \sqrt{\frac{\sum_{i=1}^{n_k} D_{i_k}^2}{n_k}} = \sqrt{\frac{D_{1_k}^2 + D_{2_k}^2 + \dots + D_{n_k}^2}{n_k}} \rightarrow D_q = \frac{1}{t} \sum_{k=1}^t D_{qk} \quad (4)$$

Where D_{qk} = Quadratic Mean Diameter of i -specie (cm); D_{i_k} = diameter of individual i -tree (cm); n_k = total number of samples trees of k -specie; D_q = Quadratic Mean Diameter of mixed stand (cm); t = Number of species in the mixed stand; i, n and $k \in \{1, 2, 3, \dots\}$.

Several studies have used these approaches to determine D_m and D_q . In the context of mixed stands (Karaçam-Kızılçam) studied in this works, D_m and D_q of each tree species (i) was calculated separately and the average of two species data was obtained for the mixed stand. D_m and D_q are interconnected as they offer a comprehensive view of stand structure. A stand with high D_m but low D_q may indicate dominance of similar-sized trees. Conversely, high D_m coupled with high D_q reveals greater diversity in tree sizes. The combination of these two measures provides a more precise characterization of stand composition (Yavuz et al., 2010; Mısır, 2012; Kalıpsız, 1984; Günel, 1981; Ruiz-Peinado et al., 2021).

❖ Calculation of Stand Height Curves [$H = F(D)$]

In forest management, Tree Height (H) is an important variable collected during inventories and used for the quantitative description of the structure of trees and settlements (Lei et al., 2009). Indeed, the tree height is important to determine the station index as well as the stand volume (Ahmadi et al., 2013).

By linking heights to diameters, the resulting function helps to explain the statistical relationship between these descriptive variables (Yavuz et al., 2010), as indicated by the following relationships:

$$\text{Korsun Model (1935)} \quad H = e^{[b_0 + b_1 \ln(D) + b_2 (\ln D)^2]} \quad (5)$$

$$\text{Assmann Model (1943)} \quad H = b_0 + b_1 D + b_2 D^2 \quad (6)$$

$$\text{Prodan Model (1951)} \quad H = 1.3 + \frac{D^2}{b_0 + b_1 D + b_2 D^2} \quad (7)$$

$$\text{Petterson Model (1955)} \quad H = 1.3 + \frac{D}{(b_0 + b_1 D)^3} \quad (8)$$

$$\text{Freeze Model (1964)} \quad H = e^{[b_0 + b_1 (\ln D) + b_2 D]} \quad (9)$$

$$\text{Loetsch et al. (1973)} \quad H = 1.3 + \left(\frac{D}{b_0 + b_1 D} \right)^2 \quad (10)$$

Where: H = Tree height (m); $D = D_{1.30}$ = Individual tree diameter at 1.30 m (cm); b_0 , b_1 and b_2 are Coefficients.

To describe the direction of the progression of Heights (H) and Diameters (D), several authors have used the linear or non-linear regression method. Padari et al. (2009) used regression height function to determine the stand height in Estonia. The non-linear regression technique demonstrated the functional and two-dimensional relationship [$f(D) = H$] between H and $D_{1.30}$ at species level (Pretzsch, 2009; Curtis, 1967; Mensah et al., 2018; Ogana et al., 2020). To establish the height curves and determine the mathematical function best suited to each tree species and to each stand type, some non-linear regression equations (D - H) were used in this study (Meyer, 1940).

❖ Calculation of Stand Mean Tree Height (H_m)

The Stand Mean Height of trees is an important measure for assessing forest growth and productivity. The high-precision aboveground photogrammetry method also makes it possible to estimate the average (mean) height of trees in a stand (Balenović et al., 2015). Another method is to determine the average height of the average tree in the stand from the height curve function [$H = F(D)$] considering the square average diameter (Padari and al., 2009; Yavuz et al., 2010).

It is common to determine the average height of an even-aged person by calculating, among other things, the arithmetic average height (H_m) or the Lorey Mean Height. The average tree height (m) of the dominant and co-dominant trees of the leading species in the stand is expressed as Lorey's mean tree height, where each tree is weighted according to its basal area. Commonly, the Stand Arithmetic Mean Height is calculated by taking the sum of the heights of all sample trees in a given area and dividing it by the total number of sample trees in that area. In Türkiye, several studies have been conducted to assess the Arithmetic Average Height of trees in different types of forest stands (Yavuz et al., 2010). In this study, the arithmetic method was used to estimate the average height of the stand, according to the following expression:

$$H_{m_k} = \frac{1}{n_k} \sum_{i=1}^{n_k} H_{i_k} = \frac{1}{n_k} \sum_{i=1}^{n_k} (H_{1_k} + H_{2_k} + \dots + H_{n_k}) \rightarrow H_m = \frac{1}{t} \sum_{i=1}^t H_{m_k} \quad (11)$$

Where H_{i_k} = height of the individual tree for the k -specie (m); H_{m_k} = arithmetic mean height (m) of k -species; t = total number of specie in mixed stand, and n_k = total number of trees of k -species. H_m = arithmetic mean height of mixed stand (m); i, n et $k \in \{1, 2, 3, \dots\}$.

❖ Calculation of Stand Dominant Height (H_{100})

Kramer (1959) and Loetsch-Zörer-Haller (1973), cited by Rennolls (1978), proposed that the top or dominant stand height should be taken as (i) the average height of a fixed percentage of trees present in the area, (ii) the maximum height found in a sample of trees, or (iii) the average height of a fixed or specific number of dominant trees taken per unit area. According to Hart method, the estimation method based on 100 dominant trees per hectare has emerged over time and is recommended by several authors who have argued that it is the average height of the 100 dominant trees taken per hectare (Hummel, 1955; Hamilton, 1975 cited by Rennolls, 1978). Hummel method (1955) based on 100 trees/ha was biased (1–5%) compared to that of $n < 100$ trees in plots of 0.15 ha (Fries, 1974 cited by Rennolls, 1978) already showed that the. For simplification, the dominant height of a stand can also be the height of the 10 dominantly selected trees per 0.1 ha (Matern, 1976 cited by Rennolls, 1978). The dominant height may be less biased when considering the heights of trees in a number of randomly selected 0.01 ha plots (Rennolls (1978).

Gaudin (1996) estimates that the Mathematical Dominant Height corresponds to the average height of a given number of trees chosen from among the most imposing in height and/or in diameter. This last approach was used in this study such as follow:

$$H_{100} = \frac{1}{n} \sum_{i=1}^n H_i \quad ; \quad i \text{ and } n \in \{1, 2, 3, \dots\} \quad (12)$$

Where: n = number of the sample dominant trees; H_i = sample dominant tree height; H_{100} = Average dominant height.

Indeed, a number of selected trees varying between 4 and 8 dominant trees (1 tree per 100 m²) were selected in experimental plots (0.04-0.08 ha). Arithmetic means of the dominant sampled trees height (H_{100}) was calculated (Kahriman et al., 2017; Ruiz-Peinado et al., 2021).

❖ Calculation of the Stand Tree Density per Hectare (N)

In silviculture, the density of trees per hectare is defined as the number of trees in an area of one hectare. It is a crucial indicator of stand productivity. Optimal tree growth is made possible by a well-managed density, which has a direct impact on the quality of the wood produced (Ruiz-Peinado et al., 2021). Tree density per hectare is particularly important in a mixed conifer stand, due to the complexity of the forest structure resulting from the interaction between different species. The structural diversity of a mixed stand can be assessed using the density of trees per hectare. A balanced density favors the harmonious coexistence of species, while excessive density can lead to harmful competition. In general, a forest inventory is required to determine the number of trees per hectare (Yavuz et al., 2010; Misir et al, 2012). Technologies such as remote sensing, satellite images and field surveys are used in modern methods (Błaszczak-Bak et al., 2022). Stand representativeness is often ensured by random or systematic sampling. The number of trees per plot, species distribution and other parameters related to stand structure are all included in the data collected (Ruiz-Peinado et al., 2021). In this study, two species of trees were inventoried in all the experimental plots, namely the Anatolian Black Pine (*Pinus nigra*) and the Turkish Red Pine (*Pinus brutia*). The number of each tree species (n) has been converted into hectares (N_i).

The values obtained were added to obtain the total number of trees per hectare in the mixed stand (N). This method has also been used by several authors (Yavuz et al., 2010). The expression of this relationship is:

$$N = \sum_{k=1}^n N_k \Rightarrow N_k = \frac{S_{ha}}{S} n_k ; (i, n \text{ et } k \in \{1, 2, 3, \dots\}) \quad (13)$$

Where N_k = Number of trees per hectare for k -specie; S = Size of experimental plot (m^2); n_k = Number of trees in the experimental plot for k -specie; $S_{ha} = 1\text{ha} = 10,000 \text{ m}^2$; N = Number of trees per hectare in mixed stand (ÇkÇz).

❖ Calculation of Stand Basal Area (G)

The Stand Basal Area (G) is the sum of the basal areas of all living trees in a stand. It is usually expressed in square meters per hectare (m^2/ha). The single-tree Basal Area can be measured directly in the field by one of two methods: (i) angle count sampling or (ii) fixed area plot measurement. The individual Tree Basal Area (g_i) is the cross-sectional area of a tree stem measured at breast height over bark. According to the Techniques for Measuring Stand Basal Area (DECCW, 2010), the Basal Area of a tree and that of a forest stand can be illustrated as in Figure 56.

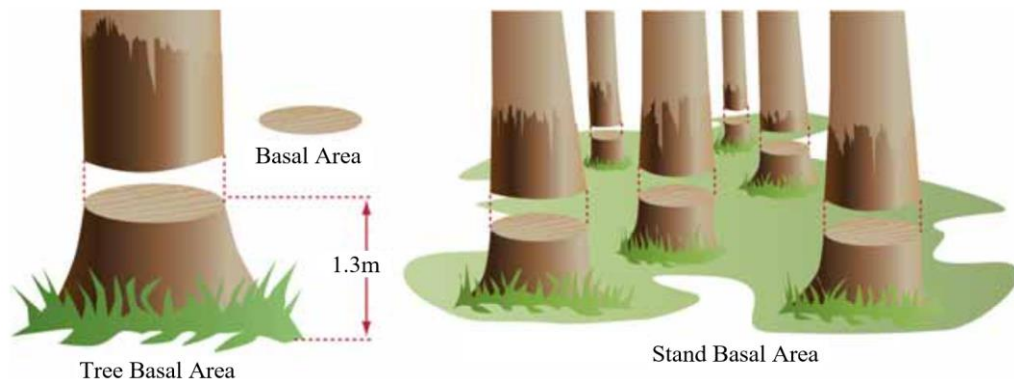


Figure 56. Illustrations of the basal areas of a tree and a forest stand

According to Günel (1981), BA is an indicator of the use degree of the stand growth environment for the same habitat and the same age. It is the surface area of a cut stump at a height of 1.30 meters on a tree (Figure 56). Several studies have shown that it can be obtained from the tree diameter at 1.30 m (Yavuz et al., 2010; Günel, 1981; Ruiz-Peinado et al., 2021).

In this study, concerning the mixed stands of *Pinus nigra* (Karaçam) and *Pinus brutia* (Kızılçam), single-tree basal area was calculated from the Diameter at Breast Height ($D_{1.30}$) of each tree and for each species. The basal area of the stand depends on the tree species. Stand Basal Area for ÇkÇz mixed stand was obtained by summing all the basal areas of all trees (per hectare), according to follow expression.

$$G = \frac{S_{ha}}{S} \sum_{k=1}^n G_k \Rightarrow G_k = \sum_{i=1}^{n_k} g_{i.k} \Rightarrow g_i = \left(\frac{\pi}{4} D_i^2\right) \text{ with } i, n \text{ et } k \in \{1, 2, \dots, n\} \quad (14)$$

Where G = Basal Area (m^2/ha) of mixed stand; G_k = Basal Area (m^2) for k -specie; $S_{ha}=1 \text{ ha}=10,000 \text{ m}^2$; S = Size of sample plot (m^2); D_i = Diameter at 1.30 m of i -tree (cm); g_i = Basal Area of i -tree; n_k = number of sampled trees for each k -specie in sample plot. n = total number of all mixed trees in plot.

❖ Estimation of Stand Volume (V)

Volume (V) is a particularly important dendrometric criterion for characterizing a stand (Gaudin, 1996). It is a matter of converting the sum of the volumes of all the trees in the sampling area to hectares. For this, the constant-size unit plot method was used. This method is based on the use of the tree volume equation (Yavuz and Mısır, 2013). To establish a volume table of a forest stand, Alemdag (1962) recommends 50–100 trees for a Forest Operation Enterprise (Orman İşletme Şefliği) scale, 100–500 trees for a region scale (Akdenir, Marmara, etc.) scale, and 1000–5000 trees for the countrywide. According to the unit plot method, all the trees in the sampling plots (height ≥ 1.30 m) are grouped into diameter ($D_{1.30}$) classes (Ruiz-Peinado et al., 2021). Within each diameter class of each species, the average diameter and/or average height were calculated and used to develop the single-entry or double-entry equations of volume using the linear or non-linear regression.

$$V = \frac{S_{ha}}{S} \sum_{k=1}^n V_k \Rightarrow V_k = \sum_{i=1}^{n_k} V_{i.k} \Rightarrow V_i = \left(\frac{\pi}{4} D_i^2\right) * H_i \text{ with } (i, n \text{ et } k \in \{1, 2, 3, \dots\}) \quad (15)$$

Where V = Tree Volume in mixed stand (m^3/ha); $S_{ha} = 1 \text{ ha} = 10,000 \text{ m}^2$; S = Sample plot size (m^2); V_t = Volume for t -specie (m^3/ha); V_i = volume of i -tree (m^3); D_i = Diameter at 1.30 m of i -tree; n_k = number of sampled trees for each k -specie in sample plot; n = total number of all mixed trees mixed in plot.

For each corresponding diameter class, the number of trees (frequency) was determined and multiplied by the calculated single tree volume. The total volume per diameter class and the total volume of the sampling plot were calculated. This volume was converted to hectares to find the stand volume (V). This method was therefore used according to the following expressions (Yavuz et al., 2010; Günel, 1981). The number of trees mentioned is used to establish a volume equation that allows the calculation of the volume of trees of a particular species in a given experimental plot. As part of the TUBITAK project, volume equations for Anatolian Black Pine (*Pinus nigra* Arnold subsp. *Pallasiana*) and Turkish Red Pine (*Pinus brutia* Ten.) have been developed (2022) in the context of mixed stands. These volume equations are given in the follow expression:

- For Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana* (Lamb.)): $V_{Çk}$
Performance criteria: $R^2 = 99.4$; $Sy.x = 0.0308 \text{ m}^3$; $F = 20903$

$$V_{Çk} = 0.046642 - 0.013051D_{1.30} + 0.00108D_{1.30}^2 \quad (16)$$

- For Turkish Red Pine (*Pinus brutia* Ten.): $V_{Çz}$
Performance criteria: $R^2 = 99.8$; $Sy.x = 0.033 \text{ m}^3$; $F = 47969$

$$V_{Çz} = 0.030357 + 0.00001579D_{1.30}^2 \quad (17)$$

Where $D_{1.30}$ = tree diameter at 1.30 m; $V_{Çk}$ and $V_{Çz}$ are tree volumes of specie.

In this study, the equations (16) and (17) were used to estimate the single-tree volume in each species. The trees counted in the sample plot were used to calculate the stand volume.

❖ Determination of Stand Productivity (SI)

Site Productivity, also called Site Index, Site Quality or Site Classification, is the amount of production a stand can produce at a certain age. Site quality refers to the inherent ability of a forest to produce biomass by growing trees. It is the production potential or capacity of a site (Günel, 1981; Skovsgaard and Vanclay, 2007; Skovsgaard and Vanclay, 2013; Maclean and Bolsinger, 1973). Mixed forest stands can be more productive than pure stands or monocultures (Bielak et al., 2014). Since the 20th century, the major principle of site evaluation in even-aged forests has been the use of stand height as an indicator of productivity, with or without the effects of silvicultural treatments on stand growth.

There are three main approaches to determining the Site Index: Direct, Indirect, and Mixed Methods (Günel, 1981). According to several studies, the Direct Methods used to determine the productivity of a forest stand are linked to certain factors such as the characteristics of (i) the habitat or growth environment (geocentric indicators), (ii) climate, (iii) soil flora (phytocentric indicators), the hereditary capacities of the tree(s) that make up the stand, and (iv) the silvicultural operations applied, such as soil cultivation, fertilization, or cutting techniques (Günel, 1981; Pretzsch, 2009; Massenet, 2009; Yener, 2018; Yavuz et al., 2010). Direct methods are very rarely used, not only because of their high costs and the complexity of the sources of information, but also because the growth of trees is influenced by several factors that allow the use of Indirect Methods (Mısır, 2003; Yener, 2018). According to the Indirect Method (Polymorphic and Anamorphic), several studies have determined the site productivity for even-aged and/or uneven-aged forest stands (Oğuzoğlu and Ozkan, 2015). Stand height is the first fundamental approach to site classification (Skovsgaard and Vanclay, 2007).

The Polymorphic Method is based on the stem analysis of selected trees and allows the development of Height Index Curves that are not similar and correspond to the different elasticity limits of the growth medium (Günel, 1981). In Türkiye, normality equations were obtained by Kalıpsız (1963) for Larch, Akalp (1978) for even-aged spruce stands, and Carus (1998) for beech tree. However, Mısır et al. (2012), Yavuz et al. (2010) and Akalp (1978) used the Polymorphic Method to analyze the Site Index. The indirect method based on the Anamorphism Curve Approach of 100 trees per hectare (Günel, 1981; Ercanlı, 2010; Akalp, 1978; Kalıpsız, 1984) can be used to determine the Site Index. Considering the age (independent) and dominant tree height (dependent) variables obtained from the field survey, a single or double entry equation can be developed with the regression analysis method. However, the Guide Curve Technique (Single curve) can be used to generate Site Index Curves (Skovsgaard and Vanclay, 2007).

❖ Calculation of Stand Density Index (*SDI*) and Density Ratio (*SDR*)

The Stand Density Index (*SDI*), or Reineke's Stand Density Index, is a metric used to evaluate the density of a tree stand by measuring the number of trees per unit area, the quadratic mean diameter, and the basal area, which is related to the diameter of the average tree, at breast height ($D_{1.30}$).

Stand Frequency is used to determine the optimal spacing of trees within a stand. This index not only determines the concentration of trees within a given area but also identifies the competition levels and site utilization by each species. The Stand Density Index is used to estimate tree growth, probability of survival, and stem shape, as well as to determine management strategies that will help achieve production goals. This index can be applied to any type of tree stand as it is an essential parameter. The Stand Density Index allows us to assess how stands compare to the average and interact with other stands (Ruiz-Peinado et al., 2021; VanderSchaaf, 2009). Several authors have indicated that SDI can be directly estimated at the site (Ducey and Valentine, 2008; Dean et al., 2021). But Reineke (1933) demonstrated that in full-density stands, there exists an exponential relationship between the number of trees per unit area and the quadratic mean diameter. This relationship is commonly referred to as Reineke's Law and has been verified by subsequent studies (Zeide, 2004; VanderSchaaf, 2009). To quantify this relationship, Reineke developed a Stand Density Index (*SDI*) that compares the current stand density to an equivalent density in a stand with a quadratic mean diameter of 10 inches (D_q) (Reineke, 1933; Curtis, 1970).

According to references cited by Yavuz et al. (2010), previous studies in Türkiye have employed the polymorphic method with temporary data to establish SI (Bonitet) tables for certain tree species, including Red Pine (Alemdağ, 1962), Black Pine (Kalıpsız, 1963), Scots Pine (Alemdağ, 1967), Beech (Carus, 1998), Elm (Kapucu et al., 1999), and Chestnut (Kapucu et al., 2002). Additionally, Yavuz et al. (2010) indicates that others have utilized the anamorphic method with temporary data for Bonitet table development (Kalıpsız, 1984; Akalp, 1978, Günel, 1981). Trunk analysis data have also contributed to the establishment of Bonitet tables (Akalp, 1978; Aydın, 2008). In this research, the Reineke method was used to calculate the Stand Density Index (*SDI*) values (VanderSchaaf, 2009) and Stand Density Ratio (*SDR*) for mixed stands of ÇkÇz (Yavuz et al., 2010; Curtis, 1970; Ducey and Knapp, 2010). The relationship between the number of trees per unit area and the quadratic mean diameter can be used to express the follow equation based on Reineke's Law:

$$SDI = N \left(\frac{D_q}{25.4} \right)^{b_0} \quad \text{and} \quad SDR = N / e^{13.187 - 1.842 \ln D_q} \quad (18)$$

Where: *SDI* = Reineke's Stand-Density Index; *SDR* = Stand Density Ratio; *N* = Number of trees per unit area (hectare); D_q = Quadratic Mean Diameter (cm); b_0 = Exponent of Reineke's equation (−1.605).

❖ Calculation of Stand Mixing Ratio (R_S)

In silviculture, Stand Mixing Ratio, also known as Stand Mixing Rate or Mixing Proportion, is an important measure that quantifies the relative proportion of different tree species within a mixed forest stand. It represents the ratio between the number of individuals of a specific species and the total number of trees in the stand. In a mixed stand, interactions between species are an aspect that can be studied to measure the behavior of site productivity in terms of increase or decrease due to interactions between species (Pretzsch et al., 2015; Pretzsch et al., 2009; Pretzsch and Schğtze, 2016). Calculating the stand-mix ratio generally requires field research and statistical analysis. For more precise assessments, advanced technologies such as remote sensing can also be used. Generally, data are collected and mixing ratio (R_S) can be determined not only by the number of trees (N) but also by their basal area value (G) or their volume (V) by specie (Pretzsch and Schütze, 2021; Dirnberger et al., 2017; Sprauer and Nagel, 2015; Yavuz et al., 2010). In this study, the tree volume approach was used to determine the mixing rate in different stand types (ÇkÇz):

$$R_S = \frac{V_{Çk}}{V_{Çk} + V_{Çz}} \quad (19)$$

Where R_S = Stand Mix Ratio of ÇkÇz; $V_{Çk}$ = Volume of Çk specie (*Pinus nigra*); $V_{Çz}$ = Volume of Çz specie (*Pinus brutia*).

❖ Calculation of the Stand Internal Variability (C_v)

The variability in a natural forest stand is based on the behavior of tree characteristics such as diameter at breast height ($D_{1.30}$), tree height (H), volume (V), etc. It is measured by the Coefficient of Variation (C_v) and makes it possible to interpret the heterogeneity or homogeneity between the variables. Coefficients of variation (C_v) are also used to describe the structure of a forest stand when they are linked, in particular, to the diameter and height of the trees (Pretzsch, 2009; Yavuz et al., 2010). C_v (%) is determined by a proportionality relationship between the arithmetic mean diameter in the stand and the standard deviation. It can be also calculated using the Site Density Index (SDI) of dominant tree on the sum of SDI of all tree species in stand (Ruiz-Peinado et al., 2021). In this study, the approach adopted by Yavuz et al. (2010), was used to calculate the C_v (%) in 46 sample stands.

$$C_V(\%) = \frac{S_d}{D_m} * 100 \quad (20)$$

Where C_V is Coefficient of Variation (%) in Diameter at Breast Height ($D_{1.30}$); S_d is Standard Deviation; D_m is Stand Arithmetic Means Diameter ($D_{1.30}$).

The Standard Deviation (S_d) was determined from the descriptive analysis of the stand arithmetic mean diameters (D_m). This method of calculating the C_V allowed us to determine the variation within the arithmetic mean diameter (D_m) in each of 46 sample stands (ÇkÇz). It should be noted that as the C_V increases, the associated variable (D_m) becomes increasingly heterogeneous. Conversely, when C_V decreases, the variable (D_m) is distributed more homogeneously. If the standard deviation is zero ($S_d = 0$), the coefficient of variation is also zero and highlights the absence of variation.

b. Estimation of Above/Below-Ground Biomass and Carbon Storage

➤ Calculation of Single Tree Volume and Biomass

In fact, several authors have shown that the volume of a tree can be determined by several mathematical relationships, the most commonly used of which are Huber's, Newton's, or Smalian's formulas (MFLNRO, 2011; Yavuz, 1999). From the diameter values measured on the sampled trees, the actual single-tree stem volume (V_{stem}) was estimated using the following Smalian formula (Yavuz et al., 2010):

$$\text{Total tree stem volume} \quad V_{stem} = V_{stump} + V_{section} + V_{top} \quad (21)$$

$$\text{Tree stump volume} \quad V_{stump} = \frac{\pi}{4} D_{0.3}^2 * L_{0.3} \quad (22)$$

$$\text{Tree section volume} \quad V_{section} = \frac{\pi}{4} (D_{1.3}^2 + D_{3.3}^2 + \dots) * L_s \quad (23)$$

$$\text{Tree top volume} \quad V_{top} = \frac{\pi}{12} D_{top}^2 * L_{top} \quad (24)$$

Where V = volume (m^3); D = diameter on the section (cm); L = section length (m).

After obtaining the stem volume (V_{stem}) of each tree, which does not take into account the volume of the branches, the volume of the section of wood (V_w) was calculated, while its dry mass (M_w) was obtained after drying at a high temperature. Elemental analysis was used to determine the carbon ratio of the section of wood ($\%C_w$). These three data points (M_w , V_w , and $\%C_w$) were used to determine the dry mass of each stem (M_{stem}) and their carbon stock (C_{stem}). This is a conversion that can be interpreted by the stages presented in Figure 57 (Yavuz et al., 2010; Çömez, 2012; Mısır et al., 2018).

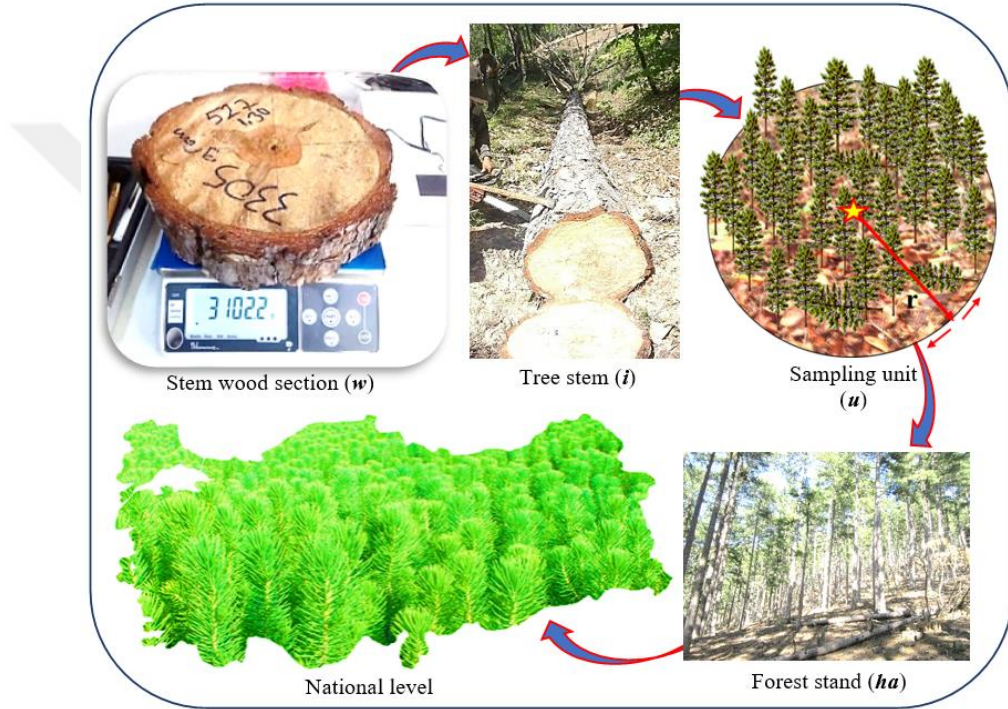


Figure 57. Biomass conversion scheme at the ecosystem scale

According in Figure 57, the tree stem biomass and wood section dry mass were calculated as the following expressions:

$$B_{stem} = \frac{M_w * V_{stem}}{V_w} \Rightarrow V_w = \frac{\pi}{4} d_w^2 * h_w \quad (25)$$

The tree stem carbon storage was obtained by the following expression:

$$C_{stem} = \frac{\%C_w * B_{stem}}{M_w} \quad (26)$$

Where B_{stem} = tree stem biomass (kg); V_{stem} = tree stem volume (m^3); V_w = wood section volume (m^3); M_w = wood section dry mass (kg); d_w = wood section diameter (cm); h_w = thickness of the wood section (m).

➤ Calculation of the Single tree Bark Biomass and Carbon Amount

To determine the biomass of the tree stem bark (M_{bark} or B_{bark}) from each sample tree, the dry mass of the sample bark (M_b) from wood section (V_w) obtained as a result of drying ($105 \pm 3^\circ C$, 96 hours), has been determined. This dry weight (M_b) was converted to the scale of the tree stem (V_{stem}). The carbon ratio of the sample bark ($\%C_b$) from wood section was converted to the tree stem level (C_{bark}). The total bark biomass from all tree and the total carbon in the plot were calculated. The results were transformed to the stand level, using the following relationships (Yavuz et al., 2010):

$$B_{bark} = \frac{M_b * V_{stem}}{V_w} \quad \text{and} \quad C_{bark} = \frac{\%C_b * B_{bark}}{M_b} \quad (27)$$

Where M or B is the dry weight or mass or biomass; V is the volume and C is the carbon capacity of each corresponding element.

➤ Calculation of the Tree Branch Volume, Biomass and Carbon Content

The diameter of the large tip (d_{br}) and the length (l_{br}) of all the branches of each cut tree sample were measured. Indeed, a median branch sample was selected for the analysis of biomass (B_{branch}) and carbon (C_{branch}) stored by the branch, from the dry mass (M_{br}) and carbon ratio ($\%C_{br}$). As the shape of the branch is assimilated to a revolutionary cone, the Smalian formula was used to estimate the sample branch volume (V_{br}) and all the tree branches ($V_{i-branch}$) without the leaves (Yavuz et al., 2010), using the following expressions:

$$V_{branch} = \frac{\pi}{4} * \frac{1}{3} d_{branch}^2 * l_{branch} \Rightarrow M_{i-branch} = \frac{V_{i-branch} * M_{branch}}{V_{branch}} \quad (28)$$

The branch carbon storage was obtained by the following expression:

$$C_{i-branch} = \frac{M_{i-branch} * \%C_{branch}}{M_{branchr}} \quad (29)$$

Where M is the dry mass (g) or Biomass (kg); V_{br} is the Volume (m^3); C is carbon content (%) or amount (kg).

➤ Calculation of biomass and carbon amount of living cover, litter and dead wood

The dry mass of dead wood, litter, and living plant cover was obtained after drying in an oven at $65 \pm 3^\circ C$ for 48 hours. The mass of dead wood and living vegetation cover, each corresponding to a sampling area of $1m \times 1m$ ($1 m^2$), as well as that of dead wood corresponding to $25cm \times 25cm$ ($625 cm^2$), were then extrapolated to the level of the experimental plot, and finally to the hectare, as show in Figure 58 (next page). First, the dry weight (dry mass) was determined for samples of litter (M_l), dead wood (M_{dw}) and herbaceous cover (M_{dc}). Then their carbon ratio ($\%C_{litter}$, $\%C_{d_wood}$ and $\%C_{l_cover}$) was obtained by elementary analysis. And finally, the quantities of biomass (B_{litter} , B_{d_wood} and B_{l_cover}) and carbon (C_{litter} , C_{d_wood} and C_{l_cover}) were calculated on the scale of experimental plots and stands scale (Yavuz et al., 2010).

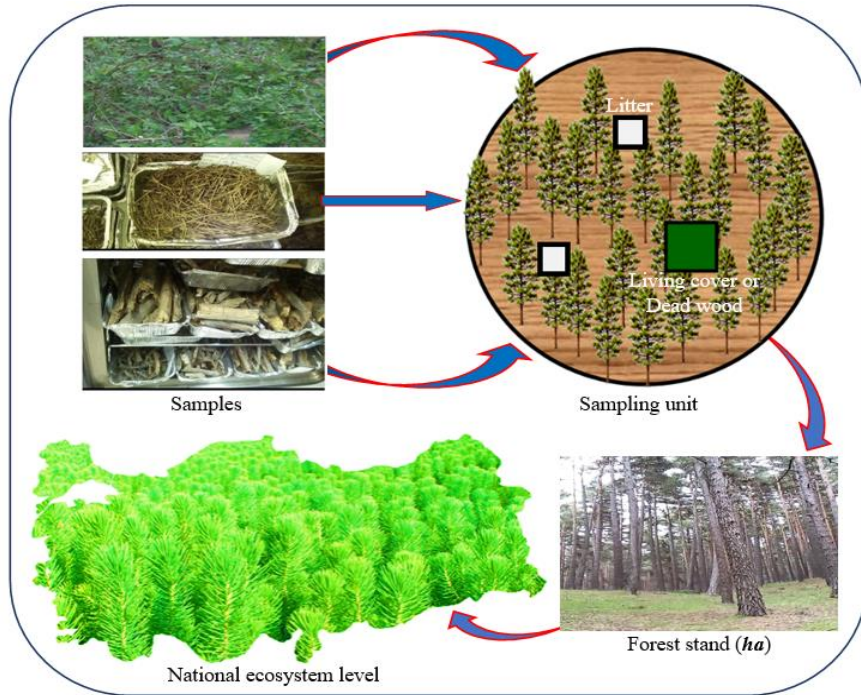


Figure 58. Process for determining the terrestrial biomass stocks

In Figure 58, the same principle of the equations (25) and (26) were used for the samples of litter, dead wood and grass coating.

➤ Calibration of Root and Organic Matter Samples

The root (A) and soil (B) samples were taken according to the images in Figure 59. Several studies carried out in temperate regions where forests were dominated by *Pinus* species, especially *Pinus nigra*, proved that the root mass present in most forest soils represents 70–85% (Yavuz et al., 2010; Misir et al., 2012).

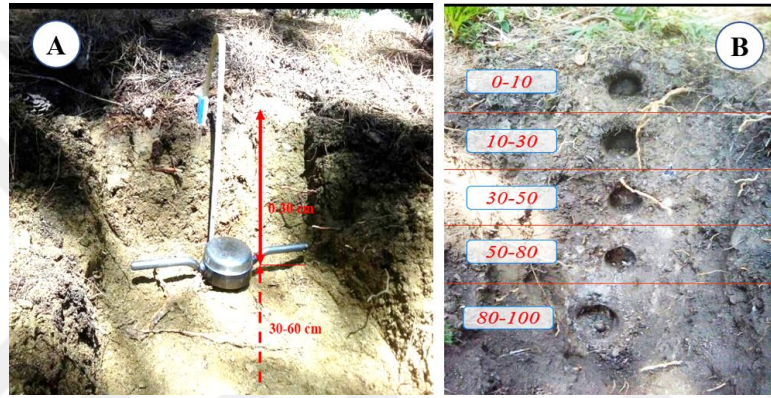


Figure 59. Sampling of roots (A) and soil organic matter (B)

In Figure 59, we see that the root samples were taken with the cylinder (long) at depths (0–30 cm, 30–60 cm and 60–90 cm). On the other hand, soil samples for organic carbon analysis were taken between 0–10 cm, 10–30 cm, 30–50 cm, 50–80 cm, and 80–100 cm. The amount of biomass and the carbon stocks were examined separately (Tolunay and Çömez, 2008; Mısır et al., 2011; Mısır et al., 2012; Mısır, 2013; Mısır and Mısır, 2013; Güner and Çelik, 2011).

➤ Determining of Biomass and Carbon Content in Roots

Biomass estimation is a common practice in the context of forest ecosystems around the world (Addo-Danso et al., 2016). In this study, and as shown in Figure 59 (A), the root samples were collected using the cylinder ($d_{C_root} = 6.4\text{ cm}$ and $h_{C_root} = 30\text{ cm}$), at multiple depths (0–30 cm, 30–60 cm and 60–90 cm) from the soil. The calculation of biomass and carbon stock in each root sample at different soil depths can be seen in Figure 60.

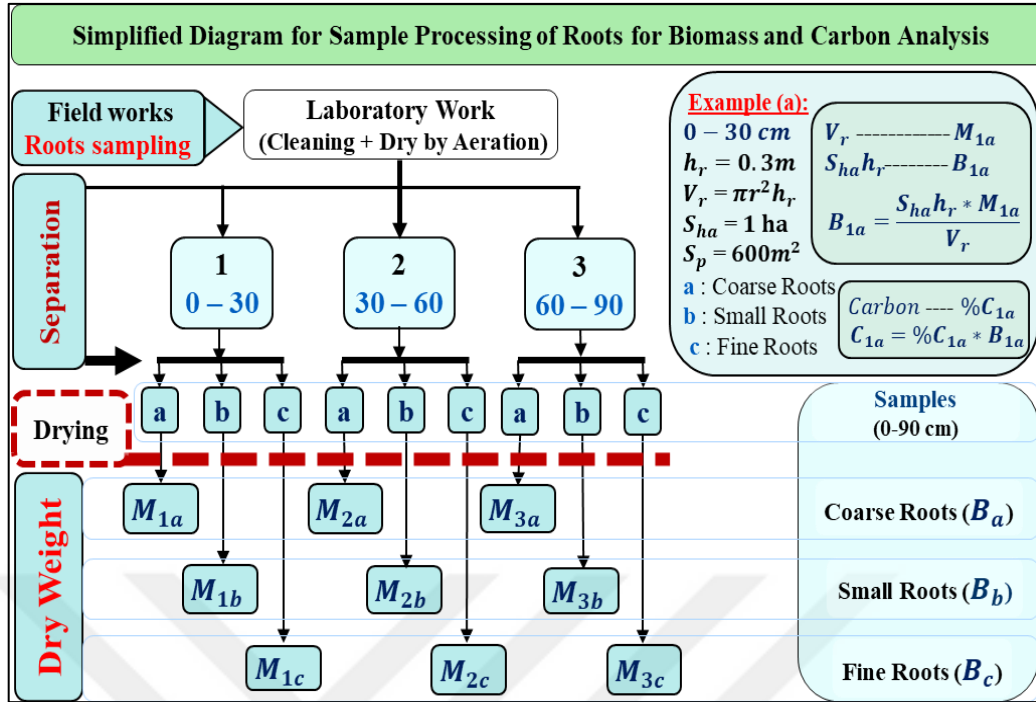


Figure 60. Diagram produced in this study to show detailed process of root treatment (cleaning, separation, drying and weighing) and estimation of biomass (B_i with $i = a, b, c$) and carbon content ($\%C$) and amount (C_i with $i = a, b, c$) for each sample root (a = coarse, b = small and c = fine) at different depths (1: 0-30 cm; 2: 30-60 cm and 3: 60-90 cm). The broken line (red) represents the oven drying phase.

The roots of each depth were divided into three groups according to their diameter: Coarse (>5), Small (2-5 mm) and Fine (<2 mm) roots. According to the Figure 60, the treatment (cleaning, separation, drying and weighing) of the roots led to obtaining the dry mass (M) of each sample as a function of its size (a = Coarse (C), b = Small (S) and c = Fine (F)) and sampling depth (1: 0-30 cm; 30-60 cm and 3: 60-90 cm). This separation method has already been used in several documented works (Misir et al., 2018). After trimming, the dry mass of these root samples was obtained after they were dried in the oven and their carbon ratio was achieved in the COSTECH Elemental Analysis. Depending on the surface (S_C) and depth (h_C) of the cylinder, the dry mass (M_{fine} , M_{small} and M_{coarse}) and carbon ratio ($\%C_{\text{fine}}$, $\%C_{\text{small}}$ and $\%C_{\text{coarse}}$) of each root sample was converted to biomass (B_{fine} , B_{small} and B_{coarse}) and carbon (C_{fine} , C_{small} and C_{coarse}) in experimental plot scale (m^2) and then to hectares (stand), such as the expression of (25) and (26) (Yildiz, 2021; Misir et al., 2012).

➤ Determining of Biomass and Carbon Stok in Soil Organic Matter

The Soil Organic Matter (SOM) samples were collected using the cylinder ($d_{soc} = 8$ cm and $h_{soc} = 10$ cm), at five different depths: 1 (0-10cm), 2 (10-30 cm), 3 (30-50 cm), 4 (50-80 cm) and 5 (80-100 cm), from the soil, as shown in Figure 59 (B). The dry mass (M_i) and carbon ration ($\%C_i$) of each soil sample was obtained after drying in the oven at $105 \pm 3^\circ\text{C}$ (2 hours) and elemental analysis respectively ($i = 1, 2, 3, 4$ and 5). The carbon content was used to convert the soil mass (M_{SOC_1} , M_{SOC_2} , M_{SOC_3} , M_{SOC_4} and M_{SOC_5}) to carbon stocks (t/ha) of each SOM sample (C_{SOC_1} , C_{SOC_2} , C_{SOC_3} , C_{SOC_4} and C_{SOC_5}) and from experimental plot to unit area (Yildiz, 2021; Misir et al., 2018).

2.2.5. Statistical Analysis of Data

a. Information Processing and Analysis Tools

All necessary information has been encoded into multiple Excel files of Microsoft Office software, in which it has been organized, purified, synthesized, and prepared for transmission in statistical analysis software (SPSS v22.0) and spatial mapping in ArcGIS 10.0 (Töreyn et al., 2010). Several operations were carried out using these tools. In SPSS v22.0 software, the distribution and normality of the data were studied in the descriptive data analysis. The relationship between the height (H) and diameter at breast height ($D_{1.30}$) of all trees in mixed natural stands (*Pinus nigra* - *Pinus brutia*) was analyzed. Prediction models (biomass and carbon storage) were developed at several levels. Firstly, using Diameter at Breast Height ($D_{1.30}$) as the sole predictor, *Single-Entry* allometric equation were obtained for each individual tree species (68 *Pinus nigra* and 70 *Pinus brutia*) and for their various components (branches, foliage, bark, stem, and single-trees) separately. Next, *Double-Entry* equation models were developed for each individual tree using $D_{1.30}$ and H . Similarly, *Multiple-Entry* models were obtained for biomass prediction and carbon storage at ecosystem scale (individual tree, litter, dead wood, living cover, roots). For stand level, Quadratic Mean Diameter (D_m), Mean Height (H_m), Basal Area (G), Mixture Ratio (R_s), Site Index (SI), Tree Density (N), Site Density Index (SDI), Clown Closure (CC) and Stand Age (A_s) were tested as independent variables.

Finally, the same variables were used in the Multi-Layer Perceptron (MLP) algorithm of the Artificial Neural Network, to develop intelligent models for predicting biomass and carbon storage at the individual tree scale for each species, and at the ecosystem scale. The total quantities of carbon obtained in this study were distributed according to above-ground and below-ground biomass, and soil organic matter. Using ArcGIS 10.0, these quantities of biomass and carbon from natural mixed stand (*Pinus nigra* - *Pinus brutia*) ecosystems in Türkiye were projected onto maps to give a clear idea of their Spatial Distribution.

b. Modeling Approach based on Regression Analysis

In the present study, Multiple Linear and Non-linear regression analysis were carried out to expose the mathematical relationships that exist between the explanatory variables and the variables to be explained. The regression approaches were used to test the prediction model that best meets the research expectations (Yavuz et al., 2010). Some linear and non-linear equations using in modeling are presented in follow relationships:

Compound	$y = b_0(b_1^x)$	(30)
Growth	$y = e^{b_0+b_1x}$	(31)
Exponential	$y = b_0e^{b_1x}$	(32)
S-Curve	$Y = e^{b_0+\frac{b_1}{X}}$	(33)
Power	$y = b_0(x^{b_1})$	(34)
Inverse	$y = b_0 + \frac{b_1}{x}$	(35)
Logistic	$y = \frac{1}{\frac{1}{x} + b_0(b_1^x)}$	(36)
Linear	$y = b_0 * b_1x$	(37)
Logarithmic	$y = b_0 * b_1 \ln x$	(38)
Quadratic	$y = b_0 + b_1x + b_1x^2$	(39)
Cubic	$y = b_0 + b_1x + b_1x^2 + b_1x^3$	(40)
Multiple Linear	$y = b_0 + b_1x_1 + b_2x + b_3x_3 + \dots + b_nx_n \pm \varepsilon$	(41)

y and x represents dependent and independent variables respectively. $b_0, b_1 \dots b_n$ represent parameters, ε is random error and n is number of independent variables.

Indeed, A statistical method called multiple linear regression (MLR), or just multiple regression, makes use of many explanatory variables to forecast the value of a response variable. Modeling the linear relationship between the explanatory (independent) factors and response (dependent) variables is the aim of multiple linear regression. Since multiple regression uses more than one explanatory variable, it is essentially an extension of ordinary least-squares (OLS) regression (Hayes, 2023). The non-linear regression approach was used to derive single-entry equations for stand mean height and stand mean diameter, tree components of above-ground biomass, and carbon storage. Multiple regression analysis was used to model linear relationships between independent variables with individual tree biomass and carbon storage, and the stand total biomass and carbon storage.

The importance of independent variables was tested with Stepwise method and in Artificial Neural Network (ANN) approach. In the concept of the Stepwise algorithm, variables are added or removed from the model step by step based on predefined criteria like $p < 0.1$ (Add) or $p > 0.1$ (Remove). This approach allows to (i) save time because only the variables that contribute significantly to the prediction are added, (ii) avoid overfitting by keeping only the important variables, and (iii) facilitates the selection of variables in complex models. The best variables were selected to build the above-ground and stand biomass and carbon models using regression analysis. These models were compared with models developed with Multi-Layer Perceptron Algorithm (Özçelik et al., 2010; Şenyurt et Ercanlı, 2019; Ercanlı et al., 2018; Çalışkan et Sevim, 2018; Sakıcı ve al., 2018; Addo-Fordjour et al., 2013).

c. Modelling Approach based on Artificial Neural Networks (ANN)

➤ Artificial Neural Network (ANN) Concept

Artificial Neural Networks (ANNs) are mathematical or computational systems closely inspired by human biological neural networks or nervous system. Figure 61 explicitly highlights the architecture of the artificial and biological neuron.

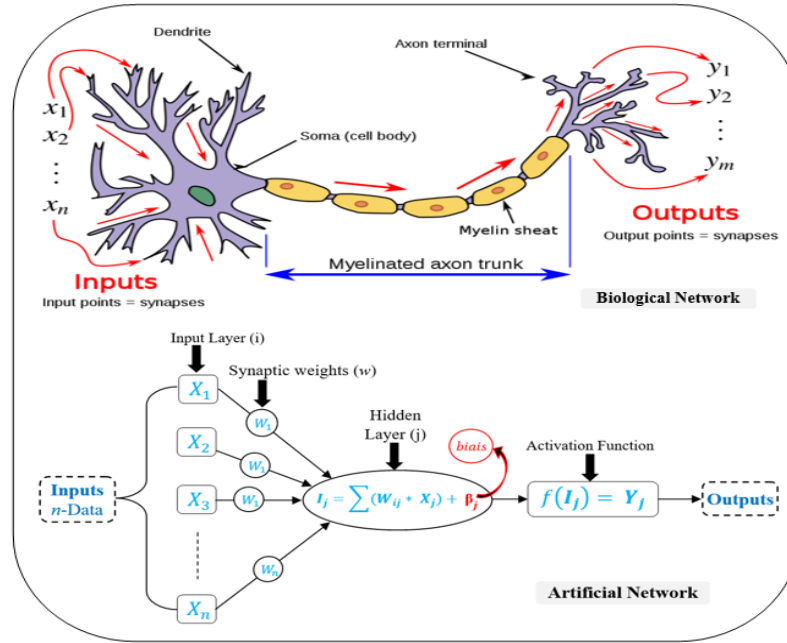


Figure 61. Illustration of a biological and Artificial Neural Network architectures

Where: I_j is Input function (weighted sum); W_i is the interconnection vector (synaptic weight); X_j is the signal (input variable); β_j is the error; Y_j is the output function.

In a biological network, information enters through the dendrites which form the synaptic input layer. They are then processed and conducted into the myelinated axon trunk (made up of myelin sheath) and are extracted at the level of the terminal axons which constitute the synaptic output layer (Figure 61). The myelinated axon membrane, which represents the hidden layer, maintains a flow of signal from the inputs through the dendrites (hidden) to the outputs (Output layer). Compared to the artificial neuron (Figure 61), the dendrites of the biological neural model correspond to the information input layer (independent variable). ANN is a machine learning method that mimics the functioning of the human brain (neuronal system) by using algorithms to analyze data. An Artificial Neural Network is made up of interconnected neurons, each of which is characterized by three essential elements: synaptic weight, bias and activation function. It is also consisting of Input, Hidden, and Output layers with connected neurons/nodes (Mohseni-Dargah et al., 2022; Baheti, 2023). Each layer comprising a number of artificial neurons. The input layer receives the input data (independent variables) and the output layer produces the predictions or final results (Output). Between the input and output layers, there may be one or more hidden layers, which also contain more artificial neurons.

ANNs are non-linear statistical data modeling tools based on the intelligent learning. For several years, its scope has significantly expanded, and ANN is now considered an alternative to traditional modeling methods based on linear regression (Şenyurt and Ercanlı, 2019; Do Santos et al., 2018; Nguyen et al., 2019) when dealing with highly complex data (health, geographic, imaging, finance, automotive, biometrics, etc.).

In forestry, several scientists and studies have recognized their application and interest in modeling of the complex relationships between independent and dependent variables in different ecological process (Baughman and Liu, 1995; Aldrich, et al., 1994; Zeng and Chen, 2021; Meradi et al., 2006; Živković et al., 2009; Srivastava et al., 2012; Şenyurt and Ercanlı, 2019; Ercanlı et al. 2017; Ercanlı and Kaya, 2019; Huang et al., 2014; Schmitt et al., 2001; Sakıcı and Özdemir, 2018; Bolat, 2021; Cywicka et al., 2022; Ercanlı and Bolat, 2017; Gopal and Woodcock, 1999; Peng and Wen, 1999). It is based on the various Algorithm that the mains commonly used are Radial Basic Function (simple structure with 3 layer) and Multi-Layer Perceptron (more complex architecture with several hidden layer: Deep Learning) techniques. The activation function's main task is to convert the node's summed weighted input into an output value that can be passed on to the next hidden layer or output (Baheti, 2023). The main difference between the two approaches are particularly these structure, connectivity and modeling.

In SPSS v22.0 software, the main ANN architectures widely used in modeling are Radial Basic Function and Multi-Layer Perceptron. Particularly, Multi-Layer Perceptron (MLP) algorithm is used to optimize the independent variables and enabled the selection of those that were most likely to influence the model. To better express the various options in the process of utilizing this algorithm in this study, the analysis of this algorithm (MLP) in the literature allowed us to design the diagram shown in Figure 62. According to Figure 62, the Muti-Layer Perceptron (MLP) algorithm was used in this study to develop prediction models of biomass and carbon storage in natural and mixed forest ecosystems (*Pinus nigra* and *Pinus brutia*) in Türkiye. The configuration of the process for utilizing this algorithm is based on (i) the selection of the perceptron itself, allowing for the calibration of its various layers (Input, Hidden, and Output), (ii) the selection of the direction of information flow (Feedforward) as the network architecture ($\rightarrow$ Input $\rightarrow$ Hidden $\rightarrow$ Output), and (iii) the choice of learning type (Deep or Supervised), leading to the confirmation of the error propagation type and the selection of the activation function (Sigmoid).

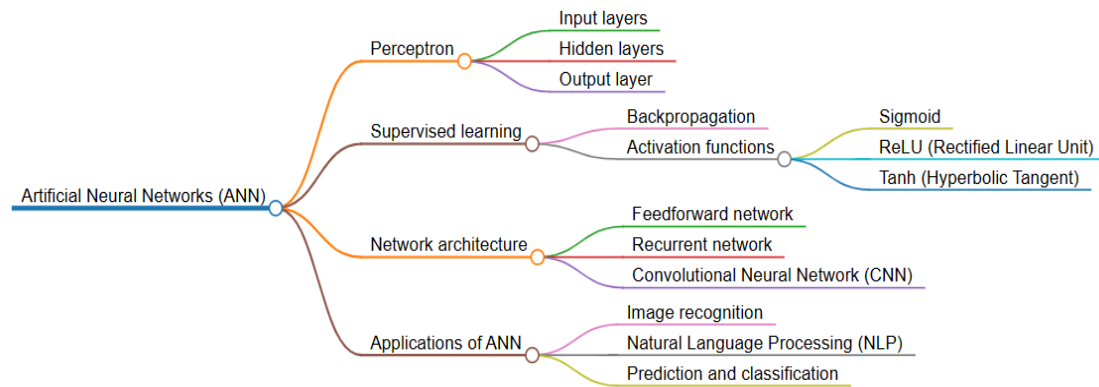


Figure 62. Diagram of most components for knowledge of AAN components

Indeed, Deep Learning is a subfield of machine learning that utilizes Artificial Neural Networks with multiple layers to model and solve complex problems. Its deep-layered structure allows hierarchical representation of data, facilitating automatic learning of intricate features. Widely applied in image recognition, machine translation, speech recognition, among others, it demonstrates remarkable efficacy in modeling complex natural processes. The scope of Supervised Learning extends to a broader category, encompassing various algorithms, some of which do not rely on neural networks.

➤ Multi-Layer Perceptron (MLP) in the Deep Learning

In contrast to Supervised Learning, Deep Learning specifically focuses on the use of deep neural networks. Deep Learning is often associated with complex tasks, involving the modeling of highly nonlinear relationships and the capture of intricate features. While Supervised Learning can use various models to represent data, Deep Learning favors the use of deep neural network architectures to learn hierarchical representations. Multi-Layer neural networks (MLP) are a fundamental component of Deep Learning. In other words, Deep Learning, as a subfield of machine learning, incorporates Multilayer Perceptron (MLP) neural networks to model complex and abstract relationships within data. The Multi-Layer Perceptron (MLP) algorithm, an architecture within Artificial Neural Networks, is employed for addressing classification and prediction challenges. Comprising multiple layers of neurons interconnected by synaptic weights, MLP excels in modeling intricate nonlinear relationships between input and output variables.

This adaptability is particularly advantageous in addressing complex issues, such as predicting biomass accumulation and carbon storage in forest ecosystems (Pellegrini et al., 2021; Khan et al., 2020; Srivastava et al., 2012; Özçelik et al., 2017). A Multi-Layer Perceptron (MLP) is a type of feedforward Artificial Neural Network that consists of at least three layers of nodes. It generates a predictive model for one or more dependent variables based on the values of predictor (independent variables) and can distinguish data that is not linearly separable. An intriguing aspect of MLP is its capability to assess model robustness through sensitivity analysis. This analysis determines the importance of each input predictor in the neural network's robustness. Indeed, the resulting chart illustrates independent variables and their importance as a percentage (%). This normalized importance indicates how much the independent variable influenced the obtained model. It corresponds to the ratio of importance values divided by the highest importance values. The whole process consists of extracting the most efficient variables for modeling based on the normalization of independent variables. This MLP-ANN technique ensures stability in synaptic weight and bias convergence. The MLP-ANN learning process involves several steps that have been used in this study and several others (Shen et al., 2020; Ercanlı and Kaya, 2018; Khan and al., 2019). In SPSS v22.0 software, these steps involve organizing and distributing variables, calibrating algorithm architecture, training and testing the algorithm, and determining output options.

➤ Application of MLP: Data Organization and Breakdown (partitions) in SPSS

Figure 63 illustrate the organization (selection and partition) of data in algorithm interface. According to Figure 63, the first step consisted of defining the model variables (independent and dependent) and dividing them into 2 groups, namely Training Data Group (60-80%) for model training and Testing Data Group (20-40%) for model validation. This step is following by the MLP computing.

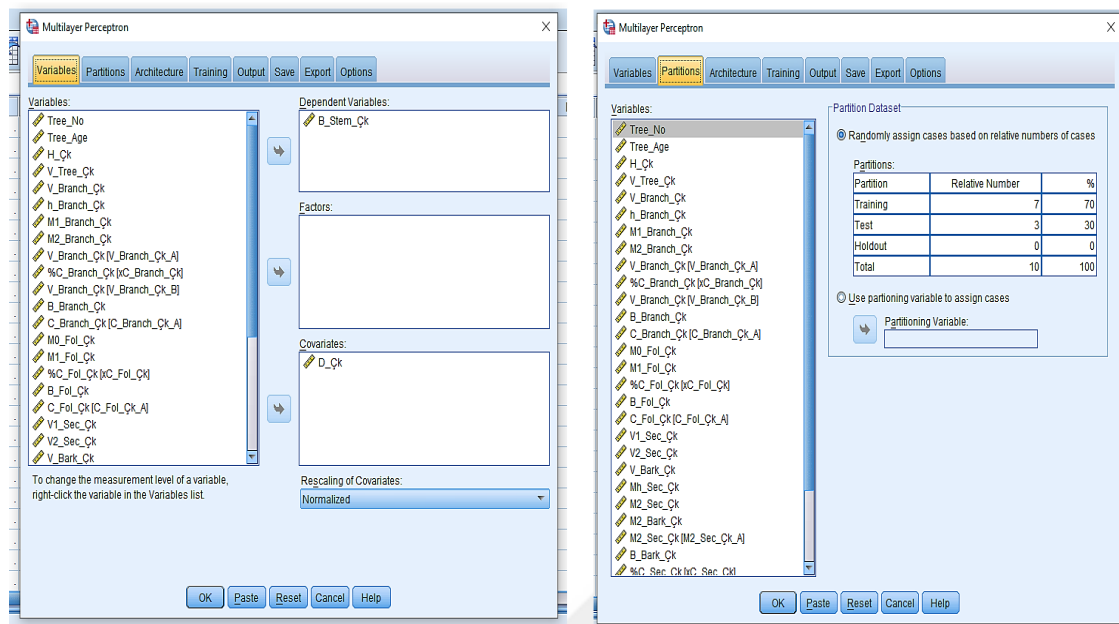


Figure 63. Input variables and partitioning data organization in MLP learning

➤ Application of MLP: Computing (Architecture) in SPSS

○ Hidden Layer Calibration

The calibration of hidden layers consists of defining or selecting the number of hidden layers, the number of nodes in a layer, the activation functions in the hidden layer (Sigmoid) and in the output layer (Sigmoid), the rescaling of scale-dependent variables (Normalized), and their correction factor. Figure 64 illustrates step 2, which consists of calibrating the architecture of the MLP network. According to Figure 64, the parameters of the MLP architecture were modified in turn according to the expected results on the model performance based on the minimization of quadratic errors and the maximization of the correlation coefficient between observed and predicted data. The number of hidden layers was varied between 1 and 2. On the other hand, the number of nodes in this layer was adjusted as needed. In this crucial second step, activation functions (Sigmoid) were selected for the hidden layer and output layer.

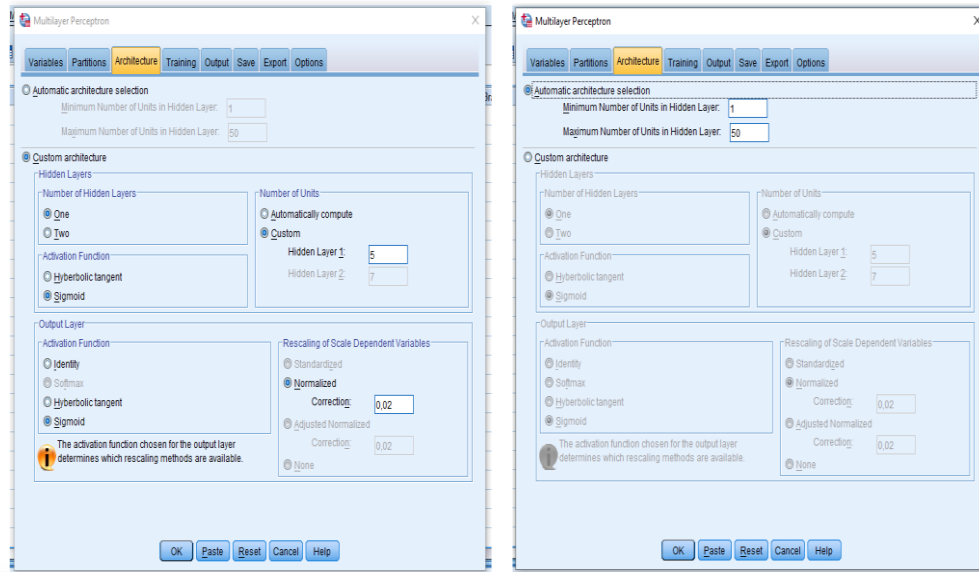


Figure 64. MLP-ANN Architecture calibration in SPSS 22.0 Software

○ Calibration of Activation Functions in the MLP-ANN

Activation functions are important in neural networks because they introduce non-linearity into the model. Without an activation function, a neural network would simply be a linear regression model and would not be able to model complex relationships between input and output variables., the most commonly used activation functions in MLP-ANN architecture are presented in follow relationships (Živković et al., 2009; Baheti, 2023; Çalışkan ve Sevim, 2018).

The Linear Activation Function (Purelin): given by the follow relationship:

$$Y_i = f(X_i) = X_i \quad (42)$$

It transforms input values (X_i) to a positive output (Y_i) if the input is greater than zero and to zero if the input is less than or equal to zero. It is often used in neural networks to model classification, image recognition, and natural language processing problems.

The Tan Hyperbolic Activation Function (tanh): given by the relationship:

$$Y_i = \tanh(X_i) = \frac{e^{X_i} - e^{-X_i}}{e^{X_i} + e^{-X_i}} \Rightarrow \tanh(X_i) = 2\text{sigmoid}(2X_i) - 1 \quad (43)$$

The tanh function is similar to the sigmoid function, but it transforms input values (X_i) into an output (Y_i) between -1 and 1. It is often used in neural networks to model regulation or prediction problems.

The Radial Basic Activation Function (radbas): given by the relationship:

$$Y_i = e^{[-(X_i)^2]} \quad (44)$$

Radial Basic Activation Function is characterized by its bell shape, which gives maximum response when the input (X_i) of the neuron is at an optimal distance from the center of the bell. It is used for tasks of classification or prediction (Y_i) of continuous values in several domains (pattern recognition, dynamical systems, prediction of time series, etc.).

Triangular Basic Activation Function (tribas): given by the relationship:

$$Y_i = 1 - \text{abs}(X_i) \Rightarrow \text{if } -1 \leq (X_i) \leq 1 \text{ otherwise, } Y = 0 \quad (45)$$

Function is a triangle shape with an upward slope (Y_i) and a gentle downward slope often used for the representation of variables (X_i) whose values lie between specific bounds.

Sigmoid Function (logsig): given by the follow relationship:

$$Y_i = \frac{1}{1 + e^{-X_i}} \quad (46)$$

The function transforms input values (X_i) into an output (Y_i) between 0 and 1. It is a logistical function.

In this study, Sigmoid Function (logsig) was selected in training and testing process of MLP algorithm. It allows the network to learn and represent non-linear relationships between the input and output data. They also help to normalize the output of each neuron to a specific range, which can improve the stability and performance of the network.

Sigmoid function is commonly used in neural networks because it is (i) differentiable, (ii) facilitates backpropagation, and (iii) allows modeling binary classification problems where the output must be interpreted as a probability. When a model uses the Sigmoid function in a binary classification task, it learns to adjust the weights and biases of the network to minimize the error between the model's predictions and the actual values of the classes (Liu et al., 2014).

The function decides if the neuron's input is important for the prediction process using simple mathematical operations. From its functions, the graphical interpretation of the main 12 activation functions and Sigmoid particularly, is presented in Figure 65.

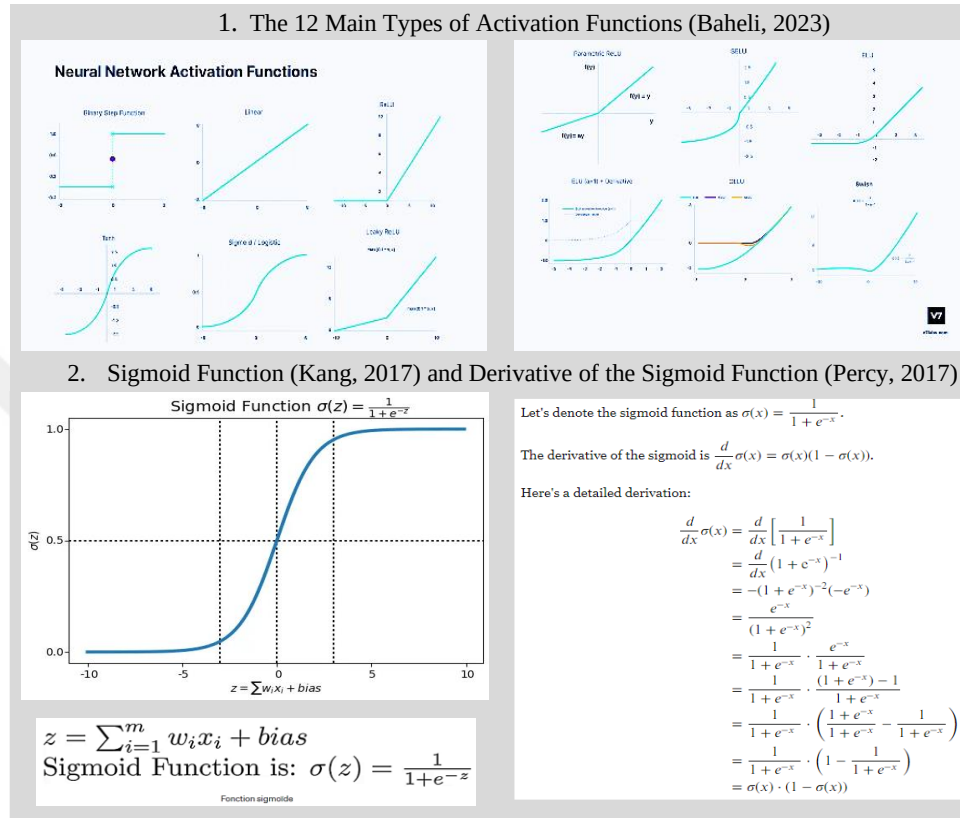


Figure 65. Illustration of different activation functions in ANN

According to several approaches developed (Živković et al., 2009; Kang, 2017), the sigmoid function produces results similar to those of a step function, with output ranging from 0 to 1. The point at which the curve intersects 0.5 at $x=0$ sets the rules for activation: if the output of the sigmoid neuron is ≥ 0.5 , it produces the value 1. On the other hand, when x is very negative, the output is around 0 (Kang, 2017). The curve of the sigmoid function is smooth, without jerks, and the derivative of this sigmoid function $[\sigma(x) \cdot (1 - \sigma(x))]$ as proposed by Percy (2017), is simple and differentiable in all directions. When z is very negative, the output is about 0. If x is very positive, the output is about 1. However, the deviation is more obvious with (between the two outer dashed vertical lines on Figure 65), where x is neither too large nor too small. It corresponds to the aims of biomass and carbon modeling. It was used as the activation function in this study (Živković et al., 2009; Baheti, 2023; Khan et al., 2019).

○ Data Normalization in the MLP-ANN Algorithm

The scaling of dependent variables was normalized to a correction factor of 0.02. The choice was made to normalize the data rather than standardize it. Both play a useful role. Data standardization (centering reduction) involves transforming the data so that it has a mean of 0 and a standard deviation of 1. This allows all variables to be put on the same scale, thus eliminating differences in magnitude between variables. Data Standardization is useful when you want to compare the relative importance of different variables and when you want to avoid certain variables with higher magnitudes dominating model learning. Data Normalization involves resizing the data to bring it back into a specific range, usually between 0 and 1. This can be useful when you want to preserve linear relationships between variables but want to avoid problems related to magnitude differences.

Normalization is often used when the absolute values of variables are important for model interpretation. In order to prevent normalized values from being 0.0 to 1.0 when scaling dependent variables when the Sigmoid activation function is used in the output, a correction factor (0.02) was included. This measure prevents some validation data from lying beyond the extreme values of 0.0 or 1.0. In such a situation, when the average value approaches the extreme values, the derivative of the sigmoid function tends towards 0 and yet no learning occurs: It is the stagnation of the learning process (Tsintikidis, 1997, cited by Srivastava and Tripathi, 2012. Indeed, Nguyen et Ogunbona (2017) explore the potential causes of stagnation in deep learning, examining factors such as convergence issues, saturated gradients, local plateaus, etc. They propose solutions and techniques to overcome these obstacles and improve learning in deep neural networks.

○ Training option of MLP-ANN Algorithm

The training phase options of the architecture that were used in this study are presented in Figure 66.

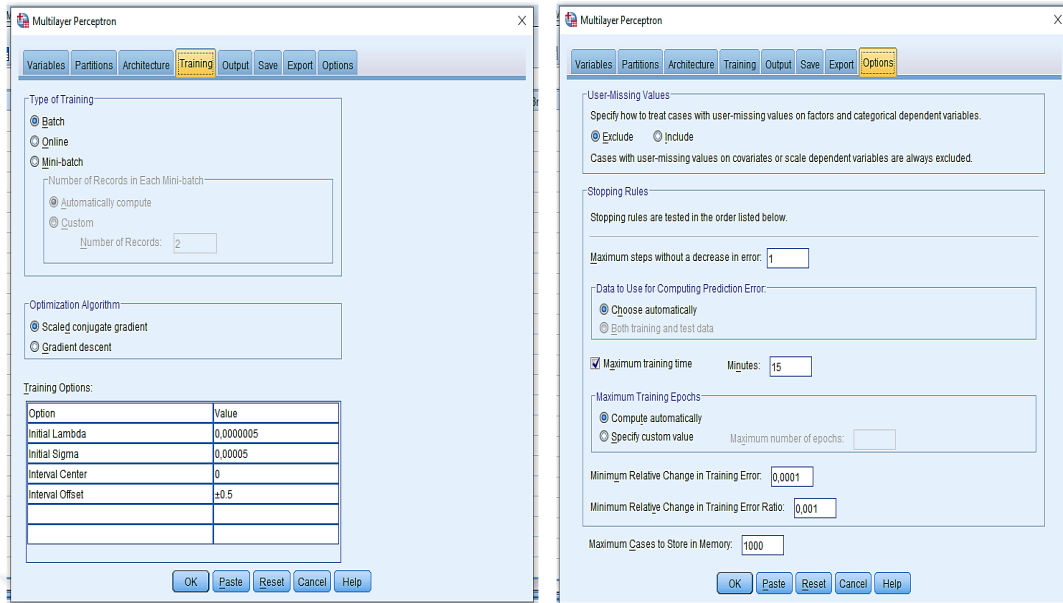


Figure 66. Illustration of the training and option interfaces of the MLP-ANN

In Figure 66, the training and options interfaces of the MLP present the details manipulate in this study. The Batch training type is the method that updates the neural network's weights using the complete set of training data at each iteration (a full pass of the training data set through the neural network). To optimize the MLP, the Gradient Descent Optimization Algorithm calculates the partial derivatives of the loss function with respect to the network's weights, then updates the weights in the opposite direction of the gradient using a fixed learning rate. The main difference between Gradient Descent and Scaled Conjugate Gradient lies in the method of adjusting weights. In this work, the Scaled Conjugate Gradient was used because it is a more advanced method for optimizing weights in MLP. Unlike gradient descent, Scaled Conjugate Gradient uses an iterative approach that combines the properties of the conjugate gradient method with adaptive scaling of learning steps. This method estimates an optimal search direction that minimizes the loss function while automatically adapting the size of learning steps. This allows for faster convergence and better handling of ill-conditioned gradient problems. The training options were left at their default values. There are Initial Lambda, Initial Sigma, Interval Center, and Interval Offset:

(i) Initial Lambda is the initial penalty parameter used in the error backpropagation algorithm. The penalty is a technique for regularizing the model and avoiding overfitting. The Initial Lambda option allows you to specify the initial value of this parameter.

(ii) Initial Sigma is the initial scaling parameter used in the error backpropagation algorithm. Scaling is a technique for adjusting the model's learning rate. The Initial Sigma option allows you to specify the initial value of this parameter.

(iii) Interval Center is the center of the range of initial values for the weights and biases of the neural network. The Interval Center option allows us to specify the central point of this range.

(iv) Interval Offset is half the width of the range of initial values for the weights and biases of the neural network. The Interval Offset option allows you to specify the distance of this range from the previously specified center.

○ Backpropagation Error in MLP-ANN Architecture

To train the Multilayer Perceptron algorithm, the backpropagation algorithm calculates the local errors between the model's predictions and the actual values, then uses this local error to adjust the weights and biases during the network's learning phase. During each learning process (backpropagation), local errors appear between the input layers and the hidden layers, and also between the hidden layers and the output layers (Živković and al., 2009). These errors are:

(i) The Local Error in Hidden (j) Layer (Input $\rightarrow$ Hidden) : The Local Error in Hidden Layer refers to the error signal calculated at each neuron in Hidden layer. It is represented by follow expression:

$$\beta_j = f(I_{i \rightarrow j}) * (\beta_k - W_{ij}) \quad (47)$$

Where: β_j is Local Error in Hidden Layer; β_k represent the error of the element in the following layer; $f(I_{i \rightarrow j})$ is the activation function between i-neuron to j-neuron; W_{ij} is the weight of interconnects between i-neuron and j-neuron.

(ii) The Local Error in Output (k) Layer (Hidden $\rightarrow$ Output) : The Local Error in Output Layer refers to the error signal calculated at each neuron in Output layer. It is represented by follow expression:

$$\beta_k = f(I_{j \rightarrow k}) * (y_k - O_k) \quad (48)$$

Where: β_k is Local Error in Hidden Layer; y_k represent the target output value of j -layer; $f(I_{j \rightarrow k})$ is the activation function between j -neuron to k -neuron; O_k is output of the k -neuron. At each iteration, the weights are updated to minimize the error and improve the model's performance. The algorithm works by propagating the error from the output layer to the hidden layers, using the derivative of the activation function to determine the relative importance of each weight in error backpropagation. This allows the model to gradually adjust and optimize its ability to accurately predict target values. The activation function is applied at each hidden node and each output node in the network. During training, the input function from neuron i to neuron j is represented by the global transfer function (Živković et al., 2009). The global transfer function of the information from the i -neuron to j -neuron is represent by the follow relationship:

$$T_{i \rightarrow j} = f(I_j) = f(\sum W_{ij} * X_j) \quad (49)$$

Where: $T_{i \rightarrow j}$ is the global transfer function from i -neuron to j -neuron. I_j is Input function (weighted sum); W_{ij} is the weight of interconnects between i -neuron and j -neuron; X_j represent the signal (input variable) at the connection; β_j represent the error (biais) that occurs and quickly corrected by backpropagation.

○ Output of MNL network

At the end of an MLP-ANN learning process, the elements of presentation of the results are summarized in Figure 67 (next page). In the architecture of the MLP (Multi-Layer Perceptron) obtained after learning, the terms “Synaptic Positive Weight ($W > 0$) and “Synaptic Negative Weight ($W < 0$) refer to the synaptic weights of the connections between neurons. Synaptic weights represent the strength or influence of a connection between two neurons. They are used to weigh the importance of signals that flow through the neural network. Positive and negative weights indicate the direction of the connection's influence. When $W > 0$, it means that the synaptic weight is greater than zero. This indicates an excitatory connection, where a positive signal from a preceding neuron is strengthened when transmitted to a subsequent neuron. Positive synaptic weights are often used to amplify signals and promote the activation of the next neuron.

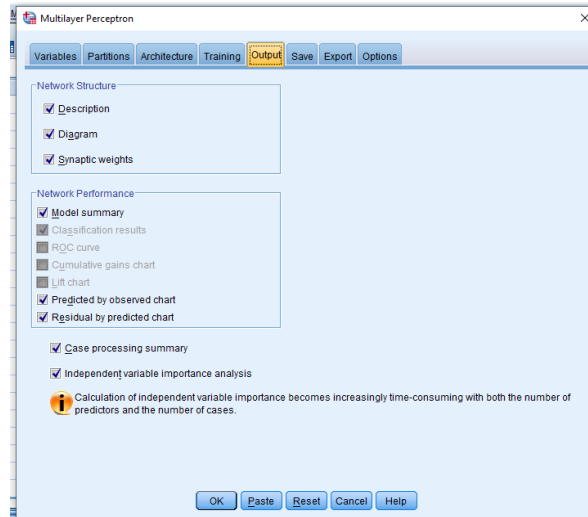


Figure 67. Main Outputs element to obtain the result of MLP-ANN learning

When $W < 0$, it means that the synaptic weight is less than zero. This indicates an inhibitory connection, where a positive signal from a preceding neuron is weakened or suppressed when transmitted to a subsequent neuron. Negative synaptic weights are often used to inhibit signals and regulate the activity of the next neuron. Synaptic weights, whether positive or negative, play a crucial role in the learning and functioning of the MLP, as they determine how signals are propagated through the network and how neurons respond to inputs (Goodfellow and al., 2016).

d. Spatial Distribution of Biomass and Carbon Stocks in Natural Mixed Forest Ecosystems in Türkiye

Within the scope of this research project, the geospatial representation aimed to create multiple thematic maps illustrating the overall distribution of biomass and carbon stocks based on available areas within the mixed natural forest ecosystems of *Pinus nigra* and *Pinus brutia* in Türkiye. This technique was used by Shumilo et al. (2021) to draw up maps (Yield Maps: sunflower yield statistics), as part of a study entitled “Is soil Bonitet an Adequate Indicator for Agricultural Land Appraisal in Ukraine”. Djaouga et al (2021) were used data of biomass and carbon calculated from tree (above-ground) of vegetation formation of reserved forest in Benin. Data pertaining to these forest stands were extracted from current management plans (2018), synthesized, and utilized in the context of the TÜBİTAK 118O311 Project, conducted within the Laboratory for Forest Biomass and Carbon Yield Analysis and the Forest Management Laboratory at Karadeniz Technical University.

The methodology involved the use of a Shapefile dataset (.shp) containing all Department of Forest Operations (DFO) along with their respective areas, distributed across 113 Forest Management Directorates (DGF) belonging to 10 Regional Directorates of Forestry throughout Türkiye. Subsequently, about 350 of these DFOs, primarily composed of mixtures of *Pinus nigra* - *Pinus brutia*, were selected and used for the cartographic representation of their biomass and carbon stocks. It is worth noting that biomass and carbon stocks of roots and soil organic matter were considered only for the depth of 0 to 30 cm. Next, the general average data concerning biomass and carbon stocks for these ecosystems were used to estimate their total capacities at the ecosystem scale. In other words, the overall averages of biomass and carbon were then multiplied by the areas of each stand of *Pinus nigra* and *Pinus brutia*. All the information was organized in an Excel file (.xls) and imported into ArcGIS 10.3 (Töreya et al., 2010), the mapping software used to produce the maps (WGS1894). These maps were designed separately for each component of biomass and carbon, whether aboveground or belowground. This approach facilitated the precise visualization of the spatial distribution of biomass and carbon stocks within the studied forest ecosystems.

e. Performance criteria and Models' Validation

The performance of the models mainly depends on their ability to predict the experimental output data with accuracy. The main mathematical expressions of the different validation criteria used to select the best models are given as follows (next page):

In this study, the validation of models was guided by several traditional criteria. The evaluation of the null hypothesis was carried out with the t-Student test at 95% for the mean residual value. The decision to choose robust and pragmatic models was based on the value of statistical criteria such as the p-value at 5% ($p < 0.05$) or 1% ($p < 0.01$), Sum of Squared Error (SSE), Mean Square Error (MSE), Root Mean Squared Error (RMSE), Relative Root Mean Squared Error (%RMSE), and/or Adjusted Coefficient of Determination (R_{Adj}) or Coefficient of Correlation (R^2).

$$SSE = \sum_{i=1}^n (t_i - o_i)^2 \quad (50)$$

$$MSE = \sum_{i=1}^n \left(\frac{(t_i - o_i)^2}{n - p} \right) \quad (51)$$

$$RMSE = \sqrt{\sum \left(\frac{(t_i - o_i)^2}{n - p} \right)} \quad (52)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^n (t_i - o_i)^2 (n - 1)}{\sum_{i=1}^n (t_i - u_i)^2 (n - 1)} \right) \quad (53)$$

$$\%RMSE = 100 * \sqrt{\sum \left(\frac{(t_i - o_i)^2 / (n - 1)}{\sum (o_i / n)} \right)} \quad (54)$$

Where: t_i is the parameters; o_i is the predicted output value for the parameters; n is the number of data point; p represents the number of attributes within the model; u represents average values of parameters.

3. RESULTS

3.1. Results from Stand Parameter Analysis

Parameters for characterizing natural mixed stands of *Pinus nigra* and *Pinus brutia* in Türkiye were calculated from 46 samples, in accordance with the methodology described in Section 2.2.4. of this document. These parameters are mainly Stand Productivity or Site Index (SI), Age (A_s), Quadratic Mean Diameter (D_q), Average Height (H_m), Number of Trees or Density (N), Dominant Height (H_{100}), Basal Area per hectare (G), Volume (V_s), Mixing Ratio (R_s), Site Density Index (R_s), Site Density Ratio (R_s) and Internal Variability (C_v). It is important first to indicate the basic information on these experimental plots.

3.1.1. Basic information on the Sample Plots

Along with the field data, the analysis of forest management plans helped to better understand the Natural Mixed Stands of ÇkÇz surveyed in this research by providing additional characteristic information. Table 17 (next page) displays the basic information acquired on the stand analysis, which includes details such as the Regional Directorate of Forestry (RDF Directorate of Forest Management (DFM), Directorate of Forest Enterprise Units or Forest Sub-District Directorates (DFE), Stand types (S_T), size of experimental plots (S_p), Site Index (SI), Stand Aspect (S_A), and Geographical Coordinates (X, Y and Z).

Based on Table 17 (next page), the study analyzed 13 different types of mixed stands of ÇkÇz, which varied based on the crown closure and development stage determined by the corresponding diameter class. A total of 47 experimental units were delimited in 21 Directorate of Forest Management (DFM), distributed across 13 Forest Operations Directorates (DFO) located in 10 Regional Directorates of Forestry (RDF) in Türkiye. The size of the experimental plots varied between 400 m² ($r = 11.28$ m), 600 m² ($r = 13.82$ m) and 800 m² ($r = 15.96$ m). These different sizes were determined more or less according to the different levels of crown closure, corresponding to 3 (71-100%), 2 (47-70%), and 1 (71-100%), respectively, and appreciated in the field. The average altitude of all experimental plots is 858.64 m, with minimum and maximum values of 169 to 1,650 m respectively.

Table 17. Basic characteristic information of experimental plots

No	RDF	DFM	DFO	Stand Type	SI	S_p (m ²)	Coordinates (m)		
							X	Y	Z
1	Ankara	Nallıhan	Andız	ÇkÇzbc1	3	600	317182	4447931	1040
2	Balıkesir	Edremit	Burhaniye	ÇkÇzb3	4	400	504816	4357245	709
3	Balıkesir	Edremit	Çınarlıhan	ÇkÇzd2	4	400	511422	4392713	622
4	Balıkesir	Edremit	Çınarlıhan	ÇkÇzcd3	4	400	511468	4392558	594
5	Bursa	Orhaneli	Meyran	ÇkÇzbc2	2	600	678976	4397386	845
6	Bursa	Orhaneli	Harmancık	ÇkÇzc2	4	600	686997	4386548	1024
7	Bursa	Orhaneli	Karabayır	ÇkÇzc3	2	400	674650	4443668	1204
8	Çanakkale	Bayramiç	Evciler	ÇkÇzd3	3	400	483410	4401436	371
9	Denizli	Denizli	Denizli	ÇkÇzc3	3	600	690728	4169073	1645
10	Denizli	Denizli	Kocabaş	ÇkÇzcd2	3	600	713030	4178680	1151
11	Denizli	Denizli	Kocabaş	ÇkÇzc1	3	600	717559	4178700	583
12	Isparta	Göhlhisar	Gölova	ÇkÇzc2	4	600	720184	4120556	289
13	Isparta	Göhlhisar	Gölova	ÇkÇzc2	5	600	700238	4119385	169
14	Isparta	Burdur	Aziziye	ÇkÇzcd2	4	600	253225	4149173	1393
15	Isparta	Burdur	Aziziye	ÇkÇzc2	4	600	251237	4152950	1294
16	Isparta	Burdur	Aziziye	ÇkÇza0	4	400	252166	4146449	1280
17	Kütahya	Tavşanlı	Alabarda	ÇkÇzbc3	4	400	691647	4377629	811
18	Kütahya	Emet	Emet	ÇkÇzc2	4	600	696175	4353103	987
19	Kütahya	Gediz	Karadona	ÇkÇzab3	3	400	708239	4309933	948
20	Kütahya	Gediz	Karadona	ÇkÇzab3	3	400	708477	4309959	925
21	Kütahya	Gediz	Karadona	ÇkÇzab3	3	400	708693	4310037	892
22	Kütahya	Gediz	Karadona	ÇkÇzbc2	3	400	717179	4308419	957
23	Kütahya	Gediz	Karadona	ÇkÇzc1	5	600	717142	4308303	1052
24	Kütahya	Gediz	Karadona	ÇkÇzbc2	4	600	709808	4309253	1002
25	Kütahya	Gediz	Karadona	ÇkÇzbc2	4	600	709520	4308544	1121
26	Kütahya	Gediz	Karadona	ÇkÇzbc2	4	600	709152	4308667	1012
27	Kütahya	Gediz	Karadona	ÇkÇzc2	4	600	709215	4308315	1060
28	Kütahya	Gediz	Karadona	ÇkÇzbc2	5	600	701105	4311047	768
29	Kütahya	Gediz	Karadona	ÇkÇzbc2	5	600	701462	4310310	848
30	Kütahya	Gediz	Muratd*	ÇkÇzc2	3	400	720006	4313971	988
31	Kütahya	Gediz	Muratd*	ÇkÇzcd3	3	400	718359	4312594	1034
32	Kütahya	Gediz	Muratd*	ÇkÇzcd3	3	400	718537	4313060	991
33	Eskişehir	Mihalıççık	Kartal	ÇkÇzc1	5	600	367375	4428302	972
34	Bolu	Göynük	Hacıosm*	ÇkÇzbc2	4	600	307522	4472768	675
35	Bolu	Göynük	Hacıosm*	ÇkÇzbc2	4	600	307505	4472800	673
36	Bolu	Göynük	Hacıosm*	ÇkÇzbc2	4	600	307529	4472726	678
37	Bolu	Göynük	Hacıosm*	ÇkÇzc2	4	600	309985	4476760	760
38	Bolu	Göynük	Dedeler	ÇkÇzbc2	5	600	319213	4464466	809
39	Bolu	Göynük	Dedeler	ÇkÇzbc2	5	600	319192	4464525	798
40	Bolu	Göynük	Dedeler	ÇkÇzc2	5	600	319114	4464361	814
41	Bolu	Göynük	Ilıca	ÇkÇzc2	4	600	300721	4471012	606
42	Bolu	Göynük	Ilıca	ÇkÇzc2	4	600	300711	4470895	626
43	Bolu	Göynük	Ilıca	ÇkÇzbc2	4	600	300749	4470964	609
44	Bolu	Göynük	Himmet*	ÇkÇzbc2	4	600	312377	4453991	743
45	Bolu	Göynük	Himmet*	ÇkÇzbc1	4	800	312457	4454067	730
46	Bolu	Göynük	Himmet*	ÇkÇzbc1	4	600	312427	4454147	729
47	Ktamon*	Gerze	Dikmen	ÇkÇzcd3	3	400	690182	4616638	525

NB: *Himmetoğlu; *Kastamonu; *Muratdağı; *Hacıosman

3.1.2. Results from Distribution Analysis of Sample Plots by Stand Type

This study focused on different types of mixed stands (ÇkÇz) composed of Anatolian Black Pine (*Pinus nigra*) and Turkish Red Pine (*Pinus brutia*). Observations of the data show that seven types of stands were explored, and their distribution according to crown closure and diameter class, led to the results presented in Table 18.

Table 18. Distribution of stands by crown closure and development stage

Crown Closure	Stand Types and corresponding Diameter Classes							Total	
	ÇkÇza	ÇkÇzab	ÇkÇzb	ÇkÇzbc	ÇkÇzc	ÇkÇzcd	ÇkÇzd	n	%
	1-7.9		8-19.9		20-35.9		36-51.9		
0	1	/	/	/	/	/	/	1	2.13
1	/	/	/	3	2	/	/	5	10.64
2	/	/	/	9	10	4	1	24	51.06
3	/	5	2	3	2	4	1	17	36.17
Total (%)	1 (2,13)	5 (10.64)	2 (4.26)	15 (31.92)	14 (29.79)	8 (17.02)	2 (4.26)	47 (100)	
Stand Type	Young	Young & post-pole	Post-pole	P-Pole & Fine	Fine Wood	Fine & Medium	Wooded		

From the observations of the Table 18, the results show that the stand types explored in this study are consist of 31.91% of ÇkÇzbc, 27.79% of ÇkÇzc, 17.02% of ÇkÇzcd, 10.64% of ÇkÇzab, 4.26% of ÇkÇzb, 4.26% of ÇkÇzd and 2.13% of ÇkÇza. It therefore appears that the different stages of development brought together in this research are *a*, *ab*, *b*, *bc*, *c*, *cd*, and *d*. But in the rest of the work, the ÇkÇza was not considered due to its very small number and the outliers that it can represent.

3.1.3. Results from Distribution of Sample Plots by Site Productivity

The productivity of the forest stands examined (Site Index or Bonitet) on 47 sample plots in this study was evaluated based on information gathered from the forest management plans used in TÜBİTAK Project 118O311. According to the 6 age classes, the stand productivity (I, II, III, IV and V) were grouped into three main appreciation categories, as

that Good (I and II), Medium (III) and Poor (IV and V). The observations of the distribution allow us to obtain the results presented in Table 19.

Table 19. Distribution of sample stands by Site Index and Age Class

Age class		Site Index (<i>Bonitet</i>)			Total	
		Good	Medium	Poor	n	%
I	0-20	-	4	2	6	12.77
II	21-40	-	-	3	3	6.38
III	41-60	1	4	5	10	21.28
IV	61-80	1	1	10	12	25.53
V	81-100	1	3	7	11	23.40
VI	>100	-	1	4	5	10.64
Total	6	3	13	31	47	100

The results in Table 19 show that 65.96% of stands have poor productivity (IV and V), 27.66% have a medium productivity (III), and only 0.064% have a rich site index (I and II). The most represented age groups are 61-80 years (25.53%), 81-100 years (23.40%) and 41-60 years (28%).

3.1.4. Results from Distribution Analysis of Sample Plots in Age Classes

According to their type and development stage, the 46 forest stands studied as part of this study were grouped into the 6 main age classes. The results are presented in Table 20.

Table 20. Distribution of sample plots in 6 age classes

Stand Types	Age Class					
	I	II	III	IV	V	VI
	1 - 20	21 - 40	41 - 60	61 - 80	81 - 100	>100
ÇkÇzab	4	3	/	/	/	/
ÇkÇzb	1	1	/	/	/	/
ÇkÇzbc	/	1	5	3	4	2
ÇkÇzc	/	/	3	5	5	1
ÇkÇzcd	/	/	1	4	2	1
ÇkÇzd	/	1	/	/	/	1
Total	5	4	9	12	11	5

from the results of Table 20, we observed that 12 samples were taken from age classes between 61 and 80 years, 11 from 81-100 years, 9 from 41 to 60 years, 4 from 21-40 years, 5 from 1-20 years, and 5 from 100 years and above.

3.1.5. Results from Main Forest Stand Parameters Calculation

The main parameters estimated from 47 samples of natural mixed ÇkÇz stands consisting of Stand Age (A_S), Stand Tree Number (N), Stand Average Diameter (D_m), Stand Average Height (H_m), Stand Top Height (H_{100}), Stand Quadratic Diameter (D_q), Stand Basal Area (G) and Stand Volume (V_S). The results are recorded in Table 21.

Table 21. Summary of estimated stands parameters

Plot No	Stand Type	A_S	N	D_m	D_q	H_m	H_{100}	G	V_S
		(year)	(ha)	(cm)	(cm)	(m)	(m)	(m ² /ha)	(m ³ /ha)
1	ÇkÇzbc1	40	333	14.45	15.77	8.51	10.22	6.51	36,357
2	ÇkÇzb3	31	1550	16.95	18.12	15.08	15.83	39.97	252,354
3	ÇkÇzd2	35	725	27.15	28.60	15.61	16.85	48.18	376,444
4	ÇkÇzcd3	48	575	28.22	29.61	16.39	17.37	41.32	324,700
5	ÇkÇzbc2	83	867	19.60	21.19	14.52	15.61	30.55	217,984
6	ÇkÇzcc2	91	700	23.91	26.21	14.38	16.66	37.78	222,833
7	ÇkÇzc3	79	1275	20.57	22.30	13.73	15.52	49.80	363,762
8	ÇkÇzd3	104	800	19.41	22.67	19.80	21.11	32.30	272,757
9	ÇkÇzc3	49	433	19.86	22.48	18.96	23.70	17.21	130,284
10	ÇkÇzcd2	97	600	23.19	25.71	22.66	23.07	31.16	265,339
11	ÇkÇzc1	88	383	22.71	23.81	14.39	16.39	17.06	122,278
12	ÇkÇzc2	91	483	21.93	23.21	12.10	12.20	20.44	151,846
13	ÇkÇzc2	57	933	14.85	15.64	10.46	12.11	18.95	112,901
14	ÇkÇzcd2	115	433	23.10	24.88	12.30	12.62	21.08	172,519
15	ÇkÇzc2	76	467	18.60	19.57	11.22	12.00	14.04	98,728
16	ÇkÇzbc3	72	1075	17.89	18.44	14.29	15.86	28.70	176,291
17	ÇkÇzc2	81	950	16.39	17.97	9.00	9.75	24.11	153,857
18	ÇkÇzab3	16	1000	9.70	9.97	6.22	7.58	7.81	47,364
19	ÇkÇzab3	19	1375	8.55	9.37	6.28	7.72	9.48	64,669
20	ÇkÇzab3	16	1325	9.30	9.58	4.56	6.33	9.55	60,017
21	ÇkÇzbc2	60	850	24.44	25.73	11.31	15.25	44.19	284,030
22	ÇkÇzbc3	50	825	28.27	29.68	12.15	15.53	57.09	410,441
23	ÇkÇzb3	20	1325	12.04	12.57	6.86	9.70	16.45	85,827
24	ÇkÇzbc3	52	1075	23.21	24.05	13.05	15.43	48.84	293,814
25	ÇkÇzab3	29	1375	11.61	13.52	7.08	10.63	19.75	112,961
26	ÇkÇzab3	15	1450	9.25	10.71	7.82	13.63	12.60	79,581
27	ÇkÇzcd2	69	800	30.28	31.68	14.19	17.53	63.07	419,099
28	ÇkÇzcd2	67	800	30.34	31.70	15.50	19.00	63.15	478,509
29	ÇkÇzc2	71	800	23.50	25.15	15.55	21.83	39.75	268,443
30	ÇkÇzcd3	68	825	26.70	27.45	14.37	16.78	48.82	316,701
31	ÇkÇzcd3	76	800	29.66	30.52	15.47	20.53	58.53	412,732
32	ÇkÇzc1	121	517	17.38	21.31	7.94	7.94	20.20	150,479
33	ÇkÇzbc2	59	550	23.44	24.50	12.25	13.96	25.93	191,311
34	ÇkÇzbc2	101	217	24.24	25.34	12.21	12.21	10.93	73,722
35	ÇkÇzbc2	98	250	24.23	24.85	12.24	14.20	12.13	88,683
36	ÇkÇzc2	78	417	26.68	30.38	13.39	15.30	30.21	141,158
37	ÇkÇzbc2	92	550	12.52	14.90	9.60	10.30	9.59	66,069
38	ÇkÇzbc2	98	617	10.73	12.80	10.62	12.30	7.94	50,657
39	ÇkÇzc2	96	417	17.08	18.78	13.24	15.10	11.54	82,203
40	ÇkÇzc2	60	267	23.99	24.63	13.49	16.40	12.71	93,382
41	ÇkÇzc2	64	217	27.26	27.74	13.22	18.40	13.09	96,398
42	ÇkÇzbc2	121	817	15.38	16.20	14.48	15.00	16.83	104,212
43	ÇkÇzbc2	62	283	16.75	18.55	10.32	13.80	7.66	57,201
44	ÇkÇzbc1	46	300	16.60	17.56	8.37	9.88	7.26	46,117
45	ÇkÇzbc1	79	633	19.02	20.63	7.46	9.30	21.17	140,681
46	ÇkÇzd3	91	450	23.54	27.72	17.30	18.92	27.16	244,218

The descriptive analysis (Table 21) led us to the results in Table 22.

Table 22. Summary of descriptive analysis of forest stand parameters

	<i>N</i>	<i>A_S</i>	<i>D_m</i>	<i>H_m</i>	<i>H₁₀₀</i>	<i>G</i>	<i>D_q</i>	<i>V_S</i>
	46	46	46	46	46	46	46	46
Mean	732.79	68.07	20.097	12.389	14.507	25.876	21.398	182.868
Std. Deviation	362.116	28.668	6.127	3.797	4.157	16.341	6.086	120.120
Minimum	217	15	8.550	4.560	6.330	6.510	9.370	36.357
Maximum	1550	121	30.340	22.660	23.700	63.150	31.700	478.509
Skewness	,574	-,216	-,233	,164	,139	,801	-,367	,803
Kurtosis	-,498	-,644	-,863	,195	-,324	-,511	-,718	-,404

According to the results of Table 22, the descriptive analysis reveals negative values of Skewness and Kurtosis, indicating a distribution flatter and wider than the normal distribution on one hand, and positive values on the other hand, signaling a distribution concentrated around the mean with rare and high extreme values. Despite this, observations appear to be distributed between the maximum and minimum values, with averages serving as important indicators of variability. Indeed, the examination of Table 22 emphasizes significant variability in the distribution of data for each parameter. The gaps between maximum and minimum values indicate a marked dispersion among the 46 studied samples, suggesting substantial diversity in the measured results. The means, as a central measure, also provide important references within this diversity, contributing to a comprehensive understanding of the particular characteristics of mixed natural forest stands (*Pinus nigra* - *Pinus brutia*) in Türkiye.

3.1.6. Results from Stand Diameter-Height Relationships Analysis

To analyze the relationship between tree height and diameter for each species studied, tree data measured in the experimental plots were used. Viable data were calibrated to explain the influence of diameter on the height of each tree.

a. Observations on the Stand Height-Curve for *Pinus nigra* Tree Species

In the 46 forest stand types, the mathematical relationship between tree height ($H_{\text{Çk}}$) and diameter ($D_{1.30}$) for Anatolian Black Pine (*Pinus nigra*) or Karaçam (Çk) tree species was analyzed using non-linear regression.

Using the diameters ($D_{1.30}$) of 70 sampled trees whose height ($H_{\zeta k}$) was also measured, the $H_{\zeta k} = F(D_{\zeta k})$ models are presented in Table 23.

Table 23. Models of stand height curve relationships for Anatolian Black Pine

Model Summary and Parameter Estimates for <i>Pinus nigra</i> (Çk)									
Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	,650	126,268	1	68	,000	4,265	,340		
Logarithmic	,647	124,837	1	68	,000	-14,949	8,688		
Inverse	,612	107,109	1	68	,000	21,163	-198,40		
Quadratic	,653	63,062	2	67	,000	2,579	,470	-,002	
Cubic	,654	41,508	3	66	,000	,199	,743	-,012	,000
Compound	,593	98,932	1	68	,000	6,414	1,027		
Power	,618	109,885	1	68	,000	1,352	,697		
S	,609	106,007	1	68	,000	3,214	-16,264		
Growth	,593	98,932	1	68	,000	1,858	,027		
Exponential	,593	98,932	1	68	,000	6,414	,027		
Logistic	,593	98,932	1	68	,000	,156	,974		

Independent variable: $D_{\zeta k}$ / Dependent Variable: $H_{\zeta k}$

The results in Table 23 show the 11 statistical models, their parameters as well as their different performance indicators. All these models are statistically significant at 1% (p-value <0.01). These models show that tree diameter can explain variability in *Pinus nigra* tree height in stands mixed with *Pinus brutia*. For the case of our context, the most efficient model is the Quadratic model followed by Linear, Logarithmic, Power, Inverse, S-Curve, Growth, Exponential and Logistic models. Their coefficient of correlation ranged between 0.593 to 0.653. Using the diameter ($D_{1.30}$) as a predictor, we estimate that the Quadratic model can predict 65.3% (F=63.062) of the variability in tree height ($H_{\zeta k}$) for *Pinus nigra* tree species in these stand types, with relatively low prediction errors (Std. Error = 1.548 m). However, there remains some unexplained error in the model (RMSE = 2.078 m). The mathematical expression of the model is as follows:

$$H_{\zeta k} = 2,5792691 + 0,46965015D_{1.30} - 0,0023455D_{1.30}^2 \quad (55)$$

The graphic representation of the $H_{\zeta k} = F(D_{\zeta k})$ equation is presented in Figure 68.

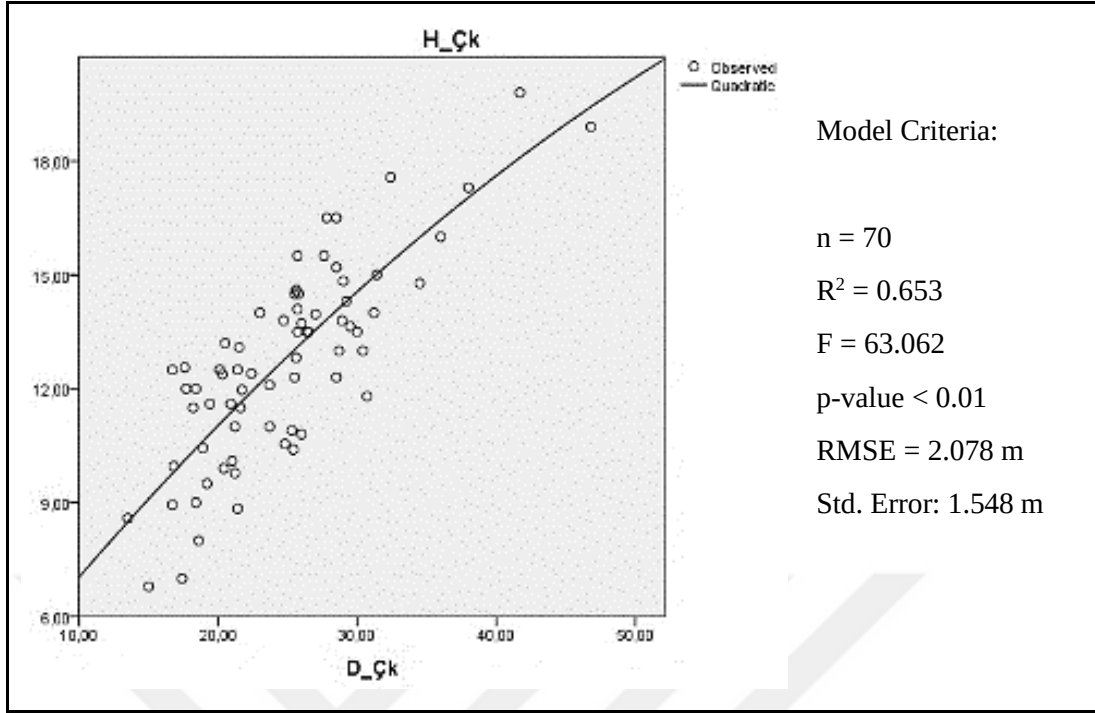


Figure 68. Height Curve model for A. Black Pine (*Pinus nigra*) stands

According to Figure 68, the prediction model produced by the statistical relationship between tree height and diameter is a Parabola-shaped Curve, which means that the data show an exponential growth trend in the prediction of tree height by diameter. According to Equation (55), the quadratic coefficient, which determines the shape of the curve, is negative ($b_2 = -0,0023455$). The quadratic curve is Concave, and therefore characterized by a downward opening. It represents the curved relationship between tree diameters and height, where changes in tree diameter ($D_{Çk}$) have a non-linear effect on height variation in *Pinus nigra* species. In addition to the quadratic effect ($-0,0023455D_{1.30}^2$), changes in tree height as a function of diameter, are indicated by the linear coefficient ($b_1 = 0,46965015$).

b. Results from Stand Height-Curve Analysis for *Pinus brutia* Tree Species

In the 46 forest stand types, the mathematical relationship between tree height ($H_{Çz}$) and diameter ($D_{1.30}$) for Turkish Red Pine (*Pinus brutia*) tree species was analyzed using non-linear regression. Using the diameters ($D_{Çz} = D_{1.30}$) of 65 sampled trees whose height ($H_{Çz}$) was measured, the $H_{Çz} = F(D_{Çz})$ models are presented in Table 24.

Table 24. Models of stand height curve relationships for Turkish Red Pine

Model Summary and Parameter Estimates for <i>Pinus brutia</i> (Çz)									
Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	,613	99,584	1	63	,000	4,973	,336		
Logarithmic	,583	87,961	1	63	,000	-13,366	8,427		
Inverse	,524	69,246	1	63	,000	21,531	-184,635		
Quadratic	,616	49,737	2	62	,000	6,964	,182	,003	
Cubic	,626	33,996	3	61	,000	-2,983	1,390	-,043	,001
Compound	,602	95,151	1	63	,000	7,135	1,024		
Power	,597	93,164	1	63	,000	1,837	,617		
S	,557	79,371	1	63	,000	3,174	-13,785		
Growth	,602	95,151	1	63	,000	1,965	,024		
Exponential	,602	95,151	1	63	,000	7,135	,024		
Logistic	,602	95,151	1	63	,000	,140	,976		

Independent variable: $D_{Çz}$ / Dependent Variable: $H_{Çk}$

The results in Table 24 show the 11 statistical models, their parameters as well as their different performance indicators. All these models are statistically significant at 1% (p-value<0.01). These models show that tree diameter ($D_{1.30}$) can explain variability in *Pinus brutia* tree height ($H_{Çz}$) in these mixed stands type. For the case of our context, the most efficient model is the Quadratic model followed by Linear, Compound, Exponential, Logistic, Growth, Power, Logarithmic, S-Curve and Inverse models. Their coefficient of correlation ranged between 0.583 to 0.616. Using the diameter ($D_{1.30}$) as a predictor, we estimate that the Quadratic model can predict 61.6% ($F = 49.737$) of the variability in tree height ($H_{Çz}$) for *Pinus brutia* tree species in these stand types, with relatively low prediction errors (Std. Error = 2.048 m). However, there remains some unexplained error in the model (RMSE = 2.534 m). The mathematical expression of the model is as follows:

$$H_{Çz} = 6,9644901 + 0,1824599D_{1.30} + 0,0027552D_{1.30}^2 \quad (56)$$

The graphic representation of the function $H_{Çz} = F(D_{Çz})$ is presented in Figure 69 (next page).

The prediction model produced by the statistical relationship between tree height and diameter is a Quadratic Parabola-Shaped Curve (Figure 69). This means that the data show an exponential growth trend in the prediction of tree height ($H_{Çz}$) by diameter ($D_{Çz}$).

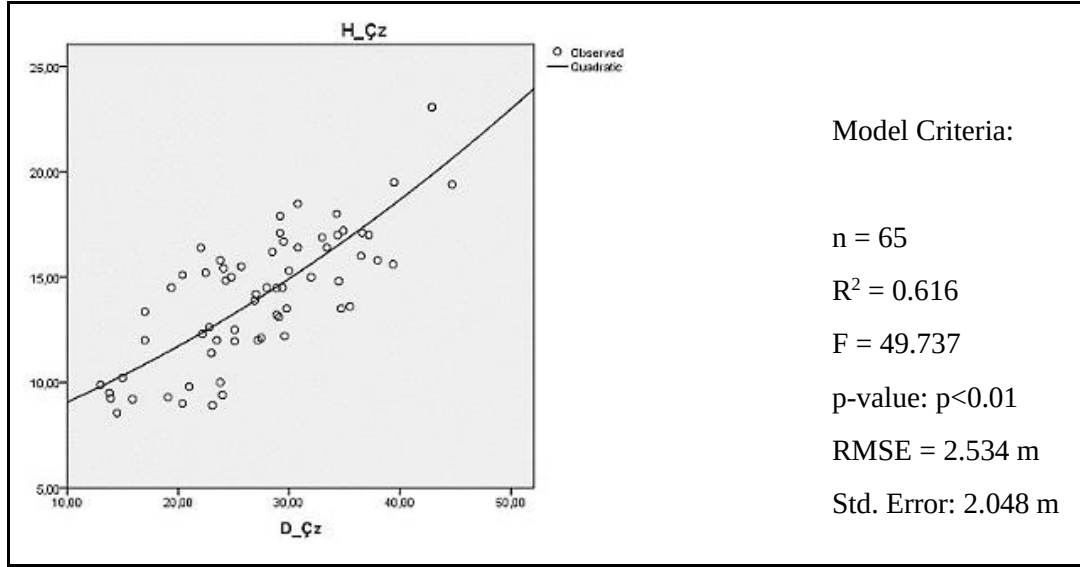


Figure 69. Height Curve Model for T. Red Pine (*Pinus brutia*) stands

Equation (56) shows that the quadratic coefficient that determines the shape of the quadratic is positive ($b_2 = 0,0027552$). In addition to the quadratic effect ($0,0027552D_{1.30}^2$), the linear coefficient ($b_1 = 0,1824599$) showing changes in tree height as a function of diameter is a contributor to the slope of the curve. In other words, it determines at what point the quadratic curve is inclined upwards (convex).

3.1.7. Results from Other Forest Stand Parameters Analysis

Other stand parameters were analyzed: Stand Density Index (*SDI*), Stand Density Ratio (*SDR*), Stand Mix Ratio (R_S) and Stand Internal Variability (C_V).

a. Results from the Analysis of Stand Density Index and Ratio

In this study, Reineke's relationship (1933) with $b_0 = 1.605$, was used to calculate the Stand Density Index (*SDI*) for each species in 46 sample stands. This approach was based on the relationship between the number of trees and the quadratic mean diameter, and the resulting values were aggregated to determine the *SDI* of the mixed stand of *P. nigra*-*P. brutia* (ÇkÇz). In general, the results obtained in this study show that, in *Pinus nigra* stands, the maximum (5194 trees/ha), minimum (104 trees/ha) and average (1032 trees/ha) *SDI* are higher than the maximum (4629 trees/ha), minimum (73 trees/ha) and average (799 trees/ha) *RDS* in *Pinus brutia*.

The density index is significant across all 46 samples of natural mixed stands of ÇkÇz analyzed in this study. In terms of Site Density Ratio (*SDR*), with an average of 0.38 ± 0.23 *SDR*, the highest density ratio is 0.87 and the lowest is 0.10. It is observed that 37% of the 46 sample stands have a density ratio between 0.1 and 0.25, while 34% have a density ratio between 0.25 and 0.50. The remaining 29% of stands have a high *SDR* value ranging from 0.50 to 1. It should be noted that less than half of the natural mixed stands of ÇkÇz have a high *SDR*.

b. Results from Stand Mixing Ratio (R_S) Analysis

The mixture ratio (R_S) between the two species *Pinus nigra* (Çk) and *Pinus brutia* (Çz), where Çk is dominant specie and Çz is subordinate specie, was evaluated in 46 experimental plots of natural mixed stands ÇkÇz. The results showed that the number of Çk trees was greater than the number of Çz trees in the studied stands. The mixing ratio was significant in all 46 Natural Mixed Stands of ÇkÇz. For example, stand ÇkÇzc2 had a ratio of 0.90 (Çk) and 0.10 (Çz). This means that *Pinus nigra* (Çk) represented 90% of the tree in the sample plot, while *Pinus brutia* (Çz) represented 10%. In summary, the mixture ratio varied between 0.52 to 0.90 in favor of the Çk species.

c. Results from Stand Internal Variability (C_V) Analysis

The coefficient of Variation was estimated by using the arithmetic mean diameter and the Standard Deviation ($S_D = 6.126$), which were obtained from the descriptive analysis of the diameter variable. There is a diameter variation among the number of trees in each of the 46 natural mixed stands of ÇkÇz analyzed. The proportion of diameter variation ranges from 20.19% to 71.65%, indicating a high heterogeneity of tree diameter distribution within the stands. The C_V values range from 14.51% to 31.44%, indicating a moderate to high level of variability in tree diameter within the stands.

3.2. Results from Above/Below-Ground Biomass and Carbon Stocks Analysis

The results of the above-ground volume, biomass, and carbon of single-tree and stand level, were realized. Tee volume was the important step in process of biomass estimation.

3.2.1. Results from Tree Volume Analysis

The volume of tree component and Single-tree of 68 *Pinus nigra* trees ($V_{Stem_Çk}$, $V_{Branch_Çk}$ and $V_{T_Çk}$) and 70 *P. brutia* trees ($V_{Stem_Çz}$, $V_{Branch_Çz}$ and $V_{T_Çz}$) was determined. The results are grouped in frequency (f) and in diameter classes ($D_{1.30_Çk}$), in Table 22.

Table 25. Tree Volumes (m^3) estimated and grouped in diameter classes

Species	$D_{1.30}$ Class	f	V_{Stem}	V_{Branch}	V_{Tree}
Anatolian Black Pine (<i>Pinus nigra</i>) (Çk) n=68	0-8	3	0,02764	0,00438	0,03203
	8-16	14	0,63591	0,08894	0,72486
	16-24	32	6,57608	0,66894	7,24505
	24-32	15	6,30882	0,83238	7,14119
	32-40	4	3,42703	0,35310	3,78014
Turkish Red Pine (<i>Pinus brutia</i>) (Çz) n=70	0-8	1	0,00030	0,00022	0,00054
	8-16	16	0,94850	0,10151	1,04990
	16-24	20	4,32560	0,44715	4,77290
	24-32	27	10,3679	1,21598	11,58389
	32-40	5	3,38970	0,50335	3,89299
	40-48	1	1,55940	0,09048	1,64987

In Table 25, stem, branch, and single-tree volumes were grouped into 6 diameter classes with an 8 cm range, spanning from 0 (minimum) to 40 (maximum) for 68 *Pinus nigra* trees, and from 0 to 48 for 70 *Pinus brutia* trees species. Tree frequency was utilized to distribute the 68 *Pinus nigra* trees into these 5 diameter classes, and 70 *Pinus brutia* trees into the 6 diameter classes according to their volume. For all sample trees, the total volume for all 68 *Pinus nigra* trees is 18.9233 m^3 . The total for all 70 *Pinus brutia* trees studied in this research is 22.9501 m^3 . The results presented in Table 25 provide valuable information on the distribution and variability of volume within individual trees and their components in in natural mixed forest stands of ÇkÇz in Türkiye.

3.2.2. Results from Above-Ground Biomass Analysis

This section presents the results of analysis biomass amounts for aboveground pools calculated from samples components of 68 trees of the *Pinus nigra* species, 70 trees of the *Pinus brutia* species, including 138 branches, 138 bark and 138 foliage, from of 96 litter, 46 deadwood and 46 living cover samples taken from the 46 sample plots.

a. Results from Analysis of Biomass of Individual Trees and their Components

This research examines different component (stem, branches, bark, foliage, and single-trees) of the 68 trees of the *Pinus nigra* specie and 70 trees of the *Pinus brutia* specie, and explores their respective average, minimum and maximum amounts of biomass.

❖ Results from Biomass Analysis for *Pinus nigra* Tree Species

The results of the average, maximum and minimum of biomass quantities for each individual tree and components of 68 trees of *Pinus nigra* species, such as the stem ($B_{\text{stem}_\text{Çk}}$), branches ($B_{\text{branch}_\text{Çk}}$), bark ($B_{\text{bark}_\text{Çk}}$), foliage ($B_{\text{foliage}_\text{Çk}}$) and single-tree ($B_{\text{tree}_\text{Çk}}$), are presented in Figure 70.

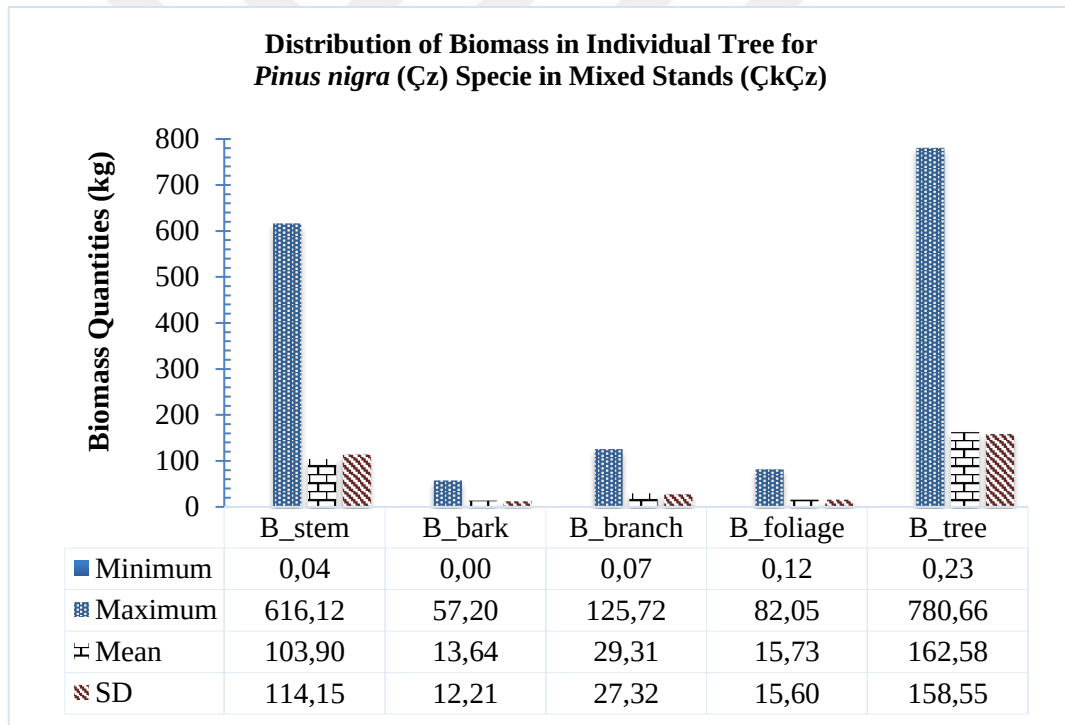


Figure 70. Biomass allocation in *Pinus nigra* tree species (n = 68)

The results presented in Figure 70 provide valuable information on the distribution and variability of biomass amounts within individual trees and their components in *Pinus nigra* species in natural mixed forest stands of ÇkÇz in Türkiye.

❖ Results from Biomass Analysis for *Pinus brutia* Tree Species

The results of the average, maximum and minimum of biomass quantities for each individual tree and components of 70 trees of *Pinus brutia* species, such as the stem ($B_{\text{stem}_\text{Çz}}$), branches ($B_{\text{branch}_\text{Çz}}$), bark ($B_{\text{bark}_\text{Çz}}$), leaves ($B_{\text{foliage}_\text{Çz}}$) and the single-tree ($B_{\text{tree}_\text{Çz}}$) are presented in Figure 71.

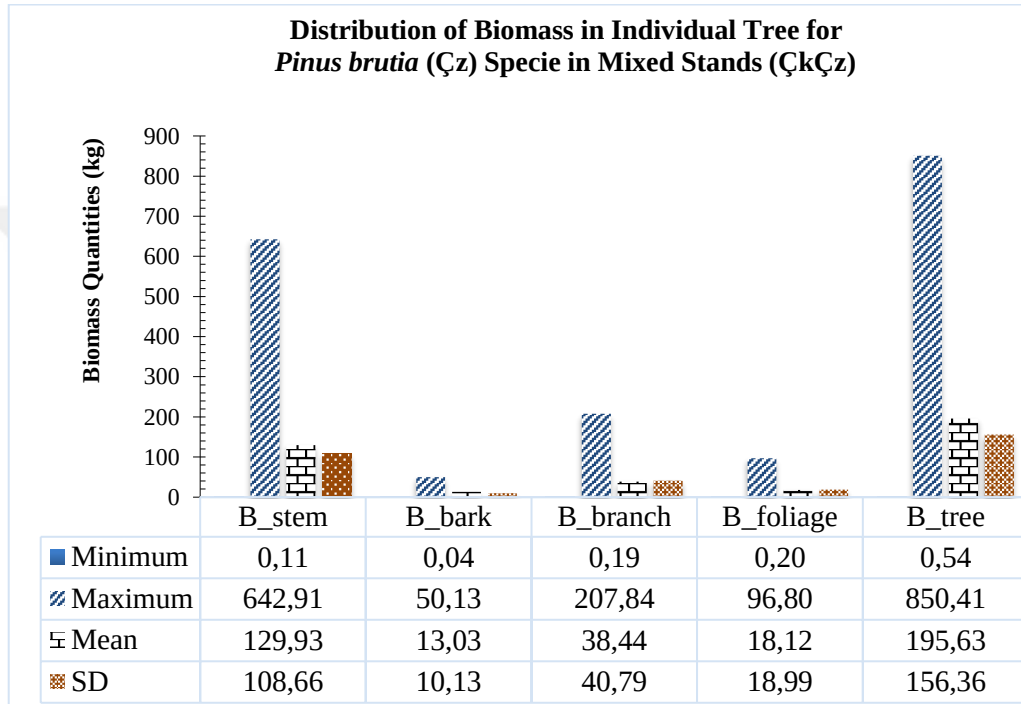


Figure 71. Biomass allocation in *Pinus brutia* tree species (n = 70)

The research findings presented in Figure 71 provide valuable insights into the distribution and variability of biomass amounts within the individual tree and component pools of *Pinus brutia* tree species in natural mixed forest stands of ÇkÇz in Türkiye.

b. Results from Analysis of Litter, Deadwood and Living Cover Aboveground Terrestrial Biomass

For this category, we used the terms “land surface” to indicate all three components of above-ground biomass, namely litter, dead wood and cover. The distribution of the number of samples of litter, deadwood and living plant cover used for the analysis of aboveground land biomass is presented in Table 26.

Table 26. Distribution of aboveground terrestrial biomass samples

Stand Types	Number of samples				Total
	Plots	Litter	Living Cover	Dead Cover	
ÇkÇzab	5	10	5	5	25
ÇkÇzb	2	4	2	2	10
ÇkÇzbc	15	30	15	15	75
ÇkÇzc	14	28	14	14	70
ÇkÇzcd	8	16	8	8	40
ÇkÇzd	2	4	2	2	10
Total	46	92	46	46	230

A total of 230 aboveground surface biomass samples, including 92 of litter, 46 of deadwood and 46 of living cover, were collected in the 46 experimental plots distributed among the 6 stand types explored (Table 26). The biomass amount of litter (B_{litter}), dead wood (B_{dwood}) and living cover (B_{livcover}) are presented in Table 27.

Table 27. Allocation of aboveground biomass of land surface pools

Plot N°	B_{Litter} (t/ha)	$B_{\text{d wood}}$ (t/ha)	$B_{\text{l cover}}$ (t/ha)	Plot N°	B_{Litter} (t/ha)	$B_{\text{d wood}}$ (t/ha)	$B_{\text{l cover}}$ (t/ha)
1	17,806	2,342	0,452	24	23,151	1,531	0,126
2	9,552	2,580	0,496	25	16,035	1,114	0,104
3	9,360	5,045	0,501	26	10,244	0,861	0,144
4	14,496	6,035	0,495	27	30,175	1,239	0,076
5	17,248	1,040	0,144	28	23,047	0,761	0,048
6	10,704	0,935	0,852	29	7,199	1,591	0,088
7	15,904	0,114	0,625	30	26,821	4,212	0,110
8	8,520	2,395	0,125	31	29,721	7,107	0,188
9	25,176	2,706	0,059	32	7,512	2,462	0,489
10	51,488	4,422	0,033	33	14,496	0,923	0,448
11	23,288	2,672	0,089	34	26,281	1,865	0,501
12	22,040	0,990	1,425	35	11,400	1,868	0,397
13	20,976	2,460	1,116	36	24,768	2,003	0,435
14	22,832	5,972	0,087	37	9,080	0,771	0,435
15	64,168	3,322	0,463	38	11,776	1,295	0,707
16	24,768	2,654	0,457	39	8,832	2,490	0,414
17	8,536	4,044	0,060	40	7,024	2,381	0,403
18	12,959	0,982	0,855	41	11,816	2,281	0,649
19	9,007	0,674	2,959	42	6,840	2,138	0,586
20	12,348	0,948	0,353	43	22,696	2,628	0,085
21	10,861	0,759	0,076	44	17,842	1,925	0,491
22	9,346	2,228	0,061	45	17,833	1,918	0,494
23	4,732	2,848	0,775	46	11,720	3,559	0,809

The descriptive analysis of the data in Table 27 led to the results in Table 28 illustrating the distribution of these observations between the maxima, minima and averages.

Table 28. Descriptive summary of surface land biomass quantities

Descriptive Statistics of terrestrial biomass quantities (kg/ha)						
Stocks	N	Min.	Max.	Sum	Mean	Std. Deviation
<i>B_{litter}</i>	46	4731,60	64168,00	802422,98	17443,978	11227,032
<i>B_{d_wood}</i>	46	114,00	7106,80	107088,10	2328,002	1531,234
<i>B_{l_cover}</i>	46	33,00	2959,15	20785,45	451,858	488,417

The research findings presented in Tables 27 and 28 provide valuable insights into the distribution and variability of biomass quantities within the terrestrial pools of natural mixed forest stands of ÇkÇz in Türkiye.

3.2.3. Results from Belowground Biomass Analysis

a. Distribution of Roots Samples by Depth and Stand Type

To analyze the biomass contained in the below-ground of ÇkÇz mixed natural forests, 208 root profile samples taken at a depth of 0–30 cm, 41 at 30–60 cm, and 31 at 60–90 cm, were used. Table 29 shows a summary of the distribution of root biomass samples.

Table 29. Distribution of root profile samples

Stand Types	Plots	Samples of Root Profile (Cylinder)			
		0-30	30-60	60-90	Total
ÇkÇzab	5	15	5	5	30
ÇkÇzb	2	6	1	1	10
ÇkÇzbc	15	45	14	8	84
ÇkÇzc	14	42	13	10	89
ÇkÇzcd	8	22	6	5	41
ÇkÇzd	2	6	2	2	12
Total	46	136	41	31	208

According to Table 29, 208 root cylinder samples were taken from the 46 experimental plots, i.e., 136 taken from the depth of 0-30 cm, 41 from 30-60 cm, and 31 from 60-90 cm.

b. Distribution of Soil Organic Samples by Profile and Stand Type

To analyze organic matter, 46 soil profile samples were collected at a depth of 0–10 cm, 46 samples at 10–30 cm, 42 samples at 30–50 cm, 41 samples at 50–80 cm, and 31 samples at 80–100 cm. Table 30 shows a summary of the distribution of soil organic samples.

Table 30. Distribution of Soil Organic Samples

Stand Types	Plots	Samples of Soil Organic Profile				
		0-10	10-30	30-50	50-80	80-100
ÇkÇzab	5	5	5	5	5	5
ÇkÇzb	2	2	2	1	1	1
ÇkÇzbc	15	15	15	14	14	8
ÇkÇzc	14	14	14	13	13	10
ÇkÇzcd	8	8	8	7	6	5
ÇkÇzd	2	2	2	2	2	2
Total	46	46	46	42	41	31

A total of 206 organic soil samples were analyzed to estimate biomass storage in the mixed natural forest ecosystems of ÇkÇz (Table 30). Ideally, an equal number of profiles should have been taken from each category across all 46 experimental plots. However, during the survey, various soil types were encountered, including those dominated on the surface by solid materials such as stones, and rocks. This made it challenging to penetrate the soil with sampling material (cylinders). Resulting in several damaged cylinders. As a result, there is a discrepancy in the number of samples studied due to the obstacles encountered during the collection process.

c. Results from Root Biomass Analysis

The biomass quantities of roots were determined for each category (B_{root_F} , B_{root_S} and B_{root_C}) according to the depth at which these roots were sampled. Table 31 presents the distribution of biomass in fine (< 2 mm), small (2–5 mm), and coarse (> 5 mm) roots for each depth range: 0–30 cm, 30–60 cm, and 60–90 cm.

Table 31. Biomass Allocation in the Roots of ÇkÇz Stands

Root Category	Depth (cm)	Root Biomass Amount (kg/ha)			
		Minimum	Maximum	Mean	Std. Deviation
Fine	0-30	3825,0	45228,6	20031,83	10606,8
	30-60	1400,0	14525,0	4803,95	2324,9
	60-90	127,5	12123,1	2221,84	2788,7
Small	0-30	497,4	13226,7	2959,8	2515,3
	30-60	242,5	2890,9	1428,6	700,1
	60-90	652,8	4150,0	2124,8	807,9
Coarse	0-30	279,8	48885,0	15492,9	14593,6
	30-60	258,0	34605,0	10995,3	7584,3
	60-90	746,0	11501,4	4153,8	2629,1

Examination of Table 31 reveals that the biomass is distributed in the roots at all experimental depths. The distribution of these biomass values between the maxima and the minima highlights the variability of this biomass depending on their category and their residential depth. The central measurements represented by the averages constitute significant references within this variability and help clarify the distinctive characteristics of the distribution of biomass in these belowground pools.

d. Results from Biomass Analysis in Soil Organic Matter

The results of the analysis of the biomass allocation contained in the soil organic matter sampled at different depths are presented in Figure 72 (next page).

According to Figure 72, we notice a distribution of soil mass between maximum and minimum values. Together with the averages, they constitute important indicators of variability within each soil group. Analysis of the data reveals notable variations of soil mass for each depth range. With the mean, the differences between maximum and minimum values indicate a significant degree of dispersion between samples collected at different depths, indicating a wide range of recorded results.

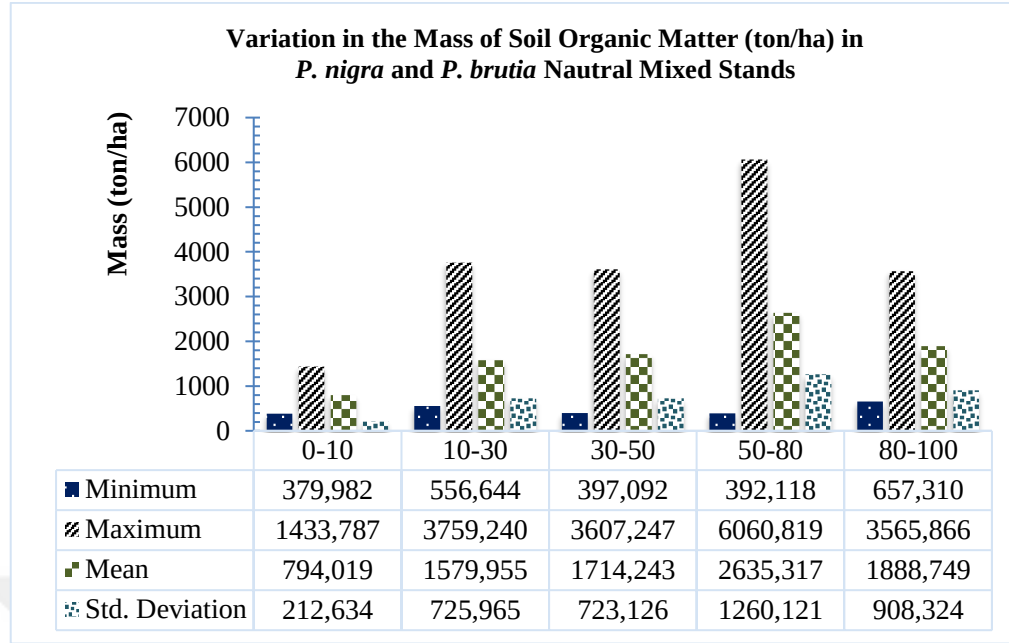


Figure 72. Variation in the mass of soil organic mass in the ÇkÇz mixed stands

3.2.4. Results from Aboveground Carbon Stocks Analysis

a. Results from Carbon Stocks Analysis in Individual Trees

❖ Results from Carbon Stocks Analysis in *Pinus nigra* Tree Species

For each of the 68 *Pinus nigra* trees, the carbon amount was determined for in the stem ($C_{\text{stem}_\text{Çk}}$), branches ($C_{\text{branch}_\text{Çk}}$), bark ($C_{\text{bark}_\text{Çk}}$), leaves ($C_{\text{foliage}_\text{Çk}}$) and the single-tree ($C_{\text{tree}_\text{Çk}}$). Figure 73 (next page) show the results of examining of their average, minimum and maximum values.

Upon analyzing the data provided in Figure 73, it becomes evident that the carbon quantities for the 68 *Pinus nigra* trees encompass a wide spectrum. Observations, however, demonstrate a dispersion between maximum and minimum values, and averages are important markers of a significant variability of carbon stocks within each tree components and individual tree. Means, as central measurements, provide meaningful benchmarks within this diversity and contribute to a good understanding of unique traits in carbon distribution in *Pinus nigra* tree species and their components.

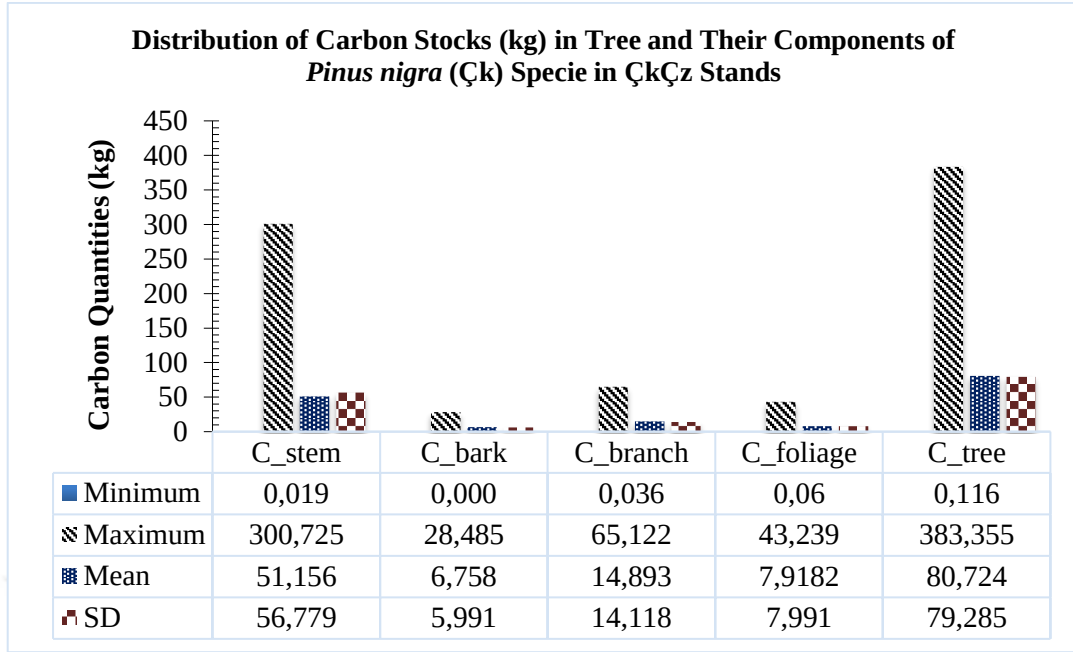


Figure 73. Carbon stocks allocation in *Pinus nigra* tree species (n = 68)

❖ Results from Carbon Stocks Analysis in *Pinus brutia* Tree Species

For each of the 70 *Pinus brutia* trees, analysis estimated the ration and quantity of carbon present in the stem ($C_{stem_Çz}$), branches ($C_{branch_Çz}$), bark ($C_{bark_Çz}$), leaves ($C_{foliage_Çz}$), and the overall single-tree ($C_{tree_Çz}$). Figure 74 show the results of examining of their average, minimum and maximum values.

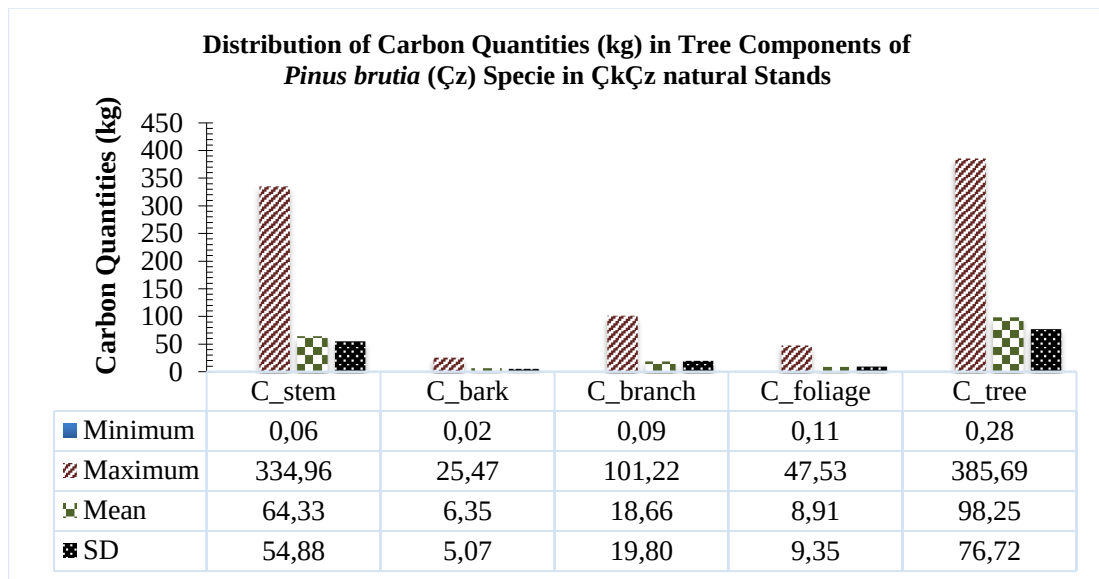


Figure 74. Carbon stock allocation in *Pinus brutia* tree species (n = 70)

Upon analyzing the data provided in Figure 74, it becomes evident that the carbon quantities for the 68 *Pinus nigra* trees encompass a wide spectrum. Observations, however, demonstrate a dispersion between maximum and minimum values, and means are important markers of a significant variability of carbon stocks within each tree components and individual tree. Means, as central measurements, provide meaningful benchmarks within this diversity and contribute to a good understanding of unique traits in carbon distribution in *Pinus nigra* tree species and their components.

b. Results from Carbon Stocks Analysis in Land Surface Pools

The carbon storage capacities of litter (C_{Litter}), dead wood (C_{D_wood}), and living cover (C_{L_cover}) were analyzed, and the results were recorded in the Table 32.

Table 32. Carbon stocks in land surface pools in ÇkÇz stands

Plot No	C_{Litter} (kg/ha)	C_{D_wood} (kg/ha)	C_{L_cover} (kg/ha)	Plot No	C_{Litter} (kg/ha)	C_{D_wood} (kg/ha)	C_{L_cover} (kg/ha)
1	7834,46	207,92	1117,09	24	3731,76	1124,21	48,63
2	3639,31	213,96	1256,46	25	11278,85	1267,22	26,31
3	4071,60	213,08	2376,20	26	22603,23	2048,71	15,44
4	6479,71	217,40	2845,50	27	10828,92	1234,46	39,52
5	7813,34	65,66	487,76	28	10072,28	411,84	689,70
6	5127,22	381,70	437,58	29	8138,69	1144,64	525,64
7	7808,86	263,44	54,04	30	9566,61	2750,70	39,76
8	3731,76	48,63	1124,21	31	31185,65	1546,72	195,50
9	11278,85	26,31	1267,22	32	10724,54	1340,27	187,62
10	22603,23	15,44	2048,71	33	4020,46	1912,81	25,50
11	10828,92	39,52	1234,46	34	4704,04	450,60	413,22
12	10072,28	689,70	411,84	35	3985,69	319,72	1447,02
13	8138,69	525,64	1144,64	36	4488,50	476,27	171,25
14	9566,61	39,76	2750,70	37	5370,67	340,55	29,56
15	31185,65	195,50	1546,72	38	4542,16	1069,30	27,85
16	10724,54	187,62	1340,27	39	1859,52	1374,16	398,40
17	7834,46	1117,09	207,92	40	11401,77	780,71	61,74
18	3639,31	1256,46	213,96	41	6943,07	549,01	53,79
19	4071,60	2376,20	213,08	42	4932,49	421,31	73,71
20	6479,71	2845,50	217,40	43	9761,74	632,04	37,94
21	7813,34	487,76	65,66	44	10855,04	366,56	21,09
22	5127,22	437,58	381,70	45	3736,39	746,37	41,06
23	7808,86	54,04	263,44	46	12901,00	2082,59	52,86

Based on the data obtained on the quantities of carbon stored by terrestrial pools (C_{Litter}), $C_{\text{D_wood}}$ and $C_{\text{L_cover}}$), and broken down in Table 32, the description values are proposed in Figure 75.

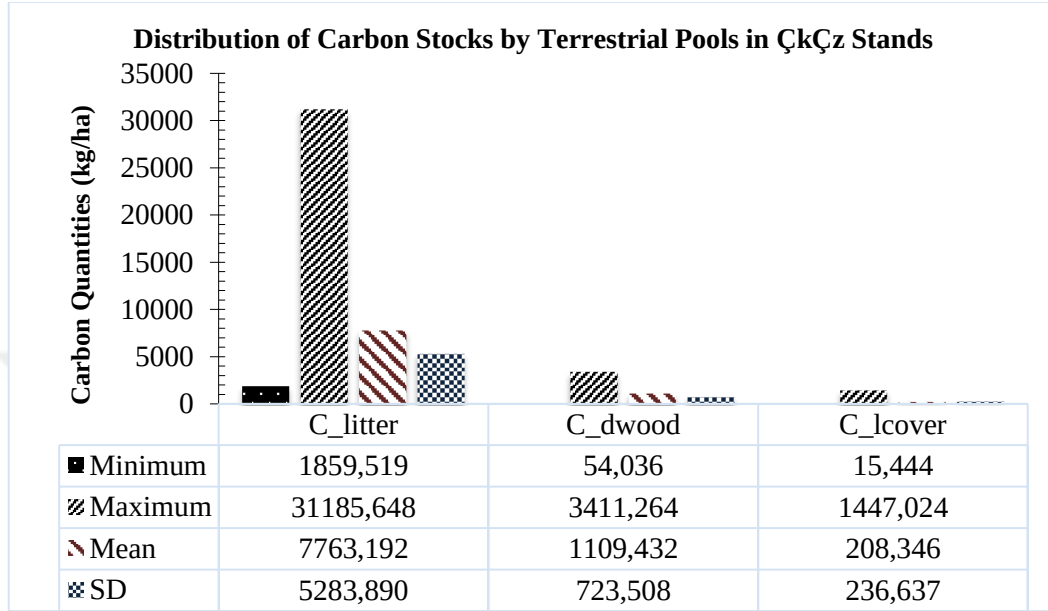


Figure 75. Carbon allocation in litter, deadwood and living cover pools

It is clear from examination of the data in Figure 75 that litter, deadwood and live cover store significant quantities of carbon. The distribution of these carbon stock values between maxima and minima shows significant variability in each pool. The averages also indicate a considerable diversity of carbon stocks in these pools present at the soil surface of aboveground biomass. These means, as central measures, provide meaningful references within this variability and help to clarify the distinctive features of carbon distribution in these pools.

3.2.5. Results from Belowground Carbon Analysis

a. Results from Carbon Stocks Analysis in Roots

The carbon analysis in this section focuses on the distribution of carbon stocks within the root systems of natural mixed forest ecosystems of *Pinus nigra* and *Pinus brutia*. The variability of total carbon stocks in all sample fine roots (C_{root_F}), small roots (C_{root_S}) and coarse roots (C_{root_C}) at various soil depths, is illustrated in Figure75.

Table 33. Carbon allocation in roots in ÇkÇz stand

Root Category	Depth (cm)	Root Carbon Amount (kg/ha)			
		Minimum	Maximum	Mean	Std. Deviation
Fine	0-30	1987,09	21800,19	9642,54	5144,36
	30-60	672,09	6972,94	2306,21	1116,05
	60-90	61,21	5819,88	1066,63	1338,73
Small	0-30	245,20	6520,74	1460,51	1244,86
	30-60	116,42	1387,82	685,82	336,10
	60-90	313,38	1992,27	1001,48	400,49
Coarse	0-30	134,29	24638,04	7411,22	6934,64
	30-60	123,86	16612,63	5278,47	3640,95
	60-90	358,15	5521,43	1994,08	1262,14

Examination of Table 33 reveals that the carbon stocks are distributed in the roots at all experimental depths. The distribution of these carbon stocks values between the maxima and the minima, highlights the variability of this carbon depending on the root category and their residential depth. The central measurements represented by the means constitute significant references within this variability and help clarify the distinctive characteristics of the distribution of carbon stocks in these belowground pools.

b. Results from Carbon Stocks Analysis in Soil Organic Matter

In order to derive outcomes concerning carbon stocks in soil organic matter, carbon content was determined through respective analyses. Based on the data regarding the quantities of biomass stored by soil organic matter, the variation in carbon stocks at each experimental depth is summarized in Figure 76 (next page).

Figure 76 shows that the distribution of carbon stocks in SOM falls between the highest and minimum values. They form significant indicators of carbon variability within each soil depth when combined with the averages. Significant differences in carbon stocks are visible for every depth range. A considerable degree of dispersion across samples taken at different depths is indicated by the mean and the variances between the maximum and minimum values, which together show a broad range of recorded results.

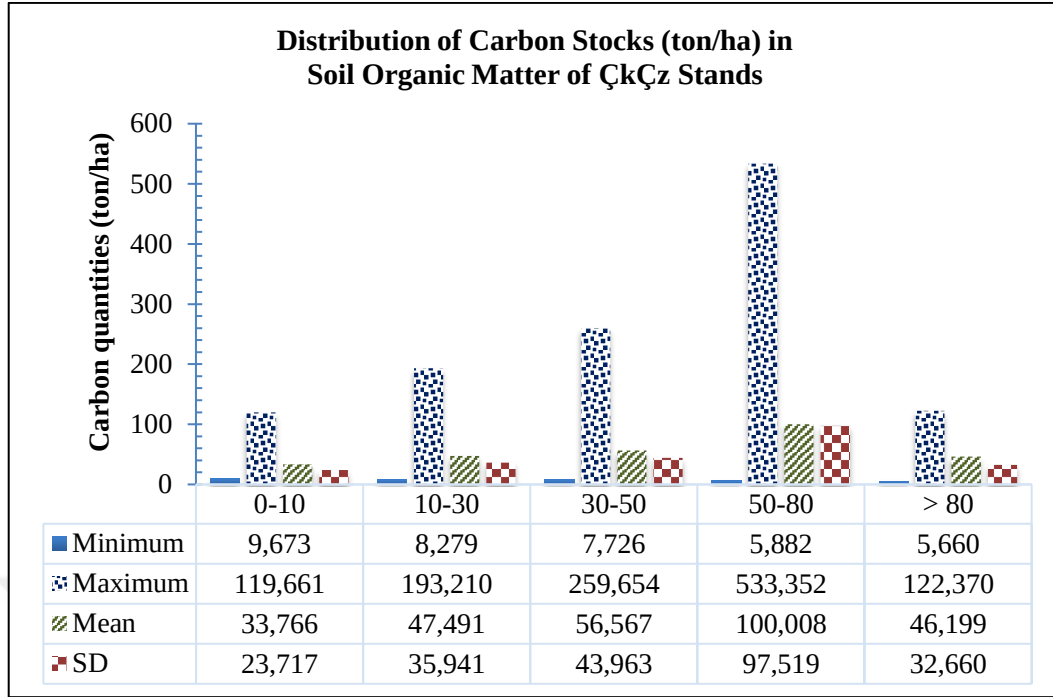


Figure 76. Carbon allocation in Soil Organic Matter (SOM) in ÇkÇz stands

3.3. Results from Tree and Ecosystem Biomass and Carbon Modeling in Natural Mixed Stands of *Pinus nigra* and *Pinus brutia*

The above-ground biomass and carbon storage prediction models concern trees and its components for Anatolian Black Pine (*Pinus nigra*) or Karaçam (Çk) and Turkish Red Pine (*Pinus brutia*) or Kızılçam (Çz). The ecosystem biomass and carbon storage models concern all natural mixed forests of ÇkÇz (Türkiye). In this context, diameter ($D_{1.30}$) was used as a predictor to model the biomass amount of each individual tree (B_{Tree}) and its different components such as stem (B_{Stem}), bark (B_{Bark}), branches (B_{Branch}), and foliage ($B_{Foliage}$). In these results, the single-entry models used Diameter ($D_{1.30}$) as the main independent variable (predictor). In double-entry models, diameter ($D_{1.30}$) and height (H) were used. For the prediction of biomass and carbon storage at the ecosystem scale, the results present multiple-entry models obtained using stand parameters (SI , N , D_m , H_m and CC , etc.) as predictors. In this section, results present all single-entry (individual tree and tree components), double-entry (individual tree) and multi-entry (stand) models developed in the non-linear and/or Multiple Linear regression (MLR) methods (non-linear and multi-linear), and the Artificial Neural Network (MLP-ANN) method.

3.3.1. Results from Tree Biomass Modeling in ÇkÇz Stand

a. Variables using in Tree Biomass Modeling of *Pinus nigra* Species

The results of the descriptive analyzes of the variables (dependent and independent) used in the modeling of the biomass of the 68 Anatolian Black Pine (*Pinus nigra*) or Karaçam (Çk) and its different components are presented in Table 34.

Table 34. Summary variables using to model biomass of *Pinus nigra* trees

Descriptive Statistics of the Tree Biomass Variables for <i>Pinu nigra</i> (Karaçam)						
Variables	Unity	N	Min.	Max.	Mean	SD
$D_{\text{Çk}}$	cm	68	1.10	38.20	20.25	7.28
$H_{\text{Çk}}$	m	68	.65	22.25	11.472	4.14
$B_{\text{stem_Çk}}$	kg	68	.041	616.115	103.902	114.148
$B_{\text{bark_Çk}}$	kg	68	.000	57.199	13.641	12.214
$B_{\text{branch_Çk}}$	kg	68	.072	125.718	29.310	27.315
$B_{\text{foliage_Çk}}$	kg	68	.120	82.048	15.729	15.598
$B_{\text{tree_Çk}}$	kg	68	.232	780.660	162.581	158.547

As shown in Table 34, two estimators ($D_{1.30(\text{Çk})}$ et H) were used to develop biomass prediction models for the main components of 68 trees of *Pinus nigra* species. Diameter ($D_{1.30(\text{Çk})}$) was used as the main estimator to establish the single-entry non-linear models. It was only combined with height (H) when the double-entry equation was developed for the whole tree.

b. Variables using in Tree Biomass Modeling of *Pinus brutia* Specie

The results of the descriptive analyzes of the variables (dependent and independent) used in the modeling of the biomass and carbon storage of the 70 Turkish Red Pine (*Pinus brutia*) or Kızıldağ (Çz) and its different components are presented in Table 35 (next page).

Table 35 displays the utilization of two estimators ($D_{1.30(\text{Çz})}$ and $H_{\text{Çz}}$) in the development of biomass prediction models for the components of 70 *Pinus nigra* trees examined in this study. Diameter ($D_{1.30(\text{Çz})}$) served as the primary estimator for establishing single-entry models. However, for the entire tree, it was used with $H_{\text{Çz}}$ to develop the double-entry equation.

Table 35. Summary variables using to model biomass of *Pinus brutia* trees

Descriptive Statistics of the Tree Biomass Variables for <i>Pinu brutia</i> (Kızılçam)						
Variables	Unity	N	Min.	Max.	Mean	SD
$D_{\zeta z}$	cm	70	2.70	42.85	22.64	7.43
$H_{\zeta z}$	m	70	1.04	23.07	12.6224	3.83
$B_{stem_{\zeta z}}$	kg	70	.106	642.914	129.927	108.657
$B_{bark_{\zeta z}}$	kg	70	.042	50.129	13.032	10.126
$B_{branch_{\zeta z}}$	kg	70	.187	207.838	38.436	40.794
$B_{foliage_{\zeta z}}$	kg	70	.201	96.797	18.112	18.994
$B_{tree_{\zeta z}}$	kg	70	.535	850.413	195.625	156.357

c. Results from Tree Stem Biomass Modeling Using Diameter at Breast Height ($D_{1.30}$)

- Tree Stem Biomass Modeling for *Pinus nigra* using $D_{1.30}$

The development of *Pinus nigra* tree stem biomass prediction models led to the results presented in Table 36.

Table 36. Stem biomass prediction models for *Pinus nigra* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.745	178.197	1	61	.000	-138.925	11.971		
Logarithmic	.414	43.013	1	61	.000	-257.019	122.591		
Inverse	.071	4.690	1	61	.034	114.191	-236.920		
Quadratic	.894	252.402	2	60	.000	41.395	-9.017	.534	
Cubic	.898	173.208	3	59	.000	2.243	-.396	.026	.009
Compound	.814	267.538	1	61	.000	1.437	1.201		
Power	.958	1390.564	1	61	.000	.020	2.736		
S	.615	97.268	1	61	.000	4.707	-10.194		
Growth	.814	267.538	1	61	.000	.363	.184		
Exponential	.814	267.538	1	61	.000	1.437	.184		
Logistic	.814	267.538	1	61	.000	.696	.832		

Independent variable is $D_{1.30}$ and Dependent Variable is $B_{stem_{\zeta k}}$

In short, although all the models (Table 36) are statistically significant at 1% (p-value<0.01), the results show that the six best models for predicting tree stem biomass of *Pinus nigra* specie in the natural mixed stands of ÇkÇz are the Logistic, Exponential, Growth, Compound, Quadratic and Power models (R^2 ranger between 0.814 and 0.958).

The very high -performance model is the *Power* model ($R^2 = 0.958$). The results show that 95.8% of the variability in stem biomass ($B_{stem_Çk}$) is explained by tree diameter ($D_{1.30}$) raised to a certain power. Power model has high statistical significance ($F = 1390.564$), and explains an important proportion of the variation in the data around the mean. Between model-predicted and observed tree stem biomass quantities, the average error is relatively low (Std. Error = 0.296 kg). After model fitting, there is a small amount of variance not explained by the model, representing the sum of squared residuals or the sum of squared deviations between observed and predicted tree stem biomass quantities (RMSE = 1,389 kg). The mathematical expression of the stem biomass equation is given by the following relationship:

$$B_{stem_Çk} = 0.0197422D_{1.30}^{2.7362835} \quad (57)$$

where $B_{stem_Çk}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator). The graphical expression of the tree stem biomass Model is presented in Figure 77.

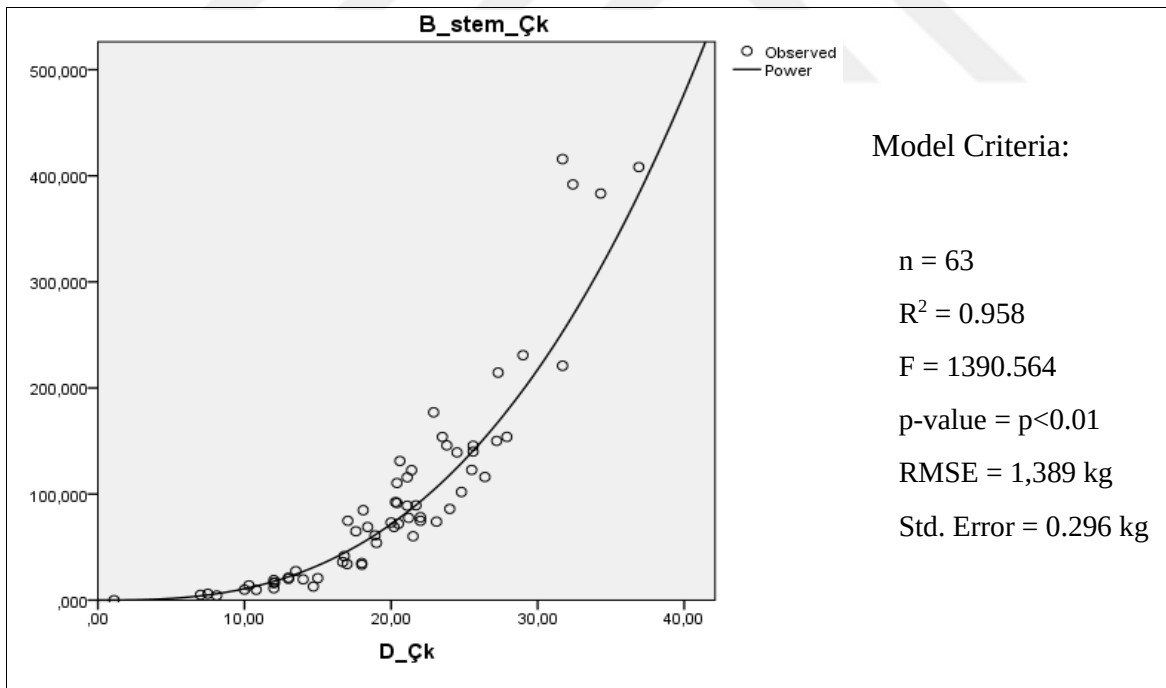


Figure 77. Graphical representation of the Power model for predicting tree stem biomass of *Pinus nigra* specie in ÇkÇz mixed stands

The Power model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth.

The Power Curve in Figure 77 represents the relationship between tree diameters and carbon storage in the stem of *Pinus nigra* trees considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters ($D_{1.30}$) have a non-linear effect on biomass in tree stems. However, increasing tree diameter leads to an exponential increase in biomass in the tree stems of *Pinus nigra* specie. The power exponent ($b_1 = 2.736$) is indicated by the tree diameter coefficient of the intercept ($b_0 = 0.0197$).

- Tree Stem Biomass Modeling for *Pinus brutia* Using $D_{1.30}$

The development of *Pinus brutia* tree stem biomass prediction models led to the results presented in Table 37.

Table 37. Stem biomass prediction models for *Pinus brutia* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.818	274.014	1	61	.000	-131.328	11.314		
Logarithmic	.603	92.487	1	61	.000	-373.569	162.801		
Inverse	.236	18.796	1	61	.000	172.537	-971.588		
Quadratic	.891	244.372	2	60	.000	15.954	-4.767	.386	
Cubic	.891	160.227	3	59	.000	12.767	-4.152	.353	.001
Compound	.818	274.342	1	61	.000	2.015	1.178		
Power	.958	1398.558	1	61	.000	.010	2.965		
S	.805	252.272	1	61	.000	5.745	-25.946		
Growth	.818	274.342	1	61	.000	.701	.163		
Exponential	.818	274.342	1	61	.000	2.015	.163		
Logistic	.818	274.342	1	61	.000	.496	.849		
Independent variable is $D_{1.30}$ and Dependent Variable is $B_{\text{stem}_\text{Çz}}$									

In Table 37, the best principal models which can be used to predict tree stem biomass from diameter of *Pinus brutia* are Logistic, Exponential, Growth, Compound, Quadratic and Power models. These correlation coefficients are high and ranged from 0.818 to 0.958. All models are statistically significant at 1% ($p\text{-value} < 0.01$). The top-performing models for estimating tree stem biomass in *Pinus brutia* specie within ÇkÇz natural stands are Quadratic model ($R^2 = 0.891$) and Power model ($R^2 = 0.958$). Notably, the Power model attributes 95.8% of the variation in the stem biomass to the power of the tree diameter ($D_{1.30}$). The results indicate that the Power model explains the variation in the tree stem biomass of *Pinus brutia* specie very well.

The overall model is significant ($F=1398.558$; $p<0.01$), and the prediction error is relatively low (Std. Error=0.296 kg). However, there is still a certain level of error not explained by the model (RMSE=1,256 kg). The mathematical expression of the Turkish Red Pine (Çz) stem biomass model is:

$$B_{\text{stem}_\text{Çz}} = 0.0095162D_{1.30}^{2.9650923} \quad (58)$$

where $B_{\text{stem}_\text{Çz}}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator).

The graphical expression of the tree stem biomass Model is presented in Figure 78.

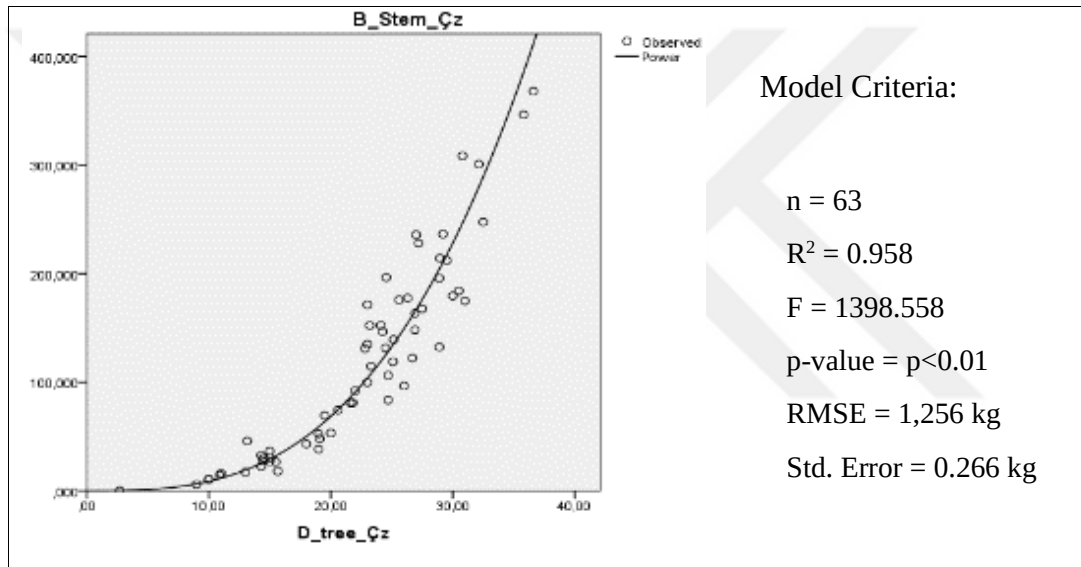


Figure 78. Graphical representation of the Power model for predicting tree stem biomass of *Pinus brutia* species in ÇkÇz mixed stands

According to Figure 78, the Power model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth. The power curve represents the relationship between tree diameters and carbon storage in the stem of *Pinus brutia* trees considered in the natural mixed stands of ÇkÇz in Türkiye. The relationship follows a power model, where changes in tree diameters ($D_{1.30}$) have a non-linear effect on biomass stock ($B_{\text{stem}_\text{Çz}}$) in tree stems. However, increasing tree diameter leads to an exponential increase in biomass stock in the tree stems of *Pinus brutia* specie. The power exponent ($b_1 = 2.9651$) is indicated by the tree diameter coefficient ($b_0 = 0.00951$).

d. Results from Tree Branch Biomass Modeling Using Diameter at Breast Height ($D_{1.30}$)

• Tree Branch Biomass Modeling of *Pinus nigra* Using $D_{1.30}$

Development of the model for predicting tree branch biomass of *Pinus nigra* species in the natural mixed stands of ÇkÇz in Türkiye led to the following model:

$$B_{\text{branch}_\text{Çk}} = 0.0308758D_{1.30}^{2.179809} \quad (59)$$

where $B_{\text{branch}_\text{Çz}}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator). This equation (60) is the best model among those obtained in Table 38.

Table 38. Branch biomass prediction models for *Pinus nigra* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.637	106.945	1	61	.000	-27.888	2.814		
Logarithmic	.390	38.983	1	61	.000	-59.983	30.535		
Inverse	.079	5.250	1	61	.025	33.575	-63.825		
Quadratic	.676	62.483	2	60	.000	-4.286	.131	.067	
Cubic	.683	42.427	3	59	.000	8.601	-2.688	.230	-.003
Compound	.721	157.915	1	61	.000	.909	1.158		
Power	.824	285.443	1	61	.000	.031	2.180		
S	.502	61.534	1	61	.000	3.431	-7.890		
Growth	.721	157.915	1	61	.000	-.095	.147		
Exponential	.721	157.915	1	61	.000	.909	.147		
Logistic	.721	157.915	1	61	.000	1.100	.863		

Independent variable is $D_{1.30}$ and Dependent Variable is $B_{\text{branch}_\text{Çk}}$

Indeed, Table 38 showcases the most effective models for estimating the tree branch biomass in *Pinus nigra* specie within the natural mixed stands of ÇkÇz. The 5 best highest-performing models are the Compound, Growth, Exponential, Logistic and Power models (R^2 ranged from 0.721 to 0.824). All models are statistically significant at 1% (p-value<0.01). Particularly, the Power model exhibits high performance ($R^2 = 0.824$). This indicates that changes in diameter explain 82.4% of the variation in branch biomass in *Pinus nigra* trees. In brief, the results indicate that the Power model provides a strong explanation for the variation in the tree branch biomass of *Pinus nigra* specie.

The model demonstrates significance at 1% ($F = 285.443$; $p < 0.01$), and the prediction error is relatively low (Std. Error = 0.519 kg; RMSE = 1.104 kg). The graphical expression of the tree branch biomass model is presented in Figure 79.

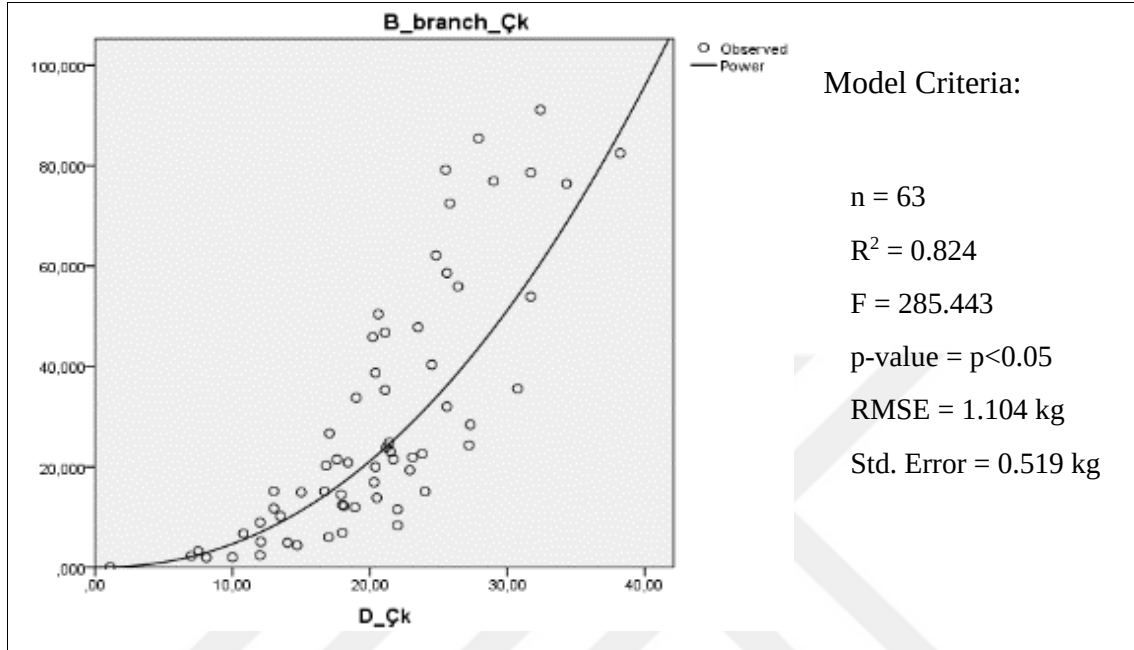


Figure 79. Graphical representation of the Power model for predicting tree branch biomass of *Pinus nigra* species in ÇkÇz mixed stands

According to Figure 79, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree branch biomass prediction. The power curve represents the relationship between tree diameters and tree branch biomass of *Pinus nigra* trees considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on biomass storage in tree branches. However, increasing tree diameter leads to an exponential increase in biomass in the tree branch of *Pinus nigra* specie. The power exponent ($b_1 = 2.9651$) is indicated by the tree diameter coefficient ($b_0 = 0.00951$).

- Tree Branch Biomass Modeling of *Pinus brutia* Using $D_{1.30}$

The development of *Pinus nigra* tree branch biomass prediction models led to the results presented in Table 39.

Table 39. Branch biomass prediction models for *Pinus brutia* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.721	157.519	1	61	.000	-37.454	3.178		
Logarithmic	.514	64.470	1	61	.000	-107.443	46.383		
Inverse	.191	14.396	1	61	.000	47.715	-271.805		
Quadratic	.784	109.153	2	60	.000	-.298	-.636	.087	
Cubic	.786	72.201	3	59	.000	8.486	-2.152	.161	-.001
Compound	.782	219.419	1	61	.000	.840	1.155		
Power	.855	360.470	1	61	.000	.008	2.599		
S	.610	95.430	1	61	.000	4.167	-21.105		
Growth	.782	219.419	1	61	.000	-.174	.144		
Exponential	.782	219.419	1	61	.000	.840	.144		
Logistic	.782	219.419	1	61	.000	1.190	.866		

Independent variable is D_{1.30} and Dependent Variable is B_{branch_Çz}

According to Table 39, the 6 most effective models applicable to estimate the tree branch biomass of *Pinus nigra* specie considered within the natural mixed stands of ÇkÇz, are the Compound, Growth, Exponential, Logistic, Quadratic and Power models (R² ranged from 0.782 to 0.855). All models are statistically significant at 1% (p-value<0.01). Particularly, the Power model exhibits high performance (R² = 0.855). This indicates that changes in diameter explain 85.5% of the variation in branch biomass of *Pinus brutia* trees. The model demonstrates significance at 1% (F = 285.443; p<0.01), and the prediction error is relatively low (Std. Error = 0.463 kg). However, there remains some unexplained error in the model (RMSE = 1.108 kg). The mathematical expression of the Turkish Red Pine (Çz) branch biomass model is:

$$B_{\text{branch}_\text{Çz}} = 0.0078042D_{1.30}^{2.5994818} \quad (60)$$

where $B_{\text{branch}_\text{Çz}}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator).

The graphical expression of the tree branch biomass model for *Pinus brutia* specie is presented in Figure 80 (next page).

The prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree branch biomass prediction. According to Figure 80, the power curve represents the relationship between tree diameters and tree branch biomass of *Pinus brutia* specie considered in the Natural Mixed Stands of ÇkÇz in Türkiye.

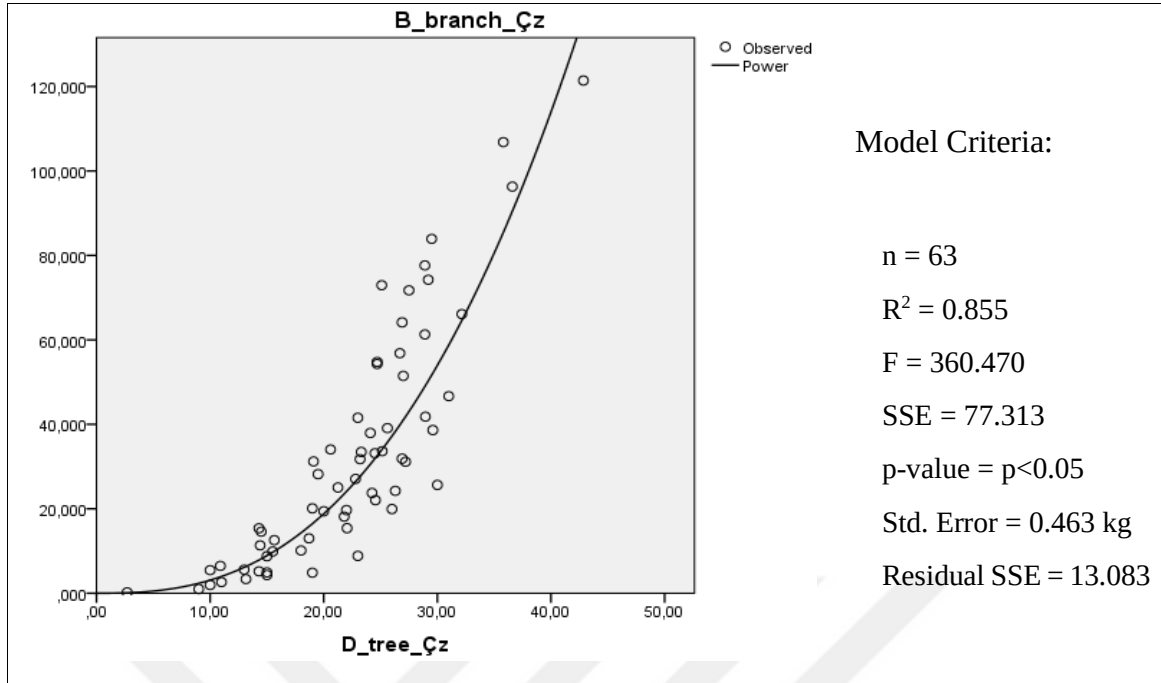


Figure 80. Graphical representation of the Power model for predicting tree branch biomass of *Pinus brutia* species in ÇkÇz mixed stands

This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on biomass storage in tree branches. However, increasing tree diameter leads to an exponential increase in biomass in the tree branch of *Pinus brutia* specie. The power exponent ($b_1 = 2.9651$) is indicated by the tree diameter coefficient ($b_0 = 0.00951$).

e. Results from Tree Foliage Biomass Modeling Using Diameter at Breast Height

- Tree Foliage Biomass Modeling of *Pinus nigra* Using $D_{1.30}$

Development of the model for predicting tree foliage biomass of *Pinus nigra* species in the natural mixed stands of ÇkÇz in Türkiye led to best following *Power* model:

$$B_{\text{foliage}_\text{Çk}} = 0.0420243D_{1.30}^{1.8880609} \quad (61)$$

where $B_{\text{foliage}_\text{Çk}}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator). This equation (62) is the best model among those obtained and presented in Table 40.

Table 40. Foliage biomass prediction models for *Pinus nigra* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.618	98.529	1	61	.000	-12.861	1.416		
Logarithmic	.385	38.213	1	61	.000	-31.014	16.032		
Inverse	.078	5.181	1	61	.026	17.888	-34.222		
Quadratic	.661	58.534	2	60	.000	.263	-.052	.036	
Cubic	.664	38.791	3	59	.000	4.281	-.905	.084	-.001
Compound	.683	131.559	1	61	.000	.835	1.132		
Power	.768	201.823	1	61	.000	.042	1.888		
S	.425	45.094	1	61	.000	2.774	-6.651		
Growth	.683	131.559	1	61	.000	-.180	.124		
Exponential	.683	131.559	1	61	.000	.835	.124		
Logistic	.683	131.559	1	61	.000	1.197	.883		
Independent variable is D _{1.30} and Dependent Variable is B _{foliage_Çk}									

The Compound, Growth, Exponential, and Logistic models demonstrate strong performance (with R² ranged from 0.683 to 0.768) are the top-performing models that can be used for predicting tree foliage biomass in the *Pinus nigra* specie within the natural mixed stands of ÇkÇz (Table 40). All models are statistically significant at 1% (p-value<0.01). Particularly noteworthy is the Power model, which exhibits the highest performance (R² = 0.768). Notably, the Power model attributes 76.8% of the variation in foliage biomass to the tree diameter (D_{1.30}) raised to a specific power. In summary, the results indicate that the Power model is highly effective in explaining the variation in tree foliage biomass of *Pinus nigra* specie (76.8%). The overall model is statistically significant at 1% (F = 201.823; p < 0.01), and the prediction error is relatively low (Std. Error = 0.546 kg). However, there is still some unexplained error by the model (RMSE = 0.977 kg). The graphical representation of the tree foliage biomass model is showed in Figure 81 (next page).

According to Figure 81, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree leaf biomass prediction. The power curve represents the relationship between tree diameters and tree foliage biomass of *Pinus nigra* specie considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D_{1.30}) have a non-linear effect on biomass storage in tree leaves. However, increasing tree diameter leads to an exponential increase in biomass in the tree leaves of *Pinus nigra* specie. The power exponent (b₁ = 1.8881) is indicated by the tree diameter coefficient (b₀ = 0.0420).

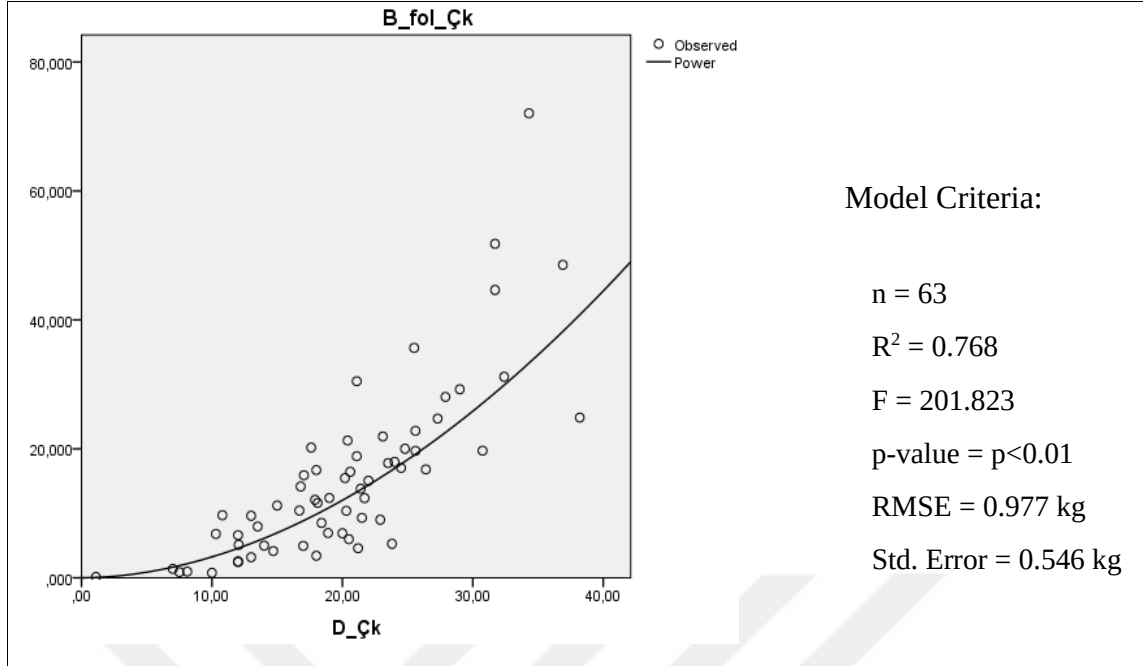


Figure 81. Graphical representation of Power model for predicting tree foliage biomass of *Pinus nigra* species in ÇkÇz mixed stands

- Results from Tree foliage biomass modeling of *Pinus brutia* using $D_{1.30}$

The predictive models for estimating tree foliage biomass in *Pinus brutia* specie within the natural mixed stands of ÇkÇz in Türkiye, led to the results the best prediction model presented by the following expression:

$$B_{\text{foliage}_\text{Çz}} = 0.0094476D_{1.30}^{2.3270575} \quad (62)$$

where $B_{\text{foliage}_\text{Çz}}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator). This equation (62) is the best model among those obtained and presented in Table 41 (next page).

The top-performing models (Table 41) that can be used to predict tree foliage biomass in the *Pinus brutia* species in the natural mixed stands of ÇkÇz are the Compound, Growth, Exponential, Logistic and Power models (R^2 ranging from 0.597 to 0.660). Particularly noteworthy is the Power model, which demonstrates the highest performance ($R^2 = 0.660$). This last model attributes 66% of the variation in foliage biomass to the tree diameter ($D_{1.30}$) raised to a specific power.

Table 41. Foliage biomass prediction models for *Pinus brutia* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.297	25.757	1	61	.000	-14.122	1.492		
Logarithmic	.241	19.357	1	61	.000	-49.101	22.439		
Inverse	.105	7.128	1	61	.010	26.431	-140.357		
Quadratic	.299	12.778	2	60	.000	-9.115	.947	.013	
Cubic	.301	8.480	3	59	.000	-.532	-.712	.103	-.001
Compound	.597	90.468	1	61	.000	.578	1.142		
Power	.660	118.371	1	61	.000	.009	2.327		
S	.468	53.638	1	61	.000	3.394	-18.597		
Growth	.597	90.468	1	61	.000	-.548	.133		
Exponential	.597	90.468	1	61	.000	.578	.133		
Logistic	.597	90.468	1	61	.000	1.730	.876		

Independent variable is D_{1.30} and Dependent Variable is B_{foliage_Çz}

The results suggest that the Power model is highly effective in explaining the variation in tree foliage biomass for *Pinus brutia* species (66.0%). The model is statistically significant at 1% (F = 118.371; p<0.01), and the prediction error is relatively low (Std. Error = 0.714 kg). However, there remains some unexplained error in the model (RMSE = 0.978 kg). The model graphical representation is given in Figure 82.

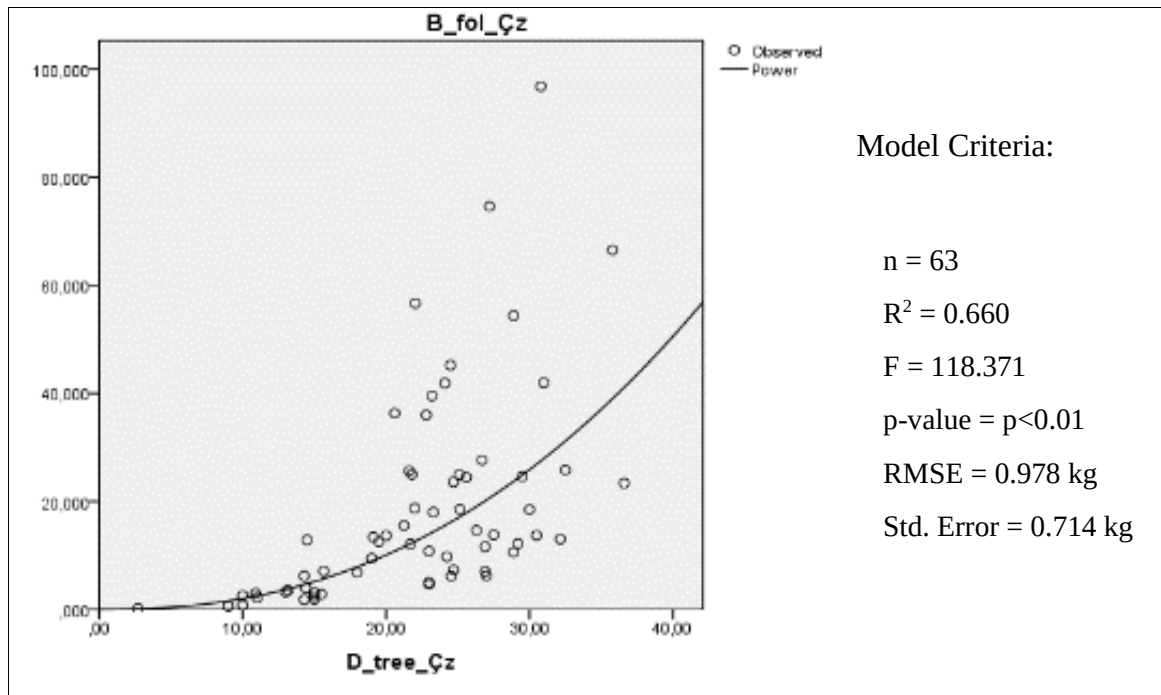


Figure 82. Graphical representation of the Power model for predicting tree foliage biomass of *Pinus brutia* species in ÇkÇz mixed stands

According to Figure 82, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree leaf biomass prediction. The power curve represents the relationship between tree diameters and tree foliage biomass of *Pinus brutia* specie considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on biomass storage in tree foliage. However, increasing tree diameter leads to an exponential increase in biomass in the tree foliage of *Pinus brutia* specie. The power exponent ($b_1 = 2.3270$) is indicated by the tree diameter coefficient ($b_0 = 0.00945$).

f. Results from Tree Bark Biomass Modeling Using Diameter at Breast Height

- Tree Bark Biomass Modeling of *Pinus nigra* Using $D_{1.30}$

The results obtained from bark biomass modeling of *Pinus nigra* trees in natural mixed stands of ÇkÇz, are presented in Table 42.

Table 42. Bark biomass prediction models for *Pinus nigra* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	,761	194,385	1	61	,000	-14,886	1,377		
Logarithmic	,627	102,475	1	61	,000	-53,663	22,592		
Inverse	,457	51,266	1	61	,000	29,239	-290,231		
Quadratic	,829	145,444	2	60	,000	3,052	-,544	,046	
Cubic	,830	95,747	3	59	,000	-,903	,142	,011	,001
Compound	,846	335,870	1	61	,000	,741	1,133		
Power	,879	441,421	1	61	,000	,010	2,306		
S	,811	261,318	1	61	,000	4,105	-33,344		
Growth	,846	335,870	1	61	,000	-,300	,125		
Exponential	,846	335,870	1	61	,000	,741	,125		
Logistic	,846	335,870	1	61	,000	1,350	,882		

Independent variable is $D_{1.30}$ and Dependent Variable is $B_{bark_Çk}$

The most effective models (Table 42) that can be used to estimate tree bark biomass of *Pinus nigra* specie within ÇkÇz's natural mixed stands, are the Quadratic, Compound, Growth, Exponential, Logistic and Power models (R^2 ranged from 0.829 to 0.879). All models are statistically significant at 1% ($p\text{-value} < 0.01$). Particularly, the Power model attributes 87.9% of the variation in tree bark biomass to the power of the diameter ($D_{1.30}$).

Overall, the results demonstrate that the *Power* model provides a robust explanation for the variation in tree bark biomass of *Pinus nigra* specie. The model is statistically significant at 1% ($F = 441.421$; $p < 0.01$), and the prediction error is relatively low (Std. Error = 0.312 kg). However, there is still some unexplained error remaining in the model (RMSE = 0.825 kg). The mathematical expression of this tree bark biomass model is given below:

$$B_{\text{bark}_\text{Çk}} = 0.0103816D_{1.30}^{2.306163} \quad (63)$$

where $B_{\text{bark}_\text{Çk}}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator). The graphical expression of the Çk tree bark biomass model is presented in Figure 83.

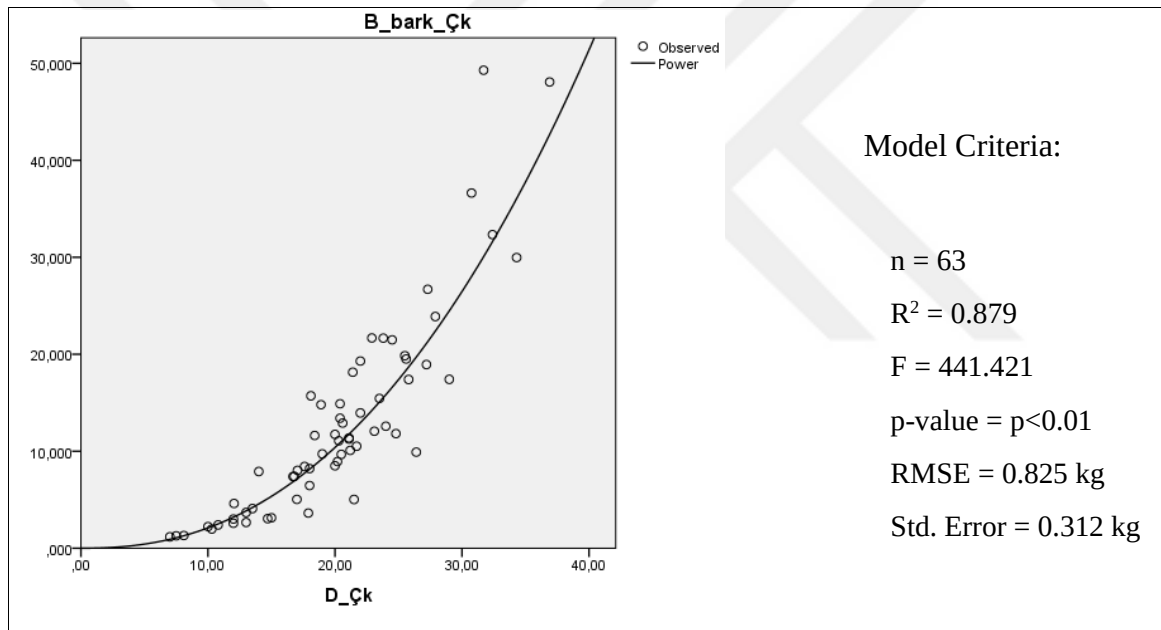


Figure 83. Graphical representation of the Power model for predicting tree bark biomass of *Pinus nigra* species in ÇkÇz mixed stands

According to Figure 83, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree bark biomass prediction. The power curve represents the relationship between tree diameters and tree bark biomass of *Pinus brutia* specie considered in the natural mixed stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on biomass storage in trees' bark. However, increasing tree diameter leads to an exponential increase in biomass in the tree bark of *Pinus nigra* specie. The power exponent ($b_1 = 2.3062$) is represented by the tree diameter coefficient ($b_0 = 0.0104$).

- Tree Bark Biomass Modeling of *Pinus brutia* Using $D_{1.30}$

The results obtained from bark biomass modeling of *Pinus brutia* trees in natural mixed stands of ÇkÇz, are presented in Table 43.

Table 43. Bark biomass prediction models for *Pinus brutia* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	,690	135,754	1	61	,000	-8,594	,911		
Logarithmic	,547	73,778	1	61	,000	-29,482	13,562		
Inverse	,235	18,759	1	61	,000	16,208	-84,496		
Quadratic	,699	69,774	2	60	,000	-4,006	,411	,012	
Cubic	,720	50,609	3	59	,000	5,731	-1,475	,115	-,002
Compound	,762	195,296	1	61	,000	,500	1,136		
Power	,905	580,785	1	61	,000	,008	2,315		
S	,778	214,024	1	61	,000	3,240	-20,403		
Growth	,762	195,296	1	61	,000	-,694	,127		
Exponential	,762	195,296	1	61	,000	,500	,127		
Logistic	,762	195,296	1	61	,000	2,001	,881		

Independent variable is $D_{1.30}$ and Dependent Variable is $B_{\text{bark}_\text{Çz}}$

The most effective models (Table 43) that can be used to estimate tree bark biomass of *Pinus brutia* specie within ÇkÇz's natural mixed stands, are the Quadratic, Compound, Growth, Exponential, Logistic and Power models (R^2 ranged from 0.699 to 0.905). All models are statistically significant at 1% ($p < 0.01$). Particularly, the Power model attributes 90.5% of the variation in tree bark biomass to the power of the diameter ($D_{1.30}$). Overall, the results demonstrate that the Power model provides a robust explanation for the variation in tree stem biomass of *Pinus brutia* specie. The model is statistically significant at 1% ($F = 590.785$; $p < 0.01$), and the prediction error is relatively low (Std. Error = 0.321 kg). However, there is still some unexplained error remaining in the model (RMSE = 0.975 kg). The mathematical expression of this tree bark biomass model is given below:

$$B_{\text{bark}_\text{Çz}} = 0.0075422D_{1.30}^{2.3148079} \quad (64)$$

where $B_{\text{bark}_\text{Çz}}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator). The graphical expression of the Çk tree bark biomass model is presented in Figure 84.

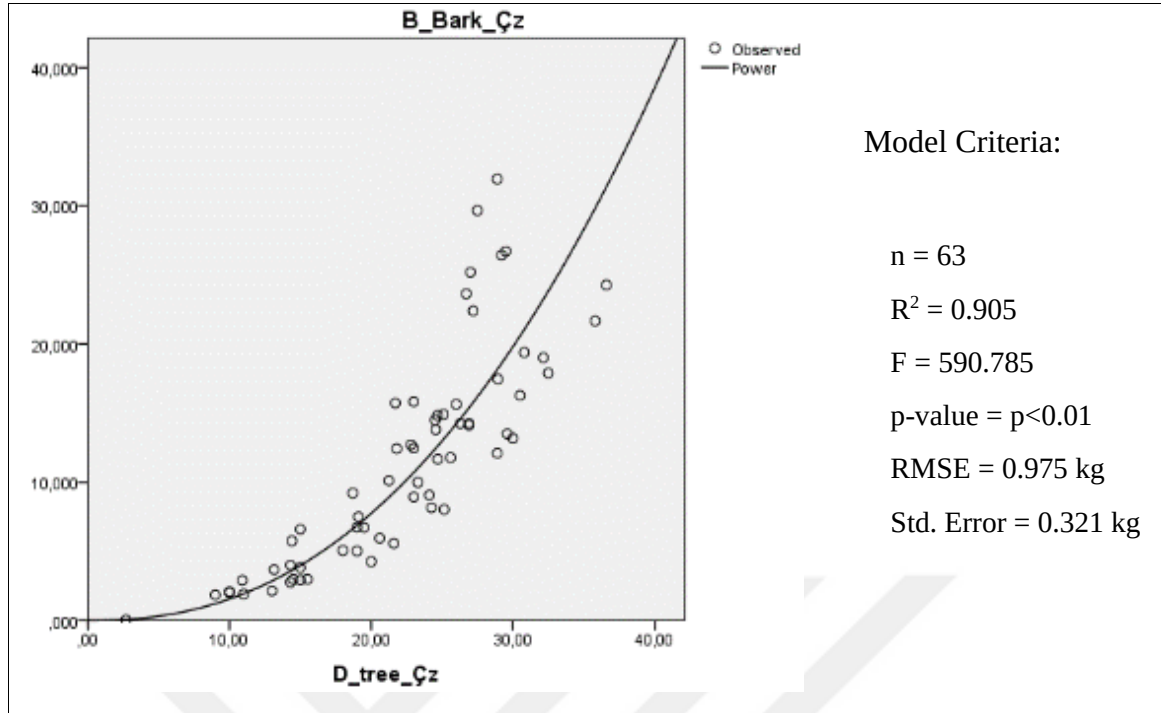


Figure 84. Graphical representation of the Power model for predicting tree bark biomass of *Pinus brutia* species in ÇkÇz mixed stands

According to Figure 84, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree bark biomass prediction. The power curve represents the relationship between tree diameters and tree bark biomass of *Pinus brutia* specie considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on biomass storage in tree's bark. However, increasing tree diameter leads to an exponential increase in biomass in the tree bark of *Pinus brutia* specie. The power exponent ($b_1 = 2.3148$) is indicated by the tree diameter coefficient ($b_0 = 0.0075$).

g. Results from Individual Tree Biomass Modeling Using $D_{1.30}$

- Individual Tree Biomass Modeling for *Pinus nigra* Using $D_{1.30}$

The predictive models for estimating single-tree biomass in *Pinus nigra* specie within the natural mixed stands of ÇkÇz in Türkiye, led to the results given in Table 44.

Table 44. Individual tree biomass prediction models for *Pinus nigra* species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	,780	216,113	1	61	,000	-196,167	17,748		
Logarithmic	,446	49,090	1	61	,000	-378,694	184,720		
Inverse	,082	5,422	1	61	,023	182,437	-368,842		
Quadratic	,917	333,360	2	60	,000	56,092	-11,710	,750	
Cubic	,922	231,540	3	59	,000	-1,032	,833	,013	,013
Compound	,838	314,585	1	61	,000	3,615	1,179		
Power	,945	1050,608	1	61	,000	,089	2,405		
S	,568	80,302	1	61	,000	5,165	-8,702		
Growth	,838	314,585	1	61	,000	1,285	,164		
Exponential	,838	314,585	1	61	,000	3,615	,164		
Logistic	,838	314,585	1	61	,000	,277	,848		
Independent variable is D _{1.30} and Dependent Variable is B _{tree_Çk}									

In Table 44, Logistic, Exponential, Growth, Compound, Quadratic and Power models presents the top-performing criteria for estimating single-tree biomass of *Pinus nigra* specie within ÇkÇz's natural mixed stands. The two most accurate models are the Quadratic model ($R^2 = 0.917$) and the Power model ($R^2 = 0.945$). All models are statistically significant at 1% ($p\text{-value} < 0.01$). Notably, the Power model attributes 94.5% of the variation in tree biomass to the power of the tree diameter ($D_{1.30}$). The results indicate that the Power model explains the variation in the total single-tree biomass of *Pinus nigra* specie very well. The overall model is significant at 1% ($F = 1050.608$; $p < 0.01$), and the prediction error is relatively low (Std. Error = 0.300 kg). However, there is still a certain level of error not explained by the model (RMSE = 1.226 kg). The mathematical expression of the Anatolian Black Pine (Çk) tree biomass model is provided below:

$$B_{\text{tree}_\text{Çk}} = 0.0894425D_{1.30}^{2.4047544} \quad (66)$$

where $B_{\text{tree}_\text{Çk}}$ is the dependent variable, $D_{1.30}$ is the tree diameters (model estimator). The graphical expression of the tree stem biomass model is presented in Figure 85.

According to Figure 85, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the single-tree biomass prediction.

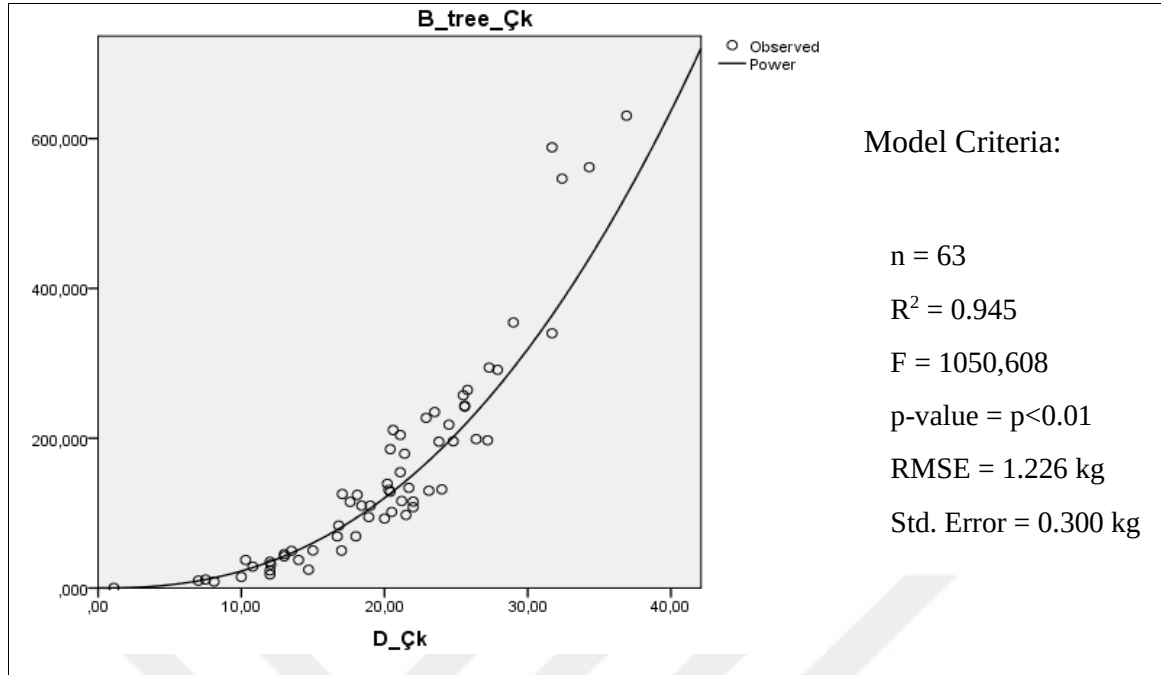


Figure 85. Graphical representation of the Power model for predicting individual tree biomass of *Pinus nigra* species in ÇkÇz mixed stands

The power curve represents the relationship between tree diameters and total tree biomass of *Pinus nigra* species considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters ($D_{1.30}$) have a non-linear effect on biomass storage in the entire tree. However, increasing tree diameter leads to an exponential increase in biomass in the whole tree of *Pinus nigra* species. The power exponent ($b_1 = 2.4048$) is indicated by the tree diameter coefficient ($b_0 = 0.0089$).

- Results from Individual Tree Biomass Modeling for *Pinus brutia* Using $D_{1.30}$

The results obtained from modeling of single-tree biomass modeling of *Pinus brutia* trees in natural mixed stands of ÇkÇz, are presented in Table 45.

According to Table 45, Logistic, Exponential, Growth, Compound, Quadratic and Power models are the top-performing models that can be used to estimate single-tree biomass for *Pinus brutia* species considering in ÇkÇz's natural mixed stands. All models are statistically significant at 1% ($p\text{-value} < 0.01$). The most accurate model is the Power model ($R^2 = 0.962$). Indeed, the Power model attributes 95.8% of the variation in the stem biomass to the power of the tree diameter ($D_{1.30}$).

Table 45. Individual tree biomass prediction models for *Pinus brutia* species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	,820	278,450	1	61	,000	-197,455	17,255		
Logarithmic	,606	93,990	1	61	,000	-568,196	248,716		
Inverse	,239	19,130	1	61	,000	266,393	-1489,578		
Quadratic	,892	247,849	2	60	,000	25,271	-7,064	,584	
Cubic	,892	162,787	3	59	,000	9,272	-3,977	,416	,003
Compound	,861	377,057	1	61	,000	4,079	1,165		
Power	,962	1532,014	1	61	,000	,033	2,712		
S	,745	177,964	1	61	,000	6,047	-22,781		
Growth	,861	377,057	1	61	,000	1,406	,153		
Exponential	,861	377,057	1	61	,000	4,079	,153		
Logistic	,861	377,057	1	61	,000	,245	,858		
Independent variable is D _{1.30} and Dependent Variable is B _{tree_Çz}									

In summary, the results indicate that the *Power* model explains the variation in the tree stem biomass of *Pinus brutia* specie very well. The overall model is statistically significant at 1% (F = 1532.014; p<0.01), and the prediction error is relatively low (Std. Error = 0.233 kg). However, there is still a certain level of error not explained by the model (RMSE = 1.149 kg). The mathematical expression of the T. Red Pine (Çz) tree biomass model is:

$$B_{\text{tree}_\text{Çz}} = 0.032914D_{1.30}^{2.7121501} \quad (66)$$

where $B_{\text{tree}_\text{Çz}}$ is the tree biomass (kg); $D_{1.30}$ is the tree diameters (cm).

The graphical expression of the tree biomass model is presented in Figure 86 (next page).

According to Figure 86, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the single-tree biomass prediction. The power curve represents the relationship between tree diameters and total tree biomass of *Pinus brutia* specie considered in the natural mixed stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on biomass storage in the entire tree. However, increasing tree diameter leads to an exponential increase in biomass in the whole tree of *Pinus brutia* specie. The power exponent ($b_1 = 2.7121$) is indicated by the tree diameter coefficient ($b_0 = 0.0329$).

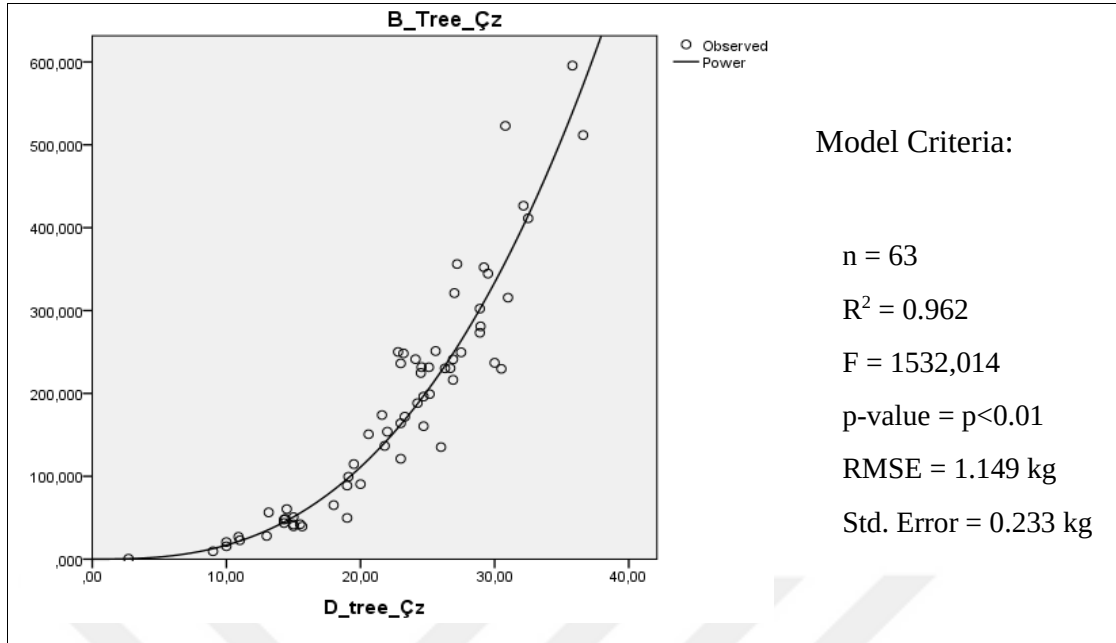


Figure 86. Graphical representation of the Power model for predicting individual tree biomass of *Pinus brutia* species in ÇkÇz mixed stands

h. Results from Individual Tree Biomass Modeling Using Artificial Neural Network (ANN) and Multiple Linear Regression (MLR)

The use of the Artificial Neural Network (ANN) method through MLP and the Multiple Linear Regression (MLR) methods, is very generally motivated by the complexity of the relationships that are assumed to emerge between several estimators (predictors) and one or more Predictands. Using Diameter at Breast Height and tree height as predictors, this method has enabled us develop practical tree biomass capacity prediction models for each of the tree species studied in natural mixed stands of *Pinus nigra* and *Pinus brutia*.

- Individual Tree Biomass Modeling of *Pinus nigra* Using $D_{1.30}$ and H in ANN-MLP and MLR

Using the Artificial Neural Network to predict the biomass of *Pinus nigra* trees in the Natural Mixed Stands of ÇkÇz in Türkiye, 25 ANN models were generated by intervening on the MLP architecture. The number of input variables remained at 2 ($D_{1.30_Çk}$, $H_{Çk}$), but the number of hidden layers varied between 1 and 2, and the number of neurons (number of units) varied between 2 and 10. Using the queries (3 neurons x 2 hidden layers) and the calibration in both processes, the algorithm generated the ANN model shown in Figure 87.

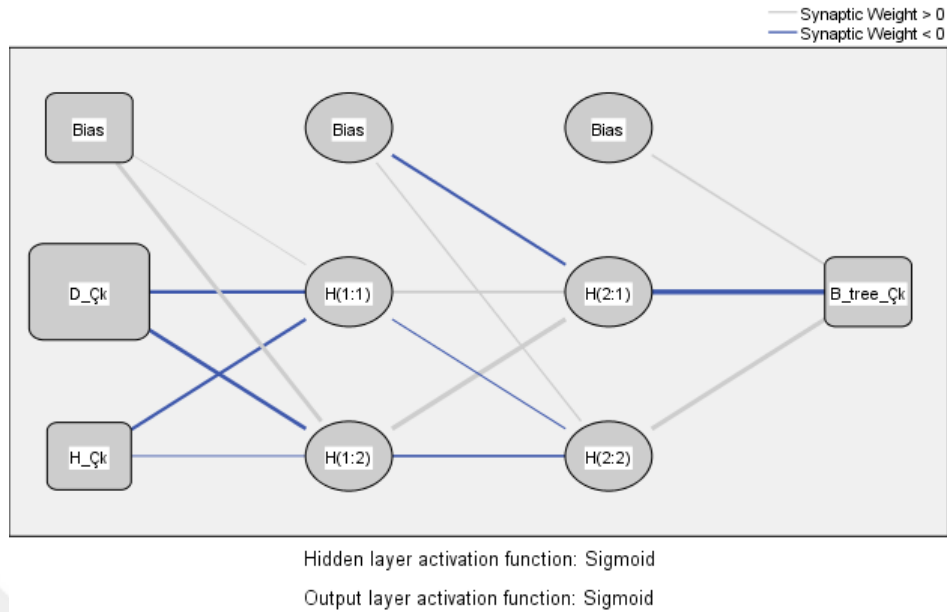


Figure 87. ANN-MLP model (1-2-2-1) of predicting individual tree biomass of *Pinus nigra* specie in ÇkÇz mixed stands

Figure 87 shows the structure of ANN Model (1-2-2-1) of prediction the single-tree biomass of *Pinus nigra* in Natural Mixed Stands of ÇkÇz. MLP algorithm used the diameter ($D_{1.30_Çk}$) and height ($H_{Çk}$), as well as two hidden layers of three neurons each, to generate the model and calculate the errors. When fitting the model, we noticed that certain connections (synaptic weights) between the layers had inhibitory effects on the output of the post-synaptic neuron ($w < 0$), the impact of which is to reduce the activity of the post-synaptic neuron due to the negative weight. For positive neurons ($w > 0$), the connection between post-synaptic neurons had an excitatory effect, with the impact on computation being an increase in its activity. For the ANN Model given in Figure 87, the allocation of variables for training performed by the MLP Algorithm, is presented in Table 46.

Table 46. Summary of *Pinus nigra* biomass data allocation in MLP

Case Processing Summary			
<i>Pinus nigra</i> (A. Black Pine)		N	Percent
Sample	Training	44	69.8%
	Testing	19	30.2%
Valid		63	100,0%
Excluded		0	
Total		63	

In Table 46, it can be seen that the MLP algorithm assigned 69.8% of the diameter and height of *Pinus nigra* trees in training the model for predicting biomass accumulation by these trees, and 30.2% of these input variables, for testing the model. The MLP algorithm also brought out the importance of each independent variable in the construction of the model for predicting the biomass of *Pinus nigra* trees in the natural mixed stands of ÇkÇz, as shown in Figure 88.

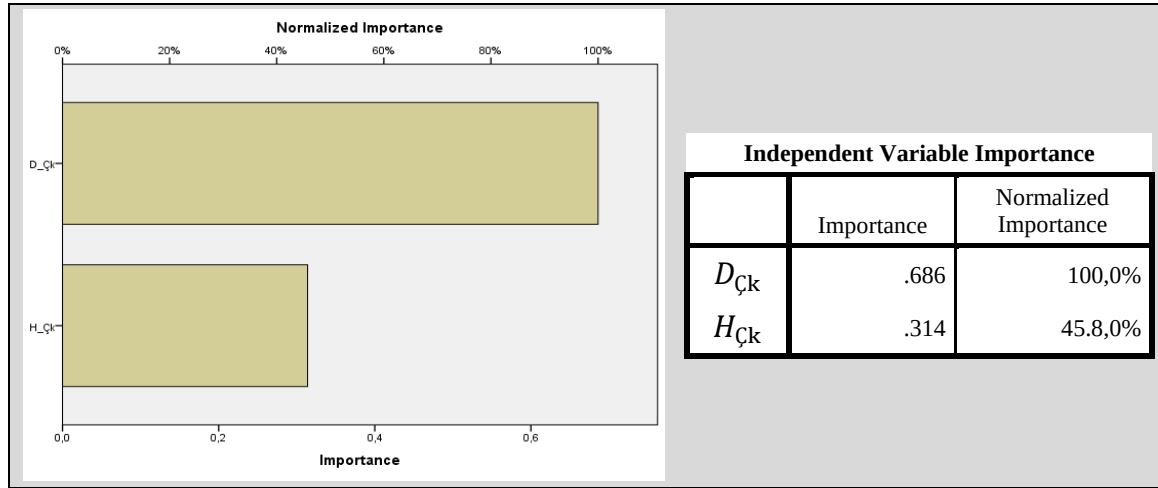


Figure 88. Importance of predictors in the modeling of individual tree biomass of *Pinus nigra* species in ÇkÇz mixed stands

In Figure 88, the tree diameter ($D_{1.30_Çk}$) influenced the training of the model biomass at 68.6%, while Tree Height ($H_{Çk}$) had a 31.4% influence. It can be seen that the diameter was used in its entirety throughout the process (100%), while only 45.8% of the tree heights supplied were used in the training model. With this distribution led to low errors in the model training and testing processes. The errors affecting model performance and calculated by MLP are summarized in Table 47.

According to our results (Table 47), the errors calculated by the algorithm in training (SSE=0.084 kg; RE=0.063 kg; $RMSE_{\text{training}} = 0.044 \text{ kg}$) and in testing (SSE=0.049 kg; RE=0.070 kg; $RMSE_{\text{testing}} = 0.051 \text{ kg}$) are relatively low. Furthermore, a strong correlation was observed between the calculated biomass data ($B_{\text{tree}_Çk}$) and the data predicted ($B_{\text{tree}_Çk_ANN}$) by the algorithm using the MLP-ANN Model 1-2-2-1 ($RMSE=0.007 \text{ kg}$. This correlation between $B_{\text{tree}_Çk}$ and $B_{\text{tree}_Çk_ANN}$ is very high with the Linear model ($R^2_{\text{Linear}} = 0.943$) and more with the Quadratic model ($R^2_{\text{Quadratic}} = 0.944$).

Table 47. Summary of *P. nigra* tree biomass model's performance indicators

Summary of Biomass Model for <i>Pinus nigra</i> Tree in ÇkÇz (1-3-3-1)			
Training	Sum of Squares Error		.084
	Relative Error		.063
	Stopping Rule Used	1 consecutive step(s) with no decrease in error	
Testing	Training Time		0:00:00.01
	Sum of Squares Error		.049
	Relative Error		.070
Dependent Variable: $B_{\text{tree_Çk}}$			

In the confidence interval at 99%, the mathematical expressions (Linear and Quadratic) of these relationships between observed and predicted values of *Pinus nigra* tree biomass in natural mixed stands of ÇkÇz, are presented as follows:

$$\text{ANN Linear} \quad B_{\text{tree_Çk_ANN}} = 21.27 + 0.86(B_{\text{tree_Çk}}) \quad (67)$$

$$\text{ANN Quadratic} \quad B_{\text{tree_Çk_ANN}} = 15.06 + 0.93(B_{\text{tree_Çk}}) - 0.000118(B_{\text{tree_Çk}})^2 \quad (68)$$

Where $B_{\text{stem_Çk_ANN}}$ is the tree biomass quantities predicted by MLP-ANN (kg); $B_{\text{stem_Çk}}$ is the observed tree biomass (kg). The graphical expression of the ANN Linear and ANN Quadratic functions established by the MLP between observed biomass quantities and those predicted values, is expressed by the following curves (Figure 89).

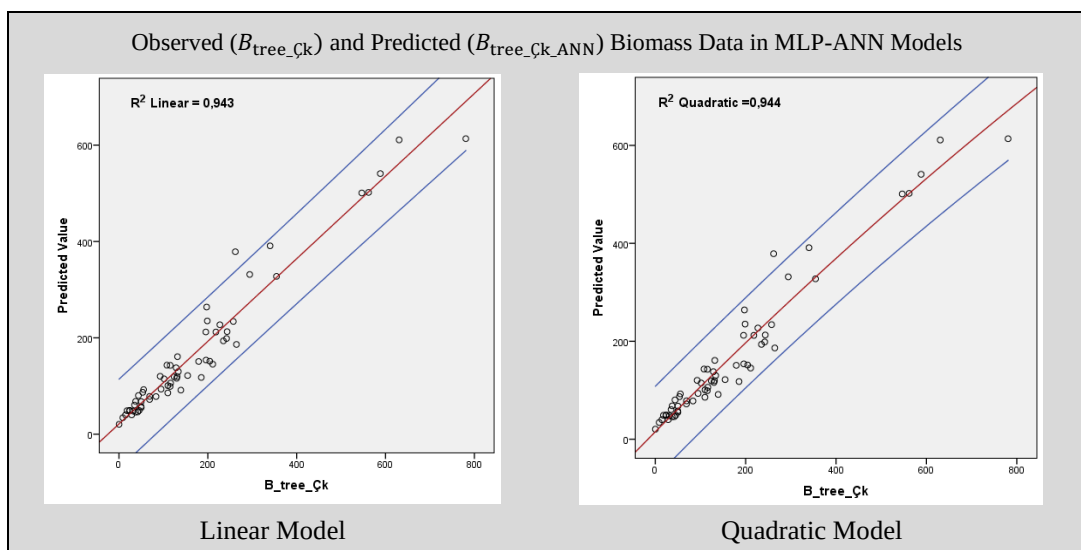


Figure 89. Graphical representations (red line) of the correlation between observed and predicted biomass values for *Pinus nigra* tree species in ÇkÇz natural stands resulting from MLP-ANN modeling

In the Figure 89, red lines represent the model curve (function) and blue lines represent the confidence intervals (99%). To establish a predictive relationship for *Pinus nigra* tree biomass involving diameter and height, multiple regression was used under Stepwise, knowing that the ANN-MLP method has already revealed the importance of variables in building an efficient model. The summary of this analysis is presented in Table 48.

Table 48. Summary of double-entry *Pinus nigra* tree biomass models

Multiple Linear Regression Biomass Models' Summary (n=63)										
<i>MLR</i> _{Çk} Models	<i>R</i> ²	<i>R</i> ² _{Adj}	<i>F</i>	Se	df1	df2	Sig.	Parameters		
								<i>b</i> ₀	<i>b</i> ₁	<i>b</i> ₂
1	.77.9	.775	214.429	76.565	1	61	.000	-244.659	20.013	/
2	.794	.787	115.279	74.745	2	60	.000	-257.897	15.272	9.471
Predictors: (Constant), <i>D</i> _{1.30_Çk} , <i>H</i> _{Çk} ; Dependent Variable: <i>B</i> _{tree_Çk}										

In Table 48, *MLR*_{Çk} model is statistically significant at 1% ($p < 0.01$). The correlation indicates that the tree diameter (*D*_{1.30_Çk}) and height (*H*_{1.30_Çk} with $p < 0.05$) can explain at 79.4% the variation in the biomass accumulation in single-tree of *Pinus nigra* in natural mixed stands in Türkiye ($R^2 = 0.794$; RMSE = 100.83 kg; Se=100.84 kg). Equations *MLR*_{Çk} is illustrated by the following relationships:

$$MLR_{\text{Çk}}: B_{\text{tree_Çk_MLR}} = -257.897 + 15.272D_{1.30_Çk} + 9.471H_{\text{Çk}} \quad (69)$$

Where *B*_{tree_Çk_MLR} is the predicted tree biomass (kg) and *D*_{1.30_Çk} is the tree diameters (cm).

In obtained regression Model 1, tree height was excluded and only diameter was implied in the model. But in Model 2, all predictors were used in model. Analysis of these coefficients led to the results shown in Table 49.

Table 49. Characteristics of *Pinus nigra* tree biomass models in MLR

ANOVA ^a						
Model $MLR_{tree_Çk}$		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1257026,719	1	1257026,719	214,429	,000 ^b
	Residual	357594,377	61	5862,203		
	Total	1614621,096	62			
2	Regression	1281203,348	2	640601,674	115,279	,000 ^c
	Residual	333417,749	60	5556,962		
	Total	1614621,096	62			
a. Dependent Variable: $B_{tree_Çk}$; b. Predictors: (Constant), $D_{Çk}$; c. Predictors: (Constant), $D_{Çk}$, $H_{Çk}$						

Coefficients ^a						
Model	$MLR_{Çk}$	Unstandardized Coefficients			t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-244.659	29.720		-8.232	.000
	$D_{Çk}$	20.013	1.367	.882	14.643	.000
2	(Constant)	-257.897	29.624		-8.706	.000
	$D_{Çk}$	15.272	2.634	.673	5.798	.000
	$H_{Çk}$	9.471	4.540	.242	2.086	.041
a. Dependent Variable: $B_{tree_Çk}$						

All coefficients are statistically significant in the model, especially at 1% (Constant and $D_{Çk}$), and 5% ($H_{Çk}$).

- Individual Tree Biomass Modeling of *Pinus brutia* using $D_{1.30}$ and Height in ANN and MLR

As developed in Section 3.3.1., the same procedure was used to develop and select a (robust) prediction model for the tree biomass of *Pinus brutia* specie (Çz) in the natural stands of ÇkÇz in Türkiye, based on the diameter and height of each tree. The data have been distributed by the algorithm, as shown in Table 50.

Table 50. Summary of mixed stand biomass data allocation in MLP

Case Processing Summary			
<i>Pinus brutia</i> (T. Red Pine)		N	Percent
Sample	Training	47	74,6%
	Testing	16	25,4%
	Valid	63	100,0%
	Excluded	280	
	Total	347	

According to Table 50, the MLP algorithm distributed the data for 74.6% of the diameter and height values in the model training, and 25.4% in the model. For common exclusion reasons (missing values, outliers, duplicates or other specific criteria), 280 exclusion cases were recorded. The MLP algorithm also brought out the importance of each independent variable in the construction of the model for predicting the biomass of *Pinus brutia* trees in the natural mixed stands of ÇkÇz, as shown in Figure 90.

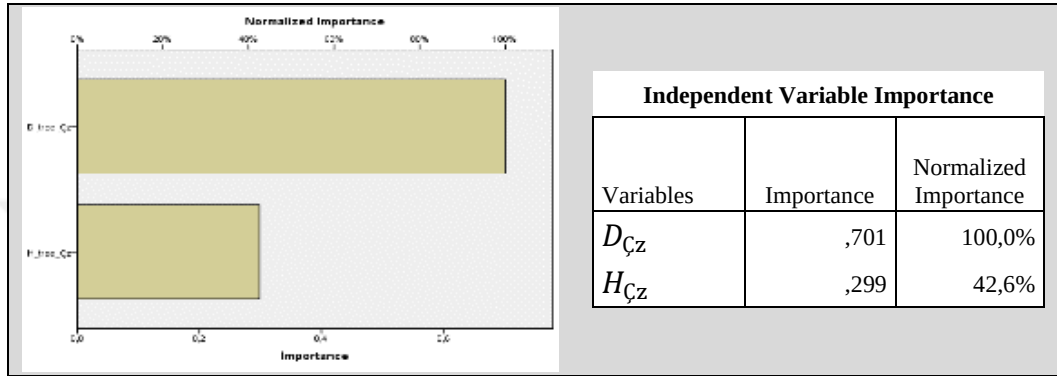


Figure 90. Importance of predictors in the modeling of individual tree biomass of *Pinus brutia* species in ÇkÇz stands.

In Figure 90, tree Diameter ($D_{1.30,\text{Çz}}$) had a 70.1% influence on model construction, while Tree Height ($H_{\text{Çz}}$) had a 29.9% influence. It can be seen that the Diameter was used in its entirety throughout the process (100%), while 42.6% of the tree heights supplied were used. The best ANN model proposed by the MLP algorithm for predicting the biomass of *Pinus brutia* trees in natural mixed stands of ÇkÇz is shown in Figure 91.

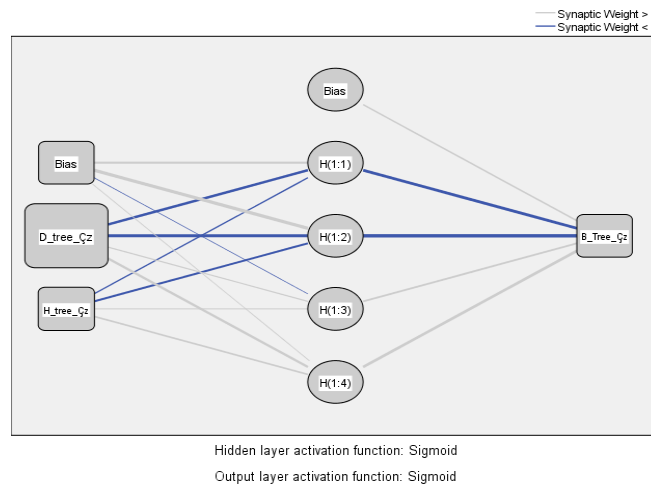


Figure 91. ANN-MLP model (1-4-1) of predicting individual trees biomass of *Pinus brutia* specie in ÇkÇz stands

According to Figure 91, the best ANN-MLP model for predicting the biomass of *Pinus brutia* trees in Natural Mixed Stands in ÇkÇz consists of 1 input layer, 1 hidden layer with 4 neurons, and an output layer (1-4-1). The summary of the model, characterized by the errors calculated by the algorithm, is shown in Table 51.

Table 51. Summary of *P. brutia* tree biomass model's performance indicators

Biomass Model Summary of <i>Pinus brutia</i> in ÇkÇz (1-4-1)		
Training	Sum of Squares Error	.169
	Relative Error	.130
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00.01
Testing	Sum of Squares Error	.040
	Relative Error	.092
Dependent Variable: $B_{\text{tree}_\text{Çz}}$		

According to results (Table 51) the errors calculated by the algorithm in training (SSE=0.169 kg; RE=0.130 kg; $RMSE_{\text{training}} = 0.059 \text{ kg}$) and in testing (SSE=0.040 kg; RE=0.092 kg; $RMSE_{\text{testing}} = 0.048 \text{ kg}$) are relatively low. Furthermore, a strong correlation was observed between the calculated biomass data ($B_{\text{tree}_\text{Çz}}$) and the data predicted ($B_{\text{tree}_\text{Çz_ANN}}$) by the algorithm using the MLP-ANN Model 1-4-1 ($RMSE = 0.011 \text{ kg}$). This correlation between $B_{\text{tree}_\text{Çz}}$ and $B_{\text{tree}_\text{Çz_ANN}}$ is very high with the Linear model ($R^2_{\text{Linear}} = 0.881$) and more with the Quadratic model ($R^2_{\text{Quadratic}} = 0.883$). In the confidence interval at 99%, the mathematical expressions (Linear and Quadratic) of these relationships between observed and predicted values of *Pinus brutia* tree biomass in natural mixed stands of ÇkÇz, are presented as follows:

$$\text{ANN Linear: } B_{\text{tree}_\text{Çz_ANN}} = 24.22 + 0.88(B_{\text{tree}_\text{Çz}}) \quad (70)$$

$$\text{ANN Quadratic: } B_{\text{tree}_\text{Çz_ANN}} = 15.63 + 0.99(B_{\text{tree}_\text{Çz}}) - 0.000217(B_{\text{tree}_\text{Çz}})^2 \quad (71)$$

Where $B_{\text{tree}_\text{Çz_ANN}}$ is the tree biomass predicted in ANN (kg); $B_{\text{tree}_\text{Çz}}$ is the observed tree biomass (kg).

Table 52 shows two models derived from $MLR_{\zeta z}$, for the prediction of *Pinus brutia* tree biomass. $MLR_{\zeta z}$ Equations illustrated by the following relationships:

$$MLR_{\zeta z}: B_{tree_{\zeta z_MRL}} = -199.255 + 12.800D_{1.30} + 8.145H \quad (72)$$

Where $B_{tree_{\zeta z_MRL}}$ is the tree biomass predicted in Multilayer Regression Analysis (kg), $D_{1.30}$ is the tree diameters (cm); H is the tree height (m).

In obtained regression Model 1, tree height was excluded and only diameter was implied in the model. But in Model 2, all predictors were used in model. Analysis of these coefficients led to the results shown in Table 53.

Table 53. Characteristics of *Pinus brutia* tree biomass model in MLR

ANOVA ^a						
<i>MLR</i> _{Çk} Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1257026.719	1	1257026.719	214.429	.000 ^b
	Residual	357594.377	61	5862.203		
	Total	1614621.096	62			
2	Regression	1281203.348	2	640601.674	115.279	.000 ^c
	Residual	333417.749	60	5556.962		
	Total	1614621.096	62			
<i>a. Dependent Variable: B_{tree_Çk}; b. Predictors: (Constant), D_{Çk}; c. Predictors: (Constant), D_{Çk}, H_{Çk}</i>						
Coefficients ^a						
<i>MLR</i> _{Çk} Model		Unstandardized Coefficients			<i>t</i>	Sig.
		<i>B</i>	Std. Error	Beta		
1	(Constant)	-244.659	29.720		-8.232	.000
	<i>D</i> _{Çk}	20.013	1.367	.882	14.643	.000
2	(Constant)	-257.897	29.624		-8.706	.000
	<i>D</i> _{Çk}	15.272	2.634	.673	5.798	.000
	<i>H</i> _{Çk}	9.471	4.540	.242	2.086	.041
<i>a. Dependent Variable: B_{tree_Çk}</i>						

$MLR_{tree_{\zeta z}}$ model has taken both predictors into account and shows a higher performance ($R^2 = 0.816$). Indeed, $D_{1.30_{\zeta z}}$ and $H_{\zeta z}$ explain 81.6% of the variance in tree biomass capacity of *Pinus brutia* in $\zeta k\zeta z$ stands. They are globally significant at 1% ($F=132.934$; $Se=87.575$; $p<0.01$).

3.3.2. Results from Tree Carbon Modeling in ÇkÇz Stands

To model above-ground carbon storage in trees of Black Pine (*Pinus nigra*) or Karaçam (Çk) and Turkish Red Pine (*Pinus brutia*) or Kızılçam (Çz) in natural mixed stands of ÇkÇz (Türkiye), the main predictor used in modeling is diameter at breast height ($D_{1.30}$). In this section, diameter ($D_{1.30}$) was used as a predictor to model the carbon storage of each single-tree (C_{Tree}) and its separate components such as stem (C_{Stem}), bark (C_{Bark}), branches (C_{Branch}), and foliage ($C_{Foliage}$). Tree height (H) was also used to model carbon storage at the single-tree scale. It was not linked separately to other tree components. The two predictors ($D_{1.30}$ and H) were used for Multi-Layer Perceptron (MLP-ANN) and Multiple Linear Regression (MLR) analysis.

a. Variables used in Tree Carbon Modeling of *Pinus nigra* Specie

The summary of the descriptive statistical analysis of the variables (dependent and independent) used in the modeling of above-ground carbon storage of 68 Anatolian Black Pine (*Pinus nigra*) trees and their various components, are presented in Table 54.

Table 54. Summary of descriptives analysis of carbon variables of *Pinus nigra*

Descriptive Statistics of the tree carbon variables for <i>Pinu nigra</i> (Karaçam)						
Variables	Unity	N	Min.	Max.	Mean	SD
$D_{Çk}$	cm	68	1.10	38.20	20.246	7.282
$H_{Çk}$	m	68	.65	22.25	11.472	4.135
$C_{stem_Çk}$	kg	68	.019	300.725	51.156	56.779
$C_{bark_Çk}$	kg	68	.000	28.485	6.758	5.991
$C_{branch_Çk}$	kg	68	.036	65.122	14.893	14.118
$C_{foliage_Çk}$	kg	68	.060	43.239	7.9182	7.991
$C_{tree_Çk}$	kg	68	.116	383.355	80.725	79.285

Min.=Minimum; Max.=Maximum; SD=Standard Deviation;

As shown in Table 54, two main estimators ($D_{1.30_Çk}$ et $H_{Çk}$) were used to explain the regression relation which exist between the carbon storage of stem ($C_{stem_Çk}$), branches ($C_{branch_Çk}$), bark ($C_{bark_Çk}$), foliage ($C_{foliage_Çk}$) and total single-tree ($C_{tree_Çk}$) for 68 tree of *Pinus nigra* specie, considered in natural mixed stands of ÇkÇz.

b. Variables used in Tree Carbon Modeling of *Pinus brutia* Specie

The results of the descriptive analysis of the variables (dependent and independent) used in the modeling of 70 tree carbon storage in *Pinus brutia* specie, or Kızılcām in local name (Çk), and their components, considered in the natural mixed stands of ÇkÇz in Türkiye, are presented in Table 55.

Table 55. Summary of descriptives analysis for carbon variables of *Pinus brutia*

Descriptive statistics of the tree carbon variables for <i>Pinu brutia</i> (Kızılcām)						
Variables	Unity	N	Min.	Max.	Mean	SD
$D_{\text{Çz}}$	cm	70	2.70	42.85	22.641	7.429
$H_{\text{Çz}}$	m	70	1.04	23.07	12.622	3.825
$C_{\text{stem_Çz}}$	kg	70	.057	334.958	64.333	54.879
$C_{\text{bark_Çz}}$	kg	70	.022	25.465	6.352	5.068
$C_{\text{branch_Çz}}$	kg	70	.094	101.217	18.656	19.803
$C_{\text{foliage_Çz}}$	kg	70	.107	47.534	8.905	9.351
$C_{\text{tree_Çz}}$	kg	70	.280	385.689	98.246	76.722
Min.=Minimum; Max.=Maximum; SD=Standard Deviation;						

As shown in Table 55, two main estimators ($D_{1.30_Çk}$ et $H_{Çk}$) were used to explain the relationship between the carbon storage of stem ($C_{\text{stem_Çz}}$), branches ($C_{\text{branch_Çz}}$), bark ($C_{\text{bark_Çz}}$), foliage ($C_{\text{foliage_Çz}}$) and total single-tree ($C_{\text{tree_Çz}}$) for 70 tree of *Pinus brutia* specie, considered in natural mixed stands of ÇkÇz.

c. Results from Tree Stem Carbon Storage Modeling Using Diameter at Breast Height ($D_{1.30}$)

- Tree Stem Carbon Storage Modeling of *Pinus nigra* Using $D_{1.30}$

Development of the model for predicting carbon storage in tree stems of *Pinus nigra* specie in the natural mixed stands of ÇkÇz in Türkiye, led to the results in Table 56

Table 56. Stem carbon prediction models for *Pinus brutia* tree specie

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.731	165.685	1	61	.000	-69.478	5.952		
Logarithmic	.404	41.329	1	61	.000	-127.790	60.809		
Inverse	.069	4.541	1	61	.037	56.315	-117.138		
Quadratic	.882	224.499	2	60	.000	21.764	-4.669	.270	
Cubic	.887	154.587	3	59	.000	.453	.024	-.006	.005
Compound	.814	266.289	1	61	.000	.689	1.203		
Power	.956	1329.836	1	61	.000	.009	2.749		
S	.613	96.573	1	61	.000	3.993	-10.235		
Growth	.814	266.289	1	61	.000	-.372	.184		
Exponential	.814	266.289	1	61	.000	.689	.184		
Logistic	.814	266.289	1	61	.000	1.451	.832		

Independent variable is D_{1.30} and Dependent Variable is C_{stem_Çk}

Although all the models (Table 56) are statistically significant at 1% (p-value < 0.01), the results show that the five best models recommended for predicting tree stem carbon storage in *Pinus nigra* specie ($C_{stem_Çk}$) in the natural mixed stands of ÇkÇz are the Logistic, Exponential, Growth, Compound, Quadratic and Power models (R^2 ranged between 0.814 and 0.956). The high-performance model is Power model ($R^2 = 0.956$). The results show that 95.6% of the variance in carbon storage in tree stems, is explained by tree diameter ($D_{1.30}$) raised to a certain power. Globally, the Power model of carbon storage in tree stems of *Pinus nigra* is significant at 1% ($F = 1329.836$; $p < 0.01$). Between model-predicted and actual tree stem carbon quantities, the average error is relatively low (Std. Error = 0.296 kg). After model fitting, there is a small amount of variance not explained by the model, representing the sum of squared residuals or the sum of squared deviations between observed and predicted tree stem carbon storage (RMSE = 1.396 kg). The mathematical expression of the model of carbon storage in tree stem of Anatolian Black Pine specie (Çk) is given by the following relationship:

$$C_{stem_Çk} = 0.0093042D_{1.30}^{2.7486228} \quad (73)$$

where $C_{stem_Çk}$ is the carbon storage in tree stems (kg); $D_{1.30}$ is the tree diameters (cm).

The Power model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth. The graphical expression of the equation (76) is presented in Figure 93.

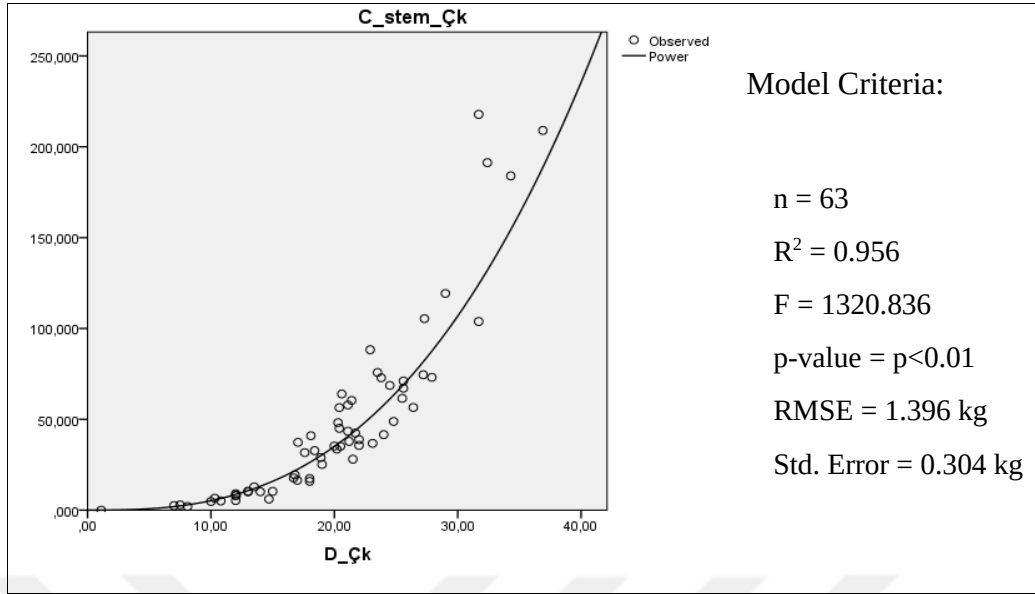


Figure 93. Graphical representation of the Power model for predicting tree stem carbon storage of *Pinus nigra* specie in ÇkÇz stands

The power curve in Figure 93 represents the relationship between tree diameters ($D_{1.30}$) and carbon storage in the tree stem of *Pinus nigra* specie considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters ($D_{1.30}$) have a non-linear effect on carbon storage in tree stems. However, increasing tree diameter leads to an exponential increase in carbon stock in the tree stems of *Pinus nigra* specie. The power exponent ($b_1 = 2.7362$) is indicated by the tree diameter coefficient ($b_0 = 0.0197$).

- Tree Stem Carbon Storage Modeling of *Pinus brutia* Using $D_{1.30}$

The results of modelling carbon storage by *Pinus brutia* tree stems in mixed ÇkÇz stands are given in Table 57 (next page). According to Table 57, all models are statistically significant at 1% ($p < 0.01$). The best models which can be used to predict tree stem carbon storage from tree diameter of *Pinus brutia*, are Logistic, Exponential, Growth, Compound, Quadratic and Power models. These correlation coefficients are high and ranged from 0.817 to 0.954. The top-performing models for estimating tree stem carbon stock in *Pinus brutia* specie within ÇkÇz natural stands, are Quadratic model ($R^2 = 0.883$) and Power model ($R^2 = 0.954$). However, Power model attributes 95.4% of the variation in tree stem carbon storage to the power of the tree diameter. The results indicate that the Power model explains the variation in the tree stem carbon stocks of *Pinus brutia* specie very well.

Table 57. Tree stem carbon prediction models for Turkish Red Pine (Çz)

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.815	267.931	1	61	.000	-63.630	5.519		
Logarithmic	.602	92.359	1	61	.000	-182.233	79.562		
Inverse	.236	18.883	1	61	.000	84.704	-475.784		
Quadratic	.883	226.008	2	60	.000	6.116	-2.096	.183	
Cubic	.883	148.178	3	59	.000	7.430	-2.349	.197	.000
Compound	.817	271.884	1	61	.000	1.011	1.177		
Power	.954	1269.240	1	61	.000	.005	2.946		
S	.798	240.457	1	61	.000	5.024	-25.710		
Growth	.817	271.884	1	61	.000	.011	.163		
Exponential	.817	271.884	1	61	.000	1.011	.163		
Logistic	.817	271.884	1	61	.000	.989	.850		

Independent variable is D_{1.30} and Dependent Variable is C_{stem_Çz}

The overall model is significant at 1% (F=1269.240; p<0.01), and the prediction error is relatively low (Std. Error=0.278 kg). However, there is still a certain level of error not explained by the model (PMSE=1.248 kg). The mathematical expression of the Turkish Red Pine (Çz) stem carbon storage model is provided below:

$$C_{\text{stem}_\text{Çz}} = 0.0049637D_{1.30}^{2.9459233} \quad (74)$$

where $C_{\text{stem}_\text{Çz}}$ is the stem carbon stock (kg); $D_{1.30}$ is the tree diameters (cm).

The graphical expression of the tree stem carbon storage model is presented in Figure 94.

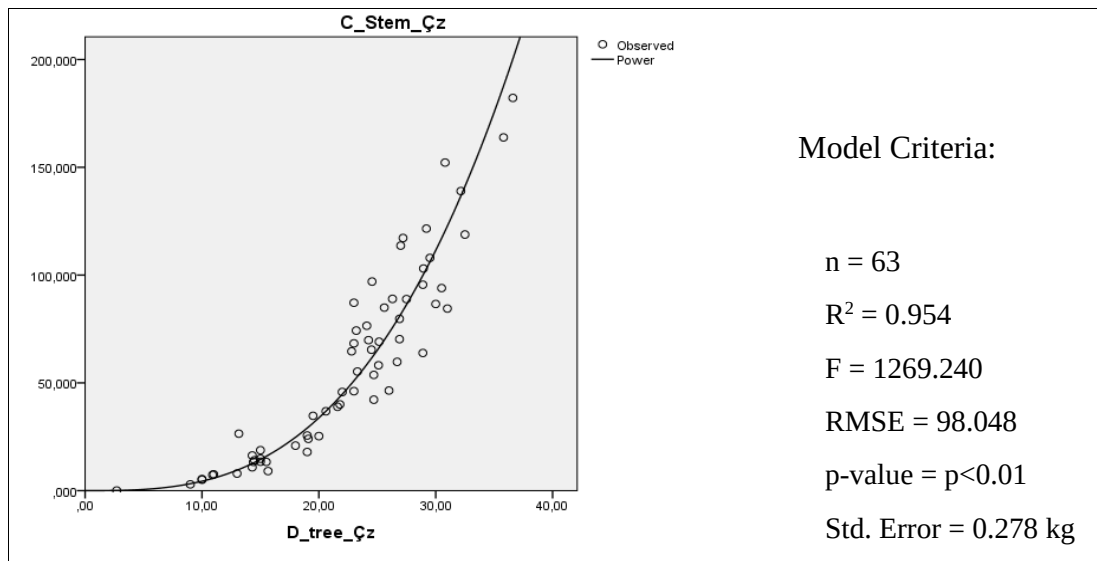


Figure 94. Graphical representation of the Power model for predicting tree stem carbon storage of *Pinus brutia* specie in ÇkÇz stands

According to Figure 94, the Power model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth. The power curve represents the relationship between tree diameters ($D_{1.30}$) and tree stem carbon storage ($B_{\text{stem}_\text{Çz}}$) of *Pinus brutia* trees considered in the Natural Mixed Stands of ÇkÇz in Türkiye. The relationship follows a power model, where changes in tree diameters ($D_{1.30}$) have a non-linear effect on carbon stocks ($B_{\text{stem}_\text{Çz}}$) in tree stems. However, increasing tree diameter leads to an exponential increase in carbon storage by the tree stems of *Pinus brutia* specie. The power exponent ($b_1 = 2.9459$) is indicated by the tree diameter coefficient ($b_0 = 0.00496$).

d. Results from Tree Branch Carbon Modeling Using Diameter at Breast Height ($D_{1.30}$)

- Tree Branch Carbon Storage Modeling of *Pinus nigra* Using $D_{1.30}$

Development of the model for predicting tree branch carbon storage of *Pinus nigra* species in the natural mixed stands of ÇkÇz in Türkiye led to the result given in Table 58.

Table 58. Branch carbon prediction models for *Pinus nigra* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.621	100.044	1	61	.000	-14.284	1.435		
Logarithmic	.380	37.404	1	61	.000	-30.632	15.562		
Inverse	.077	5.086	1	61	.028	17.047	-32.468		
Quadratic	.658	57.804	2	60	.000	-2.374	.081	.034	
Cubic	.667	39.439	3	59	.000	4.811	-1.491	.125	-.002
Compound	.722	158.230	1	61	.000	.458	1.159		
Power	.824	285.123	1	61	.000	.016	2.181		
S	.502	61.401	1	61	.000	2.749	-7.891		
Growth	.722	158.230	1	61	.000	-.781	.147		
Exponential	.722	158.230	1	61	.000	.458	.147		
Logistic	.722	158.230	1	61	.000	2.183	.863		

Independent variable is $D_{1.30}$ and Dependent Variable is $C_{\text{branch}_\text{Çk}}$

In Table 50, all models are statistically significant at 1% (p-value < 0.01). The five most effective models to predict the tree branch carbon storage in *Pinus nigra* specie within the natural mixed stands of ÇkÇz, are the Compound, Growth, Exponential, Logistic and Power models (R^2 ranged from 0.722 to 0.824). Particularly, the Power model exhibits high performance ($R^2=0.824$). This indicates that changes in diameter explain 82.4% of the variation in carbon storage in branches of *Pinus nigra* trees.

With diameter ($D_{1.30}$), the results indicate that the *Power* model provides a strong explanation for the variation in the tree branch carbon storage of *Pinus nigra* specie. The model demonstrates significance at 1% ($F=285.123$; $p<0.01$), and the prediction error is relatively low (Std. Error=0.519 kg). However, there remains some unexplained error in the model (RMSE=1.126 kg). The mathematical expression of stem carbon storage prediction model is given by following expression:

$$C_{\text{branch_}\text{Çk}} = 0.0155458D_{1.30}^{2.1811452} \quad (75)$$

here $C_{\text{branch_}\text{Çk}}$ is the tree branch carbon storage (kg); $D_{1.30}$ is the tree diameters (cm).

The graphical expression of the tree branch carbon storage model is presented in Figure 95.

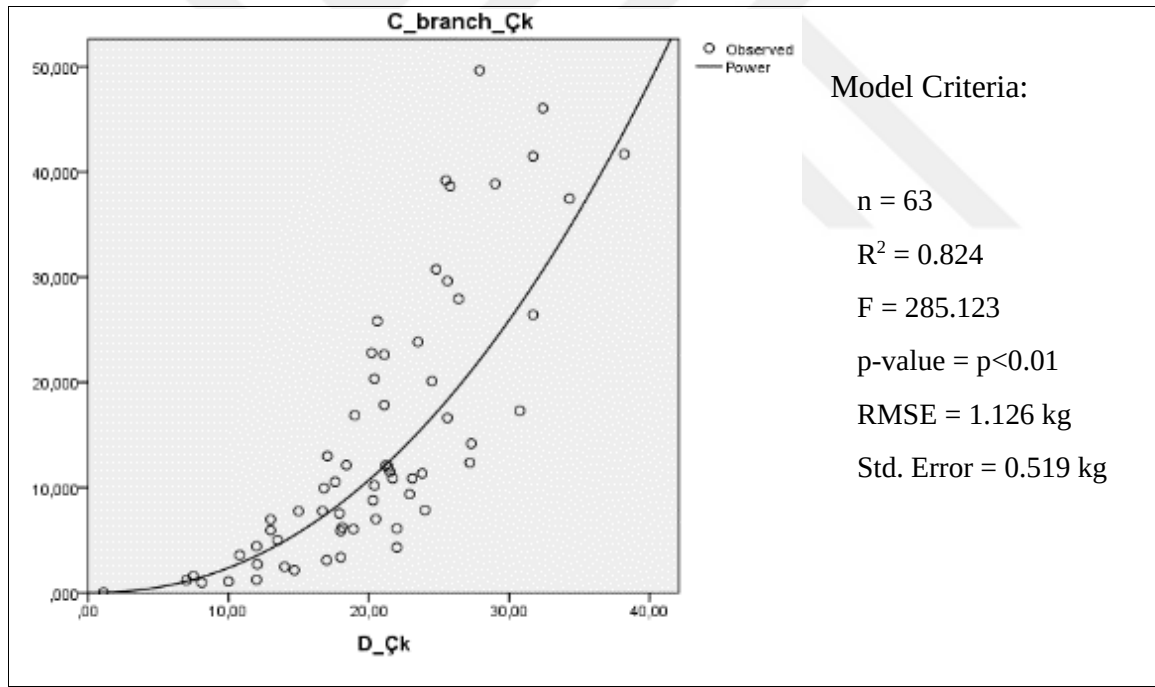


Figure 95. Graphical representation of the Power model for predicting tree branch carbon storage of *Pinus brutia* specie in ÇkÇz stands

According to Figure 95, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree branch carbon storage prediction. The power curve represents the relationship between tree diameters and tree branch carbon storage of *Pinus nigra* trees, considered in the Natural Mixed Stands of ÇkÇz in Türkiye.

This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on carbon storage in tree branches. However, increasing tree diameter leads to an exponential increase in carbon stocks in the tree branch of *Pinus nigra* specie. The power exponent ($b_1 = 2.1811$) is indicated by the tree diameter coefficient ($b_0 = 0.0156$).

- Tree Branch Carbon Storage Modeling of *Pinus brutia* Using $D_{1.30}$

Development of the model for predicting tree branch carbon storage of *Pinus brutia* species in the natural mixed stands of ÇkÇz in Türkiye led to the following best model:

$$C_{\text{branch}_\text{Çz}} = 0.0038978D_{1.30}^{2.5909269} \quad (76)$$

where $C_{\text{branch}_\text{Çz}}$ is the tree branch carbon storage model (kg); $D_{1.30}$ is the tree diameters (cm). This equation (60) is the best model among those obtained in Table 59.

Table 59. Branch carbon prediction models for *Pinus brutia* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.720	157.145	1	61	.000	-18.229	1.546		
Logarithmic	.513	64.311	1	61	.000	-52.254	22.556		
Inverse	.191	14.366	1	61	.000	23.196	-132.147		
Quadratic	.784	109.204	2	60	.000	-.069	-.318	.042	
Cubic	.786	72.197	3	59	.000	4.078	-1.034	.077	-.001
Compound	.784	221.359	1	61	.000	.412	1.154		
Power	.855	359.810	1	61	.000	.004	2.591		
S	.608	94.526	1	61	.000	3.441	-20.999		
Growth	.784	221.359	1	61	.000	-.887	.144		
Exponential	.784	221.359	1	61	.000	.412	.144		
Logistic	.784	221.359	1	61	.000	2.428	.866		
Independent variable is $D_{1.30}$ and Dependent Variable is $C_{\text{branch}_\text{Çz}}$									

Table 59 showcases the most effective models for estimating the tree branch carbon storage in *Pinus brutia* specie considered in the natural mixed stands of ÇkÇz. All models are statistically significant at 1% (p-value<0.01). The 6 best highest-performing models are the Compound, Growth, Exponential, Logistic, Quadratic and Power models (R² ranged from 0.784 to 0.855). Particularly, the *Power* model exhibits high performance (R²=0.855).

This indicates that changes in diameter explain 85.5% of the variation in branch carbon stock of *Pinus brutia* trees. The results indicate that the *Power* model provides a strong explanation for the variation in the tree branch carbon of *Pinus brutia* specie. The model demonstrates significance at 1% ($F=285.443$; $p<0.01$), and the prediction error is relatively low (Std. Error=0.519 kg). However, there remains some unexplained error in the model (RMSE=1.104 kg). The graphical expression of the tree branch carbon storage model is presented in Figure 96.

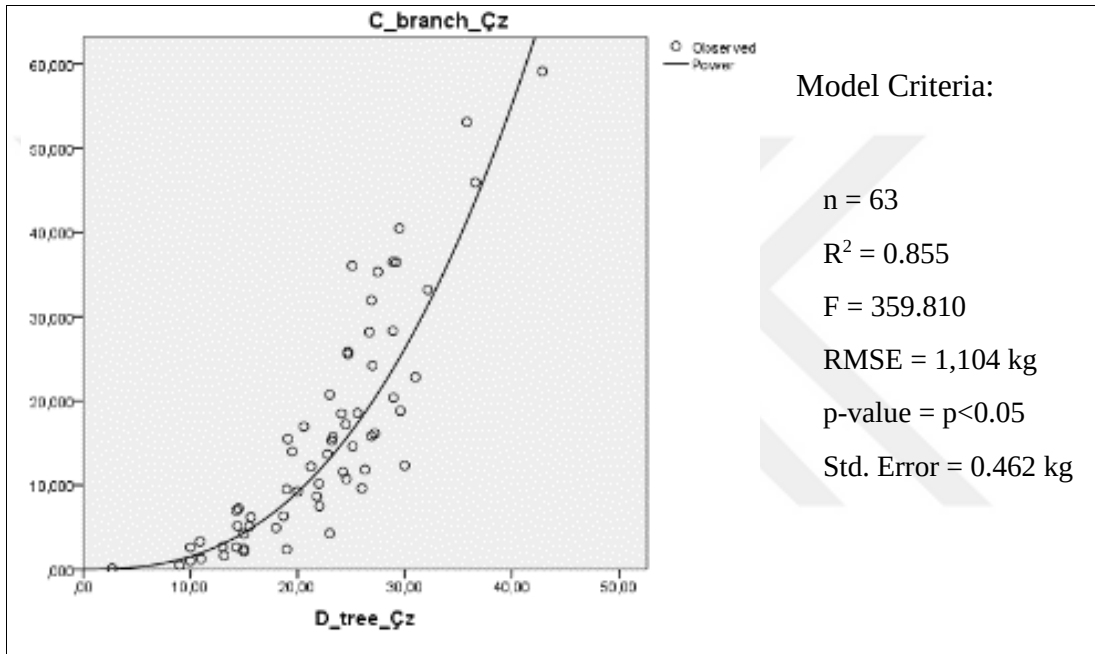


Figure 96. Graphical representation of the Power model for predicting tree branch carbon storage of *Pinus brutia* tree in ÇkÇz natural stands

Indeed, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree branch carbon storage prediction. The power curve represents the relationship between tree diameters and tree branch carbon stocks of *Pinus brutia* specie considered in the natural mixed stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on carbon storage in tree branches. However, increasing tree diameter leads to an exponential increase in carbon stocks in the tree branches of *Pinus brutia* specie. The power exponent ($b_1 = 2.5909$) is indicated by the tree diameter coefficient ($b_0 = 0.00389$).

e. Results from Tree Foliage Carbon Storage Modeling Using Diameter at Breast Height ($D_{1.30}$)

- Tree Foliage Carbon Storage Modeling of *Pinus nigra* Using $D_{1.30}$

Development of the model for predicting tree foliage carbon storage of *Pinus nigra* species in the natural mixed stands of ÇkÇz in Türkiye led to best following *Power* model:

$$C_{\text{foliage}_\text{Çk}} = 0.0211218D_{1.30}^{1.8866732} \quad (77)$$

where $C_{\text{foliage}_\text{Çk}}$ is the carbon storage model (kg); $D_{1.30}$ is the tree diameters (cm).

The equation (80) is the best prediction model among those obtained and presented in Table 54. The *Compound*, *Growth*, *Exponential*, and *Logistic* models are the top-performing models (with R^2 ranged from 0.679 to 0.764) that can be used to for predict tree foliage carbon storage in *Pinus nigra* specie within the natural mixed stands of ÇkÇz (Table 60).

Table 60. Foliage carbon prediction models for *Pinus nigra* tree species

Equation	Model Summary					Parameter Estimates			
	R^2	F	df1	df2	Sig.	Constant	b_1	b_2	b_3
Linear	.606	93.663	1	61	.000	-6.393	.707		
Logarithmic	.378	37.133	1	61	.000	-15.483	8.016		
Inverse	.077	5.100	1	61	.028	8.970	-17.138		
Quadratic	.647	54.981	2	60	.000	.063	-.015	.018	
Cubic	.650	36.512	3	59	.000	2.296	-.489	.045	.000
Compound	.679	129.193	1	61	.000	.419	1.132		
Power	.764	197.215	1	61	.000	.021	1.887		
S	.423	44.714	1	61	.000	2.082	-6.648		
Growth	.679	129.193	1	61	.000	-.870	.124		
Exponential	.679	129.193	1	61	.000	.419	.124		
Logistic	.679	129.193	1	61	.000	2.386	.883		

Independent variable is $D_{1.30}$ and Dependent Variable is $C_{\text{foliage}_\text{Çk}}$

In Table 60, all models are statistically significant at 1% (p-value < 0.01). Particularly noteworthy is the Power model, which exhibits the highest performance ($R^2 = 0.764$). Notably, the Power model attributes 76.4% of the variation in foliage carbon storage to the tree diameter ($D_{1.30}$) raised to a specific power. In summary, the results indicate that the Power model is highly effective in explaining the variation in tree foliage carbon stocks of *Pinus nigra* specie.

The overall model is statistically significant at 1% ($F = 197.215$; $p < 0.01$), and the prediction error is relatively low (Std. Error = 0.552 kg). However, there is still some unexplained error by the model (RMSE = 0.977 kg). The graphical representation of the tree foliage carbon storage model is showed in Figure 97.

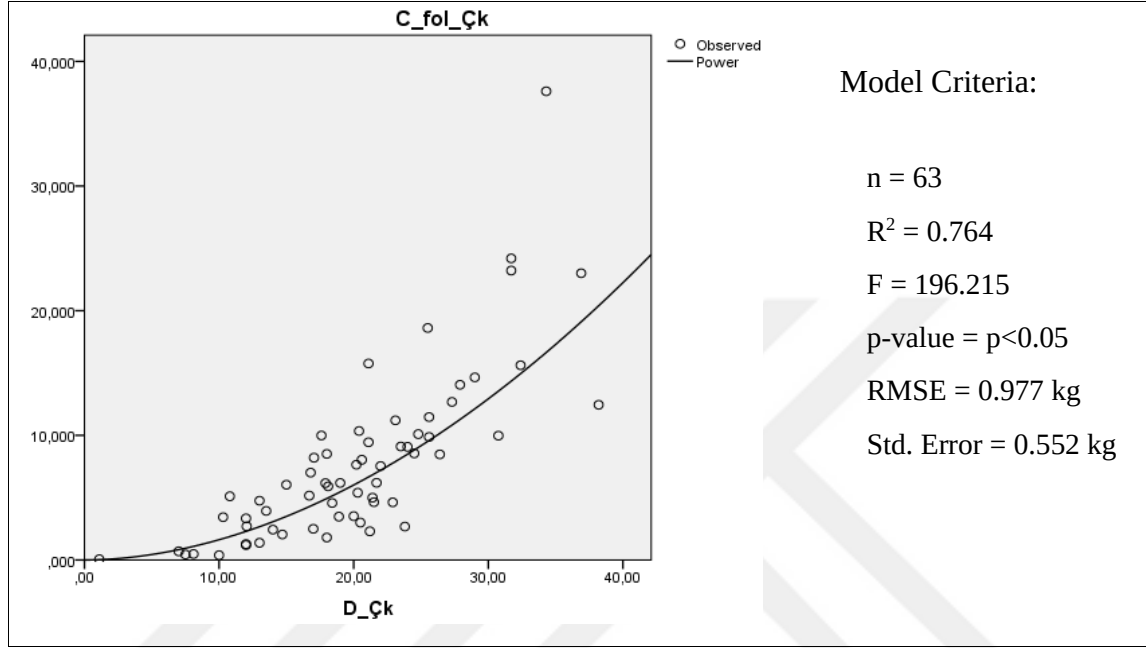


Figure 97. Graphical representation of the Power model for predicting tree foliage carbon storage of *Pinus nigra* specie in ÇkÇz stands

According to Figure 97, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree foliage carbon storage prediction. The power curve represents the relationship between tree diameters and tree foliage carbon storage of *Pinus nigra* specie considered in the natural mixed stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on carbon storage in tree leaves. However, increasing tree diameter leads to an exponential increase in carbon stocks in the tree foliage of *Pinus nigra* specie. The power exponent ($b_1 = 1.8862$) is indicated by the tree diameter coefficient ($b_0 = 0.02112$).

- Tree Foliage Carbon Storage Modeling of *Pinus brutia* Using $D_{1.30}$

Table 61 presents the results of analysis of the allometric relationship between diameter and carbon storage of *Pinus brutia* trees in natural mixed stands in ÇkÇz.

Table 61. Foliage carbon prediction models for *Pinus brutia* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.290	24.933	1	61	.000	-6.773	.725		
Logarithmic	.237	18.964	1	61	.000	-23.901	10.950		
Inverse	.104	7.054	1	61	.010	12.970	-68.709		
Quadratic	.291	12.324	2	60	.000	-4.911	.523	.005	
Cubic	.295	8.210	3	59	.000	-.099	-.407	.056	-.001
Compound	.593	88.799	1	61	.000	.289	1.141		
Power	.653	114.573	1	61	.000	.005	2.306		
S	.459	51.729	1	61	.000	2.668	-18.353		
Growth	.593	88.799	1	61	.000	-1.240	.132		
Exponential	.593	88.799	1	61	.000	.289	.132		
Logistic	.593	88.799	1	61	.000	3.454	.877		

Independent variable is $D_{1.30}$ and Dependent Variable is $C_{foliage_Çz}$

all models are statistically significant at 1% (p-value < 0.01). The top-performing models (Table 61) that can be used to predict tree foliage carbon storage in the *Pinus brutia* species in the natural mixed stands of ÇkÇz are the Compound, Growth, Exponential, Logistic and Power models (R² ranging from 0.593 to 0.653). Particularly noteworthy is the Power model, which demonstrates the highest performance (R²=0.653). The results suggest that the Power model is highly effective in explaining the variation in tree foliage carbon stocks for *Pinus brutia* species. The model is statistically significant at 5% (F=114.573; p<0.05), and the prediction error is relatively low (Std. Error=0.719 kg). However, there remains some unexplained error in the model (RMSE=0.969 kg). The mathematical expression of the model is given by the following relationship:

$$C_{foliage_Çz} = 0.00493684D_{1.30}^{2.305911} \quad (78)$$

where $C_{foliage_Çz}$ is the total carbon stock of tree foliage (kg), $D_{1.30}$ is the tree diameters (cm). This model attributes 65.3% of the variation in foliage carbon the tree diameter ($D_{1.30}$) raised to a specific power. The model graphical representation is given in Figure 98 (next page).

According to Figure 98, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree foliage carbon storage prediction. The power curve represents the relationship between tree diameters and tree foliage carbon storage of *Pinus brutia* specie considered in the natural mixed stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters have a non-linear effect on carbon storage in tree foliage.

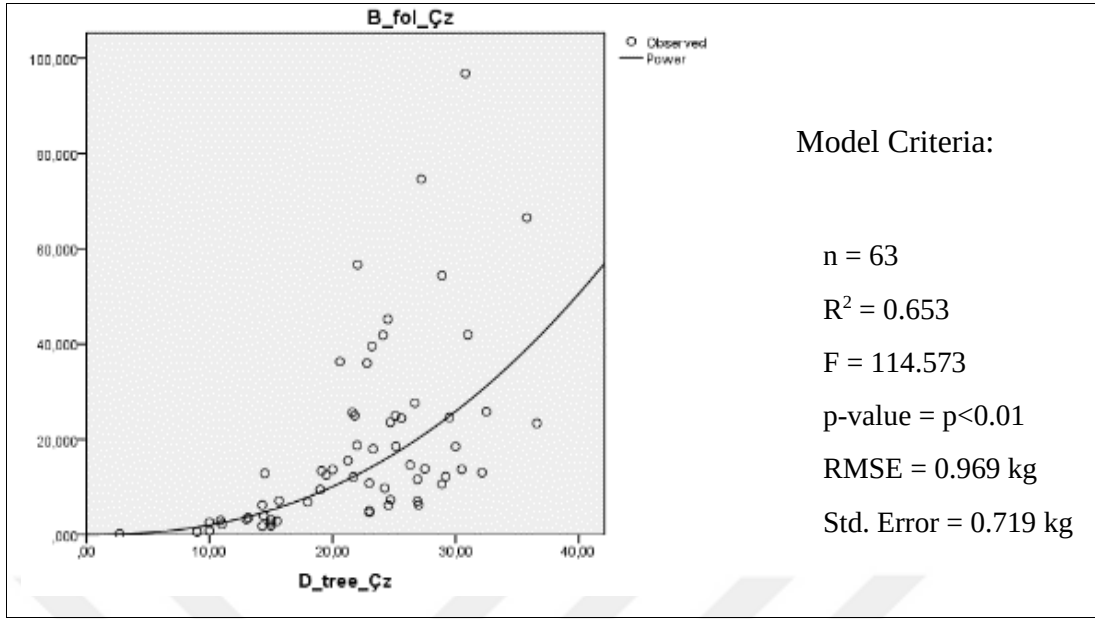


Figure 98. Graphical representation of the Power model for tree foliage carbon storage model of *Pinus brutia* in ÇkÇz stands

However, increasing tree diameter leads to an exponential increase in carbon storage in the tree foliage of *Pinus brutia* species. The power exponent ($b_1 = 2.3059$) is indicated by the tree diameter coefficient ($b_0 = 0.004937$).

f. Results from Tree Bark Carbon Storage Modeling using Diameter at Breast Height ($D_{1.30}$)

- Tree Bark Carbon Storage Modeling of *Pinus nigra* using $D_{1.30}$

The results obtained from tree bark carbon storage modeling of *Pinus nigra* species in natural mixed stands of ÇkÇz, are presented in Table 62 (next page). According to Table 62, all models are statistically significant at 1% ($p\text{-value} < 0.01$). The mathematical relationships between tree diameter and bark carbon storage in *Pinus nigra* considered in natural mixed stands of ÇkÇz, can be explained by several non-linear models. Quadratic, Compound, Growth, Exponential, Logistic and Power models presents more accurate and high performance (R^2 ranged from 0.864 to 0.907). Particularly, the Power model is the first high perform model ($R^2 = 0.907$) that can explain 90.7% of the variation in tree bark carbon storage to the power of the diameter ($D_{1.30}$). Overall, the results demonstrate that the Power model provides a robust explanation for the variation in tree bark carbon storage of *Pinus nigra* specie.

Table 62. Bark carbon prediction models for *Pinus nigra* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.805	247.416	1	60	.000	-8.471	.754		
Logarithmic	.650	111.441	1	60	.000	-30.326	12.606		
Inverse	.460	51.023	1	60	.000	15.980	-162.020		
Quadratic	.887	230.958	2	59	.000	2.001	-.333	.025	
Cubic	.890	155.778	3	58	.000	-2.558	.441	-.013	.001
Compound	.864	379.804	1	60	.000	.378	1.133		
Power	.907	585.992	1	60	.000	.004	2.379		
S	.837	307.322	1	60	.000	3.533	-34.927		
Growth	.864	379.804	1	60	.000	-.972	.125		
Exponential	.864	379.804	1	60	.000	.378	.125		
Logistic	.864	379.804	1	60	.000	2.643	.883		

Independent variable is $D_{1.30}$ and Dependent Variable is $C_{bark_Çk}$

The model is statistically significant at 1% ($F=585.992$; $p<0.01$), and the prediction error is relatively low (Std. Error=0.285 kg). However, there is still some unexplained error remaining in the model (RMSE=0.871 kg). The mathematical expression of this tree bark carbon storage model is given below:

$$C_{bark_Çk} = 0.0042858D_{1.30}^{2.3791988} \quad (79)$$

where $C_{bark_Çk}$ is the total carbon storage model (kg); $D_{1.30}$ is the tree diameters (cm).

The graphical expression of the Çk tree bark carbon storage model is presented in Figure 99.

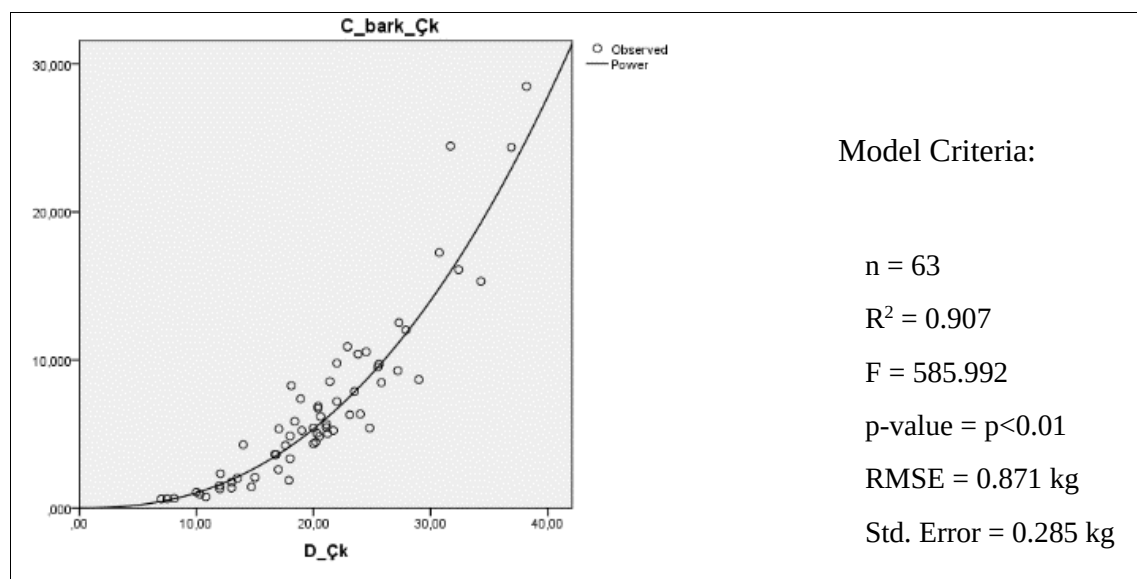


Figure 99. Graphical representation of the Power model for predicting tree bark biomass storage of *Pinus nigra* specie in ÇkÇz stands

According to Figure 99, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree bark carbon storage prediction. The power curve represents the relationship between tree diameters and tree bark carbon storage of *Pinus brutia* specie considered in the natural mixed stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on carbon storage in trees' bark. However, increasing tree diameter leads to an exponential increase in carbon storage in the tree bark of *Pinus nigra* specie. The power exponent ($b_1 = 2.3792$) is indicated by the tree diameter coefficient ($b_0 = 0.00429$).

- Results from Tree Bark Carbon Storage Modeling of *Pinus brutia* using $D_{1.30}$

The results obtained from bark carbon storage modeling of *Pinus brutia* trees in natural mixed stands of ÇkÇz, are presented in Table 63.

Table 63. Bark carbon prediction models for *Pinus brutia* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.647	111.968	1	61	.000	-4.095	.439		
Logarithmic	.517	65.309	1	61	.000	-14.226	6.556		
Inverse	.223	17.524	1	61	.000	7.867	-40.941		
Quadratic	.653	56.457	2	60	.000	-2.318	.245	.005	
Cubic	.682	42.254	3	59	.000	3.434	-.869	.065	-.001
Compound	.754	187.151	1	61	.000	.249	1.134		
Power	.896	524.191	1	61	.000	.004	2.293		
S	.770	203.809	1	61	.000	2.504	-20.198		
Growth	.754	187.151	1	61	.000	-1.391	.126		
Exponential	.754	187.151	1	61	.000	.249	.126		
Logistic	.754	187.151	1	61	.000	4.018	.882		

Independent variable is $D_{1.30}$ and Dependent Variable is $C_{bark_Çz}$

The most effective models (Table 63) that can be used to estimate tree bark carbon storage of *Pinus brutia* specie within ÇkÇz's natural mixed stands, are Compound, Growth, Exponential, Logistic, S-Curve and Power models (R^2 ranged from 0.754 to 0.896). All models are statistically significant at 1% (p-value<0.01). Particularly, the Power model is the most efficient ($R^2 = 0.896$). It attributes 90.5% of the variation in tree bark carbon storage to the power of the diameter ($D_{1.30}$). Overall, the results demonstrate that the Power model provides a robust explanation for the variation in tree stem carbon storage of *Pinus brutia* specie.

The model is statistically significant at 1% ($F = 524.191$; $p < 0.01$), and the prediction error is relatively low (Std. Error = 0.335 kg). However, there is still some unexplained error remaining in the model (RMSE = 0.966 kg). The mathematical expression is given below:

$$C_{\text{bark}_\text{Çz}} = 0.0039102D_{1.30}^{2.2925086} \quad (80)$$

where $C_{\text{bark}_\text{Çz}}$ is the carbon storage model (kg); $D_{1.30}$ is the tree diameters (cm). The graphical expression of the Çk tree bark biomass model is presented in Figure 100.

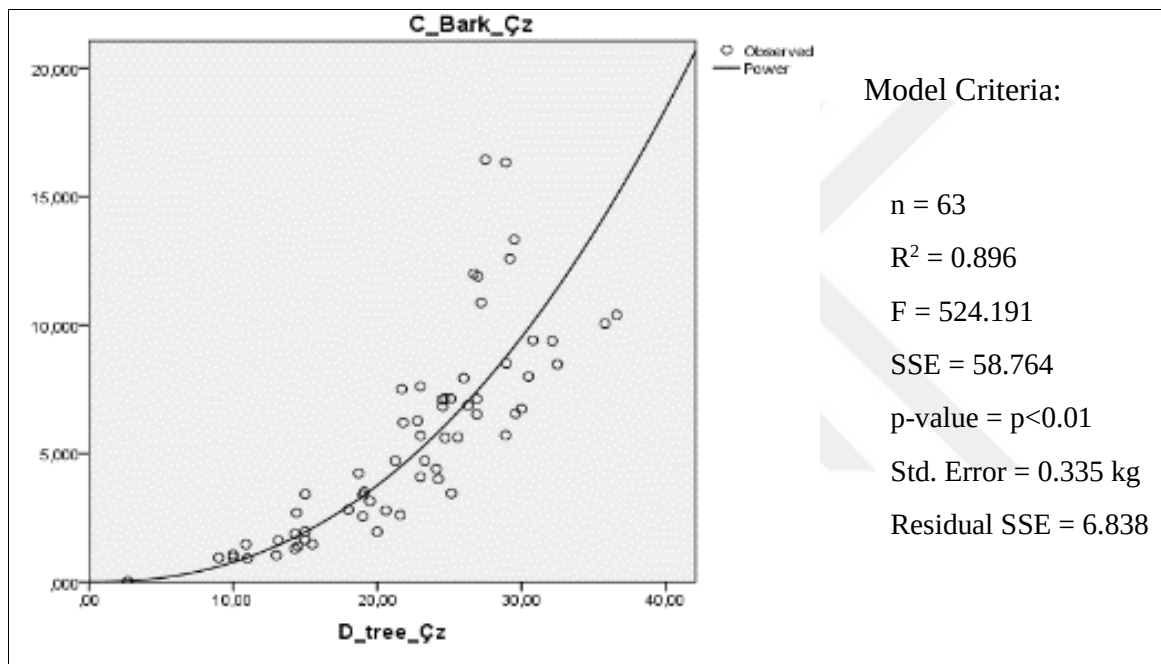


Figure 100. Graphical representation of the Power model curve for tree bark carbon storage of *Pinus brutia* specie in ÇkÇz stands

According to Figure 100, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the tree bark carbon prediction. The power curve represents the relationship between tree diameters and tree bark carbon of *Pinus brutia* specie considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters (D) have a non-linear effect on carbon storage in tree's bark. However, increasing tree diameter leads to an exponential increase in biomass in the tree bark of *Pinus brutia* specie. The power exponent ($b_1 = 2.29251$) is indicated by the tree diameter coefficient ($b_0 = 0.00391$).

g. Results from Analysis of Individual Tree Carbon Storage Modeling Using Diameter at Breast Height ($D_{1.30}$) in Non-Linear Regression

- Individual Tree Carbon Storage Modeling of *Pinus nigra* Using $D_{1.30}$

The predictive models for estimating single-tree carbon storage in *Pinus nigra* specie within the natural mixed stands of ÇkÇz in Türkiye, led to the results in Table 64.

Table 64. Individual tree carbon models for *Pinus nigra* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.769	203.537	1	61	.000	-98.608	8.877		
Logarithmic	.438	47.623	1	61	.000	-189.445	92.234		
Inverse	.080	5.295	1	61	.025	90.705	-183.720		
Quadratic	.909	299.487	2	60	.000	29.330	-6.063	.380	
Cubic	.914	208.200	3	59	.000	-.973	.591	-.011	.007
Compound	.838	314.871	1	61	.000	1.770	1.179		
Power	.943	1005.416	1	61	.000	.044	2.409		
S	.565	79.182	1	61	.000	4.460	-8.701		
Growth	.838	314.871	1	61	.000	.571	.165		
Exponential	.838	314.871	1	61	.000	1.770	.165		
Logistic	.838	314.871	1	61	.000	.565	.848		

Independent variable is $D_{1.30}$ and Dependent Variable is $C_{tree_Çk}$

In Table 58, all models are statistically significant at 1% (p-value<0.01). Logistic, Exponential, Growth, Compound, Quadratic and Power models presents the top-performing criteria for estimating individual carbon storage of *Pinus nigra* tree species considered in ÇkÇz's natural mixed stands. The two most accurate models are the Quadratic model ($R^2=0.909$) and the Power model ($R^2 = 0.943$). Notably, the Power model attributes 94.3% of the variation in tree carbon storage to the power of the tree diameter ($D_{1.30}$). The results indicate that the Power model explains the variation in the total single-tree carbon storage of *Pinus nigra* specie very well. The model is globally significant at 1% ($F=1005.416$; $p<0.01$), and the prediction error is relatively low ($SE=0.307$ kg). However, there is still a certain level of error not explained by the model ($RMSE=1.228$ kg). The mathematical expression of the Anatolian Black Pine tree carbon model is provided below:

$$C_{tree_Çk} = 0.0436999D_{1.30}^{2.4088081} \quad (81)$$

where $C_{tree_Çk}$ is the tree biomass (kg); $D_{1.30}$ is the tree diameter (cm).

The graphical expression of the tree carbon storage model is presented in Figure 101.

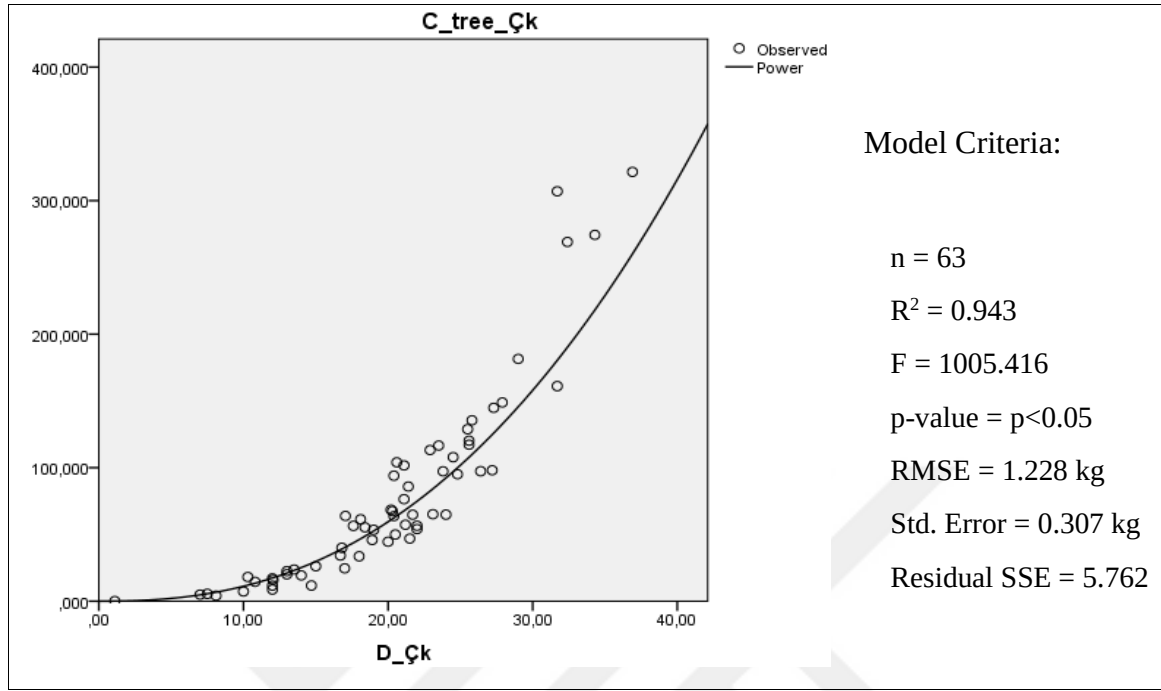


Figure 101. Graphical representation of the Power model for predicting individual tree carbon storage of *Pinus brutia* in ÇkÇz stands

According to Figure 101, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the single-tree carbon storage prediction. The power curve represents the relationship between tree diameters and total tree carbon storage of *Pinus nigra* specie considered in the Natural Mixed Stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters ($D_{1.30}$) have a non-linear effect on carbon storage in the entire tree. However, increasing tree diameter leads to an exponential increase in carbon stocks in the whole tree of *Pinus nigra* specie. The power exponent ($b_1 = 2.4088$) is indicated by the tree diameter coefficient ($b_0 = 0.0437$).

- Individual Tree Carbon Storage Modeling of *Pinus brutia* Using $D_{1.30}$

The predictive models for estimating single-tree carbon storage in *Pinus brutia* specie within the natural mixed stands of ÇkÇz in Türkiye, led to the results in Table 65.

Table 65. Individual tree carbon models for *Pinus brutia* tree species

Equation	Model Summary					Parameter Estimates			
	R ²	F	df1	df2	Sig.	Constant	b ₁	b ₂	b ₃
Linear	.795	237.151	1	61	.000	-97.089	8.495		
Logarithmic	.590	87.647	1	61	.000	-280.119	122.615		
Inverse	.232	18.459	1	61	.000	131.344	-734.639		
Quadratic	.859	183.279	2	60	.000	8.040	-2.984	.276	
Cubic	.859	120.304	3	59	.000	15.414	-4.406	.353	-.001
Compound	.860	375.061	1	61	.000	2.019	1.165		
Power	.958	1380.228	1	61	.000	.017	2.702		
S	.737	171.044	1	61	.000	5.328	-22.627		
Growth	.860	375.061	1	61	.000	.703	.153		
Exponential	.860	375.061	1	61	.000	2.019	.153		
Logistic	.860	375.061	1	61	.000	.495	.858		

Independent variable is $D_{1.30}$ and Dependent Variable is $C_{tree_Çz}$

In Table 65, Logistic, Exponential, Growth, S-Curve, Compound, Quadratic and Power models presents the top-performing criteria for estimating individual carbon storage of *Pinus brutia* tree species considered in ÇkÇz's natural mixed stands (R^2 ranged from 0.859 to 0.958). The most accurate model is the Power model ($R^2 = 0.958$). Notably, the Power model attributes 94.3% of the variation in tree carbon storage to the power of the tree diameter ($D_{1.30}$). The results indicate that the Power model explains the variation in the total single-tree carbon storage of *Pinus brutia* specie very well. The model is globally significant at 1% ($F=1080.228$; $p<0.01$), and the prediction error is relatively low (Std. Error = 0.244 kg). However, there is still a certain level of error not explained by the model (RMSE=1.144 kg). The mathematical expression of the model is provided below:

$$C_{tree_Çz} = 0.0166907D_{1.30}^{2.7019116} \quad (82)$$

where $C_{tree_Çz}$ is the single-tree total biomass (kg); $D_{1.30}$ is the tree diameters (cm).

The graphical expression of the tree carbon storage model is presented in Figure 102 (next page). According to Figure 102, the prediction model produces a parabola-shaped curve, meaning that the data show a trend of exponential growth in the single-tree carbon storage prediction. The power curve represents the relationship between tree diameters and total tree carbon storage of *Pinus brutia* specie considered in the natural mixed stands of ÇkÇz in Türkiye. This relationship follows a power model, where changes in tree diameters ($D_{1.30}$) have a non-linear effect on carbon storage in the entire tree.

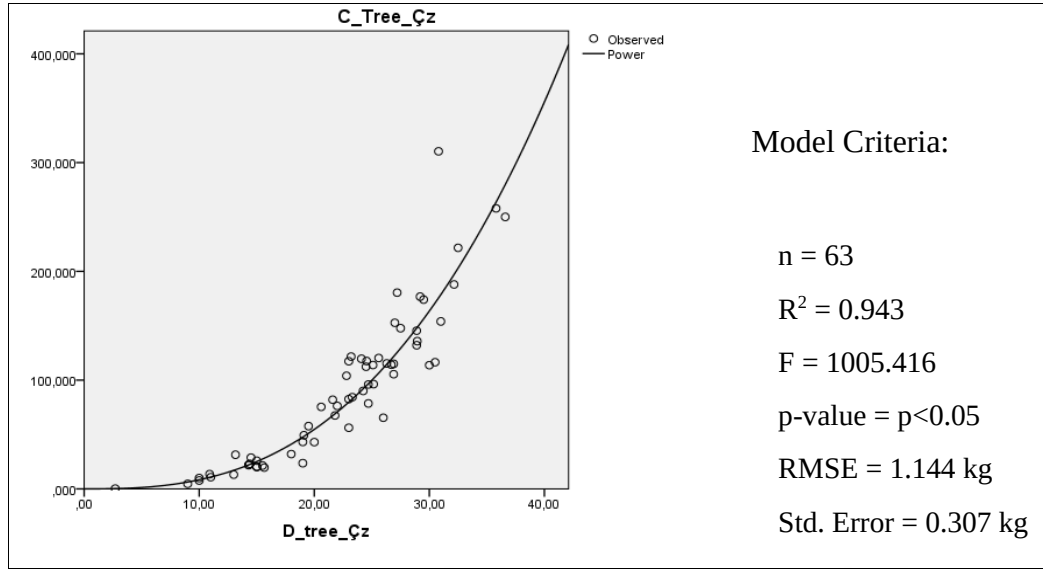


Figure 102. Graphical representation of the of Power model for individual tree carbon storage of *Pinus brutia* in ÇkÇz stands

However, increasing tree diameter leads to an exponential increase in carbon stocks in the whole tree of *Pinus brutia* specie. The power exponent ($b_1 = 2.7019$) is indicated by the tree diameter coefficient ($b_0 = 0.0167$).

h. Results from Tree Carbon Storage Modeling Using Diameter at Breast Height ($D_{1.30}$) and Height (H) in MLP-ANN and MLR

The use of Artificial Neural Network (ANN) method, specifically through MLP (Multi-Layer Perceptron), and Multiple Linear Regression (MLR) methods is commonly motivated by the complexity of the relationships expected to emerge between multiple predictors and one or more predictands. By using Diameter at Breast Height ($D_{1.30}$) and Tree Height (H) as predictors, this approach has allowed us to develop practical tree carbon storage prediction models for each of the tree species studied in natural mixed stands of *Pinus nigra* and *Pinus brutia*.

- Results from Tree Carbon Storage Modeling of *Pinus nigra* using $D_{1.30}$ and $H_{Çk}$

Using the Artificial Neural Network to predict the carbon storage of *Pinus nigra* trees in the Natural Mixed Stands of ÇkÇz in Türkiye, 25 ANN models were generated by intervening on the MLP architecture.

The number of input layers remained at 2 ($D_{1.30_Çk}$, $H_{Çk}$), but the number of hidden layers varied between 1 and 2, and the number of neurons (number of units) varied between 2 and 10. The ANN model selected in this study is illustrated by Figure 103.

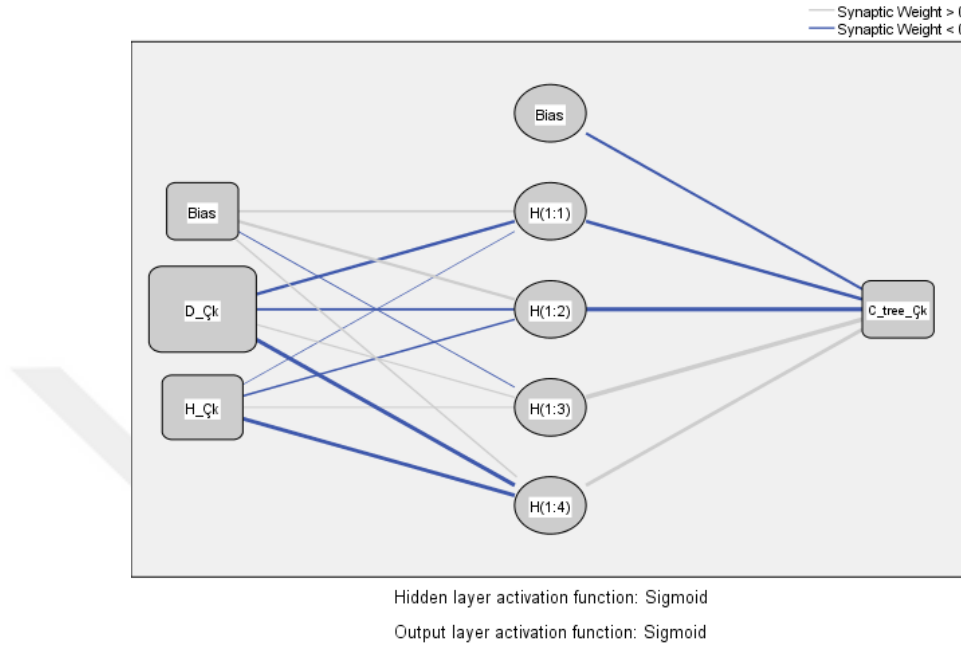


Figure 103. ANN-MLP model (1-4-1) of carbon storage for individual tree of *Pinus nigra* specie in ÇkÇz stands

Figure 103 shows the structure of ANN Model (1-4-1) of prediction the single-tree carbon storage of *Pinus nigra* in Natural Mixed Stands of ÇkÇz. To generate the model, MLP algorithm used the diameter ($D_{1.30_Çk}$) and height ($H_{tree_Çk}$), as well as two hidden layers of four neurons each. When fitting the model, we noticed that certain connections (synaptic weights) between the layers had inhibitory effects on the output of the post-synaptic neuron ($w < 0$), the impact of which is to reduce the activity of the post-synaptic neuron due to the negative weight. For positive neurons ($w > 0$), the connection between post-synaptic neurons had an excitatory effect, with the impact on computation being an increase in its activity. In the model (Figure 103), the allocation of variables for training and testing performed by the MLP Algorithm, is presented in Table 66 (next page).

In Table 66, it can be seen that the MLP algorithm assigned 68.3% of the diameter and height of *Pinus nigra* trees in the construction of the carbon storage prediction model in trees, and 31.7% of these input variables, for testing the model.

Table 66. Summary of *Pinus nigra* tree biomass data allocation in MLP

Case Processing Summary (Carbon)			
<i>Pinus nigra</i> (A. Black Pine)		N	Percent
Sample	Training	43	68.3%
	Testing	20	31.7%
Valid		63	100,0%

The MLP algorithm also brought out the importance of each independent variable in the construction of the model, as shown in Figure 104.

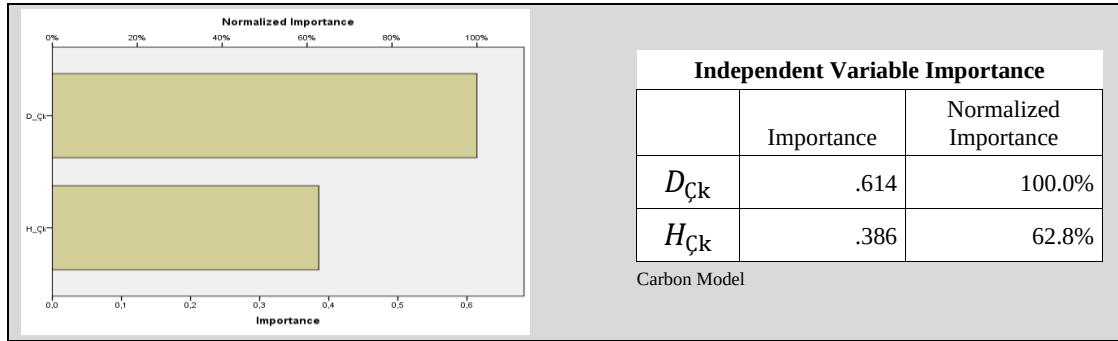


Figure 104. Importance of predictors in the modeling of individual tree carbon storage of *Pinus nigra* in ÇkÇz stands

According to Figure 104, tree diameter ($D_{1.30-Çk}$) had an influence of 61.4% on model construction, while tree height ($H_{Çk}$) had a 38.6% influence. It can be seen that the tree diameter was used in its entirety throughout the process (100%), while 62.8% of the tree heights supplied were used. With this distribution led to low errors in the model training and testing processes. The errors affecting model performance and calculated by MLP are summarized in Table 67 (next page). According to results (Table 67) the errors calculated by the algorithm in training ($SSE=0.063$ kg; $RE=0.058$ kg; $RMSE_{\text{training}} = 0.038$ kg) and in testing ($SSE=0.014$ kg; $RE=0.033$ kg; $RMSE_{\text{testing}} = 0.028$ kg) are relatively low. Furthermore, a strong correlation was observed between the calculated carbon data ($C_{\text{tree-Çk}}$) and the data predicted ($C_{\text{tree-Çk-ANN}}$) by the algorithm using the *MLP-ANN Model 1-4-1* ($RMSE = 0.0105$ kg). This correlation between $C_{\text{tree-Çk}}$ and $B_{\text{tree-Çk-ANN}}$ is very high with the Linear model ($R^2_{\text{Linear}} = 0.947$) and more with the Quadratic model ($R^2_{\text{Quadratic}} = 0.948$).

Table 67. Performance indicators of *Pinus nigra* tree biomass models in MLP

Carbon Model Summary of <i>Pinus nigra</i> in ÇkÇz (1:4:1)		
Training	Sum of Squares Error	.063
	Relative Error	.058
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00.00
Testing	Sum of Squares Error	.014
	Relative Error	.054
Dependent Variable: $C_{\text{tree}_\text{Çk}}$		

In a confidence interval at 99%, the mathematical expressions (Linear and Quadratic) of these relationships between observed and predicted values of *Pinus brutia* tree carbon in natural mixed stands of ÇkÇz, are presented as follows:

$$\text{ANN Linear} \quad C_{\text{tree}_\text{Çk_ANN}} = 9.65 + 0.89(C_{\text{tree}_\text{Çk}}) \quad (83)$$

$$\text{ANN Quadratic} \quad C_{\text{tree}_\text{Çk_ANN}} = 10.95 + 0.86(C_{\text{tree}_\text{Çk}}) - 0.000989(C_{\text{tree}_\text{Çk}})^2 \quad (84)$$

where $C_{\text{stem}_\text{Çk_ANN}}$ is the tree carbon quantities (kg) predicted by MLP-ANN (1-4-1); $C_{\text{stem}_\text{Çk}}$ is the observed tree carbon (kg).

The graphical expression of the correlation between observed and predicted tree carbon values is given in Figure 105.

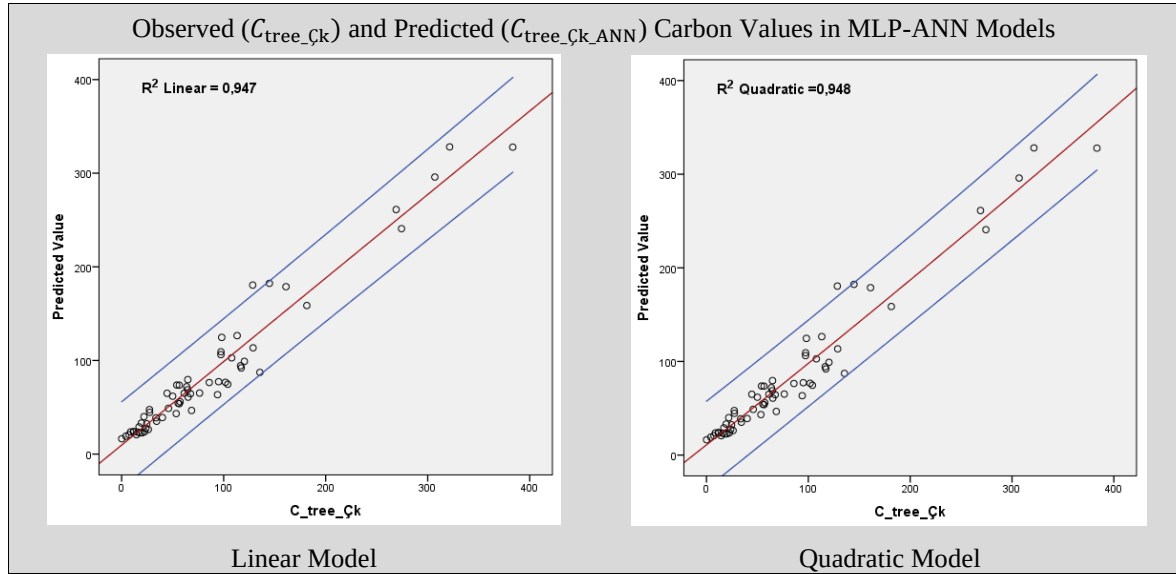


Figure 105. Graphical (red line) representations of the correlation between the observed and predicted single-tree carbon stocks of *Pinus nigra* specie in ÇkÇz stands resulting from MLP-ANN modeling

To estimate the biomass of *Pinus nigra* trees using diameter and height as predictors, the multiple regression method was adopted, using a "Stepwise" algorithm. The results of this analysis, leading to the establishment and selection of a double-entry equation, are summarized in Table 68.

Table 68. Summary of double-entry tree carbon equations for *Pinus nigra* trees

<i>Pinus nigra</i> Tree Carbon Multiple Linear Regression Models' Summary										
Model $MLR_{Çk}$	R^2	R^2_{Adj}	F	Se	df1	df2	Sig.	Parameters		
								b_0	b_1	b_2
1	.772	.768	206.621	38.826	1	61	.000	-122.-61	9.962	
2	.790	.783	112.590	37.611	2	60	.000	-129.223	7.397	5.124

Predictors: (Constant); $D_{1.30_Çk}$, $H_{Çk}$; Dependent Variable: $C_{tree_Çk}$; (n = 63)

According to $MLR_{Çk}$ data in Table 68, $D_{1.30_Çk}$ and $H_{Çk}$ are perfectly explain 79% of the variation in carbon storage in single-tree of *Pinus nigra* in ÇkÇz stands in Türkiye. This model is globally significant at 1% ($F=112,590$; $Se=37.611$; $p<0.01$;). Equations of $MLR_{Çk}$ are illustrated by the following relationships:

$$MLR_{Çk}: C_{stem_Çk_MLR} = -129.223 + 7.397D_{1.30} + 5.124H \quad (85)$$

where $C_{tree_Çk_MRL}$ is the tree carbon prediction model in Multilayer Regression Analysis (kg), $D_{1.30}$ is the tree diameters (cm); $H_{Çz}$ is the tree height (m).

In obtained regression Model 1, tree height was excluded and only diameter was implied in the model. But in Model 2, all predictors ($D_{\text{Çk}}$ and $H_{\text{Çk}}$) were used in model. Analysis of these coefficients led to the results shown in Table 69.

Table 69. Characteristics of tree carbon models for *Pinus nigra* trees in MLR

ANOVA ^a						
<i>MLR</i> _{Çk} Models		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	311469.103	1	311469.103	206.621	.000 ^b
	Residual	91953.903	61	1507.441		
	Total	403423.006	62			
2	Regression	318545.250	2	159272.625	112.590	.000 ^c
	Residual	84877.755	60	1414.629		
	Total	403423.006	62			
a. Dependent Variable: <i>C_{tree_Çk}</i> ; b. Predictors: (Constant), <i>D</i> _{Çk} ; c. Predictors: (Constant), <i>D</i> _{Çk} , <i>H</i> _{Çk}						

Coefficients ^a						
<i>MLR</i> _{Çk} Models		Unstandardized Coefficients			t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-122.061	15.071		-8.099	.000
	<i>D</i> _{Çk}	9.962	.693	.879	14.374	.000
	(Constant)	-129.223	14.947		-8.646	.000
2	<i>D</i> _{Çk}	7.397	1.329	.652	5.566	.000
	<i>H</i> _{Çk}	5.124	2.291	.262	2.237	.029
	(Constant)	-129.223	14.947		-8.646	.000
a. Dependent Variable: <i>C_{tree_Çk}</i>						

All coefficients are statistically significant in the model, especially at 1% (Constant and $D_{\text{Çk}}$), and 5% ($H_{\text{Çk}}$).

- Results from Tree Carbon Storage Modeling of *Pinus brutia* Using $D_{1.30}$ and $H_{\text{Çz}}$

As developed in Section 3.3.2., the same procedure was used to develop and select a (robust) prediction model for the tree carbon storage of *Pinus brutia* specie (Çz) in the natural stands of ÇkÇz in Türkiye, based on the diameter and height of each tree. The data have been distributed by the algorithm, as shown in Table 70.

Table 70. Summary of carbon variables allocation in MLP

Case Processing Summary (Carbon)			
<i>Pinus brutia</i> (T. Red Pine)		N	Percent
Sample	Training	41	65.1%
	Testing	22	34.9%
Valid		63	100.0%
Excluded		296	

According to Table 70, the variables (predictors) were distributed by the MLP algorithm. About 65.1% of the input values (diameter and height) were used for model training and 34.9% for model testing. For common exclusion reasons (missing values, outliers, duplicates or other specific criteria), 296 exclusion cases were recorded. The MLP algorithm also highlighted the importance of each independent variable in the construction of the model, as shown in Figure 106.

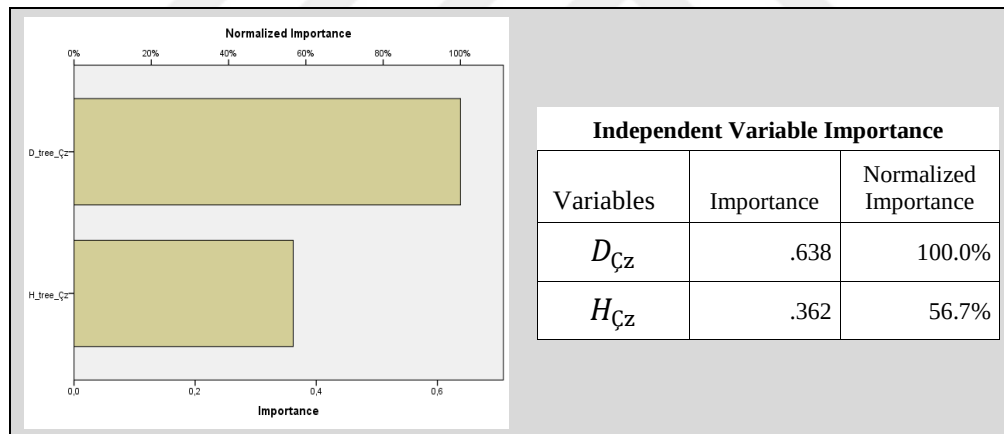


Figure 106. Importance of predictors in the modeling of individual tree carbon storage of *Pinus brutia* specie in ÇkÇz stands

In Figure 106, results indicate that the tree diameter ($D_{1.30_Çz}$) had a 63.8% influence on model construction, while Tree Height ($H_{Çz}$) had a 36.2% influence. It can be seen that the diameter was used in its entirety throughout the process (100%), while only 56.7% of the tree heights supplied were used. With this distribution led to low errors in the model training and testing processes. The best ANN model proposed by the MLP algorithm for predicting the carbon of *Pinus brutia* trees in natural mixed stands of ÇkÇz is shown in Figure 107.

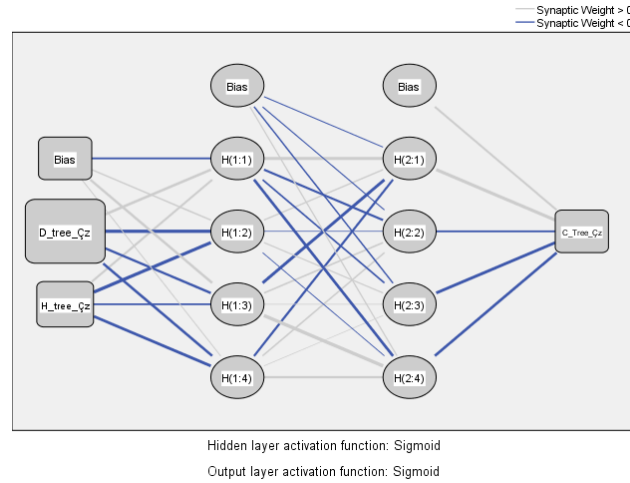


Figure 107. ANN-MLP model (1-4-4-1) for carbon storage of individual tree in *Pinus brutia* specie in ÇkÇz stands

According to Figure 107, the best ANN-MLP model for predicting the biomass of *Pinus brutia* trees in Natural Mixed Stands in ÇkÇz consists of 1 input layer, 2 hidden layer with 4 neurons (units), and 1 output layer (1-4-4-1). The summary of the model, characterized by the errors calculated by the algorithm, is shown in Table 71.

Table 71. Performance indicators of *Pinus brutia* tree carbon models in MLP

Carbon Model Summary of <i>Pinus brutia</i> in ÇkÇz (1:4:4:1)		
Training	Sum of Squares Error	.168
	Relative Error	.148
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00.02
Testing	Sum of Squares Error	.045
	Relative Error	.106
Dependent Variable: $C_{tree_Çz}$; a. Error computations are based on the testing sample.		

According to results (Table 71) the errors calculated by the algorithm in training (SSE=0.168 kg; RE=0.148 kg; $RMSE_{training} = 0.064 \text{ kg}$) and in testing (SSE=0.045 kg; RE=0.106 kg; $RMSE_{testing} = 0.045 \text{ kg}$) are relatively low. Furthermore, a strong correlation was observed between the calculated carbon data ($C_{tree_Çk}$) and the data predicted ($C_{tree_Çk_ANN}$) by the algorithm using the *MLP-ANN Model 1-4-4-1* ($RMSE = 0.005 \text{ kg}$).

This correlation between $C_{\text{tree}_\text{Çk}}$ and $B_{\text{tree}_\text{Çk_ANN}}$ is very high with the Linear model ($R^2_{\text{Linear}} = 0.868$) and more with the Quadratic model ($R^2_{\text{Quadratic}} = 0.881$). In a confidence interval at 99%, the mathematical expressions (Linear and Quadratic) of these relationships between observed and predicted values of *Pinus brutia* tree carbon in natural mixed stands of ÇkÇz, are presented as follows:

$$\text{ANN Linear} \quad C_{\text{tree}_\text{Çz_ANN}} = 15.96 + 0.82(C_{\text{tree}_\text{Çz}}) \quad (86)$$

$$\text{ANN Quadratic} \quad C_{\text{tree}_\text{Çz_ANN}} = 5.15 + 1.09(C_{\text{tree}_\text{Çz}}) - 0.000103(C_{\text{tree}_\text{Çz}})^2 \quad (87)$$

where $C_{\text{stem}_\text{Çz_ANN}}$ is the tree biomass quantities predicted by MLP-ANN (kg); $C_{\text{stem}_\text{Çz}}$ is the observed tree biomass (kg).

The graphical expression of the correlation between observed and predicted tree carbon quantities of *Pinus brutia*, is given in Figure 108.

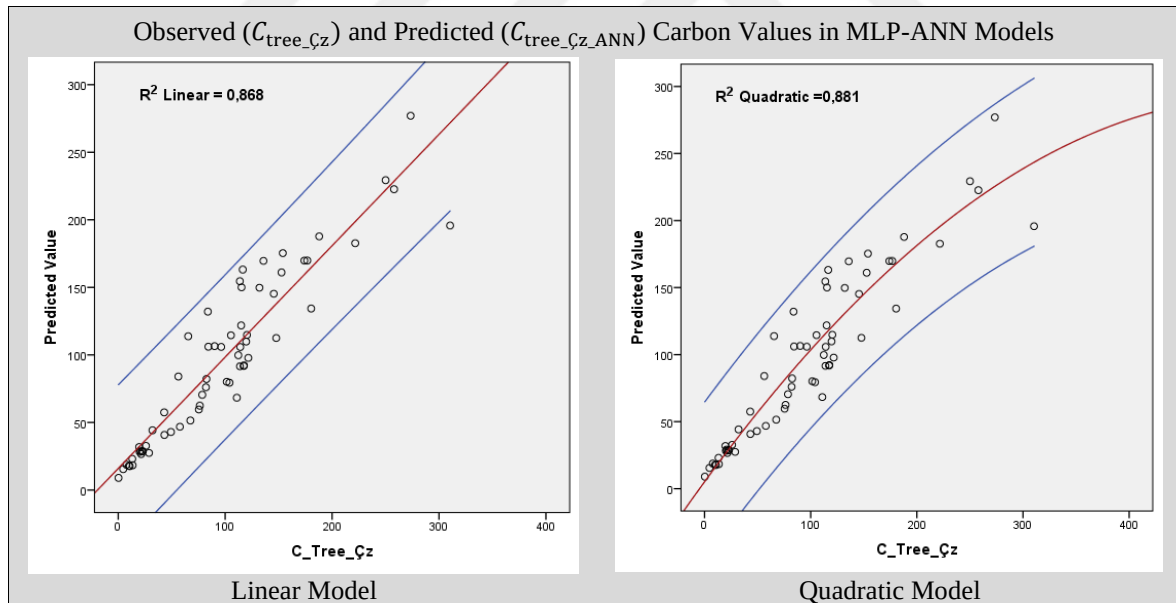


Figure 108. Graphical (red line) representations of the correlation between the observed and predicted single-tree carbon stocks of *Pinus brutia* specie in ÇkÇz stands resulting of MLP-ANN modeling

The results of the Multiple Linear Regression (MLR) analysis for the Stepwise-based model for predicting the carbon storage of *Pinus brutia* trees in the natural mixed stands of ÇkÇz are given in Table 72.

Table 72. Summary of double-entry tree carbon equation for *Pinus brutia* trees

Carbon Storage Multiple Linear Regression Models of <i>Pinus brutia</i> (n=63)										
Model <i>MLR</i> _{Çz}	<i>R</i> ²	<i>R</i> _{Adj} ²	<i>F</i>	Se	df1	df2	Sig.	Parameters		
								<i>b</i> ₀	<i>b</i> ₁	<i>b</i> ₂
1	.796	.793	237.894	32.027	1	61	.000	-94.215	8.384	/
2	.808	.802	126.417	31.305	2	60	.000	-102.668	6.229	4.638
Predictors: (Constant), <i>D</i> _{1.30_Çz} (cm), <i>H</i> _{Çz} (m); Dependent Variable: <i>C</i> _{tree_Çz}										

Table 72 shows two models derived from Multiple Linear Regression (MLR) analysis, based on Stepwise, for the prediction of *Pinus brutia* tree biomass. *MLR*_{Çz} equations are illustrated by the following relationship:

$$MLR_{\text{Çz}}: C_{\text{tree_Çz_MLR}} = -102.668 + 6.229D_{1.30} + 4.638H_{\text{Çz}} \quad (88)$$

where *C*_{tree_Çz_MRL} is the tree carbon stock (kg) predicted in Multilayer Regression Analysis, *D*_{1.30} is the tree diameters (cm); *H*_{Çz} is the tree height (m).

The *MLR*_{Çz} model has taken both predictors affected by their coefficient, into account and shows a higher performance (*R*² = 0.808). Indeed, the variance in tree *D*_{1.30_Çz} and *H*_{Çz} can explain the 80.8% of the variability in carbon storage capacity by tree of *Pinus nigra* in ÇkÇz stands. The model is statistically significant at 1% (*F*=126.417; Std. Error = 31.305; *p* < 0.05; RMSE=44.345 kg). In obtained regression Model 1, tree height was excluded and only diameter was implied in the model. But in Model 2, all predictors (*D*_{Çz} and *H*_{Çz}) were used in model. Analysis of these coefficients led to the results shown in Table 73.

Table 73. Characteristics of tree carbon models for *Pinus brutia* tree in MLR

ANOVA ^a						
<i>MLR</i> _{Çz} Models		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	244011.508	1	244011.508	237.894	.000 ^b
	Residual	62568.716	61	1025.717		
	Total	306580.225	62			
2	Regression	247779.792	2	123889.896	126.417	.000 ^c
	Residual	58800.432	60	980.007		
	Total	306580.225	62			
a. Dependent Variable: <i>C_{tree,Çz}</i> ; b. Predictors: (Constant), <i>D_{Çz}</i> ; c. Predictors: (Constant), <i>D_{Çz}</i> , <i>H_{Çz}</i>						

Coefficients ^a						
<i>MLR</i> _{Çz} Models		Unstandardized Coefficients			t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-94.215	13.051		-7.219	.000
	<i>D</i> _{Çz}	8.384	.544	.892	15.424	.000
2	(Constant)	-102.668	13.465		-7.625	.000
	<i>D</i> _{Çz}	6.229	1.220	.663	5.104	.000
	<i>H</i> _{Çz}	4.638	2.365	.255	1.961	.055
a. Dependent Variable: <i>C_{tree,Çz}</i>						

All coefficients are statistically significant in the model, especially at 1% (Constant and *D_{Çz}*), and 10% (*H_{Çz}*).

3.3.3. Results from Ecosystem Above/Below-Ground Biomass and Carbon Stocks in ÇkÇz Forest Stands in Türkiye

The total amount of biomass and carbon stored in the natural mixed stands of Anatolian Black Pine (*Pinus nigra*) and Turkish Red Pine (*Pinus brutia*) analyzed in this research is the overall sum of estimates obtained from all biomass and carbon pools. These pools concern living tree reservoirs (trees, stems, branches, bark and foliage), terrestrial reservoirs (litter, dead wood and living herbaceous plants), and belowground reservoirs (roots and soil organic matter). For the above-ground part of the ecosystems studied, the total above-ground biomass quantities and the corresponding carbon stocks have been determined for the 46 types of forest stands that were surveyed across Türkiye.

- Results from Ecosystem Tree Biomass and Carbon Stocks Analysis

To determine the biomass and carbon storage capacity of each tree species (*Pinus nigra* and *Pinus brutia*) inventoried in each experimental plot, the biomass and carbon equations of each individual tree species were used by considering the diameter as the independent variable. The results are presented in Table 74.

Table 74. Stand above-ground biomass estimated with tree biomass models

Stand Total Biomass and Carbon Estimation Using Tree Prediction Models							
Above-Ground Tree Biomass & Carbon in Ecosystem							
Plot No	N	$B_{\text{tree_stand}}$	$C_{\text{tree_stand}}$	Plot No	N	$B_{\text{tree_stand}}$	$C_{\text{tree_stand}}$
	Tree/ha	kg/ha	kg/ha		Tree/ha	kg/ha	kg/ha
1	333	25040.345	12320.205	24	1075	210432.445	103171.917
2	1550	156587.440	77127.167	25	1375	64112.908	31558.580
3	725	235240.155	115600.424	26	1450	36628.834	18064.978
4	575	201166.434	98910.890	27	800	297279.878	145402.110
5	867	129646.855	63934.273	28	800	335750.912	164111.511
6	700	126326.294	62370.966	29	800	187823.523	91944.378
7	1275	216823.949	106883.753	30	825	227881.278	111602.941
8	800	146991.541	72757.024	31	800	294537.852	144092.957
9	433	75987.441	37406.483	32	517	93976.505	46172.443
10	600	149832.503	73915.346	33	550	116399.665	57285.230
11	383	73537.777	36258.434	34	217	49080.874	24104.069
12	483	87576.274	43223.083	35	250	52820.612	26026.204
13	933	71074.793	35041.372	36	417	89691.978	44106.078
14	433	96189.313	47548.759	37	550	37037.824	18289.196
15	467	55592.713	27482.594	38	617	28671.567	14164.927
16	1075	108099.879	53332.982	39	417	47194.440	23336.134
17	950	96091.410	47325.008	40	267	54023.028	26667.526
18	1000	17762.636	8789.440	41	217	59615.521	29339.577
19	1375	23033.201	11383.026	42	817	60424.798	29852.923
20	1325	20996.619	10395.179	43	283	30596.337	15142.161
21	850	202865.329	99371.753	44	300	27105.452	13387.505
22	825	290287.816	141983.375	45	633	88195.878	43441.097
23	1325	44493.175	21962.604	46	450	143949.890	70810.197
Descriptive Summary							
Above-Ground (t/ha)			Maximum	Minimum		Mean	
BIOMASS		$B_{\text{tree_stand}}$	335.75091	17.76264		114.879911	
CARBON		$C_{\text{tree_stand}}$	164.11151	8.789440		56.465191	
Tree Carbon Content in Total Ecosystem Biomass							
Ecosystem Carbon Content in Biomass			$C_{\text{tree_stand}} = 0.49152B_{\text{tree_stand}}$			49.152%	

It is important to remember here that Carbon Amount refers to the total quantity of carbon present in the pool or environment considered (Above/Below-ground), while *Carbon Content* refers to the proportion or concentration of carbon compared to the total biomass considered.

- Results from Distribution Analysis of Ecosystem Biomass and Carbon Stocks in ÇkÇz Stands

To obtain the overall average total capacity data of ecosystems the data on above and below-ground biomass and carbon stocks were combined (Table 75).

Table 75. Stand above and below-ground biomass quantities in ecosystems

Average Ecosystem Total Biomass Stocks in ÇkÇz (t/ha)					
Stand Levels	Pools	Components	$B_{Total_Ecosystem}$		
			Maximum	Minimum	Mean
Above Ground (AG)	Tree	All	335.750912	17.76264	114.879911
	Terrestrial	Herbaceous	2.959150	0.033000	0.451858
		Litter	64.168000	4.731600	17.443978
		Dead Wood	7.106800	0.114000	2.328002
Below Ground (BG)	Roots	Fine	55.642060	6.487500	25.714332
		Small	15.651272	1.188999	5.449267
		Coarse	82.290000	0.901464	24.982966
	Soil	Organic Matter	16380.226743	1094.986008	7560.873245

The global average results of carbon stock present in the biomass of each ecosystem pools are presented in Table 76.

Table 76. Stand above and below-ground carbon quantities in ecosystems

Average Total Carbon Stocks in ÇkÇz Ecosystem (t/ha)					
Stand Levels	Pools	Components	$C_{Total_Ecosystem}$		
			Maximum	Minimum	Mean
Above Ground (AG)	Tree	All	164.11151	8.789440	56.465191
	Terrestrial	Herbaceous	1.447024	0.015444	0.208346
		Litter	31.185648	1.859519	7.763192
		Dead Wood	3.411264	0.054036	1.109432
Below Ground (BG)	Roots	Fine	26.776756	3.265259	12.370512
		Small	7.684714	0.586177	2.644700
		Coarse	39.327266	0.432703	11.968828
	Soil	Organic Matter	676.487290	31.799556	253.176683

3.3.4. Results from Ecosystem Biomass and Carbon Prediction Modeling

a. Some Predictors Used to Model Ecosystem Biomass and Carbon Storage in ÇkÇz Stands

Prediction models (linear and non-linear regression, and MLP-ANN) for ecosystem biomass and carbon storage of mixed forest of *Pinus nigra* and *Pinus brutia* (ÇkÇz) are developed in this section using stand total biomass (B_{Total_stand}) and carbon (C_{Total_stand}) data. The some forest stand parameters (predictors) are Stand Tree Number (N), Mean Diameter (D_m), Average Height (H_m), Volume (V_{stand}), Basal Area (G_{stand}), Quadratic Diameter (D_q), Top Height (H_{100}), Site Index (SI), Site Density Index (SDI), Stand Density Ratio (SDI), Variation Coefficient (C_v), Crown Closure (CC), Age Class (A_c), and Mix Ratio (R_{mixt}). Some of these parameters depend on others in the process of determining them. For example, D_m and/or H_m are used in the calculation of V , G , D_q , H_{100} , R_{mix} , and C_v . Also, N is used in the calculation of R_{mix} , SDI , and H_{100} is used in the calculation of SI . To minimize autocorrelation, parameters were sorted and models developed with D_m , H_m , CC , N , and SI as predictors. D_m is the main parameter to be involved in modeling and the Age Class in not used in models (A_c). The Statistical analysis of some predictors led to the results shown in Table 77.

Table 77. Descriptive analysis summary of stand variables

Descriptive Statistics of ÇkÇz Stand Models' Predictors					
	N	Minimum	Maximum	Mean	Std. Deviation
N	46	217	1550	732.790	362.116
D_m	46	8.55	30.34	20.097	6.127
D_q	46	9.37	31.70	21.398	6.086
H_m	46	4.56	22.66	12.390	3.797
H₁₀₀	46	6.33	23.70	14.507	4.157
G_{stand}	46	6.51	63.15	25.876	16.341
V_{stand}	46	36.357	478.509	182.8678	120.120
B_{Total_stand}	46	1129813.726	5258136.699	2431334.329	909203.491
C_{Total_stand}	46	1177819.495	5418301.446	2539542.280	932441.985

b. Results from Biomass Modeling of ÇkÇz Forest Ecosystems

The Multi-Layer Perceptron (MLP-ANN) algorithm and the Multiple Linear Regression technique were used to model stand biomass. The main variables are D_m , H_m , CC , N and SI .

- Biomass Modeling of ÇkÇz Stands Using MLP-ANN

Figure 109 presents the results of the artificial intelligence prediction model (MLP-ANN) for the biomass (B_{stand}) of mixed natural forests stands (ÇkÇz).

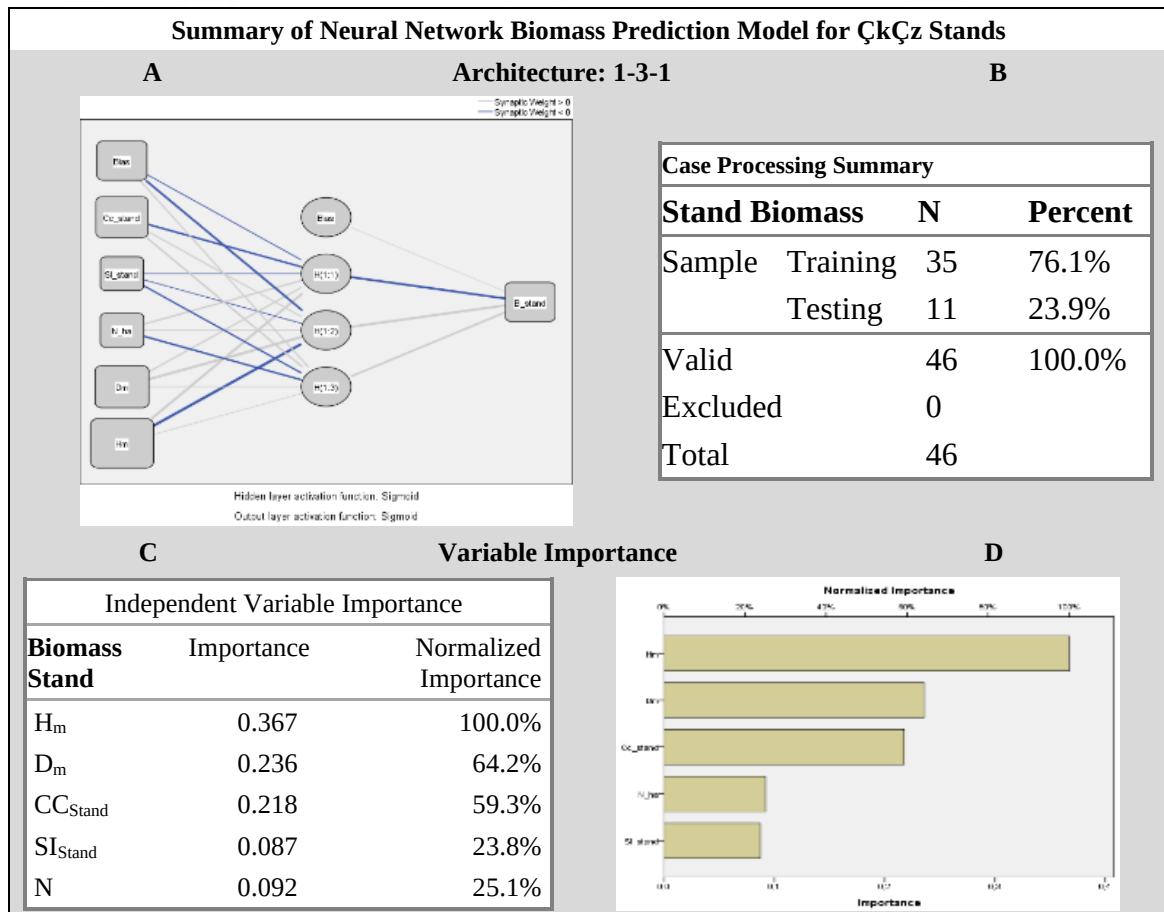


Figure 109. ANN-MLR biomass model obtained for [*Pinus nigra* – *Pinus brutia*] mixed stands

To build the biomass prediction model using MLP-ANN, the forest stand parameters (H_m , D_m , CC , N , and SI) studied in this work were introduced into the MLP algorithm. Thus, 25 calibrations were tested to identify the most robust model based on the performance data.

For this model (A) which was selected (Figure 109), the algorithm divided the data into two groups (B): the first (76.1%) for model training and the second (23.9%) for model testing. This configuration established a 1-3-1 model (A) with an input layer (predictors), a hidden layer (3 neurons), and an output layer (B_{stand}). The importance of each parameter in the construction of the model was highlighted by the algorithms. Average stand height (H_m) was the most influential predictor in model construction (36.7%). All its input data (100%) was used by the algorithm. Next, Stand Mean Diameter (D_m) contributed 23% to the construction of the model and provided 64.2% of its values entered into the algorithm. Clown Closure (CC) had an effect of 21.8%, providing 23.8% of its data, while 25.1% of the Trees' Density (N) and 23.8% of the Site Index (SI) data impacted the model setup at 9.2% and 8.7%, respectively. At the end of the training and testing processes, the Sums of Squared Errors and Relative Errors calculated by the algorithm for the chosen model were relatively low ($SSE < 0$ and $ER < 0$), as shown in Figure 110.

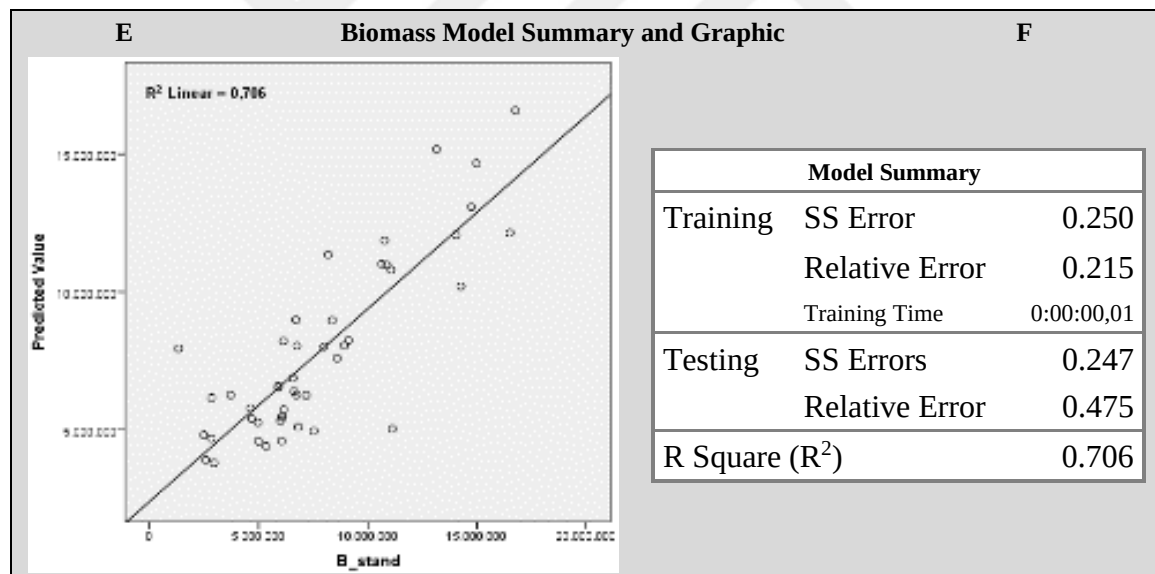


Figure 110. Performance criteria of MLP-ANN stand biomass model

The selected model shows acceptable performance in terms of errors ($RMSE=0.065$ kg/ha) and correlation ($R^2=0.706$) between the quantities of biomass stored in the ecosystems and the quantities predicted by the model (1-3-1). It therefore appears that 70.6% of the variability in biomass storage (B_{stand}) can be explained by the parameters (H_m , D_m , CC , N , SI) of these natural mixed of *P. nigra* and *P. brutia* in Türkiye.

According to results (Figure 110), the errors calculated by the algorithm in training ($SSE=0.250$ kg; $RE=0.215$ kg; $RMSE_{\text{training}} = 0.086$ kg) and in testing ($SSE=0.247$ kg; $RE=0.706$ kg; $RMSE_{\text{testing}} = 0.149$ kg) are relatively low. Furthermore, a strong correlation was observed between the calculated carbon data ($C_{\text{tree}_\text{Çk}}$) and the data predicted ($C_{\text{tree}_\text{Çk_ANN}}$) by the algorithm using the MLP-ANN Model 1-4-4-1 ($RMSE = 0.064$ kg). This correlation between $C_{\text{tree}_\text{Çk}}$ and $B_{\text{tree}_\text{Çk_ANN}}$ is very high with the Linear model ($R^2_{\text{Linear}} = 0.868$) and more with the Quadratic model ($R^2_{\text{Quadratic}} = 0.881$). In a confidence interval at 99%, the mathematical expressions (Linear and Quadratic) of these relationships between observed and predicted values of *Pinus brutia* tree carbon in natural mixed stands of ÇkÇz, are presented as follows

- Biomass Modeling of ÇkÇz Stands Using MLR

By using the same five input variables (Section 3.3.4.) same to MLP-ANN, Multiple Linear Regression Models was developed for predicting the biomass of ÇkÇz forest stands. By choosing the Stepwise method, in which variables are added (if $p < 0.1$) or removed (if $p > 0.1$) from the model step by step according to predefined criteria (avoiding over-fitting and retaining important variables), simpler, explanatory models were obtained and presented in Table 78 (next page).

With the Stepwise method, predictors were introduced step by step into the algorithm according to their importance in the construction of the model. The Stand Tree Density (N) as coefficient, was excluded from all models and particularly in the case of Model 4 with p -value of 0.68 ($p > 10\%$). Only four of the 4 predicted variables contributed to the biomass prediction models for mixed natural stands of *Pinus nigra* - *Pinus brutia* in Türkiye. The possibility of autocorrelation in the residuals of your model is suggested by a Durbin-Watson value of 1.309. The validity of inference tests and the precision of estimates in the regression model may be affected by autocorrelation in the residuals. We obtained four multiple linear regression models, statistically significant at 1% and with correlation coefficients below 50%.

Table 78. Stand biomass models obtained with MLR analysis

Results A										
Biomass Multiple Linear Regression Models of ÇkÇz Stands										
Model Summary ^e										
Model	R	R ²	Adj. R Square	Sum Squares Error (Regression)	Std. Error (Estimate) & RMSE	F	df1	df2	Sig.	Durbin-Watson
1	.430 ^a	.185	.166	7.119x10 ⁺¹²	845578.15	9.956	1	44	.003	1,309
2	.501 ^b	.251	.216	9.665x10 ⁺¹²	819994.74	7.188	2	43	.002	
3	.555 ^c	.308	.258	1.188x10 ⁺¹³	797368.90	6.226	3	42	.001	
4	.654 ^d	.428	.373	1.652x10 ⁺¹³	733424.60	7.680	4	41	.000	
Predictors: a: (Constant), CC; b: (Constant), CC, SI; c: (Constant), CC, SI, H _m ; d: (Constant), CC, SI, H _m , D _m										
Predictand: e: Dependent Variable: B _{stand}										
Results B										
Coefficients of Biomass MLR Models obtained with Stepwise Method										
Model		Coefficients		t	Sig.	p-value				
		B	Std. Error							
1	(Constant)	1157549.104	457415.365	2.531	.015	< 5%				
	CC	614217.271	194658.246	3.155	.003	< 1%				
2	(Constant)	2438736.246	793751.972	3.072	.004	< 1%				
	CC	506912.067	196654.628	2.578	.013	< 5%				
	SI	-401469.473	206264.996	-1.946	.058	< 10%				
3	(Constant)	3166387.107	864941.113	3.661	.001	< 1%				
	CC	542863.647	192198.482	2.824	.007	< 1%				
	SI	-431484.524	201218.848	-2.144	.038	< 5%				
	H _m	-59023.881	31663.210	-1.864	.069	< 10%				
4	(Constant)	2689052.800	811977.058	3.312	.002	< 1%				
	CC	642368.992	179996.232	3.569	.001	< 1%				
	SI	-514118.987	187204.479	-2.746	.009	< 1%				
	H _m	-137611.283	39532.042	-3.481	.001	< 1%				
	D _m	71642.152	24369.099	2.940	.005	< 1%				

The best MLR model is the fourth, whose relationship can be indicated as follows:

$$B_{Stand} = 2689052,800 - 137611,283H_m + 71642,152D_m + 642368,992CC - 514118,987SI \quad (89)$$

According to our findings, the Stand Average Diameter (D_m), Stand Average Height (H_m), Crown Closure (CC), and Site Index (SI) can explain 42.8% ($R^2 = 0.482$) of the variability in biomass accumulation in ÇkÇz stands in Türkiye, with a Standard Error (or RMSE) at 733424,60 kg/ha, at 1% ($p < 0.01$; $F = 7,680$).

c. Results from Carbon Modeling of ÇkÇz Forest Stand Ecosystems

As in Section 3.3.4., the MLP-ANN and MRL models for predicting carbon storage in natural mixed *Pinus nigra* and *Pinus brutia* forest stands were developed using the same processes as those for biomass.

- Results from Carbon Storage Modeling of ÇkÇz Stands using MLP-ANN

In this study, Figure 111 presents the results of MLP-ANN modeling of stand carbon storage (C_{stand}) in mixed natural forests stands (ÇkÇz).

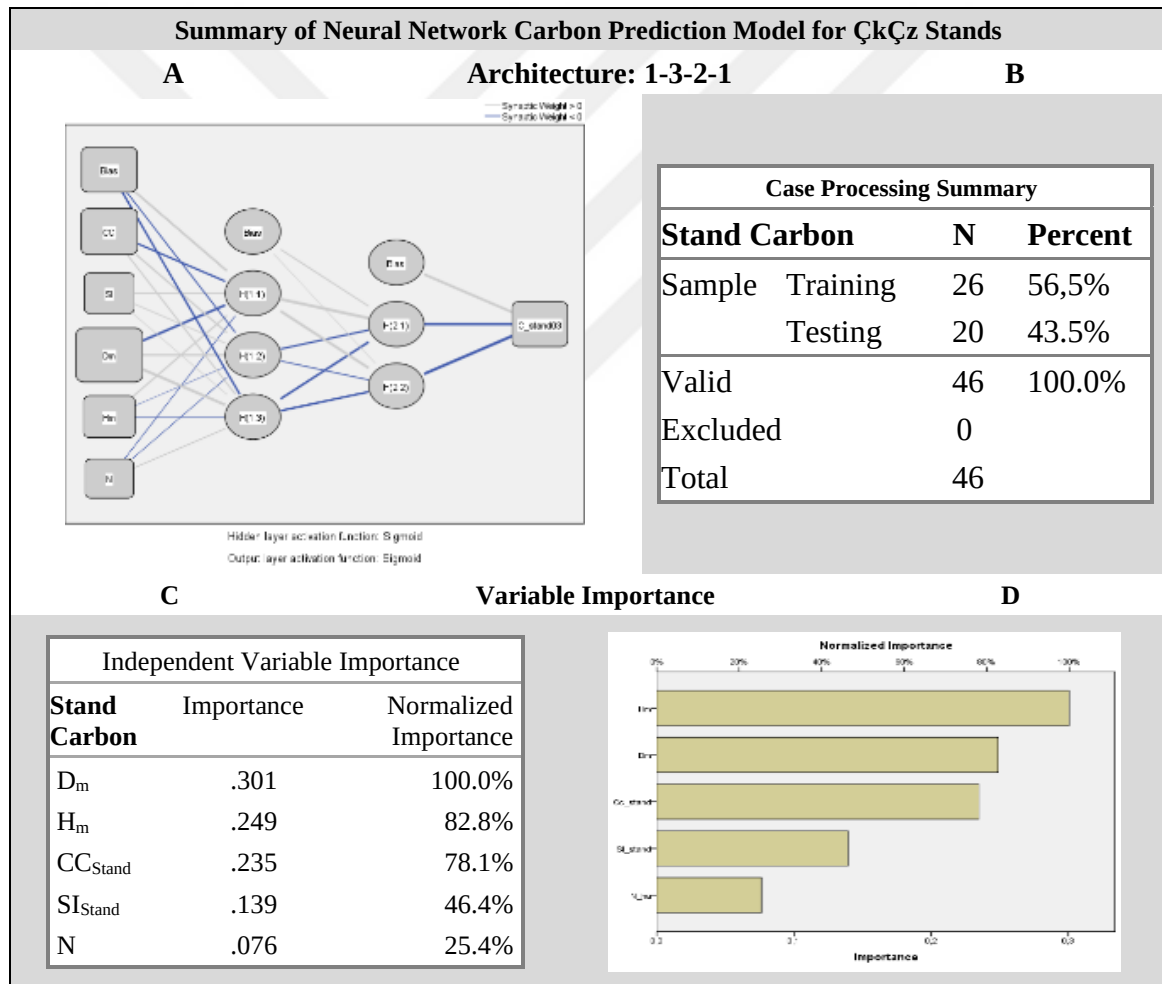


Figure 111. ANN-MLP carbon storage model obtained for [*Pinus nigra* – *Pinus brutia*] mixed stands

To construct the prediction model of carbon storage, the forest stand parameters (H_m , D_m , CC , N , and SI) were incorporated into the MLP-ANN algorithm.

Indeed, twenty-five different calibrations were tested to determine the most robust model, considering its performance data. The selected model (A) employed a data division approach (B). The first subset (58.7%) was used for model training, and the second subset (41.3%) was reserved for model testing. The resulting configuration yielded a 1-3-2-1 model (Model A) consisting of an input layer (predictors), a hidden layer (comprising 3 neurons), and an output layer (C_{stand}). The significance of each parameter in constructing the model was underscored by algorithms C and D. In 1-3-2-1 stand carbon model, Stand Mean Diameter (D_m) is the most influential predictor in model construction (30.1%). All its data (100%) was used by the algorithm. Next, Stand Average Height (H_m) contributed 24.9% to the construction of the model and provided 82.8% of its values entered into the algorithm. Clown Closure (CC) had an effect of 23.5%, providing 78.1% of its data, while 13.9% of the Site Index (SI) data and 7.6% of the Trees' Number per Hectare (N) data impacted the model setup at 46.4% and 25.4%, respectively. At the end of the training and testing processes, the Sums of Squared Errors and Relative Errors calculated by the algorithm for the chosen model were relatively low ($SSE < 0$ and $RE < 0$), as shown in Figure 112.

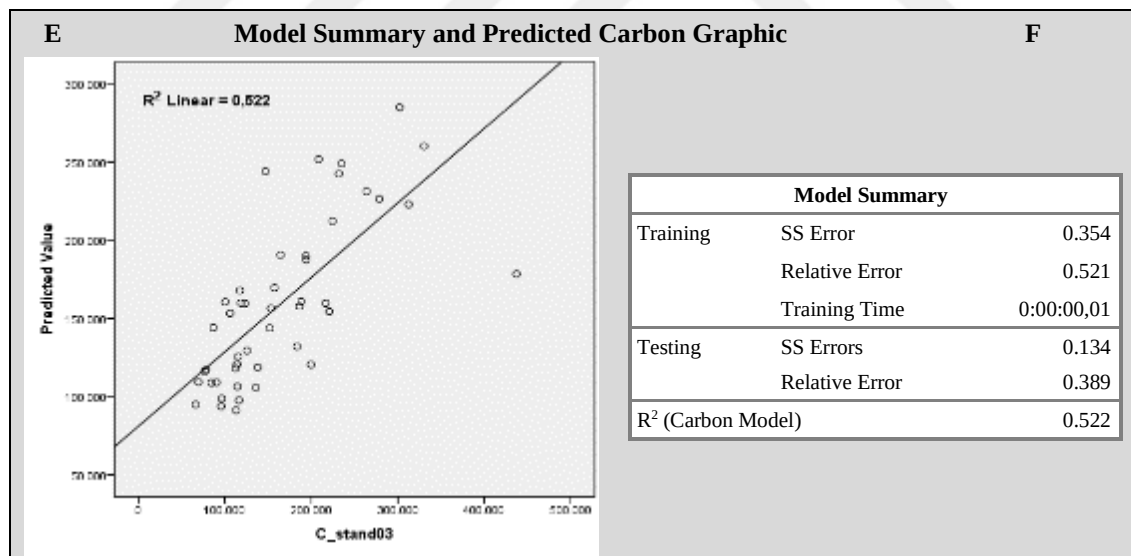


Figure 112. Performance criteria of MLP-ANN stand carbon model

Using the stands parameters (H_m , D_m , CC , N , and SI), the results (Figure 112) demonstrate a moderate correlation ($R^2 = 0.522$) between the observed carbon quantities and those estimated by the MLP 1-3-2-1 prediction model in Natural Mixed Stands in ÇkÇz, with a low error ($RMSE = 0.035$ kg/ha).

- Stand Carbon storage Prediction Modeling Using MLR

Using the same five input variables (Section 3.3.4.) as those used in MLP-ANN, multiple linear regression models were developed to predict carbon storage in ÇkÇz forest stands. By choosing the Stepwise algorithm, criteria were predefined according to which variables are added step by step (if $p < 0.1$) or removed from the model (if $p > 0.1$), avoiding over-fitting and retaining important variables. The resulting models are shown in Table 79.

Table 79. Stand carbon models obtained with Linear Regression analysis

Results C										
Biomass Multiple Linear Regression Models of ÇkÇz Stands										
Model Summary ^c										
Model <i>MLR_{stand}</i>	R	R ²	Adj. R Square	Sum Squares Error (Regression)	Std. Error (Estimate) & RMSE	F	df1	df2	Sig.	Durbin- Watson
1	.588 ^a	.345	.331	9.831x10 ⁺¹⁰	65069.38	23.218	1	44	.000	1,570
2	.703 ^b	.494	.471	1.407x10 ⁺¹¹	57850.97	21.020	2	43	.000	
Predictors: a: (Constant), D _m ; b: (Constant), D _m , N; Predictand: e: Dependent Variable: C _{stand}										
Results D										
Coefficients of Biomass MLR Models obtained with Stepwise Method										
Model		Coefficients		t	Sig.	p-value				
		B	Std. Error							
1	(Constant)	11352,579	33233,701	,342	,734	< 10%				
	D _m	7628,946	1583,243	4,819	,000	< 1%				
2	(Constant)	-104549,725	43973,419	-2,378	,022	< 5%				
	D _m	9981,780	1555,135	6,419	,000	< 1%				
	N	93,638	26,311	3,559	,001	< 1%				

As shown in Results D in Table 75, several variables were excluded from the modeling process. According to the Stepwise algorithm, two predictors were tested statistically significant at 1% (D_m and N) and were considered important in the construction of the best model. The possibility of autocorrelation in the residuals of your model is suggested by a Durbin-Watson value of 1.570. The validity of inference tests and the precision of estimates in the regression model may be affected by autocorrelation in the residuals. By the two models obtained (Results C), Model 2 outperformed Model 1, even though both were statistically significant at 1% ($p < 0.01$), with a correlation of 49.4%.

$$C_{Stand} = -104549,725 + 9981,780D_m + 93,638N \quad (90)$$

According to our findings, the Stand Average Diameter (D_m) and Stand Tree Density (N) can explain 49.4% ($R^2 = 0.494$) of the variability in carbon storage in ÇkÇz stands in Türkiye, with a Standard Error (or RMSE) at 57850.97 kg/ha, at 1% ($p < 0.01$; $F = 7,680$).

3.4. Results of Total Biomass Amount and Carbon Stocks in Mixed Forest of *Pinus nigra* and *Pinus brutia* in Türkiye

In this section, we have presented the general summary of the biomass distribution and carbon stocks of all above-ground and below-ground pools, determined in the natural mixed forests of ÇkÇz in Türkiye. Table 80 shows the general averages of the estimates obtained in this study.

Table 80. Results from distribution analysis of above/below-ground biomass and carbon stocks in ÇkÇz stands

Components	Max	Min	Mean	Total
Area (ha)	2407,15	0,35	221,13	79166,200
Total Biomass (ton)				
Single-Tree	276533,289	40,395	25403,928	9094606,048
Litter	41990,289	6,134	3857,468	1380973,457
Dead Wood	5603,852	0,819	514,802	184299,073
Living cover	1087,690	0,159	99,921	35771,881
Roots	89395,156	13,059	8212,350	2940021,167
Organic Mass	18200163,353	2658,617	1671970,966	598565606,007
Total Carbon (ton)				
Single-Tree	135920,239	19,855	12486,410	4470134,623
Litter	18687,175	2,730	1716,711	614582,413
Dead Wood	2670,570	0,390	245,334	87829,516
Living cover	501,520	0,073	46,073	16493,961
Roots	42871,359	6,263	3938,408	1409950,028
Organic C	609434,498	89,024	55986,134	20043036,006

Indeed, to estimate the total biomass and carbon stock in all mixed natural forests of *Pinus nigra* and *Pinus brutia* considered in their different ecosystems in Türkiye, forest area data obtained from forest management plans were used. The average biomass and carbon data obtained in this study were used to calculate the total biomass and carbon potential of each forest based on its area.

3.5. Results from Spatial Distribution Analysis of Biomass and Carbon Stocks in *Pinus nigra* - *Pinus brutia* Mixed Forest in Türkiye

3.5.1. Spatial Distribution of Tree Biomass and Carbon Stocks

Figure 113 presents the maps of the spatial distribution of tree biomass and carbon stocks of ÇkÇz Stands in all Forestry Sub-District Directorates in Türkiye.

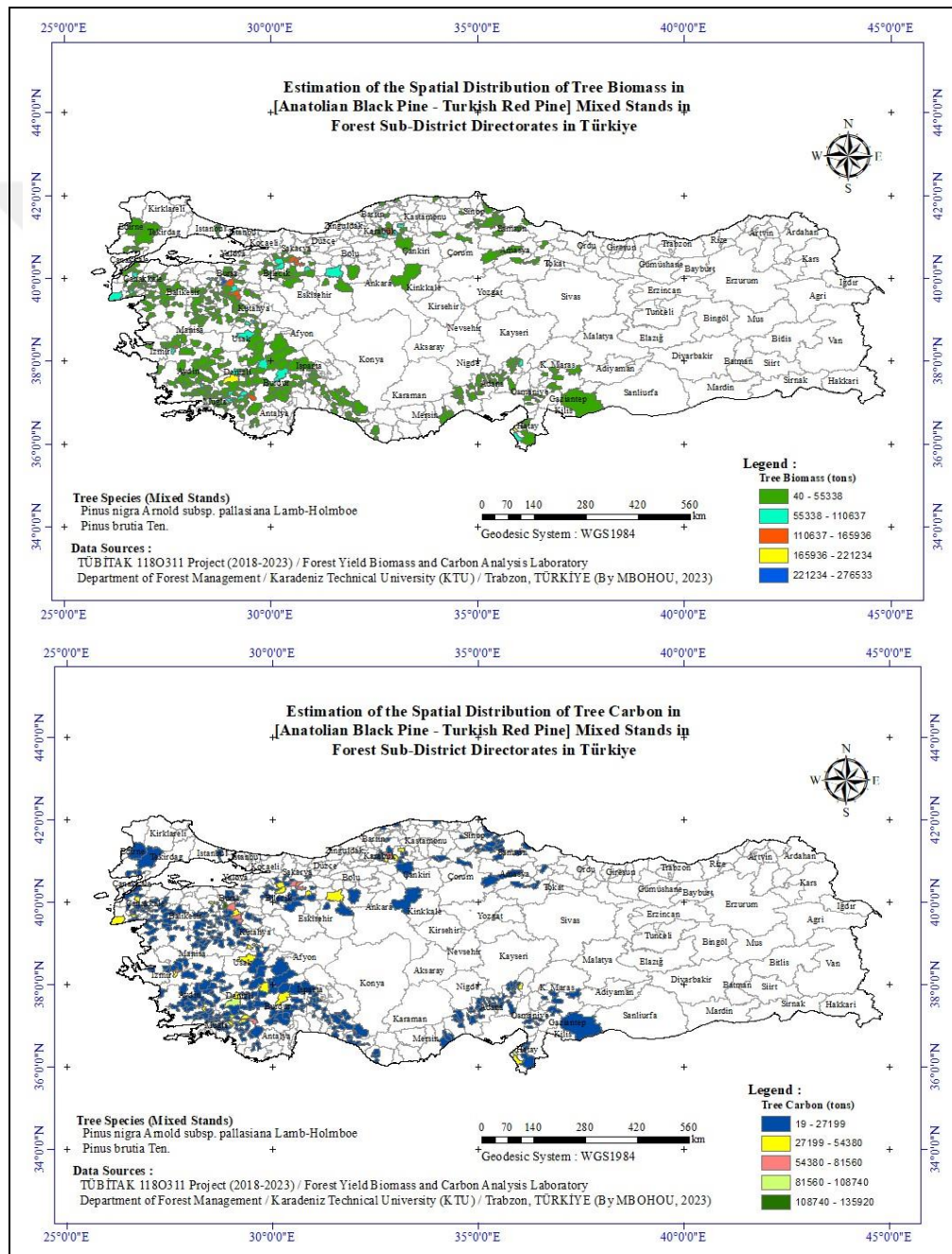


Figure 113. Spatial distribution maps of biomass and carbon stocks of trees in ÇkÇz mixed stands in forestry sub-districts directorates in Türkiye.

3.5.2. Spatial Distribution of Litter Biomass and Carbon Stocks

Figure 114 presents the maps of the spatial distribution of litter biomass and carbon stocks of ÇkÇz Stands in all Forestry Sub-District Directorates in Türkiye.

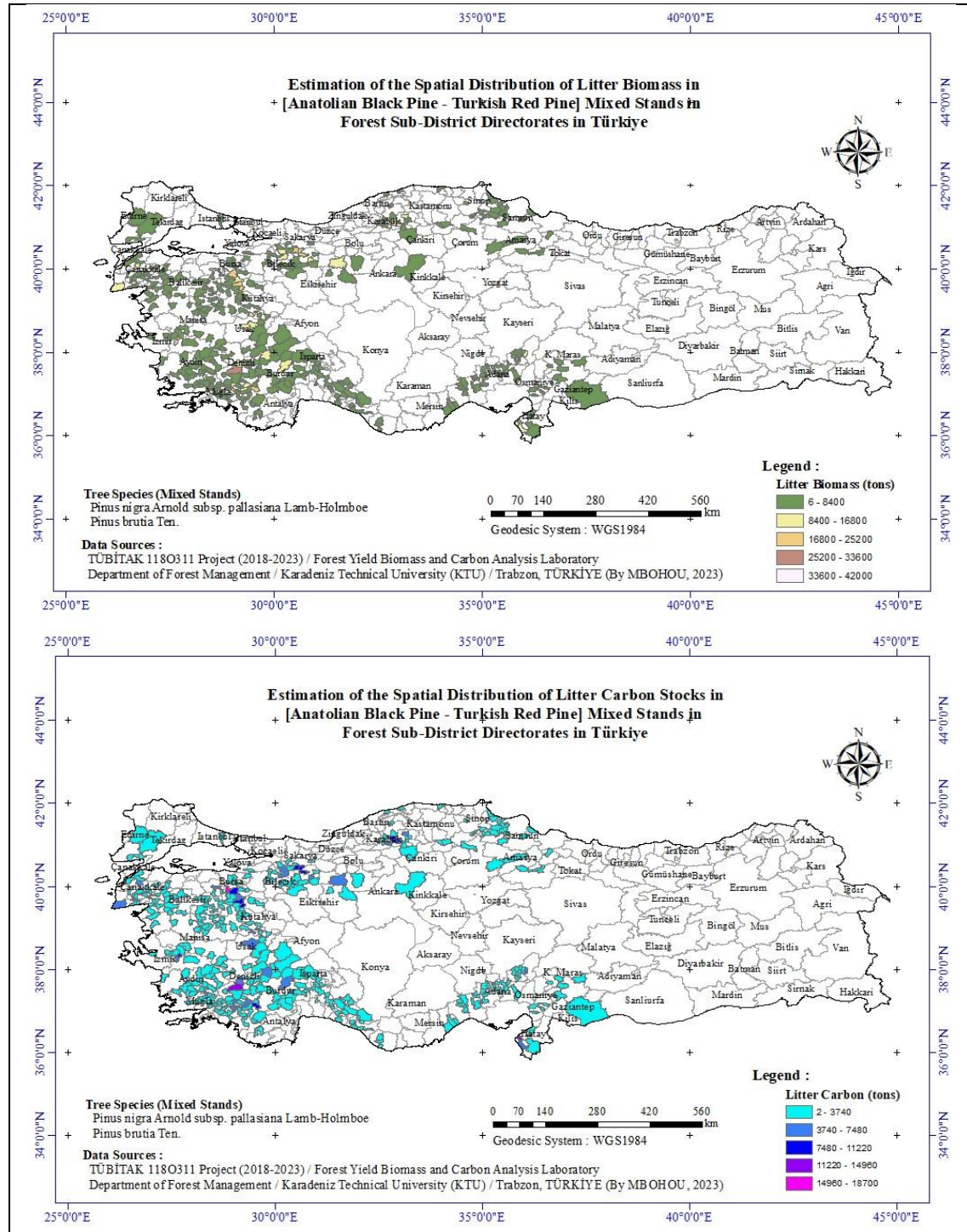


Figure 114. Spatial distribution maps of biomass and carbon stocks of litter in ÇkÇz mixed stands in forestry sub-districts directorates in Türkiye.

3.5.3. Spatial Distribution of Deadwood Biomass and Carbon Stocks

Figure 115 shows maps of the spatial distribution of deadwood biomass and carbon stocks of the ÇkÇz mixed stands in Forestry Sub-district Directorates in Türkiye.

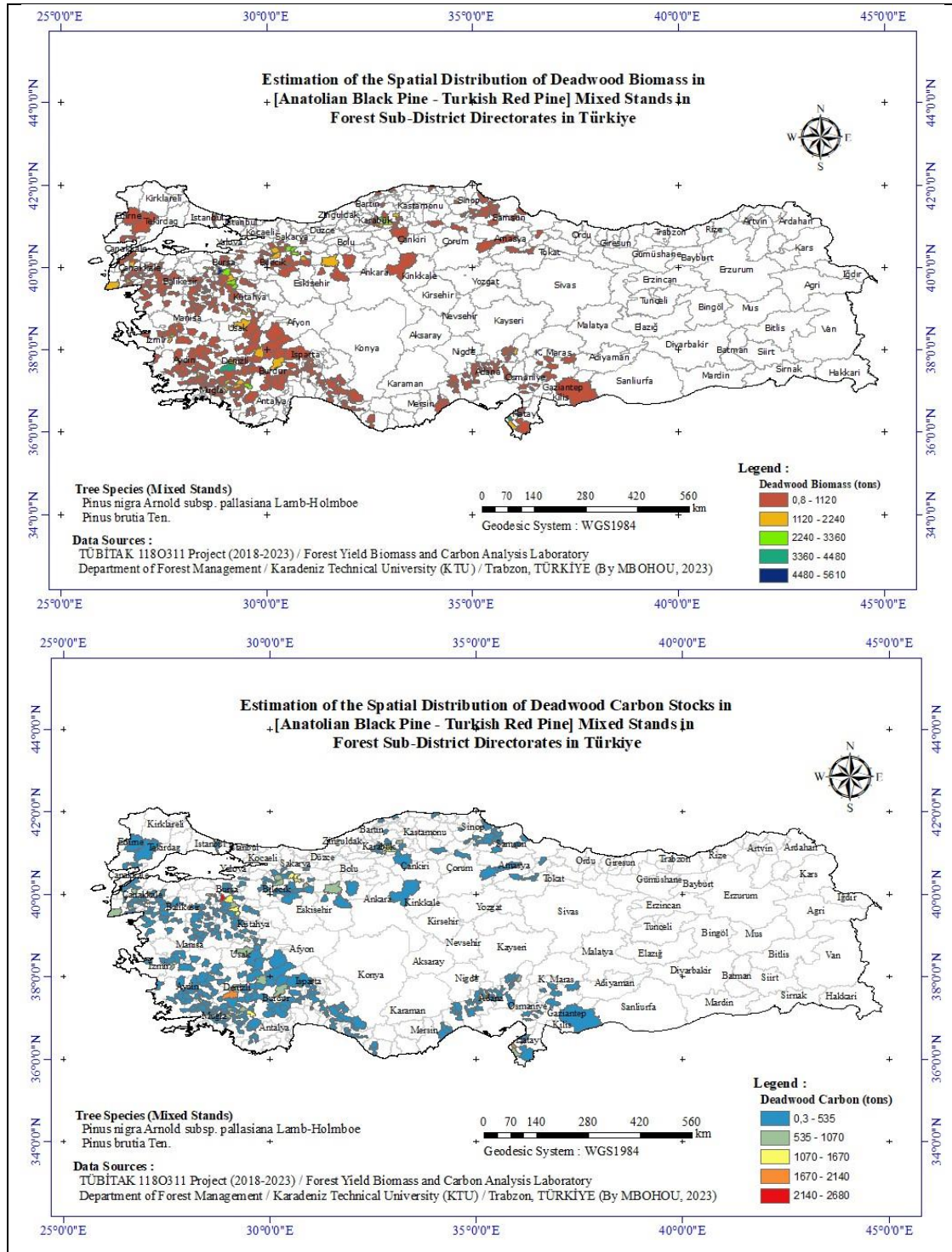


Figure 115. Spatial distribution maps of biomass and carbon stocks of deadwood in ÇkÇz mixed stands in forestry sub-districts directorates in Türkiye.

3.5.4. Spatial Distribution of Living Cover Biomass and Carbon Stocks

Figure 116 shows maps of the spatial distribution of living cover biomass and carbon stocks of the ÇkÇz mixed stands in Forestry Sub-district Directorates in Türkiye.

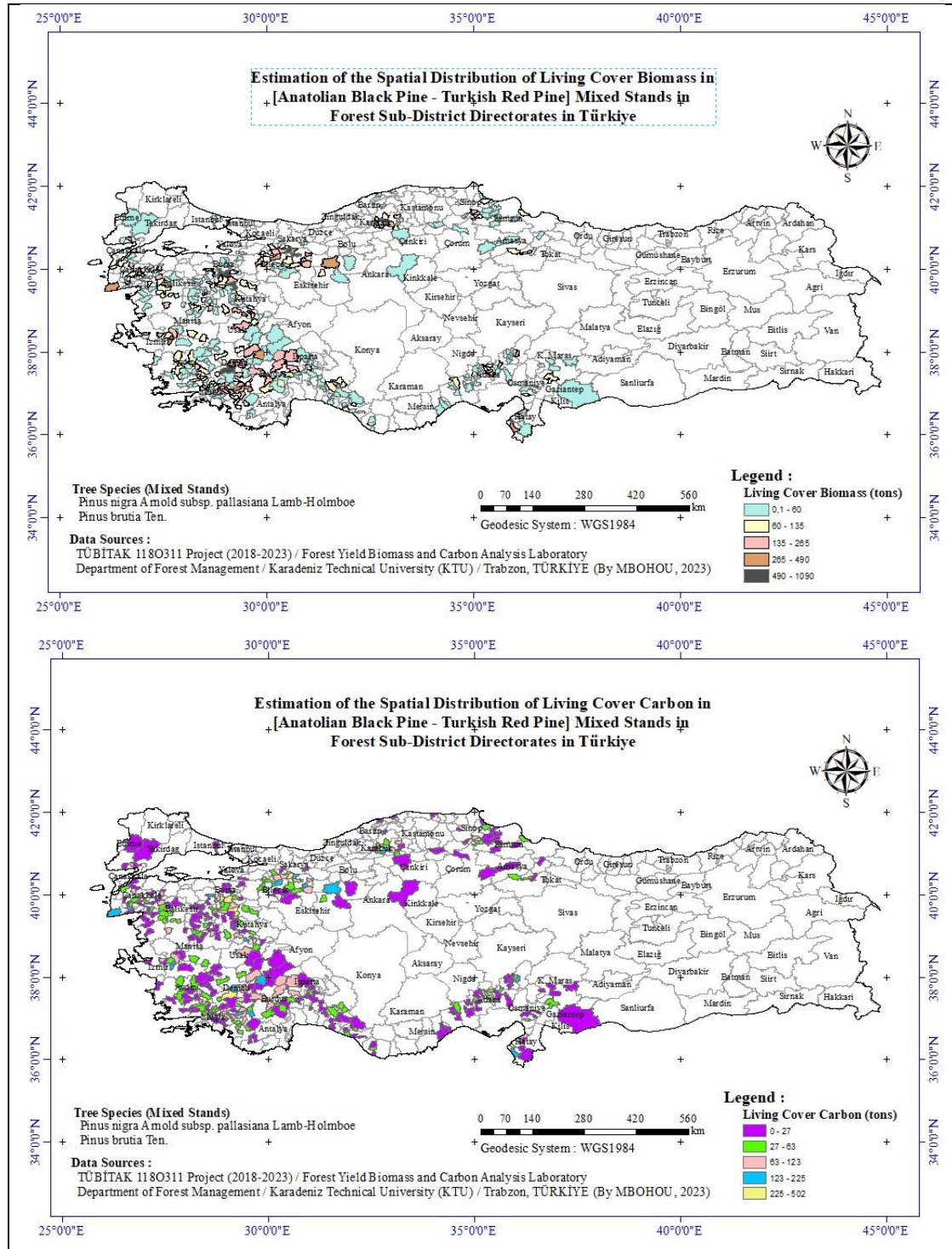


Figure 116. Spatial distribution maps of biomass and carbon stocks of living cover in ÇkÇz mixed stands in forestry sub-districts directorates in Türkiye.

3.5.5. Spatial Distribution of Root Biomass and Carbon Stocks

Figure 117 presents the maps of the spatial distribution of root biomass and carbon stocks of ÇkÇz Stands in Forestry Sub-District Directorates in Türkiye.

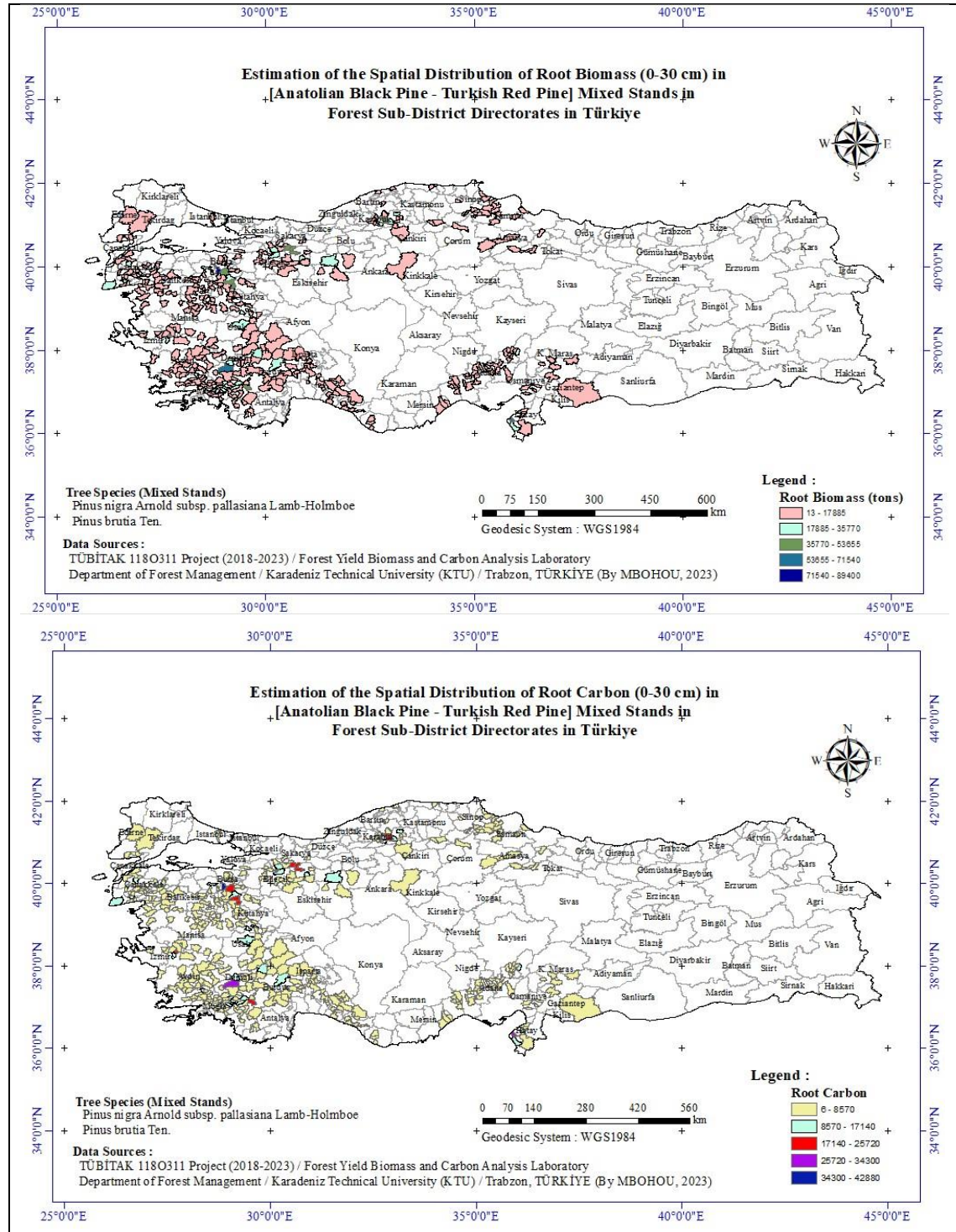


Figure 117. Spatial distribution maps of biomass and carbon stocks of roots in ÇkÇz mixed stands in forestry sub-districts directorates in Türkiye

3.5.6. Spatial Distribution of the Mass and Carbon Stocks of Soil Organic Matter

Figure 118 presents the maps of the spatial distribution of mass and carbon stocks of soil organic matter of ÇkÇz Stands in Forestry Sub-District Directorates in Türkiye.

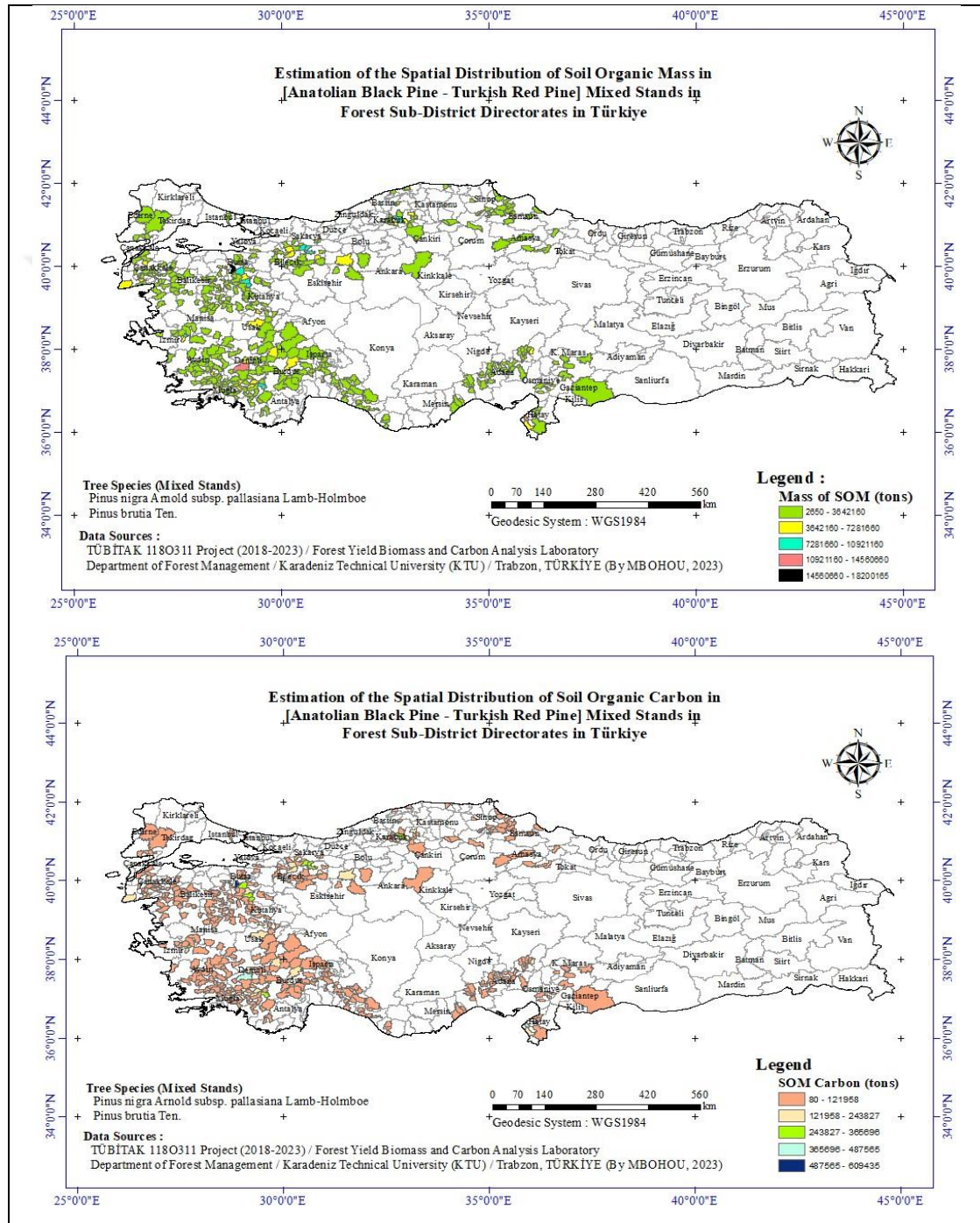


Figure 118. Spatial distribution maps of biomass and carbon stocks of soil organic matter root in ÇkÇz mixed stands of forestry sub-districts directorates

4. DISCUSSION

4.1. Characteristics of Natural Mixed Forest Stands of *Pinus nigra* and *Pinus brutia* in Türkiye

The mixed forest stands of *Pinus nigra* and *Pinus brutia*, found in Mediterranean regions, especially in Türkiye, constitute remarkable ecosystems with distinct characteristics, and provide a privileged study field for comprehending the diversity and dynamics of forest ecosystems. In Türkiye, where these stands are widespread, these characteristics are closely linked to several parameters that can be help to understand their nature and structure. In this study, the Stand Volume (V_s), Altitude (Z), Quadratic Mean Diameter (D_q), Mean Height (H_m), Site Index (SI), Age (A_s), Trees Density (N), Average Height (H_m), Stand Dominant Height (H_{100}), Basal Area (G), Site Density Ratio (SDR), Stand Mix Ratio (R_s), and Stand Internal Variability (C_V).

4.1.1. Analysis of ÇkÇz Mixed Stand Distribution

This study investigated various types of mixed stands (ÇkÇz) composed of Anatolian Black Pine (*Pinus nigra*) with Turkish Red Pine (*Pinus brutia*) in Türkiye. Based on these development stages (cf. Table 15), the surveyed forests are composed of 2.13% young stands (ÇkÇza), 4.26% post and pole stands (ÇkÇzb), 29.79% fine wooded stands (ÇkÇzc), and 4.26% medium wooded stands (ÇkÇzd). Intermediate stands represent 10.64% and include a mixture of young stands and post-polar stands (ÇkÇzab), 31.92% with a mixture of post-polar stands and finely wooded stands (ÇkÇzbc), and 17.02% comprising a mixture of finely and moderately wooded stands (ÇkÇzcd). Based on their clown closure, stands without closure (0) corresponding to very young stands represent 2.13%, those with the first (1) degree (11–40%), second (2) degree (41–70%) and third (3) degree (71–100%) of clown closure represent 10.63%, 51.06% and 36.17%, respectively. Young stands without clown closure are practically absent in the *ab*, *b*, *bc*, *c*, *cd* and *c* development stages. In the first degree of clown closure, only the *bc* and *c* stages are present. In the second degree of clown closure, stages *a*, *ab* and *b* are absent.

In the third degree of crown closure, only stand *b* is not present. Thus, we arrive at the conclusion that 87.23% of the stands analyzed in this research represent the pole and high forest, in medium development stages. Stands dominated by trees with diameters between 8 and 35.9 cm at breast height ($D_{1.30}$) are considered post-pole and fine wooded stages. This means that 65.96% of the stands studied in this research fall under these categories, specifically stages *b* and *c*, which correspond to diameter classes between 8–19.9 cm and 20–35.9 cm, respectively. Stands at intermediate development stages (*bc* and *c*) are also included in this category, which qualifies them as post, pole (sapling), and fine wooded stands. Our observations are in line with the ETFOP guideline (Section 5.4.1.) of Directive No 299, (2017) on the classification of forest stands by development stage and diameter class.

Notably, while minor variations in size due to crown closure were observed, these deviations do not compromise the representativeness of the data, given that the cover estimation was carried out in real-time. The adoption of different sample plot sizes was imperative for achieving a comprehensive depiction of the spatial diversity of the stands and ensuring the representativeness of the data. This representative dataset was crucial for extrapolating findings to encompass all-natural mixed *Pinus nigra* and *Pinus brutia* forest ecosystems in Türkiye, a methodology commonly observed in various studies. For example, Yavuz et al. (2010) and Mısır et al. (2012) have adopted similar methodologies, utilizing this approach to gather data from stands of *Pinus sylvestris* and *Abies normaniana*, respectively.

Firstly, altitude and topography are essentials in determining the types of vegetation present in a given region. Changes in temperature, atmospheric pressure and humidity caused by altitude create distinct ecological niches. This research focused on natural mixed stands of *Pinus nigra* - *Pinus brutia* (ÇkÇz), utilizing a randomized approach to establish experimental plots at various altitudes in the field. The altitudinal range spanned from 169 m to 1650 m, with a mean altitude of 858.64 m. The plots were grouped into five altitude classes, each with a range of 300 m. Natural mixed forests of *Pinus nigra* – *Pinus brutia* seem to have created specific adaptations that make them competitive and suited to this altitudinal range. The distribution of plots among altitude classes showed that 3 experimental plots were established between 160-460 m altitude, 14 plots between 460-760 m, 22 plots between 760-1060 m, 6 plots between 1060-1360 m, and 2 plots between 1360-1660 m. The predominance of plots between 460 m and 1060 m suggests an adaptive response of these ecosystems to specific environmental conditions.

However, the presence of plots at both lower and higher altitude extremes (160-1660 m) indicates a certain adaptability of the species to a diverse range of conditions. These findings are in accordance with several studies conducted in Türkiye, such as the research of Atalay and Efe (2012), which also noted variations in the distribution of *Pinus nigra* and *Pinus brutia* stands across different altitudes. Similarly, the work of Yilmaz et al. (2020) emphasized the significance of mid-altitudes in terms of biodiversity and forest stand regeneration. The correlation between altitudes and the distribution of these pine species underscores the necessity of accounting for this factor in forest management strategies and carbon sequestration. The broader ecological context provided by previous studies in Türkiye (Şenyurt et al., 2019; Sarıkaya and Avcı, 2011; Atalay et al., 1998; Atalay and Efe, 2010) has contributed to a more comprehensive understanding of altitude-based distribution patterns of forest stands. Furthermore, the observations made by Kavgacı et al. (2013) reinforced the ecological significance of altitude, specifically in relation to the classification and ordination of *Pinus nigra* forests in northwest Anatolian mountains (Alacam). Hence, altitude emerges as a pivotal factor in elucidating biomass distribution and carbon storage dynamics within natural mixed *Pinus nigra* and *Pinus brutia* forest ecosystems in Türkiye.

4.1.2. Analysis of Site Productivity in Mixed Stands of ÇkÇz

Site productivity, a crucial factor in forest management and planning, plays a pivotal role in understanding the potential growth and performance of tree species within a given area. In this context, the identification and classification of site productivity into distinct classes provide valuable insights into the varying capacities of the mixed natural forest stands of *Pinus nigra* and *Pinus brutia*. Our study revealed that a large proportion (66%) of these natural populations showed poor productivity distributed across the different age classes. Average productivity was around 27%, while only 6.38% could be estimated as having very good productivity. This suggests that some stands may maintain their productivity throughout the different growth stages, while others may experience fluctuations in productivity during specific age periods. The low productivity observed across all age classes, and particularly at ages over 41, suggests that as stands age beyond a certain point, there may be a decline in productivity, probably due to factors such as competition, ageing or disturbance over time.

On the other hand, the low percentage (6.38%) of good productivity may indicate that these mixed stands have the potential to be productive in different age classes. There are many other factors that can contribute to low site productivity. Ercanlı et al. (2010) suggested that site index estimates for any of the lower crown layer tree species in mixed stands may be in error. In this situation, they felt that site index estimation equations should be created for accurate site index estimates for lower crown layer tree species. Similar observations were reported in an analysis of the productivity of mixed *Pinus sylvestris* and *Pinus nigra* stands in the Karadeniz region (Yavuz et al., 2010). Similarly, Çatal et al. (2017) conducted work to determine free growth stages in mixed stands of *Pinus brutia* and *Pinus nigra* in the Isparta region (Türkiye). Analysis of 300 trees of each species sampled in 20 sampling areas at free growth stages of 50 cm, 75 cm, and 100 cm in height showed that productivity and structure, based on the height growth of trees in these stands, are also linked to age. For good site productivity in natural regeneration work, the authors felt that priority should be given to young stands since, between 5 and 11 years of age, the diameter of *Pinus brutia* increases from 50 cm to 100 cm and that of *Pinus nigra* from 50 cm to 100 cm between 8 and 10 years of age. In addition, Carus (1998) explored the impact of age on the productivity of pure and even-aged beech forests in the western and central Black Sea regions. The Author identified patterns consistent with the results presented in this study, when he concluded that the amount of annual stand volume increment decreases after 50 to 70 years. Although the information generated in this study is not sufficient to allow for a better understanding of the functioning and structure of mixed stands in general and those of *Pinus nigra* and *Pinus brutia*, dominance by high productivity is common in mixed forest stands. In this regard, Pretzsch and Schütze (2021) estimated that the productivity of mixed stands of Scots pine/European beech, among others, increases with species mixture in managed forests. In summary, our results (Table 16) suggest that mixed ÇkÇz stands have low productivity in the large majority regardless of their age. This study provides valuable information for forest management and highlights the importance of maintaining diverse stands to improve overall productivity. Classifying site productivity contributes to a broader understanding of ecosystem dynamics, species interactions, and the complex relationships between environmental factors and forest health. This understanding is crucial in the face of global challenges such as climate change and habitat degradation. However, to make informed management decisions, further research and long-term monitoring are essential to fully understand the complex dynamics that influence forest productivity.

It is essential to better understand the structure and functioning of mixed stands to exploit their yield to improve wood production, carbon absorption and storage.

4.1.3. Analysis of Forest Stand Age

The study presents a detailed analysis of samples collected from mixed forest stands of *Pinus nigra* - *Pinus brutia* in Türkiye. Looking at the 46 stands divided into 6 age classes, Table 17 shows that age class IV, comprising stands aged 61 to 80 years, is the most representative, accounting for 26.09% of the total. Age class V, comprising stands between 81 and 100 years old, accounts for 23.91% of total stands. The oldest stands, aged 100 years or more (VI), account for 10.90% of the total, while the youngest stands, aged 15 to 30 years, represent 10.87% (II) and 6.52% (I). Although mixed stands of ÇkÇzbc and ÇkÇzc are widely represented in several age classes, no stand type is represented in all age classes studied in this research. The minimum age is 15 years and the maximum 121 years, with a mean stand age of 68 years. The results of the study reveal significant diversity in the age structure of the ÇkÇzbc and ÇkÇzc stands. A similar study was conducted on 162 experimental plots established in mixed stands of *Pinus sylvestris* and *Fagus orientalis* in the Black Sea region of Türkiye. In this study, Kahriman and Yavuz (2012) reported that the ages of the tree species ranged from 31 to 150 years for *Pinus sylvestris* and from 33 to 117 years for *Fagus orientalis*. The presence of stands at different age classes suggests continuous regeneration and reflects ecological succession, which refers to progressive changes in species composition and forest structure over time. The non-uniform distribution of stands within age classes may be influenced by various factors, such as disturbance regimes, management practices, interspecies competition and natural regeneration. Our findings are consistent with research of Yavuz et al (2010) that also observed diversity in the age structure of mixed *Pinus brutia* and *Pinus nigra* forest stands in Türkiye, as well as a decline in the number of trees in older stands in similar geographical regions. Saatçioğlu (1979) reports that between 6 and 10 years of age, *Pinus nigra* seedlings reach biological independence with heights ranging from 0.5 m to 10 m. In contrast, for *Pinus brutia* Ten., this independence is achieved between 3 to 5 years in height. *Pinus nigra* seedlings should have a height of 100 cm between 3 and 5 years as deformations are observed at 10 years, which could influence their development and growth as there are age and height advantages between Anatolian Black Pine and Turkish Red Pine species (Genç, 1985).

Turkish Red Pine (*Pinus brutia* Ten.) reaches biological independence at 50 and 100 cm in height in 5 and 11 years respectively, while Anatolian Black Pine (*Pinus nigra* Arnold. subsp. *pallasiana*) individuals reach biological independence in 9 and 13 years recently showed that. The average time to reach a height of 80 cm is 8 years for Turkish Red Pine and 10 years for Anatolian Black Pine (Çatal et al., 2017). The age is important information for understanding the dynamics of biomass and carbon storage in these natural mixed stands, but it is also benefit to know the main characteristics of these tree species. In conclusion, the study highlights the diversity of ÇkÇzbc and ÇkÇzc stands in terms of age structure and composition. The gathered data provides insights into the age classes of the samples, ranging from 1 to over 100 years. This distribution reflects the diversity of the studied stands and offers crucial information regarding the structure and dynamics of these forest ecosystems.

4.1.4. Mixing Ration in Natural Mixed Stands

Mixed forest stands, characterized by the coexistence of multiple tree species within the same ecosystem, play a pivotal role in the diversity and stability of forests. The interaction between different plant species creates intricate dynamics that influence the composition, structure, and functionality of forest ecosystems. A crucial element of these dynamics is the concept of Mixing Ratio, which measures the relative proportion of each species within a mixed stand. In Türkiye, mixed stands of *Pinus nigra* with *Pinus brutia* hold significant importance in forest ecosystems. These two species, well adapted to the global mediterranean conditions, often coexist in natural stands. The Mixing Ratio between *Pinus nigra* - *Pinus brutia* influences competition, growth, and regeneration within these mixed stands, making it essential to characterize these relationships to guide conservation and management strategies. Analyzed from Tree Volumes, it plays a pivotal role in the diversity and stability of forests. The interaction between different species creates intricate dynamics that influence the composition, structure, and functionality of forest ecosystems. This study found that the range of mixture ratios spans from 0.524 to 0.899, consistently favoring the dominance of the *Pinus nigra* species. Significantly, this study recognizes *Pinus nigra* as the dominant species in comparison to *Pinus brutia*, although there are instances of near-equivalent and reversed mixture ratios. This aligns with observations (between 0.16 and 0.93) reported by Yavuz et al. (2010) in mixed stand of *Pinus sylvestris* with *Pinus nigra*, where *Pinus sylvestris* emerged as dominant over other species.

The implications of these findings extend to our understanding of species interactions within mixed stands. The prevalence of *Pinus nigra* as the dominant species underscores its ecological importance and competitive advantage in these ecosystems. This insight into mixture ratios contributes to informed forest management strategies aimed at preserving and enhancing the ecological dynamics and forest structure. Understanding the distribution and proportion of these two species is of particular significance for the sustainable management of Turkish forests.

4.1.5. Internal variability in Stands

The concept of internal variability within mixed forest stands of *Pinus nigra* and *Pinus brutia*, measured through diameter distribution, constitutes a fundamental pillar in the study of forest ecosystems. Internal variability within these mixed stands encompasses the remarkable diversity of tree attributes, encompassing dimensions such as size, age, spatial arrangement, and crucially, diameter distribution. At the core of this exploration lies the measurement of internal variability, particularly through the lens of diameter distribution. Our study has demonstrated that mixed stands are characterized by the coexistence of different tree species within a shared habitat, offering an intriguing perspective to explore the complex dynamics that shape ecological interactions and forest structure.

By analyzing how diameters are distributed among cohabiting species, our study has unveiled the nuanced relationships that underpin stand composition and structure. The diameter distribution model within these stands provides a unique insight into the complex interaction between species, competition dynamics, and ecological coexistence. In this context, our study shows that, in 84.8% of the analyzed stands (ÇkÇz), tree diameter is heterogeneously distributed with a proportion below 50%. This means that in 39 sample stands (85%), the proportion of heterogeneity in tree diameter is between 20% and 49%. In only 15.2% of the sample stands, the diameter of trees is distributed with a heterogeneity greater than 50%. These results confirm the high variability of tree diameter within the natural mixed stands of ÇkÇz, as previously indicated by the proportion of diameter variation and heterogeneity of distribution. The high variability observed in tree diameter within mixed stands is consistent with several previous studies. Torresan et al (2020) studied the relationship between stand productivity and different structural characteristics of mountain forests containing spruce, fir and beech in Europe.

The analysis was based on a dataset of 89 long-term plots distributed across European mountains, where the three species, common spruce (*Picea abies* (L.) Karst.), Silver fir (*Abies alba* Mill.) and European beech (*Fagus sylvatica* L.), accounted for at least 75% of basal area. Yavuz et al (2010) analyzed heterogeneity in tree diameter in mixed stands of *P. sylvestris* with, *P. sylvestris* and *P. nigra*, *P. sylvestris* and *F. orientalis*, *P. sylvestris* and *P. orientalis*, and *P. sylvestris* with *F. orientalis* and *A. nordmanniana*. The authors report that diameter heterogeneity does indeed vary in mixed forests, and increases significantly in the case of their work. The heterogeneity of tree diameter distribution within stands has ecological implications.

A diverse range of tree diameters can promote structural complexity, which in turn benefits biodiversity, ecosystem resilience, and carbon storage (Pretzsch et al., 2018). In a broader ecological context, comprehending the internal variability facilitated by diameter distribution holds significant implications. These mixed stands greatly contribute to ecosystem resilience, fostering biodiversity, and enhancing overall ecological stability. Through intricate species interactions, they influence vital processes such as nutrient cycling, carbon storage, and habitat provision. Focusing specifically on the context of *Pinus nigra* and *Pinus brutia* within their natural mixed stands in Türkiye, measuring internal variability through diameter distribution takes on increased significance. The diverse Turkish landscapes and climate variations influence the growth, competition, and coexistence dynamics of these two species. By examining diameter distribution within these mixed stands, we uncover unique adaptation strategies and ecological roles inherent to each species in different environmental niches.

4.1.6. Other Stand Parameters

The findings from this comprehensive study conducted on *Pinus nigra* and *Pinus brutia* forest stands in Türkiye, involving the analysis of 46 forest stands, yield invaluable insights into the characteristics of these ecosystems. The outcomes of our study, as presented in Table 21, provide a comprehensive depiction of a range of parameters that collectively characterize these stands. Regarding tree density (*N*), the variability ranging from 217 to 1550 trees/ha, averaging 733 tree/ha, holds significant implications. It reflects diverse tree distribution in mixed natural stands of *Pinus nigra* and *Pinus brutia* in Türkiye, influenced by competition, regeneration, and environmental factors, showcasing ecosystem complexity.

Understanding this variation is essential for characterizing these stands, providing insights into structure, health, biodiversity, and species interactions. Tree density directly relates to biomass and carbon storage, suggesting that higher density could increase carbon capture. Managing tree density is crucial for optimizing carbon sequestration, biodiversity, and resilience.

The age (A) diversity of these stands is substantial, with the oldest stand being 121 years old and the youngest 15 years old, resulting in an average age of 68.1 ± 28.7 years. This age diversity underscores the intricate dynamics of these stands. Stands aged 121 years reflect a mature and stable growth phase, having accumulated significant biomass and carbon storage over time. The 15-year-old stands, on the other hand, represent recent forest regeneration. This range of ages has significant implications for the ecosystem's resilience against disturbances and environmental changes. The average age of 68.1 years suggests a mix of mature and regenerating stands, indicating a dynamic of renewal and continuity. This age diversity can also impact the structure of vertical forest strata, with different tree cohorts contributing to varying levels of biomass and carbon storage, as Wang et al. (2023) shows in a study of in Subtropical Mixed Forests of the Zhejiang Province (China), in studying the effect of stand age on aboveground carbon accumulation. Overall, age diversity adds a layer of complexity to the characterization of these stands, highlighting their adaptation to natural fluctuations and environmental pressures.

The average diameter (D_m) of the forest stands is 20.10 ± 6.13 cm, showcasing variation from 8.55 cm to 30.34 cm. This diameter variation highlights the diversity within the mixed natural stands of *P. nigra* and *P. brutia*. Larger diameters could indicate older and potentially more carbon-rich trees, contributing to increased carbon storage and biomass. The range of diameters influences the overall structure and composition of the stands. Larger diameter trees tend to store more carbon due to their greater biomass. These trees have a longer history of growth and carbon accumulation. Conversely, smaller diameter trees might represent recent regeneration or less mature individuals. The average diameter of 20.10 cm reveals a balanced mixture of trees across various age classes and growth stages, contributing to a diverse ecosystem structure. The wide range in diameter demonstrates the complexity of these mixed stands and emphasizes the importance of managing different tree age classes for effective carbon sequestration and long-term forest health. In summary, the analysis of average diameter sheds light on the structural heterogeneity of the mixed natural stands of *P. nigra* and *P. brutia*.

The correlation between diameter, biomass, and carbon storage showcases how this study has revealed the intricate structure and dynamics of these ecosystems, providing valuable insights for sustainable management and conservation strategies. Stand Average Height (H_m) has an overall average of 12.39 ± 3.80 m, ranging from 4.56 m to 22.66 m. This range suggests varied stand stages and influences light competition and vertical habitat complexity. Furthermore, height relates to biomass, with taller trees potentially sequestering more carbon due to increased volume. This study's findings underscore the intricate vertical structure of these stands, revealing insights crucial for optimizing carbon storage, ecosystem health, and management strategies. The height diversity reflects variability in growth stages and age classes within the stands. Smaller trees may indicate recent regeneration or less favorable growth conditions, while taller trees are the product of decades of development. This range of heights showcases the complexity of interactions among tree growth, competition for light, and resource availability.

Additionally, Top Heights (H_{100}) fluctuate between 6.33 m and 23.7 m, with an average of 14.51 ± 4.16 m. This parameter influences light interception, indicating varying levels of photosynthesis and potential biodiversity niches within different canopy strata. Monitoring these heights helps assess stand health and response to environmental changes. Taller canopies will intercept lighter, creating shaded areas beneath the canopy. Conversely, lower canopies will allow lighter to reach the forest floor. These variations in light influence plant photosynthesis, which can have an impact on the overall productivity of the forest ecosystem. Changes in these heights can serve as indicators to assess the health of forest stands. These findings highlight the importance of understanding the diversity of canopy heights in natural forests of *Pinus nigra* and *Pinus brutia*. This diversity has direct implications for the ecology of these ecosystems, including light interception, photosynthesis, and biodiversity.

In this study, basal area (G), a key indicator of stand density, exhibits an average value of 25.88 ± 16.34 m²/ha across the 46 forest stands in ÇkÇz, with a range spanning from 6.51 m²/ha to 63.15 m²/ha. This variation provides valuable insights into the structure and composition of these forest ecosystems. A higher basal area typically indicates a denser tree canopy, which can have implications for various aspects of forest ecology. In this case, the average basal area of 25.88 m²/ha suggests a moderate to high stand density within the studied forest stands. The range of basal area values, from 6.51 m²/ha to 63.15 m²/ha, is quite substantial, indicating significant variation in stand density within this study area.

This variation can be attributed to several factors, including tree species composition, age structure, and past management practices. Forest stands with higher basal areas may have more mature or densely spaced trees, while those with lower basal areas could be younger or have undergone thinning or disturbances. Understanding basal area is crucial for forest management and conservation. It provides insights into forest growth, resource competition, and potential biodiversity. Forests with a balanced basal area can support a diverse range of species, while extreme values in either direction may require specific management interventions.

The stand Quadratic Mean Diameter (D_q) is a vital parameter in forestry that provides essential information about the average tree size within a forest stand. In this particular study, the reported D_q value of 21.40 cm, with a range spanning from 9.37 to 31.70 cm across the stands, offers valuable insights into the stand structure and tree size distribution. An average D_q of 21.40 cm indicates that, on average, the trees in these stands have a moderate size. This information is crucial for assessing the age and growth stage of the forest, as well as for estimating timber volume and potential timber yield. The range in D_q values from 9.37 to 31.70 cm signifies a considerable variability in tree sizes within the studied forest stands. This variation can be attributed to factors such as tree species composition, age diversity, and historical management practices.

Stands with higher D_q values likely have larger, more mature trees, while those with lower D_q values may consist of younger or smaller trees. The Total Wood Volume (V_s) of the forest stands, as reported, is a crucial parameter that quantifies the amount of timber or wood biomass present within these ecosystems. The average V_s of 182,87 m³/ha, with a standard deviation of 120.12 m³/ha, signifies the substantial variation in wood volume across the 46 stands in the study area. The fact that volumes range significantly from 36.36 to 478.51 m³/ha is noteworthy. This wide range in wood volume can be attributed to a variety of factors, including tree species composition, age, stand density, and past management practices.

Forest stands with higher V_s values typically have larger, older trees with more extensive timber resources, whereas those with lower V_s values may consist of younger or less densely stocked stands. A closer examination of the parameter distribution within these natural mixed stands of *Pinus nigra* and *Pinus brutia* underscores the considerable ranges of variation, despite deviations from the mean.

The well-distributed samples effectively represent the diversity of stands. This selection accuracy aligns with findings from a study by Yavuz et al. (2010). In the same context, Özbayram et al. (2014) delved into the Leaf Area Index (LAI) characteristics of pure stands of *Pinus brutia* and *Pinus nigra* in the Denizli region, revealing significant variations and impacts among parameters, with average LAI values of $1.59 \pm 0.38 \text{ m}^2$ (*P. brutia*) and $1.70 \pm 0.65 \text{ m}^2$ (*P. nigra*). These comprehensive analyses collectively shed light on the intricate characteristics and dynamics of *Pinus nigra* and *Pinus brutia* forest stands in Türkiye. The variability observed within each parameter highlights the complexity of these ecosystems and underscores the importance of understanding these factors for informed and effective forest management strategies. Overall, this study not only underscores the importance of employing density indices but also serves as a vital benchmark for understanding the dynamic nature of mixed *P. nigra*-*P. brutia* stands.

The observed disparities in SDI values among species, as well as the varying Site Density Ratios, offer valuable insights into the ecological nuances governing these ecosystems. It is evident that factors such as interspecific competition, environmental variations, and forest management strategies play a pivotal role in shaping the distribution of densities within these mixed stands. Our results are similar with other studies that have used similar density indices to assess forest stand structure. In numerous studies, the Stand Density Index (SDI) has been successfully applied to assess density and characterize the composition and structure of forest stands. For example, Teo et al. (2007) developed and tested Reinekes' (1933) stand density index as a measure of the density using diameter data ($D_{1.30}$) from 3–18-year-old *Mimosa scabrella* trees surveyed in 100–400 m^2 plots in the Curitiba metropolitan region (Brazil). Results showed density indices of 202, 541, and 73 trees/ha, indicating the importance of the Reineke (1933) coefficient in site SDI/SDR estimation. Their results showed that slight variations in species proportions within common forest types modified maximum SDIs. With the aim of improving the application of the Stand Density Index (SDI) in uneven-aged and mixed stands present in large-scale forest inventories, Woodall et al. (2005) observed trends in maximum SDI across diameter classes and species combinations for eight common tree species in America. Autor reported that the maximum SDI that a particular species can achieve is affected to varying degrees by the species composition of the stands concerned. Puettman et al. (1993) examined the use of the SDI in mixed stands of Red Alder (*Alnus rubra*) and Douglas-Fir (*Pseudotsuga menziesii*) in the common western forest type.

They succeeded in empirically determining SDI_{max} values for their specific forest types in local areas. On the other hand, Williams (2003) looked at SDI in even-aged hardwood stands in Ohio (USA) and identified critical limits for stand densities equivalent to stand percentage. Furthermore, Stout and Nyland (1986) studied the dynamics of SDI_{max} (study species SDI + others species SDI) in mixed hardwood stands on the Allegheny Plateau. They found that SDI values varied considerably with the proportion of black cherry (*Prunus serotina*) and sugar maple (*Acer saccharum*) in mixed hardwood stands. Noting that stand structure and density can vary according to the species present, tree density, and environmental factors, it emerges that the mixed stands of Anatolian Black Pine (*P. nigra*) and Turkish Red Pine (*P. brutia*) have significant variations in their density, with some stands having relatively low density (SDR: 0.1 and 0.25) while others have higher density (SDR: 0.50 and 1).

4.1.7. Height-Diameter Relationships in Stands

The relationship between the height of *Pinus nigra* and *Pinus brutia* trees within mixed natural stands and their diameter at 1.30 m is a pivotal aspect for understanding the dynamics of these forest ecosystems. The findings of this study indicate that diameter plays a significant role in understanding the variability in tree height growth. This diameter-height relationship aligns with the principles of allometric growth observed in numerous tree species. The study identified multiple types of mathematical relationships (Quadratic, Logarithmic, Power, Inverse, S-Curve, Growth, Exponential and Logistic) in which tree diameter explains variability in tree height growth. All models are statistically significant at 1% ($p\text{-value} < 0.01$). In the light of the results reported in Tables 23 and 24 for the models, and in Figures 68 and 69 for the graphs, this study reveals that, in natural mixed stands (*P. nigra* and *P. brutia*), the variability in tree height of each of the two species can be explained by diameter. Quadratic models in the case of two species, showing a positive high correlation between tree height and diameter, and a low error for *P. nigra* ($R^2=0.653$; $F=63.062$; $Se=1.548$ m; $RMSE = 2.078$ m) and *P. brutia* ($R^2 = 0.616$; $F=49.737$; $Std. Error=2.048$ m; $RMSE=2.534$ m) in mixed stands. The study demonstrated the existence of quadratic relationships with concave and convex trends between tree diameter (D) and tree height (H) in natural mixed stands (*P. nigra* - *P. brutia*).

The mathematical equations (56) and (57) offer profound insights into the intricate relationship between tree diameter and height within natural mixed stands of *Pinus nigra* and *Pinus brutia* in ÇkÇz, Türkiye. These equations provide a nuanced understanding of the growth patterns of these species, shedding light on the non-linear dynamics that govern their development. In the H-D relationship in *Pinus nigra* tree (Equation 56), our study unveils a concave quadratic curve ($H_{\text{Çk}} = F(D_{\text{Çk}})$) with a negative quadratic coefficient ($b_2 = -0,0023455$). This curvature reflects the downward opening nature of the curve, signifying the relationship between tree diameters ($D_{\text{Çk}}$) and height ($H_{\text{Çk}}$). The coefficient is a contributor to the slope of the curve and determines at what point the quadratic curve is inclined. With the *P. brutia* (Equation 57), our study found that the quadratic coefficient that determines the shape of the quadratic curve ($H_{\text{Çz}} = F(D_{\text{Çz}})$), is positive ($b_2 = 0,0027552$). This indicates that the relationship between tree height and diameter forms a convex curve, characterized by an upward opening. The linear coefficient in *P. nigra* H-D equation ($b_1 = 0,46965015$) and in *P. brutia* ($b_1 = 0,1824599$) influences the slope of the curve, fix the point at which the quadratic curve turns concave (56) or convex (57). Also, the quadratic effect demonstrates that the relation between H and D is non-linear and the height is influenced by diameter, with a tendency to slow down ($-0,0023455D_{1.30}^2$) or increase ($0,0027552D_{1.30}^2$) height growth as the diameter increases, in line with the quadratic nature of the relationship.

This reveals a non-linear trend in the tree height growth influenced by diameter changes. The negative quadratic coefficient emphasizes the complex relationships between tree height growth and diameter, indicating that changes in diameter lead to non-linear height variations. These linear coefficients illustrated the direction of the curve's slope, identifying the point at which the quadratic curve shifts into a convex trajectory. This equation uncovers the non-linear progression of tree height concerning diameter for *Pinus brutia* species within mixed stands dominated by *Pinus nigra*. These mathematical representations underpin the complex growth dynamics of these species. The observed non-linear trends highlight the intricate response of tree height to diameter variations within mixed stands. These findings align with previous studies that underscore the non-linear relationship between tree dimensions and growth dynamics in various forest ecosystems. These equations provide a quantifiable framework for comprehending the intricate interactions between tree diameter and height, offering valuable insights into stand composition and structure.

The distinct responses of *Pinus nigra* and *Pinus brutia* to diameter variations demonstrate the nuanced dynamics of each species within mixed stands. The mathematical representations identified in the study form the foundation of the complex growth dynamics observed in these species. The identified non-linear models highlight the intricate way in which tree height responds to diameter variations within mixed stands. Our results are comparable with those of several similar studies which have also highlighted the mathematical relationship that exists between the height and diameter of trees in forest stands. Recently, Sağlam and Sakıcı (2022) founds the correlation ($R^2 = 0.691$) between diameter and height (H-D) in a study based on the analysis of 2313 trees of Crimean pine (*Pinus sylvestris*) and stands characteristics (basal area, age, site index, average diameter and frequency) analyzed from 292 plots of natural pure forests in 5 sub-ecological regions (ecoregions) of Black Sea Region (Kastamonu and Sinop). Bolat (2021) founds best H-D model with good performance ($R^2=0.815$; RMSE=3.14 m; AIC=344.66 m) to explain the influence of diameter on the variability of the height of 300 sample trees in 180 pure stands of Anatolian Black Pine (*Pinus nigra*) in Ankara Forest District (Türkiye). The difference in the correlation from our results may be linked to the number of tree samples and the specificity of these pure stands. In Spain, Ogana et al (2020) developed new Height-Diameter models for *Pinus pinaster* using the non-linear regression technique based on the generalized H-D model (mixed effects) and the single model. They found the significative relationship between H-D of *Pinus pinaster* stands (RMSE from 2.291 to 2.649 m; R^2 from 0.513 to 0.636) and *Pins radiata* (RMSE from 2.452 to 2.704 m; R^2 from 0.523 to 0.607). These results are comparable to our own, although the authors feel that mixed-effects models (Hossfeld) perform better for *P. pinaster* ($R^2=0.886$; RMSE=1.255 m) and *P. radiata* ($R^2=0.794$; RMSE=1.775 m) due to the involvement of several stand parameters. In Türkiye, Mısıır (2010) found the best relationship between diameter and tree height of *Populus tremula* stands ($R^2=0.949$; Std. Error=1.226). Shen et al (2020) demonstrated the existence of allometric relationships between tree height and diameter using the linear method and ANN. In this case, the ANN model was found to have a higher correlation (0.754) than the non-linear regression model (0.684). In Türkiye, Yavuz et al. (2010) have also shown that diameter is a variable that may explain the variability in the height in *Pinus Sylvestris* ($R^2=0.77$; Std. Error=0.146 m) in pure stands Raptis et al. (2021) found the inclusion of dominant height and dominant diameter as predictors improved the accuracy of the Chapman–Richards model for *Pinus nigra* Arn.

In Greece. Sharma et al. (2019) fit a generalized non-linear height-diameter (H-D) model, in a study in the Czech Republic (Central Europe), on two datasets of 29,390 and 382,540 trees considered in 224 and 14,903 sample plots respectively ($R^2=0.918$; RMSE=2.779 m). Özkal et al. (2021) have shown the existence of this statistical relationship between the diameter and the height of the trees in the stands of *Abies Nordmanniana*, in the Bolu region in Türkiye. These results are close to those highlighted in our study for *Pinus Nigra* and *Pinus Brutia*, where we have also found that the diameter is a significant parameter to explain the height of the trees in the natural mixed stands of ÇkÇz.

Indeed, a larger diameter at 1.30 m is often linked to increased height, reflecting both the vertical growth of the stem and the expansion in the leaf canopy volume. These observations hold crucial implications for forest management and growth modeling in mixed *Pinus nigra* stands. By comprehending the diameter-height relationship, it becomes possible to better predict the future growth of trees and tailor management strategies accordingly (Carus and Akguş, 2018). In Portugal, Nunes et al (2022) have also shown the existence of an allometric relationship between tree diameter and height, with correlations varying between 64-64.8% and standard errors between 3.68 m and 0.003 m, in mixed forests of *Pinus pinaster*, *Arbutus unedo* and *A. dealbata* in Serra da Estrela Natural Park (20 years).

In sum, our work characterizing mixed *Pinus nigra* - *Pinus brutia* stands in Türkiye is similar to several previous studies that have also characterized various forest stand types by calculating one or more of the same parameters, notably in Poland (Bielak et al., 2014), USA (Woodland et al., 2005; Shaw, 2005), Germany (Pretzsch and Schütze, 2021), Europe (Ruiz-Peinado et al., 2021). In conclusion, this study successfully identified key forest parameters essential for characterizing forest stands, aligning with existing scientific research. The distinct features observed in the natural mixed stands of ÇkÇz support the assertion that these forests possess unique characteristics, confirming our initial hypothesis. Understanding their capacity to sequester and store carbon in biomass is crucial, emphasizing their significant role in combating climate change.

4.2. Above and Below-Ground Biomass in Natural Mixed Forest of *Pinus nigra* and *Pinus brutia* in Türkiye

4.2.1. Above-Ground Biomass in ÇkÇz Natural Mixed Stands

a. Tree Volume of *Pinus nigra* and *Pinus brutia*

The concept of tree volume (V_T) is a fundamental aspect in forestry research, offering critical insights into the structural attributes and biomass accumulation of tree species. *Pinus nigra* and *Pinus brutia*, two prevalent conifer species in Türkiye, have garnered considerable attention in studies investigating their tree volume dynamics. Tree volume serves as a key metric in understanding the overall growth, structure, and ecological significance of these species within forest ecosystems. Tree volume, often expressed in cubic meters (m^3), represents the spatial capacity occupied by a tree, encompassing its stem, branches, and foliage. *Pinus nigra* and *Pinus brutia*, both integral components of natural mixed stands, exhibit distinctive growth patterns and adaptations. The measurement of their respective tree volumes provides valuable information on their biomass accumulation, which is crucial for estimating carbon sequestration, timber yield, and ecological services these species provide. In this context, our study presented comprehensive findings on the wood volumes of *Pinus nigra* and *Pinus brutia* species, shedding light on their structural attributes across various tree components. The analysis revealed considerable variability in wood volumes among different parts of the trees for both species (cf. Table 25).

Indeed, *Pinus nigra* exhibited wood volume ranges of 0.00005 m^3 to 1.23152 m^3 for stems, 0.00004 m^3 to 0.14748 m^3 for branches, and 0.00009 m^3 to 1.32288 m^3 for the whole tree. Similarly, for *Pinus brutia*, wood volume varied between 0.00030 m^3 and 1.55940 m^3 for stems, 0.00022 m^3 and 0.15103 m^3 for branches, and 0.00054 m^3 and 1.64987 m^3 for the whole tree. The average volume is $0.24964 \pm 0.23936 m^3$ for stems, $0.02864 \pm 0.02821 m^3$ for branches, and $0.27828 \pm 0.26138 m^3$ for the whole tree. The wood volume variations reported in this study hold vital implications, not only for understanding the intrinsic characteristics of these species but also for their potential application as explanatory variables in tree volume equations for mixed or pure stands. Despite the valuable insights provided by this study, it's essential to acknowledge the relatively small sample sizes of 68 *Pinus nigra* and 70 *Pinus brutia* trees. This aspect could potentially influence the generalizability of the findings.

Moreover, the higher wood volumes observed in *Pinus brutia* could be attributed to its specific growth characteristics and adaptation to local environmental conditions. The obtained results align with previous research focused on tree growth and structure in mixed conifer stands. Notably, the volumes were estimated using Smalian relationships, a widely employed method in similar studies. Miguel et al (2018) used Smalian's Equations to find the average (0.2165 m^3), maximum (0.4806 m^3) and minimum (0.0315 m^3) volumes of 150 trees in *Eucalyptus urophylla* plantations in Brazil. In most cases, these volumes are determined for development to be used as an explanatory variable in tree volume equations in mixed or pure stands. It is worth mentioning that this study used single-entry volume equations developed for *Pinus nigra* and *Pinus brutia* based on tree diameter at 1.30 m (TÜBİTAK 113O118 Project, 2022). These equations, with high coefficients of determination ($R^2 = 0.992$ for *Pinus nigra* and $R^2 = 0.994$ for *Pinus brutia*), provided robust estimations of wood volumes. However, the study did not generate new equations with the presented data. Kahrman et al. (2016) established the volume table for *Pinus brutia* stands in various productivity classes in the Antalya and Mersin regions, using both single-entry equations (with Adj- R^2 ranging from 0.969 to 0.992) and statistically significant double-entry equations at a 5% significance level. Yavuz and Mısır (2013) also conducted research on volume table development processes in Türkiye. Özçelik et al. (2006) estimated the volume of three tree species using six different equations and obtained results similar to those obtained for *Pinus nigra* and *Pinus brutia* trees. Other authors have opted for double-entry equations.

In Tanzania, Mugasha et al. (2015) estimated tree volumes using developed allometric equations and concluded that these equations were capable of accurately calculating tree volume. To analyze the biological mass of sample stem trees, sections of wood with bark were taken during the inventory. Analysis of their diameter and thickness, with and without bark, led to the determination of their respective volumes, for each of the two species studied (*Pinus nigra* and *Pinus brutia*). For each section sampled at a given cutting height (h_{c_ck}) on tree stems, the volume over bark (v_{s_ck}) and under bark (v_{u_ck}) was determined, together with the volumes of tree bark (v_{b_ck}). For *Pinus nigra* trees, we remark that the wood sections were taken from the stems of sample trees at varying heights, ranging from 0.65 m to 15.3 m, averaging 5.35 m. The volume of the wood section samples (under bark) used in this study ranged from 0.0004 m^3 to 0.00121 m^3 , averaging $0.00036 \pm 0.00025 \text{ m}^3$.

For *Pinus brutia* trees, the samples of wood section were taken from the stems of sample trees at varying heights, ranging from 0.30 m to 11.3 m, averaging 5.68 m. The volume with bark ranged from 0.0003 m³ to 0.00151 m³, averaging 0.00040 m³. We did not find any specific recommendations on the size, dimensions, and volume of wood sections to be sampled from trees and used in forest biomass and carbon analysis. No study discussed the variation of volumes of these cross-sectional sections or the importance of such recommendations. Several previous studies used wood sections to estimate biomass based on their volume. Our observations are relevant for the accuracy they bring, particularly for *Pinus nigra* and *Pinus brutia* species in mixed stands in Türkiye, estimating the volume of sections used for each species. While not recommending a specific size, previous studies suggest using cross-sectional sections of 2 to 7 cm in thickness. For instance, Yavuz et al. (2010) sampled cross-sectional sections of 5 to 7 cm in thickness from trees such as *Pinus sylvestris* and *Pinus nigra* in mixed stands in Türkiye. The thickness of cross-sectional cuts used in this study is not far from these values, ranging from 1.79 to 7.3 cm for all trees, with an average of 4.1 cm. In sum, the knowledge of the volume of trees and their components was crucial in determining the aerial biomass capacity and carbon stock for each pool.

b. Single-tree Biomass of *Pinus nigra* and *Pinus brutia* Trees

The wealth of biomass data provides valuable information on the characteristics of *Pinus nigra* and *Pinus brutia* trees, highlighting the allocation and distribution of biomass among the different components of the tree. In other words, each component of the tree contributes uniquely to the total amount of tree biomass. In this study, the analysis of the results of the single-tree biomass shows that, for 68 trees of the *Pinus nigra* species (Figure 70), the minimum and maximum quantities varied between 0.0405 kg and 616.115 kg in the stem, 0.00001 kg and 57.199 kg in the bark, 0.1197 kg and 82.048 kg in leaves, 0.0718 kg and 125.718 kg in branches, and 0.2320 kg and 780.660 kg in the entire individual tree. The average quantities of biomass were 103.902±114.148 kg in the stem, 13.844±12.214 kg in the bark, 15.729±30.092 kg in the foliage, 33.547±44.613 kg in the branches, and 162.581±172.881 kg for the whole tree. Likewise for 70 trees of *Pinus brutia* specie (Figure 71), the observed biomass quantities range from 0.1056 kg to 642.915 kg in the stem, 0.0421 kg to 50.129 kg in the bark, 0.2005 kg to 96.798 kg in the leaves, 0.1872 kg to 207.8382 kg in the branches, and from 0.5353 kg to 850.413 kg for the whole single-tree.

For these trees, the average biomass amounts were 129.927 ± 108.657 kg for the stem, 13.032 ± 10.126 kg for the bark, 18.116 ± 18.994 kg for the foliage, 38.436 ± 40.794 kg for the branches, and 195.625 ± 156.357 kg for the whole tree. These results constitute evidence that the biomass is well distributed in a *Pinus nigra* tree and its components, in a natural population mixed with *Pinus brutia*. For *Pinus nigra* trees, stem biomass represented 63.91% of the total biomass of the individual tree, followed by branches (18.03%), leaves (9.67%) and bark (8.39%). Similarly, in *Pinus brutia* trees, stem biomass accounts for 66.42% of total individual tree biomass, followed by branches (19.65%), leaves (9.26%) and bark (6.65%). The tree stem represents the preponderant part of total biomass in both species. It is important to note that the stem plays a crucial role as the main support structure of the tree, allowing its vertical growth and stability in the environmental, climatic, and ecological conditions of its ecosystems. In comparison, the bark has a relatively small amount of biomass, while the foliage and branches also contribute significantly to the total biomass of the tree. Tree branches, which allow the tree to spread horizontally, also provide additional support for the foliage and play a key role in capturing sunlight and growing the tree in different directions. Several studies have arrived at similar results, showing that the biomass of an individual tree is distributed among all the components of that tree.

Özkaya (2004) reported significant variations in tree biomass in the fir forests of Mount Genya (Artvin) in Türkiye. According to the author, the biomass of a fir tree varies from 174.8 kg to 1808 kg in the whole tree, from 157 kg to 1601 kg in the stem, from 9.2 kg to 125.5 kg in the branches, and from 5.9 kg to 80.9 kg in the needles. He concludes that 87.83% of total above-ground dry biomass is carried by tree stems, and only 7.40% and 4.77% by branches and needles, respectively. In a study of the *Fagus orientalis* forest stand in the Sinop region of Türkiye, Kahyaoğlu (2017) reports that the maximum biomass of a tree stem is 314,4 kg and represents 77.5% of the total biomass of the tree, 54.2 kg for the branches, 30.2 kg for the bark and 7.46 kg for the leaves. In Belgium, Xiao and Ceulemans (2004) found that the biomass of a *Pinus sylvestris* tree was distributed as follows: 33.9% in the stem, 25% in the branches and 22% in the foliage. In a study of trees from pure and mixed stands of *Pinus sylvestris* in Türkiye, Yavuz et al. (2010) found that single-tree stem biomass ranged from 11.5 kg to 1582 kg, with an average of 198.99 kg. In the branches, it varied from 2.3 kg to 347.5 kg, with an average of 14.2 kg. In leaves, biomass varied from 2.8 kg to 197.1 kg, with an average of 12.2 kg. In the bark, biomass varied from 1 kg to 50 kg, with an average of 10 kg.

Tree biomass ranged from 12.7 kg to 1,788.1 kg, with an average of 233.5 kg. Although more or less large differences can exist compared to other works, our conclusions agree with previous research, demonstrating a similar scheme of variation in the biomass of trees in mixed and pure stands. Ülker (2010) reported that the biomass of *Pinus sylvestris* trees was largely constituted in the stem and varied between 12.1 t/ha and 60.1 t/ha. These biomass variations are 1.9-7.6 t/ha in the branches, 1.9-10.7 t/ha in the foliage with an average of 5.6 t/ha, 1.9-31.8 t/ha in the bark with an average of 7.6 t/ha, 21.9-110.0 t/ha in the whole tree with an average of 42.6 t/ha. These results show that tree biomass is largely stored in the stem. However, the bark stores more biomass than the branches and leaves. Mısıır et al. (2011) reported that the biomass of a *Fagus orientalis* tree in the Karadeniz region (Türkiye) ranged from 1.08 kg to 3355.62 kg. Çömez (2010) established that, for the trees of *Pinus Sylvestris*, the stem was made up of 80.90% of the total biomass of the tree. The bark represented 3.88% while the living and dry branches paid 12.14% and 2.41% respectively. Several other literary resources assert that the majority of a tree's biomass is represented mainly in its stem as shown in Table 81 (next page).

In summary, the differences observed in the results of other studies compared with this study have several sources, namely regional or local conditions, productivity status and other dendrometric, edaphic and environmental parameters influencing biomass formation in forest species worldwide. For example, height measurement can introduce imprecision in biomass calculations, as demonstrated by Vieira et al. (2008). An analysis of the biomass for a tree with a height of 13 meters and a diameter of 20 cm resulted in 127 kg using the Scatena method (1989) and 153 kg using the Chave method (2005). In the same context, Petrokofsky et al. (2012) obtained values of 136.6 kg and 164.1 kg, respectively, with the same diameter, indicating an increase of approximately 7% and 5%.

In terms of the variation of biomass quantities in individual trees and their components, our results are convincing and lead us to safely assert that *Pinus nigra* and *Pinus brutia* trees in mixed stands constitute a fundamental pillar of biomass. This discussion explores the complex interactions between tree characteristics, biomass allocation and ecosystem dynamics within these stand types (ÇkÇz) in Türkiye. Through the prism of single-tree biomass estimation, we thus uncover the essential roles played by these stands (*Pinus nigra* and *Pinus brutia*) in determining the ecological resilience and carbon sequestration potential of these unique forest ecosystems.

Table 81. Other several comparable studies of biomass allocation in tree

Tree Species	Stem	Branch	Foliage	Bark	Single Tree	References
Some References of Biomass Amount (kg)						
<i>Pinus nigra</i>	103.9	29.31	15.73	13.64	162.58	This Study
<i>Pinus brutia</i>	129.93	38.44	18.12	13.03	195.63	This Study
<i>Pinus nigra</i>	230.0	48.9	21.2	44.9	345.0	Sakıcı et al. (2016)
<i>Pinus sylvestris</i>	198.99	14.2	12.2	10	233.5	Yavuz et al. (2010)
<i>Pterocarpus erinaceus</i>	195.00	298.39	8.46	/	502.39	Ganame et al. (2020)
<i>Populus alba L.</i>	197.60	77.5	22.5	28.6	/	Kouchi et al., (2017)
<i>Picea abies</i>	37.18	36.04	2.80	/	91.42 (+root)	Picchio et al. (2022)
<i>Pinus nigra</i>	40.09	37.50	3.00	/	96.71 (+root)	Picchio et al. (2022)
Some References of Biomass Allocation (%)						
<i>Pinus nigra</i>	63.91	18.03	9.67	8.39	100	This study
<i>Pinus brutia</i>	66.42	19.65	9.26	6.66	100	This study
<i>Abies</i>	87.83	7.40	4.77	/	100	Özkaya (2004)
12 coniferous	57.1	18.7	2.9	/	79.7 (root 21.3)	He et al. (2018)
<i>F. orientalis</i>	77.5	13.36	1.84	7.44	100	Kahyaoğlu (2017)
<i>Pinus sylvestris</i>	80.90	14.55	/	3.88	100	Çömez (2010)
20 tree Species	55.97	/	/	/	/	Romero et al. (2022)
<i>Z. serrata</i>	46.3	39.9	4.6	/	/	Chen et al. (2023)
<i>Pinus nigra</i>	41.4	38.8	3.1	/	100 (+root)	Picchio et al. (2022)
<i>Picea abies</i>	40.7	39.4	3.1	/	100 (+root)	Picchio et al. (2022)

c. Land surface Biomass in ÇkÇz Natural Mixed Stands

In the context of this study, land surface biomass refers to the biomass of deadwood, litter and living herbaceous cover that were examine in natural mixed stand of *P. nigra* and *P. brutia* in Türkiye. Our study found that the terrestrial biomass in natural mixed stands as a critical endeavor in comprehending the intricate dynamics of forest ecosystems and their contributions to carbon cycling and sequestration. This discussion delves into the assessment of terrestrial biomass within natural mixed stands in Türkiye, specifically focusing on the context of diverse species compositions and ecological settings. The interplay of different tree species, including conifers like *Pinus nigra* and *Pinus brutia*, combined with the complex interactions with the surrounding environment, shapes the biomass patterns in unique ways. Natural mixed stands, characterized by the coexistence of diverse tree species like *Pinus nigra* and *Pinus brutia*, create a complex mosaic of interactions that influence biomass distribution.

Terrestrial biomass encompassing both above-ground components (deadwood, litter and living cover, serves as a crucial indicator of ecosystem health and its capacity to mitigate climate change by acting as a carbon sink. This investigation deepens our understanding of how varying environmental conditions influence biomass allocation and contribute to the resilience of these ecosystems. By quantifying the biomass in these mixed stands, our study demonstrated the contributions of these ecosystems to the overall biomass pool and gauge their implications for carbon sequestration and ecosystem stability. In this context, our research findings presented in (Table 27) provide valuable insights into the distribution and variability of biomass quantities within the land pools (litter, deadwood and living cover) of natural mixed forest stands of ÇkÇz in Türkiye. The wide range of biomass values for each component highlights the heterogeneity and complexity of the forest capacities.

The variability in litter biomass is ranging from 4,731.6 kg/ha to 64,168.00 kg/ha. Dead wood showed a broader range, from 114 kg/ha to 7,106.80 kg/ha. Living cover biomass varied between 33.00 kg/ha to 2,959.15 kg/ha. The average biomass quantities provide an overall perspective on the forest's biomass distribution. The average biomass quantities of living cover, dead wood, and litter were found to be 451.858 kg/ha, 2,328.002 kg/ha, and 17,443.978 kg/ha, respectively. This demonstrates the significant carbon storage capacity of these forest ecosystems. These results offer important data for understanding the ecological dynamics and carbon storage potential of the studied ecosystem. The study reveals substantial variations in biomass among different components of the forest. Several studies have reported results showing a similar pattern of variation in the amounts of above-ground biomass in pure and mixed stands.

In White Pine (*Pinus strobus*) forest stands in Canada (Ontario), aged 2 years, 15 years, 30 years and 65 years, Peichl and Arain (2007) found that total biomass in woody debris represented $39 \pm 23 \text{ g/m}^2$ (2 years), $79 \pm 59 \text{ g/m}^2$ (15 years), $190 \pm 138 \text{ g/m}^2$ (30 years) and $472 \pm 254 \text{ g/m}^2$ (65 years). The authors reported that litter accounted for 5.2 t/ha (15 years), 2.9 t/ha (30 years) and 4.0 t/ha (65 years) annually. They conclude that litter and branches accounted for 10%, 15% and 20% of canopy biomass in 30-, 15- and 65-year-old forests respectively. Peichl and Arain (2006) estimated that the terrestrial biomass made up of moss, grasses and shrubs represents 4226 kg/ha in young stands (2 years), 3 kg/ha (15 years), 539 kg/ha (30 years) and 514 kg/ha (65 years). This work shows that litter stores more biomass than woody debris.

To study carbon in Japanese forests according to the IPCC 2006 guide, Ugawa et al. (2012) cited by FFIP of Japan (2020), established circular plots of 1000 m² in which 2438 samples of dead wood (circular with 2 lines of 35.68 m North-South) and 2432 samples of litter (0.5 m²) in the stands of conifer, broadleaved, unidentified woody, and bamboo. The results showed averages of 4.2 t/ha (dead wood) and 4.9 t/ha (litter). These examples are in line with our results reported in mixed forest stands of *P. nigra* and *P. brutia* in Türkiye, aged between 15 - (68) - 121 years. By scrutinizing the results of terrestrial biomass analysis in natural mixed stands, we gain insights into the intricate interplay between species diversity, environmental factors, and biomass accumulation. This knowledge is pivotal for informing forest management strategies, conservation efforts, and climate change mitigation initiatives. Ultimately, the discussion underscores the vital role of terrestrial biomass in shaping the ecological fabric of natural mixed stands in Türkiye and underscores the importance of sustainable forest management for preserving these invaluable ecosystems.

4.2.2. Belowground Biomass in ÇkÇz Natural Mixed Forests

a. Root Biomass in ÇkÇz Natural Mixed Forests

The investigation into the variation of root biomass within the soil of natural mixed stands of *Pinus nigra* and *Pinus brutia* in Türkiye offers a valuable avenue for comprehending the intricacies of below-ground dynamics and their profound impact on capacities of ecosystem health and function in the carbon sequestration. In this discussion, we delve into the intricate details of root biomass distribution, placing a spotlight on the distinctive insights unearthed through our study's outcomes. Root biomass stands as a cornerstone of forest ecosystems, holding sway over crucial processes including nutrient absorption, soil reinforcement, water retention, nutrient cycling, and notably, carbon sequestration, which plays a pivotal role in mitigating climate change impacts. The variability of root biomass proffers not only essential information about species interplay and resource competition but also crucial insights into the ability of these tree species to acclimate to diverse environmental conditions. Analysis of the experimental results (cf. Table 31) has led us to synthesize the average biomass quantities in natural mixed stands of *Pinus nigra* and *Pinus brutia* in Türkiye, as shown in the diagram in Figure 119.

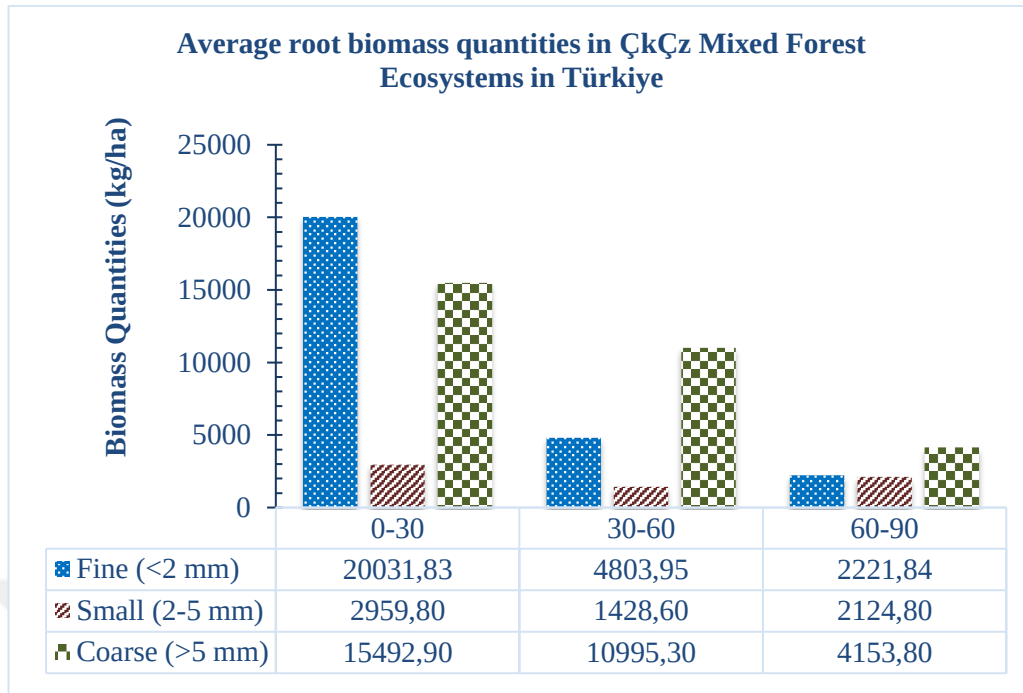


Figure 119. Average root biomass quantities as a function of size and depth in natural mixed *Pinus nigra* - *Pinus brutia* ecosystems in Türkiye

According to Figure 119, our study reveals a well-defined pattern of root biomass fluctuation within the soil of these natural mixed stands of *Pinus nigra* and *Pinus brutia*. Average data showed a high concentration of biomass in fine roots, followed by coarse and small roots in the first depth (0-30 cm). In the intermediate (30-60 cm) and final (60-90 cm) depths, biomass is highly concentrated in coarse roots, followed by fine roots and small roots. Notably, our findings demonstrate that the overall biomass distribution diverges distinctly across different root categories: fine roots accounting for 46.3%, small roots for 9.8%, and coarse roots for 43.9%. In a detailed analysis of the first soil depth, spanning from 0 to 30 cm, fine roots constituting 53.9%, small roots comprising 7.97%, and coarse roots constituting 38.1%. The biomass values ranging between 13.802 t/ha to 74.293 t/ha and an average of 37.137 t/ha, the variability of root biomass within this soil depth becomes apparent. Transitioning to the second soil depth, spanning from 30 to 60 cm, biomass oscillating between 2.891 t/ha to 42.400 t/ha, and an average of 15.316 t/ha. The distribution within this depth illustrates fine roots contributing 31.4%, small roots at 9.1%, and the bulk shared by coarse roots, at 59.5%. The discussion further extends to the final depth of 60 to 90 cm, where the values spanning from 2.176 t/ha to 18.869 t/ha and averaging 7.383 t/ha, the decreasing trend in biomass as depth increases becomes pronounced.

An observation emerges wherein fine roots exhibit higher biomass proportions than their coarse counterparts, primarily in the shallower 0 to 30 cm depth. However, beyond this threshold, the prevalence of biomass shifts towards the coarser roots, becoming more substantial. Among these varying depths, a conspicuous observation lies in the fact that biomass content is most pronounced within the uppermost layer, often associated with humus decomposition, and subsequently wanes as depth increases. Our study corroborates the notion that root biomass allocation is substantially concentrated within the topsoil, notably within the 0-30 cm range, and steadily diminishes as depth increases. This phenomenon highlights the significance of understanding below-ground biomass dynamics, particularly in the context of these mixed stands comprising *Pinus nigra* and *Pinus brutia*. Our findings contribute to a broader context of research on root biomass distribution, thereby confirming trends observed in other similar studies.

In a study in Acacia (*Robinia pseudo-acacia* L.) plantations, Tüfekçioğlu (2008) reported that root biomass was 4.018 t/ha for fine roots, 0.389 ton/ha for small roots, and 1.449 t/ha for coarse roots. According to this study, coarse roots store more biomass than fine and small roots. But other studies show the opposite in some considerations of these biomass variations. In a study of tree roots in 17 experimental soil plots in pure stands of *Pinus nigra* in the Adana-Feke region (Türkiye), using excavation method and root cylinder method, Yıldız (2021) reports that, with soil excavation method, the total biomass in tree roots varied between 2024 kg/ha and 40657 kg/ha. The variations in these biomass quantities are 536 kg/ha to 2554 kg/ha in fine roots, 654 kg/ha to 4740 kg/ha in small roots, and 549 kg/ha to 33363 kg/ha in coarse roots. With root cylinder method, such as the example in this study, Yıldız (2021) found that the total biomass in all roots sampled, varied between 606-19740 kg/ha. In these quantities, the variation is between 326-2689 kg/ha in fines roots, 0-4492 kg/ha in small roots and 0-13398 kg/ha in coarse roots.

Examining the mean values of biomass quantities in this ecosystem, it can be observed that root biomass is largely stored in fine roots, then in small roots, and in small quantities in coarse roots, at all depths. This study clearly demonstrates that, as depth increases, the biomass decreases in each category (fine, small, and coarse). This is in line with our conclusion. In the same way, Özkaya (2016) has shown that fine root biomass values are 4.70 t/ha in a group of slopes from 0 to 25%, 4.27 t/ha in a group of slopes from 26 to 50%, and 3.94 t/ha of slope >50%.

By employing the cylinder method to determine the biomass of fine and fine roots of *Pinus sylvestris* trees in pure stands, Yavuz et al. (2010) revealed that the biomass varies between 3022-7478 kg/ha in fine roots and 801-477 kg/ha in small roots. On the other hand, the biomass of coarse roots estimated using the excavation method showed an average of 9328 kg/ha. The observed trends of variation in biomass quantities based on root categories are similar to our options. It is observed that fine roots store more biomass, followed by coarse roots and small roots. However, other authors do not agree with this conclusion by showing that root biomass in boreal forests (33.8 Mg/ha) which varies according to root size, was higher in coarse roots (>5 cm) than in lower classes (<1, 1-2, 2-5 cm), which did not show any difference between them. This is what Yuan et al. (2010) indicated who carried out a literature review and Meta-Analyses on the Fine Root Biomass, Production, Turnover Rates, and Nutrient Contents in Boreal Forest Ecosystems in Relation to Species, Climate, Fertility, and Stand Age (Canada).

According to their observation, observations not similar to our conclusions were reported in temperate (Fujii and Kasuya, 2008), tropical (Maycock and Congdon, 2000), and boreal forests (Persson and Stadenberg, 2009). But these works chose the size of coarse roots as >5 cm instead of >5 mm as in our case. According to a biomass and carbon study conducted by SarıYıldız and Mert (2022) on tree roots of (*Fraxinus angustifolia* Vahl., *Alnus glutinosa* L., and *Quercus cerris*) in the Karacabey floodplain forests in Bursa (Türkiye), the total root biomass ranged from 167.7-186.8 t/ha (Ash tree) et de 49-63.6 t/ha (Alder). But graphical trends show that the quantities of fine roots (0-2 mm), small roots (2-5 mm), and large roots (5-10 mm) biomass determined using a cylinder (6.4 cm in diameter and 34 cm deep) varied with root size and different soil types (poorly drained and well-drained) of the three studied stand types. Mısır and Mısır (2012) conducted a study on tree root biomass in pure stands of *Abies nordmanniana* (Mattf.) and *Pinus sylvestris* in the Karadeniz region of Türkiye. In *Abies nordmanniana* stands, the root biomass varied between 1685-9214 kg/ha for fine roots (>2 mm). The averages for small roots (2-5 mm) and coarse roots (>5 mm) were 4097 kg/ha and 11762 kg/ha, respectively. In pure stands of *P. sylvestris*, the reported averages were 724.43 kg/ha in the fine roots (>5 mm), 1650.43 kg/ha in the small roots, and 14012.30 kg/ha in the coarse roots. These results clearly demonstrate that root biomass is significantly higher in coarse roots compared to thin and fine roots, and it decreases with root size.

In our study, fine roots stored a substantial proportion of biomass in the soil, followed by coarse roots, while small roots exhibited lower quantities at all depths, though a considerable increase was observed at depths of 60-90 cm. In these natural mixed stands (*P. nigra* and *P. brutia*), biomass is mainly concentrated within the top 0-30 cm of soil and gradually decreases with depth. In the same context, Mısır and Mısır (2013) investigated carbon storage in tree roots (fine, small, and coarse) of natural Oriental beech (*Fagus orientalis* Lipsky) stands in Northeast Anatolia, Türkiye. According to their study, the average total root biomass ranged from 17585-4682 kg/ha on north-facing slopes, and from 18511-5031 kg/ha on south-facing slopes.

The research highlighted variations in fine root biomass, which ranged from 1801-7669 kg/ha on north-facing slopes and 2205-10153 kg/ha on south-facing slopes. As for small and coarse roots, their biomass quantities varied from 3330-9060 kg/ha on north-facing slopes and 35-9752 kg/ha on south-facing slopes. These findings exhibited trends of variation similar to those observed in our study, although the biomass quantities per hectare are relatively low. With the aim of assessing root biomass in Artvin's Eastern fir and Eastern beech forests, Tüfekçioglu et al. (2002) conducted a study involving the collection of 5 root cores from 6 inventory plots. The outcomes unveiled that, within Eastern fir stands, fine roots displayed a biomass range of 11559 kg/ha, small roots had 3153 kg/ha, and coarse roots exhibited 10202 kg/ha.

In contrast, Eastern beech forests showed biomass figures of 9053 kg/ha for fine roots, 2517 kg/ha for small roots, and 7015 kg/ha for coarse roots. These investigations corroborate the patterns we have identified in the natural mixed stands of *P. nigra* and *P. brutia* in Türkiye. In a separate investigation concentrating on root biomass in pure stands of *P. sylvestris* in the Edirne-Keşan region (Türkiye), Bilmiş (2010) collected 96 root samples from four experimental plots. His findings reported that biomass levels reached 3817 kg/ha in fine roots, 950 kg/ha in small roots, and 1016 kg/ha in coarse roots. In the same *P. sylvestris* stands, Tufekcioglu (2010) obtained similar results, noting 3772 kg/ha for fine roots and 1078 kg/ha for small roots. Comparing our investigation regarding the distribution of biomass quantities across various categories, with a notable concentration in fine roots, we can infer that the trends in variation from these studies align closely with our observations.

In summary, our findings highlight the complexity of below-ground interactions and the influence of factors such as soil type, stand density, and climatic conditions on root biomass distribution. The discussion elucidates the methodologies employed to quantify root biomass, including excavation technique unlike other methods such as ground-penetrating radar. By focusing on the unique characteristics of our study's results, we reveal the variations in root biomass among different depths and stand compositions. Moreover, the study's outcomes contribute to a comprehensive understanding of how *Pinus nigra* and *Pinus brutia* stands respond to specific environmental factors in Forest ecosystem of Türkiye.

b. Mass in Soil Organic Matter in ÇkÇz Natural Mixed Forests

Exploring the variation of biomass in the soil organic matter (SOM) within natural mixed stands of *Pinus nigra* and *Pinus brutia* (cf. Figure 72) holds crucial significance in shedding light on the underlying mechanisms within forest ecosystems. This study delved into the distribution of biomass in the SOM at different soil depths (0-10 cm, 10-30 cm, 30-50 cm, 50-80 cm, and 80-100 cm) to gain insights into how the intricate interactions between trees, soil, and SOM influence the dynamics of these ecosystems. SOM constitute as a fundamental soil component, playing a vital role in regulating biogeochemical cycles, water retention, and carbon sequestration in his biomass. Diverse soil depths can encompass a variety of ecological contexts, thus affecting the decomposition of organic matter and the distribution of biomass.

Through the analysis of biomass fluctuations at varying depths, this research has illuminated the manner in which mixed stands of *Pinus nigra* and *Pinus brutia* exert an impact on the dispersion of biomass within distinct soil strata. According to the different depths examined in this research, the distribution of the quantity of biomass shows that 10.5% is stored between 0-10 cm of soil, 20.9% in 10-30 cm, 20.7% in 30-50 cm, 31.1% in 50-80 cm and 16.8% between 80-100 cm. Based on these results, the greatest quantity of biomass is stored at a depth of 50-80 cm. We can also say that 44% of biomass is stored between 0-30 cm. In other words, the greatest biomass amount of organic matter is stored in the upper part of the soil (0-30 cm). The trend also shows that the value of biomass decreases with depth (Mısır and Mısır, 2012). In the different depths, the average amounts of biomass are 794.019 t/ha in 0-10 cm, 1579.955 t/ha in 10-30 cm, 1714.243 t/ha in 30-50 cm, 2635.317 t/ha in 50-80 cm and 1888.749 t/ha in 80-100 cm.

To illustrate the variations in biomass within the organic matter of forest soils, Tolunay and Çömez (2008) analyzed the work of several researchers conducted on 1234 soil profiles collected from various types of forest stands, including conifers (916 soil profiles), broadleaves (205), and mixed (33) stands in Türkiye. The data were estimated for a soil depth of 1 meter. Based on 14 soil samples and citing Kantarci et al. (2000) and Çelik (2006) for mixed forests of Scots pine (*Pinus nigra*) and Calabrian Pine (*Pinus brutia*), the biomass varied between 0.7-20.0 Mg/ha, with an overall average of 5.5 Mg/ha. From 47 soil samples taken from pure *Pinus nigra* plantations, Tolunay and Çömez (2008) reported that biomass of soil organic matter ranged between 5.7-72.9 Mg/ha with an average of 23.0 Mg/ha. For *Pinus brutia* plantations, the authors estimated these variations to be 2.6-56.9 Mg/ha with an average of 24.2 Mg/ha (n = 30 samples). Based on 113 soil samples, organic biomass in *Pinus nigra* forest stands varied between 0.5-36.0 Mg/ha, with an average of 8.6 Mg/ha. In *P. brutia* stands, which were studied through 103 soil samples, organic matter biomass ranged from 1.2-41.8 Mg/ha, with an average of 6.0 Mg/ha. It is worth noting that a megagram (Mg) is equal to 1000 kg or 1 ton.

Comparing these results to our findings, it is evident that our data are relatively high. The estimates provided by Tolunay and Çömez (2008) were likely derived from conversion factors based on litter data obtained from these soils. This study thus highlights the variation in the quantities of biomass stored in soil organic matter of natural mixed stands (*P. nigra*-*P. brutia*). Understanding the intricacies of soil organic matter variation within these mixed stands is crucial for making informed decisions regarding forest management, as it provides insights into the resilience and functioning of these ecosystems, along with their pivotal role in combating climate change as a belowground reservoir. Moreover, the outcomes of our study can thus contribute to broader discussions on soil management strategies, carbon sequestration potential, and sustainable land use practices, especially within the context of the unique ecological conditions present in Türkiye.

4.3. Above/Below-Ground Carbon Stocks in ÇkÇz Natural Mixed Forests

4.3.1. Aboveground Carbon Stocks in ÇkÇz Mixed Stands

a. Carbon Content in Single Trees and their Components

In this research, a crucial aspect was the assessment of carbon content in various components of the aboveground compartment, including stems, branches, bark, foliage, and single-trees, within the natural mixed forest ecosystems of ÇkÇz. The wealth of carbon data also provides valuable information on the characteristics of *Pinus nigra* and *Pinus brutia* trees, highlighting the content (ratio) and distribution of carbon stock among the different components of the tree. For *Pinus nigra* trees, the minimum and maximum (average) values of carbon content varied between 45.9-58.1% (50.5%) for branches, 36.2-53.9% (50.1%) for foliage, 31.6-66.55% (49.8%) for bark, and 46.3-52.4% (48.8%) for the tree stem. For *Pinus brutia* trees, the carbon content was found to vary between 43.4-51.9% (48.7%) in branches, 34.5-56.3% (49.1%) in leaves, 42.8-56.1% (48.5%) in bark, and 46.2-57.6% (49.3%) in stem wood. These results are not far from observations supported by several other literary sources. Tolunay (2009) indicated the carbon content in stem (51.2%), in branch (54.7%), in needles (53.2%) and bark (53,5%) for *Pinus sylvestris*.

Güner et Çömez (2022) found 51,77% (tree), 54.9% (bark) and 52.1% (aboveground) for the *Pinus brutia* (Ten.) in Marmara Transition Zone. As already indicated by Lamlo and Savidge (2003), the carbon content relative to the dry mass of tree wood varies between 47.21% and 55.2% for conifer tree species and between 46.27-49.97% for deciduous species. Tolunay (2009) on *Pinus sylvestris* indicates carbon contents of 51.2% in the stem wood, 53.02% in the needles, 53.5% in the bark, and 54.7% in branches. For Erkut (2013), who studied *Fagus orientalis* trees, the carbon content was found to be 46.15% in the stem, 47.71% in the branches, 46.46% in the leaves, and 45.64% in the bark. Similarly, Laiho and Laine (1997) estimated these contents to be 51.8% in stem wood, 53.8% in needles, 53.2% in bark, and 53.1% in branch wood for the same species, *Pinus sylvestris*. Authors also indicated the carbon content in stem (50,9%), branch (52,6%), needles (54.0%) and bark (51,8%) for *Picea*. Furthermore, Peichl's results (2006) demonstrated that the proportion of carbon content in a tree was 47% in stem wood, 51% in the leaves, 46% in the bark, and 49% in the branches. These results confirm the trends observed in our study.

The study conducted by Mısırlı et al. (2010) on various components of a *Picea orientalis* tree concluded that the carbon content was 34.3% in the stem, 37.5% in the branches, 46.8% in the foliage, and 44.3% in the bark. In Poland, Janyszek et al. (2015) conducted a study on "the amount of carbon in the undergrowth biomass of main types of forest stands in Poland" on forest stands of around fifteen forest species (both coniferous and deciduous). Their findings concluded that the highest carbon levels were observed in oak and pine forests, as well as in the older age classes of lowland beech forests, where carbon concentration in dry matter ranged from 60 to 81%. On the other hand, the lowest concentrations were identified in lowland spruce forests, mountain fir forests, and alder forests, with carbon concentrations ranging from 39 to 41%. According to Gao et al. (2016), the average total C content (comprising of both volatile and non-volatile carbon) in the stem wood and bark of the principal tree species found in Canada's boreal forests was 50.5% and 56.2%, respectively.

Ma et al. (2018) found that the mean C content in stem wood varied between 50.5% and 47.7% for conifers and deciduous broad-leaved trees, but it was 46.6% and 48.4% for roots. They also came to the conclusion that major latitudinal patterns in plant C content were caused by climatic conditions and living forms. The mean C content of trees in boreal and temperate forests, separated into conifers and angiosperm trees, was found by Martin et al. (2018) to range from 46.5% in angiosperm temperate forests to 50.1% in conifer temperate forests. Previous estimates by Thomas and Martin (2012) ranged from 43.4% to 55.6% for wood C content in temperate/boreal biomes across species; however, they also noted that the mean C fraction in stem wood was 48.8% for angiosperm species and 50.8% for conifer tree species. This study affirms that carbon pool concentrations can vary based on age, stand types, and species. When considering all of these studies, it becomes evident that there is a strong convergence in the estimates, even with minor deviations on the order of 6-10%. However, our results align with the most accurate trend.

b. Carbon Stock in Single Trees and Their Components

Understanding the dynamics of carbon stocks in forest ecosystems is of paramount importance in the context of climate change mitigation and sustainable forest management. This discussion focuses on the variation of above-ground carbon stocks in natural mixed stands of *Pinus nigra* and *Pinus brutia*, specifically delving into the single-tree carbon content and stocks within the ÇkÇz natural stands (cf. Figure 73).

The above-ground carbon stocks encompass various components of trees, including stem, branches, bark, and foliage. These components play a critical role in carbon sequestration and storage. Studying the distribution of carbon content and stocks among these components provides insights into the overall carbon dynamics of these forest ecosystems. It sheds light on how different parts of the tree contribute to carbon accumulation and their potential in mitigating climate change by acting as significant carbon reservoirs. In the context of mixed stands, understanding the allocation of carbon across different components becomes even more pertinent due to the coexistence of different tree species. *Pinus nigra* and *Pinus brutia* have distinct characteristics that can influence their carbon allocation patterns. Exploring the carbon stocks of these species within mixed stands allows us to quantify their individual and collective contributions to carbon sequestration. Furthermore, the concept of single-tree carbon content and stocks adds granularity to our understanding of carbon distribution. It enables us to evaluate how much carbon each individual tree can potentially sequester and store, reflecting the ecological significance of every tree within the stand.

Our study observed significant variations in carbon stocks among the different tree components (stem, branch, branch and foliage). For the 68 *P. nigra* trees examined in this study, the carbon stocks exhibit a variation between the minimum and maximum values. Specifically, the carbon stocks were observed to range between 0.019 kg and 300.725 kg for stems, from 4.10^{-6} kg to 28.485 kg for barks, between 0.060 kg and 43.239 kg for foliage, from 0.036 kg to 65.122 kg for branches, and from 0.116 kg to 383.355 kg for the single-tree. In terms of the average total carbon stock, the recorded observations indicate 51.156 ± 56.779 kg for stems, 6.759 ± 5.978 kg in bark, 7.918 ± 7.991 kg in foliage, 14.892 ± 14.118 kg for branches, and 80.724 ± 79.285 kg for the entire tree. For the 70 *Pinus brutia* trees studied, the carbon quantities range from 0.057 kg to 334.958 kg for tree stem, from 0.022 kg to 25.465 kg for bark, between 0.107 kg and 47.534 kg for foliage, from 0.094 kg to 101.217 kg for branch, and between 0.280 kg and 385.689 kg for the single-tree. Additionally, the average total carbon quantities were observed to be 64.333 ± 54.879 kg in stems, 6.352 ± 5.068 kg in bark, 8.905 ± 9.351 kg in foliage, 18.656 ± 19.803 kg in branches, and 98.246 ± 76.722 kg in the entire tree. In our constate, the tree stem carbon amount represents 63.37% of the total tree carbon amount in *P. nigra*, and 65.48% in *P. brutia*. The bark has a relatively low value. Its carbon stock represents 8.37% of the total tree carbon in *P. nigra*, and 6.47% in *P. brutia*.

For the tree foliage, the carbon amount represents 9.81% for *P. nigra* and 9.06% for *P. brutia*. In tree branches, carbon amount represents 18.45% in a *P. nigra* tree and 18.99% in a *P. brutia* tree. To remember, we specially observed that, in a tree (*P. nigra* or *P. sylvestris*), biomass (above-ground) is predominantly stored in the stem. This is reflected in the carbon distribution. In other words, the stem wood stores more carbon than any other tree component (above-ground). For example, Mısır and Mısır (2013) arrived at this conclusion by indicating that the stem of *Fagus orientalis* stores 81.5% of the carbon in a tree. Other confirmations of this trend in carbon distribution within trees are provided by Yavuz et al. (2010), who found that 62.2% of the carbon is stored in the tree stem of *Pinus sylvestris*. Our study thus provides insights into comprehensible values concerning carbon distribution within a tree and highlights that the amount of carbon varies among tree components. Several other studies have reported results showing similar trends. In a similar study, Tolunay (2009) indicated that 70.2% of carbon was stored in the tree stem of *Pinus sylvestris* in Türkiye. In Denmark, Skovsgaard et al. (2006) stated that 68.8% to 72.1% of the total tree carbon was found in the stem wood of the species *Picea abies*, further supporting this trend.

In another study conducted in Finland on *Pinus sylvestris* tree species, it was determined that the carbon stored in the stem wood represented between 45.4% and 73.1% of the total above-ground carbon (Laiho and Laine, 1997). Broadly speaking, carbon is unevenly distributed within a tree. In a study of 59 trees from Eastern spruce (*Picea orientalis*) stands in the Research and Teaching Forest of the Faculty of Forestry at KTU (Türkiye), Mısır et al. (2007) reported that the stem of these trees stored 78.5% of the tree's carbon, while the other components accounted for 13,0% (bark), 7,0% (foliage), and 2,0% (branches). This distribution trend is similar to what was found in the present study for Anatolian Black Pine and Turkish Red Pine. To assess the aboveground biomass and carbon storage in the Oriental beech (*Fagus orientalis* Lipsky.) forests of the Sinop region (Türkiye), Kahyaoğlu (2017) observed that the stem alone stored 77.9% of the total carbon in the tree. The other components accounted for 13% in branches, 7.3% in bark, and 1.8% in foliage. Within the scope of TÜBİTAK Project 118O311, analyzing biomass and carbon in trees from mixed stands of *Pinus nigra* in the Gediz region (Kütahya, Türkiye), Öztürk (2021) indicated that the carbon content retained in a single tree stem accounted for 69.03% of the total stock (65.96 kg). The branches, leaves, and bark accounted for only 11.40%, 8.84%, and 10.73%, respectively.

Öztürk (2021) estimated that, in mixed stands of both *Pinus nigra* and *Pinus brutia* in the Gediz locality, the average amounts of carbon stored in a tree's wood, equivalent to 32.08 kg of carbon, were distributed as 67.27% in the stem, 12.69% in branches, 11.56% in bark, and 8.48% in foliage. Compared to our results and focusing on the specific case of mixed stands of *P. nigra* and *P. brutia*, the differences are noticeably significant. This could be due not only to the limited number of trees used but also to the choice of averaging values from both species. In our case, we calculated the averages for each tree species separately. Despite this, in terms of percentage and distribution trends (from largest to smallest), it can be said that the values are close. In summary, it is clearly observable that the carbon content is more or less half of the biomass in a tree and its components. There is a less variable trend among these content levels, regardless of the component. The variation in their averages is low, especially in the case of *Pinus nigra* and *Pinus brutia* in a natural mixed stand. However, it is evident to conclude that carbon storage capacity is unevenly distributed within a tree in general, and particularly in the case of mixed stands of *Pinus nigra* and *Pinus brutia*. Our study aligns with several others in showing that the trend in the distribution of carbon stock in a tree, the primary carbon reservoir is its stem followed by its branches, foliage, and finally its bark.

c. Carbon Content in Litter, Deadwood and Living Cover

In this study, the carbon content of different terrestrial pools, including litter, dead wood, and live vegetation cover, was carefully analyzed. The research revealed considerable variation in carbon content among these components. Specifically, the carbon content ranged from 32.4% to 53.8% in litter, 41.6% to 51.0% in dead wood, and 38.9% to 51.6% in live vegetation cover. Comparisons were drawn with other studies, such as Bülbul (2012) investigation on Eastern spruce stands and Stakenas et al. (2020) research on Lithuanian hemi-boreal forests, which reported similar trends. In our study on mixed stands of *P. nigra* and *P. brutia*, slightly lower average carbon content values were observed. Litter exhibited an average carbon content of 44.3%, dead wood had 47.7%, and live vegetation cover contained 43.4% carbon content. Our results are also very close to those of Karataş et al. (2017) that found 45.9%, 44.3%, 42.7%, 41.5.3% and 36.8% for Litter of *Cedrus libani* afforestation stands at a, a3, b2, b3, c2 and c3 stages in Türkiye, respectively.

d. Carbon Stocks in Litter, Deadwood and Living Cover

In this section, we consider these three pools as components of the aerial part of the land surface ecosystem. The data presented in Table 32 and Figure 75 further illustrated the variations in carbon stocks across land surface (terrestrial pools). Indeed, litter carbon stocks ranged from 1.860 to 31.185 t/ha with an average of 7.763 t/ha. Dead wood stocks varied from 0.054 to 3.411 t/ha with an average of 1.109 t/ha and living cover stocks ranged from 0.015 to 1.447 t/ha with an average of 0.208 t/ha. The study reveals substantial variations in aboveground biomass among litter, Deadwood and Living Cover components in mixed forest stands (ÇkÇz). Litter stores more carbon than dead wood and plant cover in the mixed forests of ÇkÇz in Türkiye. In other words, this study reveals that litter accounts for 85.50% of these three pools, followed by dead wood (12.22%) and low vegetation cover (2.29%). These findings underscore the intricate dynamics of carbon distribution in mixed natural forest ecosystems.

The distinctive carbon content characteristics within different terrestrial components emphasize the need for localized assessments and the recognition of their distinct roles in carbon storage. In comparison, the Forest Carbon Primer reported that United States (U.S.) forests stored 6% of carbon in litter, 6% in dead wood, and 54% in the soil, highlighting the importance of considering these components in carbon management strategies (Hoover and Riddle, 2020). In Ukraine, Bilous et al. (2019) conducted a study on coarse dead wood in Oak Forest stands, emphasizing carbon storage and decomposition characteristics. They estimated that carbon stock accounted for 4.5% of the total biomass of coarse woody debris and 4.8% in the litter, with a combined total of 9.3% of the total biomass. Investigations by Gao et al. (2014) as part of their work on "Carbon storage in biomass, litter, and soil of different plantations in a semiarid temperate region of northwest China" concluded that litter carbon storage varied between 2.4 tC/ha and 7.9 tC/ha. The authors estimated that litter carbon storage in *Pinus tabuliformis*, *Picea crassifolia*, *Larix gmelinii*, and *Populus simonii* plantations averaged 3.6 tC/ha, 7.9 tC/ha, 5.7 tC/ha, and 2.4 tC/ha, respectively. In their study of the natural stand in the Black Sea region of Türkiye, Mısır et al. (2012) documented litter carbon content ranging from 26.2% to 50.6%, with litter storing nearly 5.93 t/ha, and the live ground cover carbon stocks varied from 69 kg/ha to 1016 kg/ha. In the mixed forests of Japan, FFPRI (2020) reported that litter and deadwood store 4.9 tC/ha and 4.2 tC/ha respectively.

In Romania, Chivulescu et al. (2022) recently reported that litter and deadwood could store between 8.0-17 tC/ha and 17 tC/ha respectively. According to Çömez (2010), variations in carbon stocks in terrestrial pools of *Pinus sylvestris* forests in the Sündiken mountains (Türkiye) could range from 8.42 to 20.93 t/ha in the litter, 0.46 to 1.49 t/ha in deadwood, and 0.04 to 3.53 t/ha in the herbaceous mass. Babur (2018) estimated litter carbon stock to be 27.49 t/ha in *Pinus sylvestris* stands, 19.72 t/ha in Cedar (*Cedrus Libani* A. Rich) stands, and 11.91 t/ha in Eastern beech (*Fagus orientalis*) stands. In the Natural Mixed Stands of *P. nigra* and *P. brutia* within the Forest Operations Directorate of Gediz (Kütahya), explored as part of the TÜBİTAK project, Öztürk (2021) reported carbon storage capacities of 6.90 t/ha in the litter, 0.94 t/ha in deadwood, and 0.21 t/ha in live ground cover. Whole non-living woody biomass (deadwood) is the main component of forest types that plays a vital role in improving and maintaining biodiversity (Lo Monaco et al., 2020). The works of Miura (2012) provided a general description of the national carbon inventory of forest soils, emphasizing carbon stocks of deadwood, litter, and soil in the forest sector of Japan. This investigation highlighted carbon stocks ranging between 0 to 2.84 kg/m² in the litter and 0 to 8.67 kg/m² in deadwood.

The significance of deadwood in the functioning of forest ecosystems in the temperate continental climate of the Southern Carpathians in Romania was studied by Chivulescu et al. (2022) across three research sites (3 x 1 ha) established to investigate the synergy between deadwood and climate change mitigation effects. According to the author, the average volume of deadwood ranged between 50 m³/ha and 200 m³/ha. Deadwood stored between 8 tC/ha with 17 tons of biomass/ha, and 14.33 tC/ha with 30 tons of biomass/ha. The study concludes that biomass, and consequently carbon stocks, decrease with increasing altitude. Tolunay (2011) analyzed the distribution of forest litter in Türkiye (2004) based on 591 samples from conifer stands and 371 samples from deciduous stands. The author noted significant variation based on forest type. According to the author, the carbon stock in litter from productive forests is 66.11 Tg, with 52.84 Tg in coniferous forests and 6.96 Tg in deciduous forests (1 Tg=1 million kg). These findings underline the importance of localized assessments and the distinct roles these components play in carbon storage. Our findings not only echo previous studies but also provide a nuanced perspective on carbon content dynamics within these ecosystems.

4.3.2. Belowground Carbon Stocks in ÇkÇz Mixed Stands

a. Carbon Content of Roots in ÇkÇz Mixed Forests

The study of carbon stocks in the roots of natural mixed forest ecosystems of *Pinus nigra* and *Pinus brutia* in Türkiye is of paramount importance for our understanding of carbon dynamics within these ecosystems. By examining different types of roots (fine, small, and coarse), the study facilitates the understand of their capability for carbon storage of these key tree components. This study highlights the variation in the carbon stocks within root categories and different depths. Firstly, it was observed that the carbon content in the roots varied from 39.7% to 57.6%, with an average of 48.9%. This was not influenced by root type but was distributed across all categories. These observations are similar to those of Bülbül (2012), who reported that that the proportion of carbon in roots could vary between 43-55% for fine roots, 36-51% for small roots, and 32-47% for coarse roots. While our observations generally align with these ranges, they do indicate some fluctuations based on root size.

b. Root Carbon Stocks in ÇkÇz Mixed Forests

From 208 root samples collected at different soil depths (0-30 cm, 30-60 cm, and 60-90 cm) in 46 experimental plots, and sorted by size into fine roots (<2 mm), small roots (2-5 mm), and coarse roots (>5 mm), significant variations were observed in carbon quantities (cf. Table 33). The analysis of these results led us to a synthesis of the distribution of biomass in the roots, as shown in the diagram in Figure 120 (next page). According to our findings (Figure 120), carbon stocks in different root categories decreases with depth. Fine roots largely store carbon at the surface (0-30 cm), followed by coarse roots and finally small roots. However, at intermediate depths (30-60 cm), coarse roots became more imposing and stored more carbon than fine and finally thin roots. The same trend was observed at depths of 60-90 cm. Indeed, fine roots exhibited the highest carbon stocks at 0-30 cm depth, with an average of 9.643 t/ha, followed by coarse roots (7.411 t/ha), and small roots (1.461 t/ha). At 30-60 cm depth in the soil, carbon quantities of fine roots decreased compared to those at 0-30 cm. It was observed that, at 30-60 cm, coarse roots had higher carbon stocks (5.279 t/ha), followed by fine roots (2.306 t/ha) and small roots (0.686 t/ha). At this depth, fine roots stored more carbon than small roots but less than coarse roots.

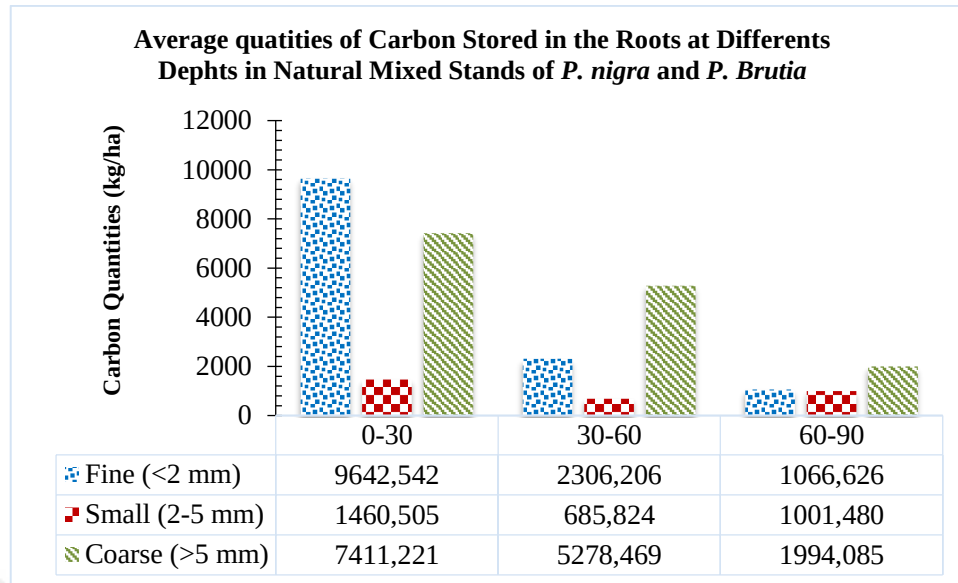


Figure 120. Summary of carbon distribution in tree roots of ÇkÇz mixed stands

Conversely, fine roots at 60-90 cm had the lowest carbon stocks (1.067 t/ha) followed by small roots (1.002 t/ha), and finally, coarse roots (1.994 t/ha). At this depth (60-90 cm), fine roots stored less carbon than both small and coarse roots. In this depth range, fine roots exhibited carbon quantities ranging from 0.061 t/ha to 5.820 t/ha. For small roots, carbon quantities ranged from 0.313 t/ha to 1.992 t/ha, and for coarse roots, carbon quantities exhibited variability from 0.358 t/ha to 5.221 t/ha. In the context of interactions between root categories and depths, this study found that fine roots were the most influential in carbon storage at all depths, with their influence diminishing as depth increased. Small roots showed relatively similar performance to fine roots at greater depths, suggesting their significant contribution to deep carbon sequestration. Coarse roots displayed the greatest variation in carbon storage with depth, with very low values at 60-90 cm. These observations are based on the allocation proportions shown in Table 82.

Table 82. Carbon allocation (%) by root category and depths in ÇkÇz Stands

Roots	Carbon Allocation in Roots of ÇkÇz Stands (%)			
Depths (cm)	0-30	30-60	60-90	0-90
Fine	0.5208	0.2788	0.2626	0.4219
Small	0.0789	0.0829	0.2465	0.1021
Coarse	0.4003	0.6382	0.4909	0.4760
C in Depths	0.6202	0.2681	0.1317	

The analysis of the proportions (%) of carbon allocation in the different root categories in ÇkÇz mixed forests provides significant insights into carbon distribution at different soil depths (Table 82). For fine roots, for example, 52.08% of their carbon is stored in the superficial depth of 0-30 cm, and the rest is distributed in the depths 30-60 cm (27.88%) and 60-90 cm (26.26%). This predominance suggests increased root activity and a substantial contribution to carbon sequestration in the superficial layer. However, at depths of 30-60 cm and 60-90 cm, a transition to coarse roots is observed, with a marked transition occurring, with a substantial increase in carbon stock in coarse roots, representing 63.82% and 49.09% respectively and suggesting adaptation to the deeper substrate. Over the entire experimental depth (0-90 cm), carbon stored in fine roots represents the second highest stock (42.19%) after coarse roots (47.60%) and ahead of small roots (10.21%). This variability reflects the complex adaptive strategies of trees in response to edaphic conditions, highlighting the importance of understanding the diversity of root types in the context of carbon sequestration and forest dynamics.

Based on experimental depths, the study reveals that 62.02% of ecosystem carbon is retained in the first superficial layer (0-30 cm), with the remainder distributed in the deep roots at 30-60 cm (26.81%) and 60-90 cm (13.17%). According to these observations, such heterogeneity in carbon storage is crucial, to be taken into account in studies of ecosystems and the carbon cycle. It underlines the importance of detailed root assessments. Variations within and between carbon stocks of different root categories and at different depths reveal interesting trends in carbon storage. Fine roots store more carbon at shallow depths (0-30 cm), while coarse roots tend to store more carbon at greater depths (30-90 cm), while small roots occupy an intermediate depth.

In summary, there is a general trend of decreasing carbon stocks as soil depth increases, in line with the uneven distribution of resources in the soil. These carbon storage variations between depths and root categories reflect trees' adaptation to nutrient and water access at different soil depths, as well as soil structure, which can significantly impact carbon sequestration in forest ecosystems. In other words, these variations can be attributed to the different nutrient absorption functions and strategies of each root category, as well as the variable resource availability in the soil at different depths. This understanding is crucial for assessing the contribution of roots in natural mixed forest stands of *Pinus nigra* and *Pinus brutia* to carbon sequestration in forest ecosystems.

Our findings can be compared to those references proposed by other literary sources. This study found that the carbon content in the roots of natural mixed forest stands (*P. nigra* and *P. brutia*) averaged 48.9%. Güner et al. (2019) also found a similar value (48.8%) in their study of Maritime pine (*Pinus pinaster* Aiton.) stands. In Türkiye, particularly in the Black Sea region, Mısır and Mısır (2013) examined carbon storage capacities in the dry mass of roots from two significant forest stands. In *Abies nordmanniana* (Fir) stands, the results obtained from 15 samples leading to 60 root cylinder samples showed that these roots could store an average of 11.86 t/ha in coarse roots and 4.10 t/ha in fine roots, while the stock ranged from 1.69-9.21 t/ha in small roots.

In pure stands of *Pinus sylvestris*, Mısır and Mısır (2013) observed average carbon quantities stored at 14.012 t/ha in coarse roots, 0.724 t/ha for fine roots, and 1.650 t/ha for roots overall. They concluded that roots could store carbon variably depending on their size. In both cases, the trend appears to be reversed compared to our results, where fine roots store the majority of carbon. One common observation is that in our findings, the carbon stocks of fine roots and those of coarse roots tend to balance out. Using the sequential coring performed by a cylindrical soil corer (6 cm in diameter and 10 cm long), Dimitrova (2015) used the trenching method to analyze root (< 1; 1-2; 2-5; 5-10 cm) biomass and carbon storage capacity in the soil (0-50 cm) of four types of forest stands distributed across three different regions in Bulgaria. This study reports that the total carbon stock value in the roots (fine and coarse) is 38.7 t/ha in Scots pine (*Pinus sylvestris*) stands, 26.2 t/ha in Oak (*Quercus*) stands, 22.7 t/ha in Norway spruce (*Picea abies*) stands, and 11.8 t/ha in Common beech (*Fagus sylvatica*) stands. Compared to the results obtained in the case of mixed stands of *P. nigra* and *P. brutia*, these stocks are relatively low.

Similar results observed in the work of Güner and Çömez (2014), who used the root pulling method in various types of *Pinus nigra* plantations in Türkiye. Across older to younger stands, these studies assumed that carbon stocks in the root system were 30.478 t/ha in Çkc3 stands, 22.113 kg/ha in Çkb3 stands, 20.546 t/ha in Çkc2 stands, 18.597 t/ha in Çkb2 stands, 3.821 t/ha in Çka3 stands, and 0.834 t/ha in Çka stands. Similarly, the root excavation technique was experimented on 150 trees by Tolunay et al. (2017) in various types of stands of two species in the Istanbul region. In fact, in the *Pinus pinea* (Çf) stands, this study reported that carbon stocks in the root biomass reached 18.340 t/ha in Çfc stands, 11.250 t/ha in Çfb stands, 9.720 t/ha in Çfcd stands, and 3.690 t/ha for Çfa stands.

In the *Pinus pinaster* (Çm) stands, Tolunay et al. (2017) indicated that roots stored 23.610 t/ha in Çmcd stands, 18.740 t/ha in Çmc stands, 14.130 t/ha in Çmb stands, and 2.130 t/ha for Çma stands. In Cedar (*Cedrus*) plantations, 40 sample trees were excavated from the soil for the analysis of their root carbon storage capacity. This is how Karataş et al. (2017) were able to demonstrate that the roots of these trees, in different types of Cedar Forest stands (*Cedrus libani* A. Rich), stored 19.380 t/ha in Sc3 stands, 15.050 t/ha in Sc2 stands, 9.350 t/ha in Sb3 stands, 5.450 t/ha in Sb2 stands, 2.160 t/ha in Sa3 stands, and 0.580 t/ha in Sa stands. These references clearly indicate that carbon storage capacities by roots in forest stands also vary with forest types, and also with other stand characteristics (clown closure, age, average diameter, average height, etc.). This could therefore explain why mixed stands of *P. nigra* and *P. brutia* exhibit higher carbon quantities. The findings indicates that the overall average carbon stocks are 12.371 t/ha for fine roots, 2.645 t/ha for small roots, and 11.968 t/ha for coarse roots. These overall average results can be compared to those of several other studies (Table 83).

Table 83. Other several comparable studies of carbon stocks in roots

Stands (Tree Species)	Average Root Carbon Stocks (kg/ha)				References
	Fine	Small	Coarse	Total	
<i>Pinus nigra</i> + <i>Pinus brutia</i> (Mixed)	12370,51	2644,70	11968,83	26984,04	This study
<i>Pinus nigra</i>	1286	1431	8400	11117	Yıldız (2021)
<i>Fagus orientalis</i>	/	/	6540	/	Yağcı (2010)
<i>Fagus orientalis</i>	4759	2617	8306	15682	Mısır et al. (2013)
<i>Pinus sylvestris</i>	2030-2490	640-960	1290-2820	/	Yavuz et al. (2010)
<i>Pinus sylvestris</i>	/	/	/	38770	Dimitrova et al. (2015)
<i>Abies nordmanniana</i>	1620	1645	2949	/	Mısır et al. (2012)
<i>Robinia pseudoacacia</i>	533	389	1591	/	Tüfekçioğlu et al. (2008)
<i>Abies nordmanniana</i>	1620	1645	2949	/	Mısır et al. (2012)
<i>Quercus frainetto</i>	/	/	/	26170	Dimitrova et al. (2015)
<i>Fagus sylvatica</i>	/	/	/	11850	Dimitrova et al. (2015)
<i>Picea abies</i>	/	/	/	22720	Ostonen et al. (2005)

Fine roots, due to their higher abundance and increased turnover rates, contribute to a substantial portion of the total belowground carbon pool. On the other hand, coarse roots, with their slower decomposition rates, tend to store more carbon over time.

The work of Mısır and Mısır (2013) on carbon storage in tree roots (fine, small, and coarse) of natural Oriental beech (*Fagus orientalis* Lipsky) stands in the Northeast Anatolia (Türkiye) reported that carbon storage ranged from 361-2764 kg/ha on north-facing slopes and 445-2764 kg/ha on south-facing slopes for fine roots, from 251-2360 kg/ha on north-facing slopes and 393-2559 kg/ha on south-facing slopes for small roots, and finally from 436-5628 kg/ha on north-facing slopes and 1378-7629 kg/ha on south-facing slopes for coarse roots. On average, these forests store 4682 kg/ha on north-facing slopes and 5031 kg/ha on south-facing slopes. In comparison to our results, it is important to note that carbon is predominantly stored in coarse roots, unlike our findings which highlight fine roots. The differences in carbon stocks between the root types can be attributed to their functional traits and interactions with soil properties. Fine roots are adept at nutrient and water uptake, making them vital for nutrient cycling and growth. This could influence their carbon allocation patterns. Small roots, while less abundant, can still contribute significantly to carbon storage due to their intricate branching structure that enhances soil exploration and resource acquisition. These results have implications for understanding the dynamics of carbon sequestration in these forest ecosystems. The distinct carbon storage capacities of different root types emphasize the need to consider root-specific contributions when assessing overall carbon budgets and potential responses to changing environmental conditions. Furthermore, these findings contribute valuable insights to forest management strategies aimed at enhancing carbon sequestration and mitigating climate change impacts natural and mixed forests of *P. nigra* and *P. brutia* in Türkiye. This study unveils the importance of this knowledge for carbon management and underscores the crucial role of roots in climate regulation through the carbon sequestration. By gaining a deeper understanding of root carbon stock dynamics, we can implement effective strategies to mitigate climate change in Türkiye.

4.3.3. Carbon Stocks in the Soil Organic Matter (SOM)

The study of carbon stocks in the soil organic matter of natural mixed forest ecosystems of *Pinus nigra* and *Pinus brutia* in Türkiye provides a valuable window into the interaction between these ecosystems and the global carbon cycle. This research project has unveiled crucial data about the carbon storage capacity within these ecosystems, as well as the observed variations in their carbon stocks at different soil depths.

The findings of this study (Figure 76) reveal significant trends in the variations of biomass and carbon stocks in soil organic matter in *Pinus nigra* - *Pinus brutia* mixed stands. Identifying the carbon storage capacity of SOM at various soil depths sheds light on the significance of these ecosystems as carbon sinks, playing a critical role in mitigating climate change. The variation in carbon stocks across different soil depths provides valuable insights into carbon sequestration processes and the mechanisms governing this distribution. Between 0 to 100 cm of depth, carbon content in the dry mass of soil organic matter ranged from 0.007% to 0.12%. At different depths, the average carbon contents in the mass of organic matter were obtained as 0.042% (0-10 cm), 0.032% (10-30 cm), 0.034% (30-50 cm), 0.035% (50-80 cm) and 0.025% (80-100 cm). with an overall average of 0.0336% (0-100 cm). In soil depths of 0–10 cm, the carbon stored in soil organic matter (SOM) ranged from 9.673 t/ha to 119.661 t/ha, with an average of 33.766 ± 23.717 t/ha. At depths of 10–30 cm, the carbon quantities ranged from 8.279 t/ha to 193.210 t/ha, with an average of 47.491 ± 35.941 t/ha. Within the 30 cm to 50 cm soil depths, the carbon stocks showed variability from 7.726 t/ha to 269.567 t/ha, with an average of 56.567 ± 43.963 t/ha. In soil depths of 50-80 cm, the carbon stored in SOM ranged from 5.882 t/ha to 533.352 t/ha with an average of 100 t/ha. And in soil depths of 80-100 cm, it appears that the carbon stored in SOM ranger from 5.660 t/ha to 122.370 t/ha, with an average of 46.199 ± 32.660 t/ha. However, it has been observed that 13.3% of the total carbon stock was stored in the first depth (0-10 cm), while the remainder was distributed as 18.8% in 10-30 cm, 20.4% in 30-50 cm, 35.2% in 50-80 cm, and 12.3% in 80-100 cm. The distribution trend of carbon in the soil organic matter has also been observed in 7, 14, and 30-year-old plantation stands of *Pinus massoniana* (Lamb.). Examining carbon stocks at a depth of 0-20 cm in these stands, He et al. (2021) reported that about 44.6%, 43%, and 30.2% of the total ecosystem stock were found at this depth for the respective age groups. These values are far superior to our results obtained for natural stands ranging in age from 15 to 121 years. This study highlights that, in the natural mixed stands of *Pinus nigra* and *Pinus brutia* in Türkiye, the quantity of carbon in the soil organic matter increases from the surface to a depth of 80 cm and begins to decrease beyond that. Previous studies can be compared with these findings. Conducting a study in Karacabey Floodplain Forest in Bursa (Türkiye), SarıYıldız et al. (2022) assessed soil organic carbon (SOC) stocks in ash, alder, and oak tree stands, comparing them with adjacent ecosystems like Calabrian pine forest, grassland, cropland, and sand dunes, considering soil depths (0-130 cm).

Their findings revealed that among the tree species, alder stands demonstrated the highest SOC (3.97%), accumulating a total of 405 t/ha. Ash trees followed with 3.11% SOC (393 t/ha), while oaks exhibited 2.43% SOC (293 t/ha), respectively. In a study conducted in young and old Fir (*Abies nordmanniana*) stands, pastures, and agricultural sites in the Kastamonu region (Türkiye), SarıYıldız et al. (2017) examined the impact of different land uses on soil organic carbon and total nitrogen storage capacity. Considering a depth of 0-20 cm in this study, the results showed that the average soil organic carbon storage capacity is 50.2 tC/ha in pastures, 48.6 tC/ha in young stands, 47.4 tC/ha in old stands, and 32.3 tC/ha in agricultural sites. Yağdı (2018) also analyzed the total organic carbon, total nitrogen, organic matter, bulk density, texture, pH, EC, available useful phosphorus (P), useful potassium (K), useful sodium (Na), useful magnesium (Mg), beneficial calcium (Ca), in 81 soil samples from forest, pasture, and agricultural sites, at depths of 0-5 cm, 5-10 cm, and 10-20 cm (Ankara-Çamkoru). It was observed that soil organic matter stored 124.44 t/ha, 61.19 t/ha, and 11.73 t/ha, respectively, at a depth of 0-20 cm. These studies confirm that soil organic carbon varies depending on land use type and age of forest stands. This view was shared by Rai et al. (2021) who reported that SOC varies considerably between forest stands. Their work estimated that SOC in 4 forest stands in the eastern Himalayan region of India varied between 75.9 and 107.7 t/ha in a depth of 0-60 cm.

Our average results are also similar to those of Açıl (2022) which supported this with his work on the variation of soil organic carbon based on different land use types in the Yeniçağa locality in Bolu (Türkiye). The author demonstrated that forest soils stored up to 35.32 g/l between 0-10 cm, 22.43 g/l between 10-20 cm, 19.04 g/l between 20-40 cm, and 15.13 g/l between 40-80 cm. Differences were also observed in the quantities distributed at these various depths, decreasing as the depth increases. In the Dayda forests of the Kastamonu region, SarıYıldız and Savacı (2023) examined the effects of elevation (871 m and 1189 m), exposure (sunny and shaded), and tree species (*Pinus sylvestris*, *Pinus nigra*, *Fagus orientalis*, and *Quercus*) on soil macronutrient stocks (C, N, P, K, Ca, and Mg) within the 0-30 cm soil depth. Specifically for forest stands, they reported that the average soil organic carbon capacity was higher in *Fagus orientalis* (57.7 t/ha) compared to *P. sylvestris* (53.1 t/ha), *P. nigra* (46.0 t/ha), and *Quercus* (39.7 t/ha). In a similar vein, Maetouq (2021) further reported that Scots pine and Black pine stands in the Kastamonu region stored up to 39.8 t/ha and 41.7 t/ha, respectively.

According to Tahmaz (2016), the organic carbon stock in soils was 79 t/ha in *Pinus nigra* stands, 73 t/ha in *Pinus sylvestris* stands, and 67 t/ha for *Quercus*. Tolunay and Çömez (2008) had already indicated that average capacities could vary between 18.3-448.0 t/ha with a mean of 78 t/ha in Scots pine stands, between 6.7-296.5 t/ha with a mean of 71.6 t/ha in Black pine stands, between 5.1-279.1 t/ha with a mean of 82.3 t/ha in Oak stands, and between 27.8-227.3 t/ha with an average of 77.9 t/ha in Eastern beech stands. In the Vezirköprü District (Samsun), Yilmaz (2021) investigated the impact of land use and vegetation cover on soil organic carbon storage in relation to certain soil characteristics. The study concludes that soil carbon stocks can vary between 12.45 to 94.10 t/ha with an average of 53.356 t/ha in the 0-20 cm depth range in forest soils, and from 5.16 to 8.86 t/ha in the 20-40 cm depth range.

In summary, these observations are similar to the findings of our study in natural mixed stands of *Pinus nigra* and *Pinus brutia* in Türkiye. However, Kocamanoğlu (2022) found 35.7 t/ha for the soils of the Oriental Spruce (*Picea orientalis* (L.) Link) reforestation stands in the locality of Karadağ (Türkiye). Furthermore, it is noted that the trends in carbon stock variations can thus be explained by the specific characteristics of a given forest soil. In Iran, Picchio et al. (2022) reported that soil organic matter in *Pinus nigra* forests stored an average of 40.36 t/ha and 30.08 t/ha of carbon between 0-10 cm and 10-20 cm depth, respectively. Similarly, the authors reported that soils in *Picea abies* forests stored an average of 32.45 t/ha and 24.85 t/ha between 0-10 cm and 10-20 cm respectively. According to Picchio et al. (2022), the carbon amount in the upper soil layer (0–10 cm) was higher than that in the lower soil layer (10–20 cm) in both plantations and the control area.

Such knowledge is pivotal for sustainable forest resource management in Türkiye, especially in the context of climate change. The capacity of forest ecosystems to store carbon has direct implications for greenhouse gas emissions regulation and biodiversity preservation. This study has demonstrated that understanding carbon stocks in soil organic matter is essential to assess the effectiveness of forest ecosystems as carbon reservoirs. The implications of these findings are paramount in guiding environmental policies, forest management practices, and global climate change mitigation efforts. In this discussion, we will delve into the implications of these results and the contributions of this study to environmental science and decision-making. In essence, this study underscores the importance of accurately assessing biomass and carbon stocks in diverse components of mixed natural forests, specifically those combining *Pinus nigra* with *Pinus brutia*.

The findings confirm that these ecosystems serve as vital carbon sinks, playing a pivotal role in addressing climate change. The study also validates the hypothesis that various elements in both aboveground and belowground biomass, along with forest soil, significantly store carbon. Additionally, the research successfully utilizes these variables to construct predictive models, offering insights into the intricate dynamics of biomass accumulation and carbon sequestration in forest ecosystems.

4.3.4. Summary of Biomass and Carbon Allocation in ÇkÇz Mixed Forests Ecosystems

General estimates of biomass and carbon in mixed forests of *Pinus nigra* and *Pinus brutia* have revealed significant variations in their distribution among different aboveground and belowground pools. This variation can be observed in Table 84.

Table 84. Distribution of biomass quantities and carbon stocks in ecosystems

ÇkÇz Forest Stand Average Biomass Quantities and Carbon Stocks (t/ha)							
Stand	Pools	Components	Biomass (B)		Carbon (C)		
			B	% in all B (AG + BG)	C	% in C	% in B
Above Ground (AG)	Tree	All	114.88	60,24	56.465	61,20	49,15
		Herbaceous	0.452	0,24	0.208	0,26	46,11
	Land Surface	Litter	17.444	9,15	7.763	8,41	44,50
		Deadwood	2.328	1,22	1.109	1,20	47,66
Below Ground (BG)	Roots	Fine	25.714	13,48	12.370	13,41	48,11
		Small	5.449	2,86	2.644	2,87	48,53
		Coarse	24.983	12,82	11.968	12,69	47,91
Soil Organic Matter (OM)			7560.873	/	253.177	/	3.35

In this Table 84, apart from the soil organic matter, it can be observed that trees constitute the largest portion of aboveground biomass, accounting for 60.24% of the total ecosystem biomass. This significant share is followed by roots at 29.16%, litter at 9.15%, deadwood at 1.22%, and herbaceous cover at 0.24%. Regarding the internal variation in carbon stocks, reflected by the size of the biomass of each corresponding component and excluding soil organic matter, trees constitute the primary aboveground carbon pool, representing 61.20% of the total stock, followed by roots at 28.98%, litter at 8.41%, deadwood at 1.20%, and herbaceous cover at 0.23% of the total ecosystem stock, excluding soil organic matter.

Despite the substantial mass of this organic matter, its carbon capacity accounts for only 3.35% (253.29 t/ha) of its mass (7560.87 t/ha). Beyond soil organic matter, the aboveground biomass and carbon stock represent 70.85% and 71.07% of the ecosystem, respectively. However, only 29.15% of the biomass and 28.93% of the carbon stock are sequestered in belowground ecosystems. These observations are consistent with those mentioned in other previous studies finds in literature. Based on 1159 soil pits, Tolunay et al. (2007) examined factors influencing organic carbon storage in forest soils in Türkiye. They revealed that the amount of carbon stored in forest soils was 77.8 t/ha. This value is lower than what we found for mixed stands of *P. nigra* and *P. brutia*. The method of these estimates was based on conversion and expansion coefficients (Durkaya et al., 2020).

In Canada, Peichl and Arain (2006) indicated that above-ground carbon stocks increased with stand age, from 3 t/ha (2 years) to 40 t/ha (15 years), 52 t/ha (30 years), and 100 t/ha (65 years). In the below-ground part, the authors indicated that forest soils stored 37 t/ha, 39 t/ha, 39 t/ha, and 56 t/ha for 2, 15, 30, and 65 years, respectively. The stands examined in our study ranged from 15 to 121 years old, suggesting an even greater increase in carbon. Aside from carbon stored in soil organic matter, our results (71.04% and 28.96%) are quite similar to those of Cao and Woodward (1998), who observed that 80% of carbon was stored above-ground and 40% below-ground. In the same way, Gao et al. (2014) reported that the amounts of carbon stored in forest ecosystems were 281 t/ha (*Pinus tabulaeformis*), 330 t/ha (*Populus simonii*), 375 t/ha (*Larix gmelinii*), and 469 t/ha (*Picea crassifolia*). They indicated that 59.5% to 91.1% of this carbon was trapped in the soil.

In the case of our work, a similar result was obtained, indicating that natural mixed forest ecosystems of *Pinus nigra* and *Pinus brutia* store an average of 345.45 t/ha of organic carbon. Mısır et al. (2018) conducted a study on *Fagus orientalis* stands in northern Türkiye (Trabzon) as part of the project titled Development of a Common Protocol to Assess the Impact of Forest Management Practices on Climate Change. The examination of both aboveground and belowground biomass and carbon in these ecosystems revealed that the majority of the carbon stock primarily originated from aboveground biomass and litter, accounting for 70% of the total carbon stock (Mısır et al., 2018). Our study similarly highlighted a comparable proportion, finding that 70.85% of the carbon was trapped in aboveground biomass, including litter, deadwood, and herbaceous vegetation.

4.4. Modeling of Biomass and Carbon Storage in ÇkÇz Natural Mixed Stand

Predictive modeling of biomass and carbon storage in forest ecosystems is a critical tool for understanding the dynamics of carbon cycling and the potential contributions of different tree components to carbon sequestration. In the context of natural mixed stands of *P. nigra* and *P. brutia* in Türkiye, the development of allometric models for individual trees and their components, including stems, branches, bark, and leaves, has significant implications for forest management and climate change mitigation strategies. These allometric models provide a means to estimate biomass and carbon storage based on easily measurable variables such as tree diameter at breast height (DBH) and height. The utilization of allometric equations enables to predict biomass distribution within trees and stands, offering insights into the allocation patterns of carbon among different components. These predictive models are invaluable in quantifying carbon storage potential and informing decisions related to sustainable forest management.

The outcomes of our study shed light on the accuracy and reliability of these allometric models for predicting biomass and carbon storage in natural mixed stands of *Pinus nigra* and *Pinus brutia*. By identifying the most suitable models for estimating biomass, we provide forest managers and policymakers with tools to make informed decisions regarding carbon sequestration potential, carbon trading initiatives, and forest conservation efforts. Understanding the predictive capacity of these models is central to assessing the role of these ecosystems in combating climate change. These models provide a means to estimate the carbon sequestration potential of different tree components, aiding in the formulation of effective strategies for mitigating greenhouse gas emissions and conserving carbon reservoir.

4.4.1. Biomass Modeling of Trees and Tree Components

One of the key objectives of this study was to show that complex relationships existed between independent variables such as diameter and height, and biomass accumulation by trees and their components. The modelling results led us to obtain models for each of the two species studied (*Pinus nigra* and *Pinus brutia*) in natural mixed stands in Türkiye. Table 84 (next page) provides a summary of the models obtained in this study.

Table 85. Summary of biomass models for *Pinus nigra* and *Pinus brutia* trees

Component	n	Biomass Prediction Models	R ²	SE	RMSE
Tree 1		<i>Pinus nigra</i> Specie			
Stem	63	$B_{\text{stem_}\zeta k} = 0.0197422D_{1.30}^{2.7362835}$	0,958	0,296	1.389
Branch	63	$B_{\text{branch_}\zeta k} = 0.0308758D_{1.30}^{2.179809}$	0.824	0.519	1.104
Foliage	63	$B_{\text{foliage_}\zeta k} = 0.0420243D_{1.30}^{1.8880609}$	0.768	0.546	0.977
Bark	63	$B_{\text{bark_}\zeta k} = 0.0103816D_{1.30}^{2.306163}$	0.879	0.312	0,825
Total Tree	63	$B_{\text{tree_}\zeta k} = 0.0894425D_{1.30}^{2.4047544}$	0.945	0.300	1.226
Total Tree	63	$B_{\text{tree_}dh_}\zeta k = -257.897 + 15.272D_{1.30} + 9.471H$	0.794	74.545	100,83
Total Tree	63	$B_{\text{tree_}\zeta k} (MLP - ANN) = 1 - 2 - 2 - 1$	0,944	/	0.044
Tree 2		<i>Pinus brutia</i> Specie			
Stem	63	$B_{\text{stem_}\zeta z} = 0.0095162D_{1.30}^{2.9650923}$	0.958	0.296	1,256
Branch	63	$B_{\text{branch_}\zeta z} = 0.0078042D_{1.30}^{2.5994818}$	0.855	0.463	1,108
Foliage	63	$B_{\text{foliage_}\zeta z} = 0.0094476D_{1.30}^{2.3270575}$	0.660	0.714	0,978
Bark	63	$B_{\text{bark_}\zeta z} = 0.0075422D_{1.30}^{2.3148079}$	0.905	0.321	0,975
Total Tree	63	$B_{\text{tree_}\zeta z} = 0.032914D_{1.30}^{2.7121501}$	0.962	0.233	1,149
Total Tree	68	$B_{\text{tree_}dh_}\zeta z = -199.255 + 12.800D_{1.30} + 8.145H$	0.816	60.288	87.575
Total Tree	68	$B_{\text{tree_}\zeta z} (MLP - ANN) = 1 - 4 - 1$	0.883	/	0.061

For each tree species, seven tree biomass prediction models are obtained, including five single-entry prediction models developed with tree diameter ($D_{1.30}$) and two double-entry models using tree diameter and height ($D_{1.30}$ and H) simultaneously, were obtained. In models involving two independent parameters ($D_{1.30}$ and H), one model was obtained using artificial intelligence (ANN-MLP), and one model obtained through multiple linear regression (MLR) analysis. It was observed that both the simple non-linear regression models (single-entry) and the multiple linear models (double-entry) were statistically significant at 1% (p-value < 0.01). Evaluating the performance of each model on the basis of criteria such as correlation coefficient (R^2), root mean square error (RMSE), F-statistic (F) and standard error (Se), we found that, of the many models considered, the selected models are the most robust and effective in predicting tree biomass of each species (*P. nigra* and *P. brutia*) in mixed natural stands. Coefficient of determination (R^2) values, which measure the goodness of fit of the model, indicate strong relationships between predicted and observed biomass values in this study. The correlation values ranged from moderate to high, implying that, in the models developed, the predictors enable us to effectively capture the variability of tree biomass in natural mixed stands (*P. nigra* and *P. brutia*).

a. Single-Entry Non-Linear Regression Model of Tree Biomass

All best and most perform models that utilized only the diameter at breast height ($D_{1.30}$) of the trees obtained in this study are *Power* models. The model used is one of the main sources of distortion (error) that must be considered when choosing a prediction equation. Indeed, the equation ($Y = b_0 D_{1.30}^{b_1}$) obtained for each of the nonlinear models consists of two coefficients, one of which is the intercept (b_0) or the y-intercept coefficient, and the other (b_1) is the power exponent that determines the rate of exponential growth of biomass as the tree diameter increases. Similarly, Fonton et al. (2005) analyzed the accuracy by compared sixteen models of allometric equations by calculating their adjustment, selection, and prediction uncertainty criteria. Their findings support our choice of the *Power* model for predicting aboveground biomass. For instance, they suggest avoiding the power of the logarithm of the predictor (diameter) due to poorer fit and high uncertainty.

Examining the single-input nonlinear equations (cf. Table 85), we observe that the coefficient of determination (R^2) is very high in the prediction models for single-tree biomass of *Pinus brutia* ($R^2=96,2$) and *Pinus nigra* ($R^2=0,94,5$). These coefficients also exhibited similar and very high values in stem biomass models for *Pinus nigra* (95.8%) and *Pinus brutia* (95.8%). This indicates their high predictive performance. Next, the bark biomass prediction models showed a high coefficient of determination for both species, *P. nigra* (87.9%) and *P. brutia* (87.7%). The branch biomass prediction models followed with close values of high coefficients for *Pinus brutia* ($R^2=0,855$) and *Pinus nigra* ($R^2=0,824$). Finally, the correlation coefficients of the prediction models for leaf biomass (needles) are the lowest, at 76.8% (*P. nigra*) and 66.0% (*P. brutia*). In all cases, these models perform effectively in predicting the respective biomass.

Moreover, the obtained standard errors for each model display very low values. Diameter is thus the primary predictor explaining (66% to 95.8%) the variations in biomass accumulation in a single-tree and its components (aboveground biomass). In other words, even a slight change in a tree's diameter exponentially impacts its biomass growth. For both studied species, *Pinus nigra* and *Pinus brutia*, the correlation coefficients of their models are significantly high in predicting a substantial portion of tree biomass. In these models, it was observed that Power functions have effectively captured the exponential growth relationship between biomass accumulation and tree diameter. The strong correlations validate the relevance of the obtained models for predicting biomass in *P. nigra* and *P. brutia* species within natural mixed stand conditions.

There exists an exponential relationship between the basic dendrometric parameter and the variability of accumulated biomass in a tree (either *Pinus nigra* or *Pinus brutia*) within Natural Mixed Stands in Türkiye. All five selected "single-input" nonlinear prediction models, chosen in the context of the study for both species (*P. nigra* and *P. brutia*), exhibited high coefficient of determination (R^2) values and were statistically significant ($p < 0.01$). Using allometric equations, Addo-Fordjour and Rahmad (2013) showed the existence of a strong relationship ($R^2 > 0.970$; $p < 0.05$) between biomass, diameter and height of lianas in primary and secondary forests in Ghana. Our study also highlights the existence of allometric relationships between tree diameter and its total biomass, a conclusion that aligns with the results proposed in the current study for *Pinus nigra* and *Pinus brutia* in natural mixed stands in Türkiye.

In addition to the very low Standard Errors ($Se < 0$), the coefficients of determination are higher in the case of our study for the stem biomass model ($R_{Ck}^2 = 0,958$; $R_{Cz}^2 = 0,958$), for the branch model ($R_{Ck}^2 = 0,82,4$; $R_{Cz}^2 = 0,855$), for bark ($R_{Ck}^2 = 0,879$; $R_{Cz}^2 = 0,877$), for leaves ($R_{Ck}^2 = 0,768$; $R_{Cz}^2 = 0,660$), and for total aboveground biomass ($R_{Ck}^2 = 0,945$; $R_{Cz}^2 = 0,905$). The constate from this comparison show that our models are highly practical and effective in predicting the biomass of these tree species in natural mixed stands. This indicates that the nonlinear regression models, specifically the power model, were able to satisfactorily extract information about the variation in tree biomass based on their diameter in natural mixed stands, minimize errors, and generate accurate estimates, as evidenced by the low values of standard error and RMSE.

The low values of these statistical indicators, along with the high correlation coefficients, are reasonably better than those obtained in several other studies of similar nature. In the literature, several similar studies have attempted to elucidate the complex relationships (nonlinear, linear, and/or ANN-MLP) between diameter ($D_{1.30}$) and the accumulation of biomass in a single-tree and its main components. For example, Durkaya et al. (2019) developed prediction models for various components of aboveground and belowground biomass in natural stands of *P. nigra* in the Kızılçahamam region. For aboveground biomass, 34 sampled trees across different diameter classes were used, and diameter ($D_{1.30}$) served as the primary predictor. For belowground biomass, coarse roots (> 2 mm) were considered, and biomass was derived using expansion and conversion factors (BEF and BCEF).

Regarding aboveground biomass, Durkaya et al. (2019) propose biomass models as follows as a Quadratic model for tree stems ($R^2=0.92$; $F=175$; $Se=49$ kg), a *Power* model for stem bark ($R^2=0.91$; $F=318$; $Se=8$ kg), a Quadratic model for commercial branches with diameter greater than 4 cm ($R^2=0.60$; $F=14$; $Se=32$ kg), a Quadratic model for bark of commercial branches ($R^2=0.67$; $F=19$; $Se=13$ kg), a Logarithmic model for non-commercial branches ($R^2=0.85$; $F=19$; $Se=0.58$), a Logarithmic model for bark of non-commercial branches ($R^2=0.84$; $F=163$; $Se=0.61$ kg), a Quadratic model for leaves ($R^2=0.80$; $F=62$; $Se=12$ kg), and a Quadratic model for total aboveground biomass ($R^2=0.86$; $F=93$; $Se=137$ kg). In other way, Baudoin et al. (2018) developed allometric equations to estimate aboveground biomass of woody savannah trees in the Western Highlands of Cameroon. The proposed models were based on the diameter ($D_{1.30}$) of 103 trees from 7 mixed species, including analysis of leaves, branches, and stems.

The adjusted correlation among the nine tested models for individual trees ranged from 67.6% to 91.4%, with biases ranging from -17.06% to +2.52%. Selecting models ($R^2=90\%$) led these authors to the Quadratic, Cubic, and Polynomial models (Baudoin et al., 2018). These choices are not far from the models found feasible in our study. However, the power model proved to be more robust. The trends of these results showed slightly lower performance compared to our findings, in which bark biomass was separated from stem biomass. In a study on estimating total ecosystem biomass and carbon storage for Fir (*Abies nordmanniana* S. subsp. *bornmülleriana* (Mattf.)) Forests in the Western Black Sea Region, Mısırlı et al. (2012) developed models for predicting stem, branch, leaf, and bark biomass of trees based on diameter ($D_{1.30}$). This study proposed a Quadratic model for stem biomass ($R^2=0.815$), a *Power* model for branches ($R^2=0.739$), an *S-Curve* model for foliage ($R^2=0.594$), and a *Quadratic* model for bark ($R^2=0.469$). This also highlights the mathematical relationship between tree diameter and its biomass.

This aligns with our conclusion and demonstrates that our models are highly robust for biomass prediction (*P. nigra* and *P. brutia*). To assess biomass and aboveground carbon storage in *Fagus orientalis* forest stands in the Sinop region of northern Türkiye, Kahyaoğlu (2017) employed diameter as well as diameter and height to develop prediction models for various tree components. For the single-input model ($p<0.01$) that used diameter as the main predictor, the author obtained a Quadratic model for stem biomass ($R^2=0.815$; $Se=66.3$ kg), an exponential model for branches ($R^2=0.332$; $Se = 0.61$ kg), a linear model for leaves ($R^2=0.147$; $Se=4.8$ kg), an exponential model for tree bark ($R^2=0.521$; $Se=0.435$ kg), and a Quadratic model for the entire tree ($R^2 = 0.916$; $Se = 52.0$ kg).

For the two-input model using both diameter and height, Kahyaoglu (2017) proposed a linear model ($p < 0.01$). Given these results, our models are sufficiently appropriate for biomass prediction, displaying a very high correlation between the variables (diameter and/or height). In the context of REDD+ in Burkina Faso, Ganame et al. (2020) studied allometric relationships for aboveground biomass allocation and additivity, as well as carbon sequestration for *P. erinaceus* Poir in the Boulon-Koflände Classified Forest. In each of the 25 plots (900 m²), all trees were measured ($D_{1.30}$ and H). Noting that $D_{1.30}$ was the best independent variable for all aboveground biomass components, the best models were selected from three nonlinear models ($D_{1.30}$, H , and Crown $D_{1.30}$), using Seemingly Unrelated Regression (SUR) method. Logarithmic models were proposed with correlations ranging from 65% to 73% for leaves, 84% to 96% for branches, and 89% to 93% for stems. This study highlighted the logarithmic relationship in biomass formation based on tree diameter. This type of relationship was also obtained in our study, but Power models exhibited very high performance and accuracy. Similarly, the development of prediction models for tree and component biomass in pure and undisturbed *Pinus nigra* stands was the subject of a study in the Zonguldak region of Türkiye.

In this context, Durkaya et al. (2010) demonstrated that biomass prediction was achievable with regression models, proposing logarithmic models ($R^2 = 0.939$) for stem, linear models ($R^2 = 0.604$) for branches, linear models ($R^2 = 0.54$) for foliage, logarithmic models ($R^2 = 0.66$) for the crown (branch + foliage), and a Quadratic model ($R^2 = 0.939$) for the whole tree. These results closely align with what we obtained for *P. nigra* and *P. brutia* in natural mixed stands in Türkiye. The relationship between diameter ($D_{1.30}$) and biomass quantity in individual *Quercus* trees was highlighted by Makineci et al. (2011) in Northern Thrace, Türkiye. The study proposed an Exponential model ($TTUB = 1.0351 \times 0.0977D_{1.30}^{2.256}$) for aboveground biomass ($R^2=0.961$), an Exponential model ($KB = 1.0518 \times 0.0305D_{1.30}^{2.251}$) for bark ($R^2=0.928$), as well as for other components, such as models of foliage ($R^2=0.748$), branches ($R^2 = 0.863$), and stem without bark ($R^2 = 0.949$). Bulut (2012) also reported that that diameter ($D_{1.30}$) could be used to explain variability in the biomass of *Fagus orientalis* trees ($R^2=0.91$), as well as in stem biomass ($R^2=0.91$), in foliage ($R^2=0.843$), in bark ($R^2=0.757$), and in branch ($R^2=0.202$). Our study aligns with this modeling principle based on nonlinear regression with a single independent variable.

b. Individual Tree Biomass Modeling using Multiple Linear Regression and MLP-ANN

The incorporation of both diameter ($D_{1.30}$) and height (H) as predictors in the models (multiple linear regression) for the entire tree also demonstrated acceptable performances in predicting individual tree biomass of *Pinus nigra* and *Pinus brutia* in natural mixed stands in Türkiye. In this manner, the study revealed the intricate relationship between these variables using a multiple linear regression equation. However, the accuracy of biomass estimation with this equation is lower than that of the single-entry predictor model. In other words, the Power models derived from a single predictor (diameter) exhibited higher performance. In this specific previous case, multiple linear regression (MLR) models with diameter and height exhibited acceptable characteristics for predicting the biomass of *P. nigra* (79.4%) and *P. brutia* (81.6%) trees (Table 85). Considering the individual tree of each species, it was observed that the double-entry equations for *Pinus nigra* ($B_{tree_dh_Çk} = -257.897 + 15.272D_{1.30} + 9.471H$) and *Pinus brutia* ($B_{tree_dh_Çz} = -199.255 + 12.800D_{1.30} + 8.145H$) are capable of predicting the biomass of the respective trees. These models are statistically significant at 1% ($p < 0.01$) but have higher errors than the Power models of individual trees obtained with diameter only. This indicates that these nonlinear regression models, particularly the single-input power models for individual trees, were able to effectively extract information regarding the variation in tree biomass as a function of tree diameter in natural mixed stands, minimizing errors and generating accurate estimates, as indicated by low values of standard error and RMSE. The low values of these errors, coupled with the high coefficient of correlation, are reasonably similar to those obtained in several other studies. The main alternative to these multiple regression models has been the use of the intelligent model based on the Artificial Neural Network. As part of this study, this experiment made it possible to highlight the complex relationships which explain the influence of the diameter and height of trees on the accumulation of biomass at the level of each individual tree. Indeed, for the MLP-ANN model case, the results demonstrated a strong correlation between the observed and predicted tree biomass. This indicates that the MLP-type network structure was capable of effectively extracting information from the input data (diameter and height), correcting weight assignment errors in the connections between layers, and generating accurate estimates (biomass), as indicated by the high correlation between observed and predicted biomass values, and low bias and RMSE values for both *Pinus nigra* ($R^2 = 0.944$ and $RMSE = 0.084$ kg) and *Pinus brutia* ($R^2 = 0.883$; $RMSE = 0.047$) tree species.

Thus, the learning was proven, and it was observed that the algorithm exerted better biomass estimation for both species. Similar studies have reached similar conclusions. For example, in a comparative modeling study based on ANN and Multiple Regression Analysis (MRA), Çalışkan and Sevim (2018) found strong correlations of 85% (7-30-1) with Multi-Layer Perceptron (MLP), 82% (7-16-1) with Cascade Forward Back Propagation (CFBP) and 77% (7-1) with Multiple Regression Analysis (MRA), making it possible to explain the relationships between work phases and the total duration of log skidding operations. An overview of the observed data and those predicted values by the regression and the MLP were obtained. For Anatolian Black Pine (*Pinus nigra* Arnold subsp. *pallasiana*) is presented in Table 86.

Table 86. Observed and predicted values of *Pinus nigra* tree biomass in MLR and MLP

<i>Pinus nigra</i> Tree Biomass Models in ÇkÇz Natural Mixed Stands							
No	Observed Values	Predicted Values		No	Observed Values	Predicted Values	
		MLR	MLP			MLR	MLP
1	23,46	-3,79	33,97	33	31,45	-5,11	33,50
2	18,12	-3,61	34,02	34	28,55	-39,45	27,79
3	14,85	-46,46	27,64	35	197,25	293,87	284,01
4	37,41	55,35	51,32	36	588,28	426,05	554,42
5	131,65	223,22	162,34	37	227,11	264,76	290,36
6	42,29	-2,54	32,25	38	294,27	324,38	374,98
7	92,76	168,76	117,20	39	204,27	204,60	167,58
8	50,02	75,88	50,32	40	179,27	205,30	164,45
9	55,52	134,67	76,25	41	185,33	167,86	111,56
10	115,35	200,26	145,77	42	210,94	197,15	159,67
11	109,91	118,92	68,97	43	195,41	257,77	250,99
12	69,00	101,29	61,25	44	257,43	274,64	263,86
13	107,88	200,63	146,48	45	218,12	259,55	241,79
14	53,49	114,54	71,48	46	234,91	245,04	222,28
15	546,50	403,31	492,82	47	128,54	189,08	146,70
16	101,50	165,04	106,57	48	124,33	158,50	122,80
17	116,17	158,49	91,84	49	261,89	349,04	373,61
18	154,54	175,52	115,27	50	264,42	247,40	186,67
19	243,35	263,00	229,42	51	129,86	179,36	100,30
20	68,88	81,81	54,92	52	43,77	103,55	63,39
21	8,61	-83,72	23,95	53	115,03	129,84	89,32
22	49,62	29,63	41,25	54	561,71	405,90	463,58
23	83,38	93,00	61,68	55	340,10	355,40	371,93
24	242,18	254,48	207,30	56	780,66	525,41	629,63
25	35,04	24,90	43,91	57	354,49	325,53	340,49
26	195,92	220,76	145,93	58	630,55	516,36	630,35
27	198,74	277,49	253,32	59	130,91	169,37	114,82
28	37,36	-25,50	31,69	60	109,96	136,75	90,49
29	139,26	134,32	74,58	61	133,72	186,87	126,12
30	45,22	5,61	34,47	62	94,70	129,61	79,14
31	24,41	19,73	34,81	63	0,23	-234,94	15,92
32	50,05	35,49	39,21	/	/	/	/

Likewise for *Pinus brutia*, the observed data and the predicted data are presented in Table 87.

Table 87. Observed and predicted values of *Pinus brutia* tree biomass in MLR and MLP

<i>Pinus brutia</i> Tree Biomass Models in ÇkÇz Natural Mixed Stands							
No	Observed Values	Predicted Values		No	Observed Values	Predicted Values	
		MLR	MLP			MLR	MLP
1	27,99	30,10	50,19	33	42,11	-5,11	56,36
2	15,55	-8,54	42,61	34	229,62	-39,45	336,97
3	9,46	-37,63	36,77	35	164,01	293,87	158,95
4	121,14	201,84	162,63	36	344,60	426,05	352,80
5	90,50	152,36	111,81	37	236,22	264,76	178,51
6	39,72	61,16	59,31	38	352,23	324,38	352,94
7	88,75	115,61	81,28	39	224,68	204,60	194,72
8	22,74	-10,40	40,67	40	315,60	205,30	365,80
9	20,66	-13,84	41,16	41	356,13	167,86	270,24
10	135,19	246,51	224,46	42	248,27	197,15	191,05
11	160,47	191,83	135,34	43	251,14	257,77	226,75
12	65,18	118,78	87,69	44	230,42	274,64	207,01
13	236,94	301,78	316,71	45	188,33	259,55	209,17
14	41,88	64,42	60,96	46	280,96	245,04	352,36
15	511,70	408,49	487,85	47	203,75	189,08	155,47
16	241,17	258,11	241,96	48	230,29	158,50	306,79
17	302,29	288,59	295,11	49	241,28	349,04	216,54
18	231,58	219,35	177,44	50	199,20	247,40	207,58
19	411,29	338,91	383,10	51	216,36	179,36	225,86
20	47,80	59,04	59,98	52	136,68	103,55	100,17
21	48,82	59,99	60,21	53	153,82	129,84	120,61
22	173,94	186,03	147,07	54	595,61	405,90	473,83
23	171,84	227,67	208,67	55	522,84	355,40	413,58
24	321,09	295,96	332,56	56	426,52	525,41	394,95
25	273,24	292,83	305,62	57	480,82	325,53	569,00
26	60,45	55,98	58,00	58	231,71	516,36	179,05
27	114,72	130,81	92,11	59	154,15	169,37	264,50
28	99,54	120,97	85,19	60	249,61	136,75	221,25
29	26,89	-6,47	41,87	61	250,11	186,87	153,43
30	39,44	76,40	65,75	62	126,25	129,61	131,88
31	50,73	75,98	67,35	63	0,54	-234,94	25,49
32	150,73	158,33	115,60	/	/	/	/

Considering the models that were obtained in the different techniques, the MLP-ANN models demonstrated high performance. Which means that the data predicted in the MLP-ANN are closest to reality (Tables 86 and 87).

In other words, the algorithm intelligently interpreted the application of functionalities between the linear and nonlinear dimensions of the predictors ($D_{1.30}$ and H) and the predictand. With significant processing capacity, the created function was significantly affected by small prediction errors. The adjustments obtained by the MLP-ANN models were superior to those of the MLR. This means that there were minimal distortions in the estimates, as observed in the uniform distribution of concentrated residuals around the error line and confirmed by the normality trend of the residuals. All selected Non-linear prediction models for both species (*P. nigra* and *P. brutia*) exhibited high values of the coefficient of determination (R^2) and relatively low errors.

The regression models are statistically significant ($p < 0.01$). This indicates that these Non-linear regression models, specifically the Power models obtained, were capable of adequately extracting information about tree biomass variation based on their diameter, minimizing errors, and generating accurate estimates, as indicated by the low values of standard error and RMSE. The low values of these statistical indicators, along with the high correlation coefficients, are reasonably superior to those obtained in several other studies that are more or less similar. Similarly, several studies have also attempted to elucidate the complex relationship between dendrometric parameters of a tree (Diameter and/or Height, altitudes, etc.) and the accumulation of biomass in the tree and its main components. Durkaya et al. (2019) also put forth models using diameter and height for predicting biomass in *Pinus nigra* Arnold.

The general model for aboveground biomass (entire tree) proposed by the authors is represented by the relationship: $TA = 106.6611 - 11.5098d_{1.30} - 11.48h + 0.5972d_{1.30}^2 + 0.77h^2$ ($R^2 = 0,86$; $F = 45$ et $Se = 139$ kg). Compared to our models for predicting aboveground biomass (total tree), the coefficient of determination is higher in the model by Durkaya et al. (2019), but the standard error is much higher in their model than in the ones proposed in this study ($Se = 0.266$ kg). In addition to models using diameter alone, Kahyaoğlu (2017) proposed a two-variable model using both diameter and height, specifically a linear model ($R^2 = 0,914$; $Se = 46$ kg; $P < 0,01$). This study demonstrated that diameter and height practically influence the accumulation of biomass in a tree. Our study also arrived at this conclusion but presents a lower coefficient of determination for *P. brutia* ($R^2 = 0.825$) and *P. nigra* ($R^2 = 0.79$). Nevertheless, our models are suitable for predicting biomass in these trees.

Unlike biomass models that use diameter, the two-variable multiple linear regression equations ($D_{1.30}$ and H) proposed by Durkaya et al. (2010) for predicting stem biomass ($R^2 = 0,959$), branch ($R^2 = 0,678$), foliage ($R^2 = 0,672$), crown ($R^2 = 0,715$) and the entire tree ($R^2 = 0,959$) demonstrate a strong correlation compared to single-variable independent models (diameter) obtained in their work. Consequently, the authors suggested that empirical equations using both diameter ($D_{1.30}$) and height (H) take priority for predicting tree biomass, as their performance was higher. This differs from the conclusions of our study for *Pinus nigra* and *Pinus brutia* in natural mixed stands, as our work led to robust models with diameter alone. Additionally, the multiple linear models showed lower correlations in our study.

Other studies have delved into the approach of multiple linear regression (MLR) to show that biomass variation can be influenced by several independent variables. In this regard, Socha et al. (2006) involved diameter ($D_{1.30}$) and tree height (H), crown size (L_c), relative length of crown (L_{cr}), basal area increment (I_{ba1}), and age (A) to highlight their influence on the variability of *Pinus sylvestris* foliage biomass in the Niepolomice forest, as part of the FOREMMS EU 5FP IST project. With air-dried samples, biomass linear models were obtained for Shoots with needles (R^2 between: 0,735-0,847) and needles (R^2 between 0,723-0,833). Based on diameter and height, Karabürk (2011) indicated that variability in biomass could be explained by 88.3% in a large branch ($d > 4$ cm), 87.3% in a small branch ($d < 4$ cm), and 98.8% in an entire tree of the *Abies nordmanniana* species in the Bartın locality. In the stands of *Cedrus libani* located in Antalya (Türkiye), Ulküdür (2010) indicated that the variability in biomass accumulation was explained at 97.1% for the entire tree, 92.5% for the stem, 92.9% for large branches ($d > 4$ cm), and 94.1% for small branches ($d < 4$ cm). These studies have highlighted the complex relationship that exists between dendrometric data ($D_{1.30}$, and H) of a tree in different environments. However, our performance criteria proved to be inferior and were improved in the Artificial Neural Network (ANN-MLP) method.

The ANN-MLP models also demonstrated greater effectiveness than the MLR models. In other words, the coefficient of determination is higher in predicting tree biomass with ANN-MLP for *P. nigra* (89.7%) and *P. brutia* (84.7%) compared to MLR models for *P. nigra* (79.0%) and *P. brutia* (82.5%). The Multi-Layer Perceptron (ANN-MLP) is a widely used technique in modeling, as indicated in the analysis "A Review of Methods for Mapping and Prediction of Inventory Attributes for Operational Forest Management" (Brosofske et al., 2014).

The use of Artificial Neural Network (ANN-MLP) to predict biomass based on two variables (diameter and height) is a pragmatic and effective approach to identify the most important predictors for model construction. The Artificial Neural Network (ANN) is a Deep Learning technique that allows for the exploration of complex relationships among multiple non-linear variables (Li and Yeh, 2002 cited by Liu, 2023). In other words, this study was able to effectively extract the intricate relationship explaining the variation in biomass formation of each tree (*P. nigra* and *P. brutia*) in their mixed natural environment in terms of their dendrometric characteristics (diameter and height). To satisfy the statistical test of intercept and slope, the range between low and high intercept values may contain zero (0), and the range between low and high slope values must contain one (1). The MLP-ANN prediction models for tree biomass of *Pinus nigra* and *Pinus brutia* that we proposed in this study have successfully passed this test with a high level of confidence ranging from 88% to 94.4% (Puig-Arnabat et al., 2013). Same of several studies, ANN were used to extract efficiency information. In the regions of Burdur (Mediterranean) and Erzincan (Eastern Anatolian) in Türkiye, Özçelik et al. (2010) estimated stem volume using diameter (11-75 cm) and height (4.5-27 m) as predictors for four tree species, including 96 *Pinus brutia* Ten., 107 *Abies cilicica* Carr., and 67 *Cedrus libani* A. Rich. (Mediterranean region), and 89 *Pinus sylvestris* L. (Eastern Anatolian region).

Prediction techniques for volume estimation were based on (1) Artificial Neural Network (ANN) models using two algorithms (BP: Back Propagation and CC: Cascade Correlation) and the Kalman's Learning Rule, compared to other methods such as (2) Centroid Method (C), (3) Standard Volume Equation (SVE), and (4) Taper Equation (TE). Evaluating the effectiveness of the four models in explaining the variability of volume based on diameter and height for each of the four tree species, the authors reported correlation coefficients R^2 and RMSE that ranged between 97.5-99.6% (RMSE between 0.1097-0.0303 m³) for 1-BP, between 97.9-99.6% (RMSE between 0.1294-0.0283 m³) for 1-CC, between 98.5-99.7% (RMSE between 0.4598-0.0590 m³) for SVE, 99.9% (RMSE between 0.0691-0.0116 m³) for TE, and finally between 98.9-99.8% (RMSE between 20.81-0.1001 m³). The observation compared to our study is that the modeling process based on Back Propagation is the same, and evaluating model efficiency based on RMSE allows for error comparison. In this regard, ANN models show low values. Our conclusions have demonstrated similar trends in relatively low errors (RMSE between 0.087-0.024 kg) in the case of tree biomass for *P. nigra* and *P. brutia* in mixed stands in Türkiye.

In Brazil, the predictive relationship between tree volume and their diameter and height was highlighted in a study based on the use of Perceptron algorithm, Sigmoid Activation Functions and Resilient Propagation of ANN. In their study, Miguel et al. (2016) found that variability in tree volume was primarily explained by changes in diameter ($R^2 = 0.994$; RMSE = 1.75%), and also by tree height associated with diameter ($R^2 = 0.989$; RMSE = 2.22%). This study is comparable to our results in terms of the method leading to a similar conclusion. Our study adopted similar approaches to highlight the relationship between tree biomass and their diameter and height in the natural mixed stands of *Pinus nigra* and *Pinus brutia* in Türkiye.

In four forest types located in the state of Minas Gerais in Brazil, Abreu et al. (2020) conducted a study involving 1479 trees (414 in Cerrado Sensu Stricto, 266 in primary forests, 448 in secondary forests, and 351 in transitional forests) to compare modeling approaches (Linear Fixed and Mixed Models, and Artificial Neural Networks and Support Vector Machine) for individual tree volume, involving their diameter ($D_{1.30}$), height (H), and the number of branches (N). The study highlighted a strong correlation between tree volume and their diameter and height. In comparison to our conclusions regarding tree biomass in natural mixed stands (*P. nigra* and *P. brutia*), the study concluded that variability in tree volume can be effectively explained (R^2 between 95.22-99.53%; RMSE between 14.63-70.01%) by these independent variables ($D_{1.30}$, H , and N).

In this comparison, the MLR (Schumacher and Hall model, 1933) ranged between 97.04-98.64% (RMSE between 19.06-48.07%). This demonstrates the strong influence of tree diameter and height on the variation of its biomass. Similarly, Do Santos et al. (2018) demonstrated a strong correlation between the leaf area of *Ormosia paraensis* and their main dendrometric characteristics (length and width), where MLP models 2-5-1 ($R^2 = 0.951$; RMSE = 10.521%), MLP 2-6-1 ($R^2 = 0.9395$; RMSE = 11.677%), and MLP 2-3-1 ($R^2 = 0.9316$; RMSE = 13.677%) showed excellent performance compared to empirical regression models (R^2 ranging from 0.80 to 0.888).

In comparison to these results, the RMSE values in our generated models are very low, which could justify their quality in explaining the variability of biomass in trees and their components for *P. nigra* and *P. brutia* in natural mixed stands in Türkiye. Leal et al. (2015) found similar results in modeling dendrometric variables of forest species, verifying that the performance of ANNs was superior to regression models. Altering the distribution of input data (%) also influences the model's performance characteristics for ANN.

De Alcantra et al. (2018) obtained similar outcomes in modeling the prediction of production and yield in Eucalyptus stands in Minas Gerais (Brazil), indicating that fluctuations in input data distribution (between 10 to 100%) significantly impacted the training and validation criteria of the models, including the Root Mean Square Error (RMSE ranging from 4.64% to 6.17%) and the correlation between observed and estimated biomass volumes of Eucalyptus stands. This observation was also made in the training process on the modeled biomass data in the present study. Vendruscolo et al. (2019) demonstrated that the diameter and relative height of *Tectona grandis* trees had a growing influence on the variation in bark thickness.

Additionally, the age of the trees also played a role, with the prediction model for increased bark thickness showing high performance in MLP models that considered diameter (R^2 ranging from 0.852 to 0.855; RMSE: 20.86-21.05%), diameter and relative height (R^2 ranging from 0.873 to 0.883; RMSE: 18.79-19.60%), diameter, relative height, and tree age ($R^2 = 0.885$; RMSE = 18.7%). Our findings are consistent with these results, indicating that changes in statistical indicators are influenced by the quantity of input variables within the MLP-ANN algorithm's structure. Collectively, these studies underscore the substantial potential of both methods in modeling variables that are both difficult to quantify and readily accessible.

4.4.2. Modeling of Carbon Storage by Tree and their Components in ÇkÇz Mixed Forest Stands in Türkiye

In the context of this study, a set of models was developed for predicting carbon storage by individual trees of *Pinus nigra* and *Pinus brutia*, two species that constitute the natural mixed forest stands observed in Türkiye. Table 88 (next page) provides a summary of the proposed models.

According to Table 88, seven carbon storage prediction models were developed for each tree species (*Pinus nigra* (Çk) and *Pinus brutia* (Çz)), including 5 nonlinear models based on a single predictor (diameter at breast height) and 2 models based on two independent variables (diameter and height). The models based on two predictors ($D_{1.30}$ and H) consist of one model derived from the Multi-Layer Perceptron (MLP-ANN) and another from Multiple Linear Regression Analysis. Similar to the biomass modeling cases, the model selection was based on performance indicators, such as the correlation coefficient, Root Mean Square Error (RMSE), and Standard Error (Se).

Table 88. Summary of carbon models for *Pinus nigra* and *Pinus brutia* trees

Component	n	Carbon Prediction Models	R ²	Se	RMSE
Tree 1		<i>Pinus nigra</i> Specie		(kg)	(kg)
Stem	63	$C_{\text{stem}_\zeta k} = 0.0093042D_{1.30}^{2.7486228}$	0,956	0,304	1,396
Branch	63	$C_{\text{branch}_\zeta k} = 0.0155458D_{1.30}^{2.1811452}$	0.824	0.519	1,126
Foliage	63	$C_{\text{foliage}_\zeta k} = 0.0211218D_{1.30}^{1.8866732}$	0.764	0.552	0,976
Bark	63	$C_{\text{bark}_\zeta k} = 0.0042858D_{1.30}^{2.3791988}$	0.907	0.285	0,870
Total Tree	63	$C_{\text{tree}_\zeta k} = 0.0436999D_{1.30}^{2.4088081}$	0.943	0.307	1,228
Total Tree	63	$C_{\text{tree}_\zeta k} = -129.223 + 7.397D_{1.30} + 5.124H$	0.790	37.298	70.313
Total Tree	63	$C_{\text{tree}_\zeta k}(ANN) = MLP1 - 5 - 1$	0.936	/	0.012
Tree 2		<i>Pinus brutia</i> Specie			
Stem	63	$C_{\text{stem}_\zeta z} = 0.0049637D_{1.30}^{2.9459233}$	0.928	0.268	0,941
Branch	63	$C_{\text{branch}_\zeta z} = 0.0038978D_{1.30}^{2.5909269}$	0.855	0.462	1,104
Foliage	63	$C_{\text{foliage}_\zeta z} = 0.0204937D_{1.30}^{2.3059106}$	0.697	0.518	0,693
Bark	63	$C_{\text{bark}_\zeta z} = 0.0039102D_{1.30}^{2.2925086}$	0.896	0.335	0,966
Total Tree	63	$C_{\text{tree}_\zeta z} = 0.0166907D_{1.30}^{2.7019116}$	0.958	0.244	1,144
Total Tree	63	$C_{\text{tree}_\zeta z} = -102.668 + 6.229D_{1.30} + 4.638H$	0.808	31.305	44.345
Total Tree	63	$C_{\text{tree}_\zeta z}(ANN) = MLP 1 - 4 - 4 - 1$	0.881	/	0.064

a. Single-Entry Non-Linear Regression Modeling of Single-Tree Carbon Storage

Diameter was the only dendrometric parameter used in the nonlinear regression to explore its influence on carbon storage in tree and its components (branches, foliage, bark, and stem). Several nonlinear models (Quadratic, Logarithmic, Exponential, etc.) were found suitable for predicting carbon storage in *Pinus nigra* and *Pinus brutia* trees within Natural Mixed Stands in Türkiye. However, the Power model ($C = b_0 D_{1.30}^{b_1}$) showed exceptional performance for all components of each tree and for the entire tree as well. Examination of the selected equations (Table 88) for each component reveals the nonlinear relationship between tree diameter and carbon storage. This nonlinearity is reflected by the power coefficient or y-intercept coefficient (b_1). In all obtained equations, this value is greater than 1, indicating an exponential diameter-carbon growth. The scale coefficient (b_0) determines the amplitude of carbon for a given diameter.

In all equations, it is significantly greater than 0, indicating an exponential carbon storage for a given diameter. The correlation between this diameter and carbon storage showed a strong relationship in all selected models. The high values of the coefficient of determination (R^2) and the low values of the standard errors (SE) and root mean square error (RMSE) indicate that the adjusted power model is capable of satisfactorily explaining the observed variation in carbon based on diameter. This suggests that the power model successfully captures the nonlinear growth trends of carbon in response to diameter variations. In other words, it was found that diameter is a significant dendrometric indicator, satisfactorily explaining the variability in carbon storage for *Pinus nigra* ($R^2 = 0.943\%$) and *Pinus brutia* ($R^2 = 0.896\%$).

Similarly high correlations, low RMSE, and SE values were observed for these trees' stems, leaves, bark, and branches (Table 66). Power model equations accurately quantified and predicted carbon stocks based on tree diameter in Natural Mixed Stands of *P. nigra* and *P. brutia* in Türkiye. This nonlinear relationship between diameter and carbon storage aligns with observed growth patterns in forest environments. Several studies have supported the practicality of allometric equations in predicting carbon storage in trees growing in various forest ecosystems worldwide. Similar work was conducted by several authors. In oak stands in the northern Thrace region of Türkiye, Makineci et al. (2011) developed statistically significant carbon prediction models, with correlation coefficients obtained for all components of individual trees, including leaves (75%), branches (86.3%), bark (92.6%), stem without bark (94.4%), and individual tree (96.1%). Similar work was conducted by Kahyaoğlu (2017) on *Fagus orientalis* Lispky in forest stands in Sinop, Türkiye.

Indeed, determining the best prediction model for storage by using tree diameter as the main predictor led to the proposal of quadratic models for stems ($R^2=0.898$; SE=26.5 kg), exponential for branches ($R^2=0.26$; SE=0.66 kg), quadratic for leaves ($R^2=0.152$; SE=2.2 kg), exponential for bark ($R^2=0.50$; SE=0.449 kg), and power for the whole tree ($R^2=0.901$; SE=0.167 kg) for predicting above-ground carbon storage. Although modeling trends are similar, these results are significantly inferior to what we obtained for *P. nigra* and *P. brutia*. The study concluded that carbon storage can be predicted using allometric equations. Similarly, Mısır et al. (2013) demonstrated that carbon stock in pure *Fagus orientalis* stands in Trabzon could be predicted at 91.6%. These studies share similar trends with our work, validating the necessity and practicability of single-input (diameter) allometric equations for predicting forest carbon storage across various tree species and growth environments.

b. Multiple Linear Regression and MLP-ANN Models of Single-Tree Carbon Storage

In the context of our study, the use of tree diameter and height to develop carbon storage prediction models for *P. nigra* and *Pinus brutia* trees led to the proposal of multiple linear regression models ($C_{dh} = b_0 + b_1 D_{1.30} + b_2 H$) and Multi-Layer Perceptron (MLP) models as presented in Table 87. These models were selected based on their coefficient of determination and error levels. Performance indicators for the carbon prediction models demonstrated that the diameter and height of an individual tree can explain 79.0% (*P. nigra*) and 80.8% (*P. brutia*) of the variation in carbon storage within their Natural Mixed Stands.

In the case of multiple linear regression (MLR), the models are statistically significant ($p < 0.01$). In these prediction equations, the constants ($b_{0-Çk} = -121,884$; $b_{0-Çz} = -113,713$) represent the points of intersection of the regression line with the vertical axis when both diameter and height values are equal to zero. This means that when the diameter and height of the trees are zero, the predicted carbon storage is b_0 coefficient (-121.9 or -113.7). However, this value may not have practical significance in the context of modeling carbon storage in forest trees. The diameter coefficient indicates that carbon storage will increase on average by b_1 coefficient ($7,103$ kg or 6.871 kg) each time the diameter changes by one unit (cm). This coefficient reflects the expected change in carbon storage for each unit change in diameter, while keeping the height constant.

Similarly, the height coefficient shows the expected change in carbon storage for each unit (m) change in the height of individual trees, while keeping the diameter constant. In other words, if the height increases by one unit (m), carbon storage will increase on average by b_2 coefficient ($5,125$ kg or 4.045 kg). Combining these coefficients for each model (Table 88), the study finds that the variation in diameter and height of an individual tree significantly influences carbon storage. Similar studies have also concluded that both diameter and height play a significant role in carbon storage by trees.

For the models based on ANN applied through Multi-Layer Perceptron (MLP), 25 alternatives including the number of neurons and activation functions were evaluated to extract the most robust and pragmatic architecture for accurate carbon storage prediction of individual *P. nigra* and *Pinus brutia* trees. Diameter and height were the main input predictors, and their importance was evaluated in the training and testing process. We noticed that the diameter largely contributed to model construction in each case. Based on performance metrics, the MLP 1-4-1 architecture for *Pinus nigra* and MLP 1-6-6-1 for *Pinus brutia* were identified as the optimal architectures for carbon storage prediction.

Ercanlı and Kaya (2019) did not find an effect of the choice of the Transfer Function on the Number of Neurons in estimating the volume of Scots Pine in the Başçatak locality (Türkiye). Validation of the models was performed by analyzing the correlation between observed and predicted carbon values and prediction errors (Table 87). The observed and predicted carbon values in the MLR and MLP-ANN methods for *Pinus nigra* are presented in Table 89.

Table 89. Observed and predicted values of *Pinus nigra* tree carbon stocks in MLR and MLP

<i>Pinus nigra</i> Tree Biomass Models in ÇkÇz Natural Mixed Stands							
No	Observed Values	Predicted Values		No	Observed Values	Predicted Values	
		MLR	MLP			MLR	MLP
1	11,68	-2,13	23,64	33	15,94	-2,89	23,40
2	8,74	-2,03	23,66	34	14,48	-20,39	20,71
3	7,30	-23,49	20,65	35	98,10	145,76	124,59
4	19,30	28,13	33,15	36	306,98	213,37	295,89
5	64,85	110,30	79,54	37	113,17	133,73	126,51
6	20,13	-2,32	22,77	38	144,79	162,17	182,36
7	44,52	84,30	64,93	39	101,73	102,74	76,72
8	24,61	36,64	32,38	40	85,87	102,85	76,46
9	27,25	65,86	47,46	41	93,97	83,47	63,48
10	56,50	99,61	73,59	42	103,99	99,14	74,58
11	53,44	58,20	43,24	43	97,26	129,16	106,25
12	33,60	49,52	38,72	44	128,83	136,82	113,43
13	54,00	99,81	73,74	45	107,84	129,53	102,75
14	27,47	56,70	44,61	46	116,57	122,54	94,31
15	269,05	200,46	261,19	47	63,72	94,94	71,92
16	49,96	81,85	61,80	48	61,35	80,39	65,00
17	57,28	77,70	55,89	49	128,48	172,53	180,47
18	76,40	87,01	65,17	50	135,48	121,82	87,23
19	120,24	130,44	99,02	51	65,13	87,35	60,79
20	34,26	40,11	35,03	52	21,85	50,83	39,96
21	4,12	-42,00	19,09	53	56,43	65,32	53,75
22	23,74	14,65	27,42	54	274,34	200,22	240,77
23	39,97	46,08	38,99	55	161,06	175,15	178,80
24	117,22	125,83	92,02	56	383,35	261,50	327,81
25	17,08	13,39	29,07	57	181,47	161,33	158,65
26	95,06	108,28	77,30	58	321,51	257,73	328,10
27	97,33	137,58	109,24	59	67,41	84,37	64,44
28	18,13	-12,40	22,56	60	55,30	68,37	54,42
29	68,50	65,49	46,56	61	64,74	92,62	68,82
30	22,50	2,09	23,86	62	45,87	64,07	48,87
31	11,71	8,26	24,03	63	0,12	-117,76	16,36
32	26,18	16,52	26,28	/	/	/	/

Likewise for *Pinus brutia*, the observed and the predicted carbon stock data are presented in Table 90.

Table 90. Observed and predicted values of *Pinus brutia* tree biomass in MLR and MLP

<i>Pinus brutia</i> Tree Biomass Models in ÇkÇz Natural Mixed Stands							
No	Observed Values	Predicted Values		No	Observed Values	Predicted Values	
		MLR	MLP			MLR	MLP
1	13,16	14,16	25,81	33	21,43	27,09	28,94
2	7,69	-4,66	21,77	34	116,45	156,10	164,60
3	4,64	-20,17	18,54	35	82,54	100,11	85,02
4	56,22	101,36	87,14	36	174,05	158,50	174,26
5	42,99	76,37	60,29	37	117,32	106,51	96,26
6	19,99	29,73	30,80	38	176,77	158,16	174,93
7	43,17	56,50	42,51	39	112,32	113,44	103,03
8	10,75	-6,78	20,58	40	153,93	163,39	177,52
9	10,02	-7,68	20,93	41	180,41	136,52	138,18
10	65,43	123,62	116,62	42	121,64	110,58	103,06
11	78,59	93,86	69,58	43	120,36	123,68	118,55
12	32,02	59,36	46,91	44	114,13	119,91	106,13
13	113,75	150,86	155,75	45	90,09	117,17	111,41
14	20,59	31,58	31,79	46	135,83	157,72	175,15
15	250,06	204,63	228,06	47	101,44	96,40	85,29
16	114,96	129,27	124,20	48	115,34	143,90	158,35
17	145,47	144,51	147,31	49	119,65	118,97	115,71
18	113,84	109,11	92,56	50	96,29	117,95	109,01
19	221,64	169,35	182,88	51	105,41	125,19	115,77
20	22,12	29,26	31,38	52	67,47	73,02	52,00
21	23,07	29,70	31,50	53	76,29	83,58	63,78
22	81,98	93,85	79,86	54	257,93	198,63	221,88
23	84,29	115,75	112,77	55	310,36	174,90	200,71
24	152,73	150,72	169,55	56	187,94	171,81	189,27
25	132,06	146,93	152,52	57	273,46	271,25	273,61
26	28,77	27,31	30,14	58	117,57	108,84	94,25
27	57,69	64,63	48,72	59	83,81	138,30	130,65
28	49,28	59,44	44,79	60	147,74	124,80	112,30
29	13,54	-4,44	21,26	61	104,02	97,89	82,09
30	19,60	37,72	34,49	62	110,92	88,02	70,73
31	25,87	38,17	35,69	63	0,28	-81,03	12,78
32	75,41	79,13	62,06	/	/	/	/

With diameter and height used to estimate carbon stocks of each individual tree species, the correlation between observed and predicted values of individual tree carbon storage (Tables 88 and 89) demonstrated strong and efficient values. MLP 1-4-1 demonstrated that variability in carbon storage can be explained by 94.8% through predicted value of *P. nigra* trees, with a low average error (RMSE = 0.058 kg), and of *Pinus brutia* (MLP 1-4-4-1) with by 88.1% in a low error (RMSE = 0.064 kg). According to Ercanlı and Kaya (2019), the selected MLP models for each species are suitable for predicting individual tree carbon storage.

When comparing Multiple Linear Regression (MLR) prediction models with MLP-ANN models based on performance criteria listed in Table 88, it was found that MLP-ANN models were more practical, robust, and effective in accurately predicting carbon storage in trees. This conclusion aligns with the findings of Şenyurt and Ercanlı (2019) who conducted a comparative study of ANN-MLP and regression models to predict volume using diameter of Crimean black pine (*Pinus nigra*) trees in the Cankırı Forests Unit in Türkiye. The study analyzed 20 trained ANN in the Radial Basis Function (RBF) and 320 trained ANN in the Multi-Layer Perceptron (MLP) architectures. According to performance criteria based on SSE (2.78), MSE (0.009), AIC (-823.3), Schwarz Bayesian Criterion (-1421.8), RMSE (0.095), and Correlation ($R^2_{MLP} = 0.934$; $R^2_{RBF} = 0.916$) between observed and predicted values, Authors proposed the ANN-MLP 1-9-1 model including only the diameter as an input variable.

For the double-entry volume model using tree diameter ($D_{1.30}$) and height (H), the study finds an ANN-MLP 2-15-1 model (SSE=0.835; AIC= -579.6; SBC= -1788.1; MSE= 0.0027; RMSE= 0.052) with the high correlation (0,980) between observed and predicted data. These results demonstrated that MLP-ANN models were highly capable in the volume prediction including $D_{1.30}$ and tree height (H). By indicating that MLP-ANN models were preferable compared to the single-entry volume equation (regression models, this conclusion aligns with the findings of our current study and contradicts the viewpoint of Abreu et al. (2020) which believe that there are no superior models and Che et al. (2019) estimated that the Support Vector Machine method is more preferable. Indeed, Abreu et al. (2020) used diameter and height of 1479 trees (414 in Cerrado Sensus Stricto, 266 in primary forests, 448 in secondary forests, and 351 in transitional forests) in Brazil, to model the variability in individual tree volume using Linear Fixed and Mixed Models and Artificial Neural Networks, and Support Vector Machine modeling approaches. They obtained 95.22-99.53% of correlation and RMSE=14.63-70.01%.

From remote sensing data, Ercanlı et al. (2017) analyzed carbon storage variation in even-aged forests of *Pinus sylvestris* in Taşköprü-Mixed, Kastamonu (Türkiye), using four Artificial Neural Network (ANN) algorithms: Feed-Forward Backpropagation (FFBP), Elman Backpropagation (EBP), Layer Recurrent (LR), and NARX, employing vegetation indices (DVI, ND57, and ND73). They indicated that models generated by ANN algorithms had an adjusted coefficient of determination (Adjusted R^2) of 65.4% (RMSE = 7.93 kg) for FFBP, 54.2% (RMSE = 9.13 kg) for EBP, 48.8% (RMSE = 9.65 kg) for LR, and 52.4% for NARX.

In contrast, the linear regression model had an adjusted R^2 of 42.5% and an RMSE of 10.22 kg. Ercanlı et al. (2017) concluded that ANN-derived models yielded significant and more accurate results compared to linear regression models, making them effective models for predicting carbon storage in individual *Pinus sylvestris* trees within mixed forest stands. The trends of these results, where Backpropagation notably exhibited a higher adjusted R^2 (65.4%) and lower RMSE (7.93 kg) among all proposed models, are similar to those of our work, which provided significantly better performance indicators and a similar conclusion regarding regression models and the ANN choice decision.

4.4.3. Modeling of Ecosystem Biomass and Carbon Storage Using MLP-ANN and MRL

Predictive modeling plays a pivotal role in understanding the intricate dynamics of biomass and carbon storage in forest ecosystems, particularly in the context of natural mixed stands of *Pinus nigra* and *Pinus brutia* in Türkiye. These models are essential tools that allow us to understand the complex relationships that exist between variables that influence the biomass accumulation and carbon storage within both above-ground and below-ground compartments of forest ecosystems. By utilizing parameters derived from forest stands, such as Mean Diameter, Average Height, Site Index, Crown Closure, and Trees density, allometric models offer insights into the relationships between these factors and the resulting biomass and carbon storage. These predictive equations provide a means to estimate how much carbon is stored in different components of the ecosystem, facilitating informed decision-making in forest management and climate change mitigation strategies.

The applicability of allometric models goes beyond merely quantifying carbon stocks; they reveal patterns and trends in how different environmental and stand-related variables influence the distribution of carbon. The selection of the most accurate and suitable models is crucial for ensuring the reliability of biomass and carbon estimates and facilitating effective carbon management and reporting. Our study presents an exploration into the utility and reliability of these allometric models for predicting ecosystem biomass and carbon storage in natural mixed stands of *Pinus nigra* and *Pinus brutia*. Using single-entry equation models, with diameter at breast height (Table 85 and 88) for individual trees, we were able to demonstrate that the above-ground biomass capacity and corresponding carbon stock based on individual trees (Table 74), are 114.88 t/ha and 56.47 t/ha respectively (Table 84).

In a similar study analyzing biomass and carbon stock estimated with allometric models based on tree diameter in forest ecosystems in West Central India, Salunkhe et al (2023) reported that biomass and carbon stock varied between 108.84 - 55.91 Mg/ha and 51.70-25.55 Mg/ha respectively. With our findings, this suggests that allometric models play a crucial role in determining above-ground biomass and carbon stock in forest ecosystems, particularly those of *Pinus nigra* and *Pinus brutia* in Türkiye. In Thailand, Pothong et al (2022) also used allometric equations involving the variables diameter, height and wood density of 78 trees, and reported that above-ground tree biomass and carbon stock was highest in secondary forests (105.3 t/ha and 47.7 t/ha) followed by 7-year fallow (38.3 t/ha and 17.4 t/ha) and 4-year fallow (10.3 t/ha and 4.6 t/ha). This provides insights into the allocation patterns of biomass components.

From a study of the aboveground biomass of 25 trees in the Ixtlan de Juarez Forest, in the Sierra Norte locality (Oaxaca) in Mexico, Martínez-Domínguez et al. (2020) founds exponential fit model ($R^2=0.989$; RMSE=12.9 kg) and highlighted the distribution of biomass storage within the studied species, noting that 22.62% of the biomass was stored in the roots, 69.61% in the stem, 5.67% in the branches, and 2.11% in the foliage. By uncovering the significance of these predictive equations, we contribute to the broader understanding of the role that such models play in supporting climate change mitigation efforts and sustainable forest management practices. This has been demonstrated through our results. The discussion on the ecosystem biomass and carbon models developed with MLP-ANN and MRL is of paramount importance to understand the effectiveness and accuracy of these modeling approaches.

The modeling of predicting forest stand biomass and carbon demonstrated that the ANN-MLP and MLR techniques can be used to explain the mathematical relationship existing between parameters of a natural mixed forest stand (*Pinus nigra* - *Pinus brutia*) and the quantities of biomass and carbon these stands store over a given period. During modeling, artificial neuron networks may present self-correlation problems. The correlation of a variable with itself at different times is called autocorrelation. In the context of neuron networks, this can occur if the input data shows a time dependency not captured by the model. It can occur in neuron networks when successive observations of training data are interdependent. Predictions may include autocorrelation due to the sensitivity of neuron networks to time sequences, as demonstrated by Chatfield and Faraway (1996) and Flores et al. (2012).

It is essential to carefully select the input variables and adjust the model accordingly to reduce this problem. The modeling of neural networks may be affected by autocorrelation, but appropriate modeling practices can mitigate these effects. The existence of correlation was highlighted between the biomass and carbon quantities determined in this study and those estimated by the models. The results also showcased that the parameters (H_m , D_m , CC , N , and SI) of these mixed natural forest stands can be considered as important predictors for estimating biomass and carbon storage in ecosystem. It is important to understand that the influence of these parameters in the construction of the model is disproportionate. In the MLP-ANN, the algorithm ranks them in order of importance and by percentage of use of each parameter.

For example, for the stand biomass, observation of the results led us to confirm that the Average stand height (H_m) was the most influential predictor in model construction (36.7%). All its input data (100%) was used by the algorithm. Next, Stand Mean Diameter (D_m) contributed 23% to the construction of the model and provided 64.2% of its values entered into the algorithm. Crown Closure (CC) had an effect of 21.8%, providing 23.8% of its data, while 25.1% of the Trees' Density (N) and 23.8% of the Site Index (SI) data impacted the model setup at 9.2% and 8.7%, respectively. A strong correlation was found between the observed biomass quantities and the estimated values predicted by the MLP 1-3-1 model ($R^2=0.706$; $RMSE=0.065$ kg). In contrast to the MLP-ANN method, the Multiple Linear Regression (MLR) method showed lower performance ($R^2=0.431$; $RMSE=271831.961$ kg).

Similar proportions are observed in the carbon model of which the significance of each parameter in constructing the model was underscored by algorithms (cf. C and D in Figure 112). In 1-3-2-1 stand carbon model, D_m is the most influential predictor in model construction (30.1%). All its data (100%) was used by the algorithm. Next, Stand Average Height H_m contributed 24.9% to the construction of the model and provided 82.8% of its values entered into the algorithm. CC had an effect of 23.5%, providing 78.1% of its data, while 13.9% of the SI data and 7.6% of the N data impacted the model setup at 46.4% and 25.4%, respectively. Using Stepwise MLR (SPSS v22), some of these parameters were eliminated and only the D_m and the N made it possible to obtain a multiple regression model. This suggests that, within a confidence range, some independent variables do not meet statistical criteria. Parameters whose confidence threshold is greater than 10%. Their weak statistical influence in the model therefore led to their elimination.

However, it can be affirmed that the Stand Average Diameter (D_m) and Stand Tree Density (N) can explain 49.4% ($R^2 = 0.494$) of the variability in carbon storage in ÇkÇz stands in Türkiye, with a Standard Error (or RMSE) at 57850.97 kg/ha, at 1% ($p < 0.01$; $F = 21.020$). Eliminating these variables indicates that these predictors do not effectively detect a significant difference. In other words, these predictors do not effectively explain carbon storage in these stand types. This may be due to high data variability (scattered data), small sample size or random errors. Using the same variables (H_m , D_m , CC , N , and SI) in MLP-ANN, we found that all the predictors used influenced carbon storage in these natural mixed stands (ÇkÇz). These observations suggest that the MLP-ANN models are more robust and efficient than the regression equations obtained. Their coefficients were found to be very high between observed and predicted data.

The use of ANNs to model biomass and carbon storage in forestry has proved its worth in several similar experiments. Like our work, several authors have used dendrometric measurements and/or forest stand parameters to demonstrate their influence on biomass accumulation and carbon storage. Sağlam and Sakıcı (2023), who used three stand parameters (Age , N , and SI) from 74 experimental plots and 109 trees to develop allometric equations ($R^2 = 0.784$; 0.684 ; and 0.780) for predicting above-ground biomass increment (total tree, stem, and branches) of Crimean pine in the Taşköprü locality (Türkiye). Da Silva et al. (2018) estimated that MLP-ANN and classical equations do not differ significantly and are rather equivalent when the training data size is large, while classical regression models (MLR) perform well with limited training data for volume estimation. Neural networks based on Radial Basis Functions and Multilayer Perceptron, and classical equations such as Schumacher-Hall and Spurr Volume Models, are equivalent to each other when a large amount of data training is used, while classical models perform better when a small amount of training data for volume estimation is used.

But Da Sylva et al. (2018) recommended radial basis function neural networks due to their flexibility with different datasets and the benefit of having their architecture built automatically by clustering techniques. In this context, this comparison was also made by Clark (1991), who concluded that ANNs are better for predicting the stem diameter of *Pinus brutia*, a similar conclusion to that of the present study. The ANNs developed in this study for predicting biomass and carbon storage in mixed and natural stands of *Pinus nigra* and *Pinus brutia* allowed the identification of the most important predictors in model construction.

For instance, the significance of mean diameter and mean height was highlighted in the obtained models. Nandy et al. (2017) conducted a similar study with the aim of highlighting the relationship between various spectral and textural variables that can explain biomass formation in the Tropical Moist Deciduous Forest (India) dominated by sal (*Shorea robusta*) and its associates, such as kamala tree (*Mallotus philippensis*), chamror (*Ehretia laevis*), golden rain tree (*Cassia fistula*), and plantations of teak (*Tectona grandis*). According to the authors, optimizing the variables using ANN led to the identification of key variables for developing a regression model, as demonstrated by their results presented in Figure 76 (see next age). The work of Nandy et al. (2017) aptly illustrates the same process that led us to recognize the significance of Mean Diameter, Mean Height, Crown Closure, Site Index, and Tree Number (by ha) in constructing prediction models for biomass and carbon storage in natural mixed stands of *P. nigra* and *P. brutia* in Türkiye.

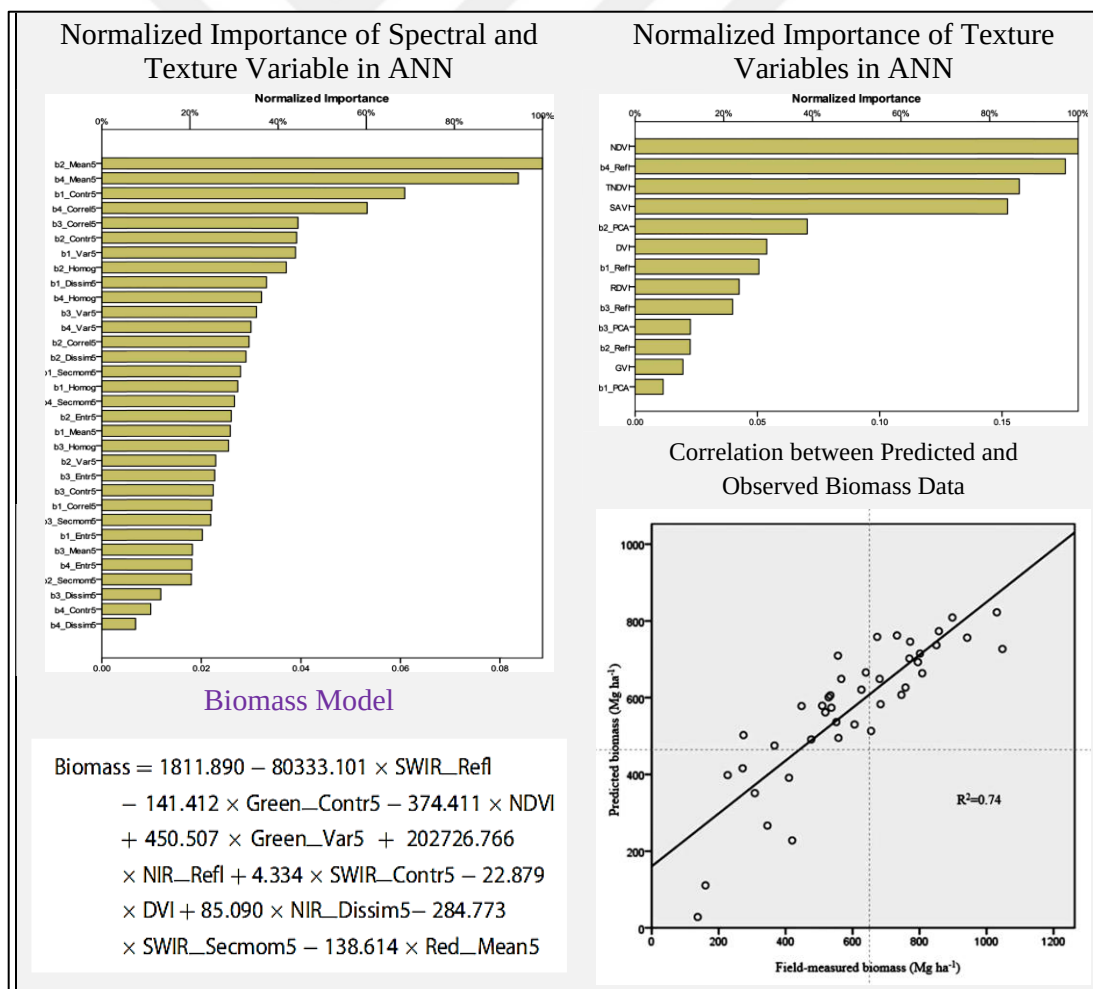


Figure 121. An example of predicting forest stand biomass by selecting predictors based on their importance using ANN (Nandy et al., 2017)

Biomass and carbon storage modeling techniques for trees in forest stands have gone further to encompass the behavior of tree stems, which constitute the main aboveground carbon pool in forest ecosystems. Our study demonstrated that tree stems stored a significant portion of biomass and aboveground carbon in mixed stands of *P. nigra* and *P. brutia*. Using six stem taper equations and multiple ANN models to compare the estimation performance of stem taper for trees in three types of forests (tropical savanna, tropical rainforest, and semi-deciduous) in Brazil, Nunes and G6rgen (2016) reported that the ANN approach is preferable for stem diameter estimation, but that the performance results were more or less similar between certain regression equations and ANN models. These conclusions are almost similar to those revealed in our study, particularly in the case of carbon storage modeling for stands. Liu et al. (2023) conducted a study titled "Ecosystem carbon storage considering combined environmental and land-use changes in the future and pathways to carbon neutrality in developed regions" based in the subtropical and tropical region (Guangdong Province) in Southern China.

To determine Net Ecosystem Productivity (ENP or Ecosystem Biomass) while accounting for Heterotrophic Respiration (HR) in a modeling process of various factors' influences on carbon storage, the prediction of Net Primary Productivity (NPP) using 16 variables in a 5-hidden-layer ANN model was employed. The study's results demonstrated high accuracy ($R^2=0.8144$; $RMSE=0.213 \text{ kgC/m}^2/\text{a}$) with ANN compared to previous studies with the Miami Model ($R^2=0.27$; $RMSE=0.260 \text{ kgC/m}^2/\text{a}$), Thornthwaite Memorial Model ($R^2=0.28$; $RMSE = 0.310 \text{ kgC/m}^2/\text{a}$), CASA Model ($R^2=0.6458$; $RMSE=0.150 \text{ kg/m}^2/\text{a}$), Synthetic Model ($R^2=0.6289$; $RMSE=0.173 \text{ kgC/m}^2/\text{a}$), and Thornthwaite Memorial Model ($R^2=0.4534$; $RMSE=0.264 \text{ kgC/m}^2/\text{a}$).

Similar to our results showing improved performance of the ANN-MLP model (R^2 between 0.87 and 0.89) for predicting carbon in mixed natural forest stands of *P. nigra* and *P. brutia* (T6rkiye) compared to the MLR model, it's evident that ANN-MLP exhibits more efficiency in capturing the effects of complex relationships between observed and estimated biomass or carbon quantities. Thus, several parameters can be utilized to establish prediction models (MLP and MLR) for aboveground and belowground biomass in a given forest stand. The modeling of aboveground and vegetative biomass was carried out by Sghaier and Abdallah (2013) on a young mixed stand of Stone Pine (*Pinus pinea*) and Maritime Pine (*Pinus pinaster* Soland. ssp *renoui* H. del Villar) in Northwestern of Tunisia.

The equations established at both the tree and stand levels allowed the authors to conclude that allometric relationships existed between stand parameters (density, mean height, mean quadratic diameter) and both stem volume and aboveground biomass. The number of neurons in the architecture of the ANN-MLP models for forest biomass and carbon is generally not a determining factor for prediction success. However, the transfer function used revealed differences compared to other functions available in the ANN architecture. This was also observed by Ercanlı and Kaya (2019) when analyzing the effect of different transfer functions and neuron numbers on volume prediction performance using ANN with single-entry (diameter) and double-entry (diameter and total height) data from 222 trees in Başçatak (Türkiye).

Based on 500 different ANN models and 100 alternative neuron numbers, the authors concluded that linear and hyperbolic tangent sigmoid transfer functions showed the best performance, while increasing the number of neurons did not have a significant impact. This highlights the importance of selecting an appropriate transfer function for predictive performance in the ANN model. In a study focusing on carbon storage prediction in Scots Pine (*Pinus sylvestris*) stands in the Taşköprü-Çiftlik forests (Türkiye), Ercanlı et al. (2017) utilized ANNs with algorithms such as Feed-Forward Backprop, Elman Backprop, Layer Recurrent, and NARX, along with Landsat TM remote sensing data (DVI, ND57, and ND73). They concluded that ANNs could serve as a suitable tool for carbon storage prediction in *Pinus sylvestris* stands. We have also arrived at a similar conclusion for Natural Mixed Stands of *Pinus nigra* and *Pinus brutia*.

The diameter of trees has proven to be highly essential and a primary predictor in the development of biomass and carbon storage models. Their distribution can thus reflect the distribution of aboveground biomass and carbon stocks in different stand types. This observation was also made by Ercanlı and Bolat (2017) in their modeling work on tree diameter distribution in 637 samples of Pine stands, based on Artificial Neural Networks (ANNs). The authors estimated that the specific ANN model based on feed-forward backprop explained over 78% of the total variation in the number of trees across diameter classes, based on percentile values (25th, 50th, and 95th) of diameters. Using Deep Learning, Ercanlı et al. (2018) also analyzed diameter distribution by focusing on the total number of trees per hectare in mixed stands of Spruce and Scots Pine in the Giresun forests.

Indeed, Ercanlı et al. (2018), the authors introduced the total number of trees from 131 experimental plots, the median value of diameter classes, and percentiles (25%, 50%, and 95%) to conclude that the deep learning algorithm is effective in minimizing errors and increasing correlation. Findings are similar to those obtained from our results regarding biomass and carbon prediction, where diameter is the primary predictor that influenced the construction of the models. In a similar vein, Khan et al. (2019) investigated the prediction of biomass in *Mentha* crop stands using an ANN model that utilizes satellite data from Landsat 8 OLI spectral bands. The measured biomass in their study showed a very strong correlation (76.2%) with the estimated biomass in the model, with a root mean square error of 2.74 t/ha. These results differ from what we have obtained for the biomass prediction model, in which we predominantly utilized the mean diameter and other dendrometric parameters.

4.5. Total Biomass Potential and Carbon Stocks, and their Spatial Distribution in all Mixed Forests of *P. brutia* and *P. nigra* in Türkiye

According to data from the General Directorate of Forestry (OGM, 2023) and the Türkiye Forest Association (TOD, 2022), the forest area of Türkiye is estimated to cover 23.245 million hectares, representing approximately 29.8% of the national territory. These forests are predominantly composed of conifers, comprising 48% of the total, with *Pinus nigra* accounting for approximately 19% and *Pinus brutia* making up 23%. Mixed forests occupy around 4.9 million hectares. Within the scope of the current research project (TÜBİTAK Project 118O311), a preliminary analysis of forest management plans was conducted to identify all mixed stands of *Pinus nigra* and *Pinus brutia*. Approximately 350 such stands, equivalent to 16.03% of the 2,184 Directorate of Forest Enterprises within the 20 Regional Directorate of Forestry, were identified as housing these mixed forest stands (*Pinus nigra* and *Pinus brutia*) across the country. The total area of these forests was estimated at 79,166,200 hectares, representing 0.341% of the national forested area and 1.62% of the total mixed forest area in Türkiye. The smallest observed area was 0.352 hectares, while the largest forest covered 2,407.151 hectares, with an average area of 221.135 hectares. From each individual area, the biomass potential and carbon stock were determined. The results were mapped in thematic maps and are presented in Section 3.5 of this document, revealing the spatial distribution of biomass potential and carbon stocks in each aboveground and belowground pool throughout Türkiye.

While analyzing the individual thematic maps, these maps reveal that both aboveground and belowground biomass as well as the corresponding carbon stocks are concentrated at 48.49% in the Aegean Sea region, which includes the Regional Forest Directorates (RDF) of Denizli (14.54%), Isparta (8.13%), Kütahya (6.18%), Muğla (9.74%), Balıkesir (4.96%), and İzmir (4.94%). This region is followed by the Marmara region, which shows a concentration of 22.64% of biomass and the corresponding carbon stock, particularly in the RDFs of Bursa (11.53%), Çanakkale (7.32%), Sakarya (3.58%), and İstanbul (0.22%). In the Mediterranean Region, 8.36% of the total biomass and carbon stocks are concentrated, with 14.23% of it located in the RDFs of Antalya (3.93%), Adana (3.87%), and Mersin (0.55%). In the Black Sea Region, one can observe a concentration of 14.04% distributed across the RDFs of Zonguldak (5.17%), Bolu (4.75%), Kastamonu (2.57%), and Amasya (1.56%). In the Southwest Anatolia Region, a low concentration of 4.21% of this biomass and carbon stocks was observed, notably in the RDF of Kahramanmaraş. In the Central Anatolia Region, a low concentration of 2.26% of this biomass and carbon stocks was also observed, notably in the RDF of Ankara (1.58%) and Eskişehir (0.67%). It can be concluded that the distribution of biomass is highly dependent on the preferred habitat zones of *Pinus nigra* and *Pinus brutia* species within mixed forest stands.

The works of Atalay and Efe (2010 and 2012) provide substantial confirmation regarding the geographical distribution of these conifer species in Türkiye, particularly for *Pinus nigra* and *Pinus brutia*. The distribution of biomass and carbon stocks is contingent upon the distribution of mixed stands of *Pinus nigra* and *Pinus brutia*. Therefore, the activity reports from forestry services and the management plans consulted in the context of the present research project confirm the observations of our study. The distribution of these types of stands is highly dependent on (i) altitudes, which influence the genetic and morphological characteristics (820-970 m) of seeds and young plants as reported by Gülcü and Bilir (2000); (ii) soil fertility, even if it may sometimes be similar at different altitudes (1300-1600), as suggested by Çerçioğlu and Bilir (2018) for natural stands of Anatolian Black Pine (*Pinus nigra* Arnold sups. *Pallasiana* (Lam.) Holmboe); (iii) soil characteristics, as documented by Sevgi and Tecimen (2022), (iv) their nutrient cycle, as observed in various regions of Europe and the United States of America, as discussed by Enescu et al. (2016). Noting a concentrated distribution within the classified forest compared to the outskirts, Djaouga et al. (2021) mapped the spatial distribution of biomass (13,04 Gt) and carbon stock (6,35 GtC) of trees in the classified forest of Ouémé in Benin.

From the perspective of the distribution of biomass and carbon stock in each above and belowground pool, observations made on the maps produced within the framework of this study provide significant insights into the capacities, extents, and limitations of the distribution ranges:

◆ For all individual trees estimated across these examined ecosystems, biomass ranges from 40.40 tons to 276,533.30 tons, with an overall average of 25,403.93 tons and a total of 9,094,606.048 tons (9.095 Mt). The carbon stocks of these trees range from 19,855 tons to 135,920.239 tons, with an average of 12,486.410 tons and a total of 4,470,134.623 tons (4.47 MtC).

◆ Regarding litter, biomass varies between 6,235 tons and 41,990.289 tons, with an average of 3,857.468 tons and a total of 1,380,973.457 tons (1.381 Mt). Similarly, litter carbon stocks range from 2,730 tons to 18,687.175 tons, with an average of 1,716.711 tons and a total of 614,582.413 tons (0.62 MtC).

◆ For deadwood, biomass distribution ranges from 0.819 tons to 5,603.852 tons, with an average of 514.802 tons and a total of 184,299.073 tons (0.184 Mt). Carbon stocks for deadwood are distributed between 0.390 tons and 2,670.570 tons, with an average of 245.334 tons and a total of 87,829.516 tons (0.088 MtC).

◆ In the herbaceous cover, biomass varies from 0.159 tons to 1,087.690 tons, with an average of 99.921 tons and a total of 35,771.881 tons (0.036 Mt). Carbon stocks in the herbaceous cover range from 0.073 tons to 501.520 tons, with an average of 46.073 tons and a total of 16,493.961 tons (0.017 MtC).

◆ It should be noted that the considered depth for belowground biomass and carbon is 0-30 cm. The results of the overall estimations indicate that the biomass of the roots is distributed between 13,059 tons and 89,395.156 tons, with an average of 8,212.350 tons and a total of 2,940,021.167 tons (2.94 Mt). Carbon stocks for the roots range from 6,263 tons to 42,871.359 tons, with an average of 3,938.408 tons, and the total is 1,409,950.028 tons (1.41 MtC).

◆ In the soil organic matter, biomass varies between 2,658.617 tons and 18,200,163.353 tons, with an average of 1,671,970.966 tons and a total of 598,565,606.007 tons (598.566 Mt). Corresponding carbon stocks are distributed between 89,024 tons and 609,434.498 tons, with a total of 20,043,036.006 tons (20.043 MtC).

In all these mixed forest ecosystems consisting of *Pinus nigra* and *Pinus brutia* in Türkiye, the total current biomass can be estimated at 612,201,277.633 tons, equivalent to 612.201 Mt (0.612 Gt). The total carbon equivalent stock of this biomass, as estimated by this research project, is approximately 26,642,026.547 tons, equivalent to 26.642 MtC (0.026 GtC). In this context, the total aboveground biomass is estimated at 10,695,650.459 tons (10.70 Mt), storing approximately 5,189,040.513 tons of carbon (5.19 MtC). On the other hand, this study found that the estimated belowground biomass consists of 2,940,021.167 tons (2.94 Mt) for roots and 598,565,606.007 tons (598 Mt) for soil containing organic matter, which stores 1,409,950.028 tons (1.41 MtC) for roots and 20,043,036.006 tons (20.04 MtC) for soil organic matter. In light of these observations, excluding the soil organic matter with its high mass, the study reveals that aboveground biomass represents 78.4%, while belowground biomass primarily in the form of roots accounts for 21.6%. Similarly, 78.63% of the carbon is stored in aboveground biomass, and 21.37% in belowground biomass. Our results exhibit trends similar to those of several previous studies.

In Türkiye, estimates proposed by Asan (1995) mention that the country's forest ecosystems store 875 million tons of carbon, with 63.1% in aboveground biomass (trees) and 36.9% in soil biomass. The General Directorate of Forestry of Türkiye has estimated that all forest ecosystems in the country store approximately 2 GtC (OGM, 2021). In light of these national estimates, it can be concluded that the carbon stored in the mixed forest biomass of *Pinus nigra* and *Pinus brutia* (0.0659 GtC), excluding soil organic matter, represents 3.312% of the stock of all national forest ecosystems estimated in Türkiye (OGM, 2021). The Ministry of Agriculture and Forestry of Türkiye had estimated that carbon stored in the soil (0-30 cm) of forest ecosystems was 55.68 t/ha (Çem, 2018). This finding is similar to our result, which estimated that carbon stored in the soils of mixed forests of *Pinus nigra* and *Pinus brutia* is an average of 56.80 t/ha.

5. CONCLUSION

In this thesis, we introduced the concept of "modeling" as the process of developing and utilizing mathematical, statistical, or computer-based representations to simulate and analyze various aspects of forest ecosystems, such as biomass formation and carbon storage. Our aim was to gain a better understanding, make predictions, and make informed decisions regarding the mixed natural forest stands of *Pinus nigra* and *Pinus brutia* in Türkiye. During this study, we conducted a comprehensive exploration to elucidate the specific characteristics of these complex ecosystems. We quantified the carbon stored in each component of biomass, both above and below ground. Furthermore, we examined the underlying mathematical relationships that govern tree growth in terms of biomass and carbon storage. We also estimated the overall potential of biomass and carbon storage for all mixed forest stands of *Pinus nigra* and *Pinus brutia*. Finally, we presented the spatial distribution of this biomass and carbon stocks throughout Türkiye. To carry out this study, we sampled 46 experimental plots located in 21 Departments of Forest Operations, distributed across 13 Directorates of Forest Management within 10 Regional Directorate of Forestry in Türkiye. From these non-permanent plots, we harvested 138 trees of *Pinus nigra* (68 trees) and *Pinus brutia* (70 trees). We collected samples of stem sections (138), foliage (138), and branches (138). Additionally, we recorded the number of trees in each experimental plot, measured their diameter at 1.30 meters, and documented the height and age of 4 to 8 average sample trees. We also collected samples of litter (92), deadwood (46), and live herbaceous cover (46), as well as samples of roots (208) and organic soil matter (206). We initiated this research by meticulously characterizing these dispersed natural mixed forest stands across various geographical and agroecological zones in Türkiye, aiming to comprehend their composition, structure, and dynamics. We examined the different types of forest stands, categorizing them based on their developmental stage (ab, b, bc, c, cd, and d) and crown closure (1, 2, or 3) following the guidelines governing the classification of forest stands in Türkiye (ETFOP, 2017). This led us to identify six types of stands present in almost all development stages and across the three crown closure classes. We also determined the age of each stand by examining growth rings on cross-sectional stem samples taken at 30 cm above ground, 1.30 m, and every 2 m on the stem in some cases, or incremental core drilling.

We found that the stands age ranged from 15 to 121 years, with an average age of 68 years. Subsequently, we differentiated between old stands (34.78%), medium to young stands (45.65%), and the youngest stands (19.57%), categorizing them into six age classes with a 20-year span each. We calculated the mean quadratic diameter, a statistical measure used to characterize the average tree size in the examined stands, by using the diameters of the selected mean trees. We conclude These forest stands exhibited a mean quadratic diameter of 21.40 cm, ranging from 9.37 cm to 31.70 cm. We calculated the mean diameter (20.10 cm) of these stands based on the number of sample trees within each stand (8.55-30.34 cm). We analyzed the altitude of each experimental plot, ranging from 169 m to 1650 m, with an average of 859 m. The categorization of this elevation range showed that 93% were situated between 460 m and 1060 m. We assessed the productivity index of these natural mixed stands based on values assigned in the forest management plans. Using six age classes, we evaluated the stands' productivity index in three categories: I (poor), II (good), and III (very good). The stands were assigned to their respective productivity class, and we estimated that 93.62% of the stands had a very good productivity index (III). One of the parameters examined in the analysis of the characteristics of these natural mixed stands (*Pinus nigra* and *Pinus brutia*) was the interrelated relationship between tree height and diameter in these stands. We unraveled this complex relationship by highlighting the type of influence exerted by tree diameter ($D_{1.30}$) on tree height growth. We employed a non-linear regression analysis that led to the identification of positive relationships characterized by statistically significant quadratic models at a 1% level of significance ($p < 0.01$), with expected performance for *Pinus nigra* ($R^2 = 0.65$; RMSE=2.08 m; SE=1.55 m) and *Pinus brutia* ($R^2 = 0.62$; RMSE=2.53 m; SE=2.05 m). We found with robustness that tree diameter at breast height (dbh) explained more than 60% of the variability in tree height growth. We examined the vertical structure of the forest stands by calculating their average height based on field-estimated samples. The average heights of these stands ranged from 4.65 m to 22.70 m, with an overall mean of approximately 12.39 m. In the same vein, we determined the top height, which refers to the height reached by the tallest or dominant trees in the stands. For the two species examined in this study, top heights ranged from 6.33 meters to 23.70 meters, with an overall average of approximately 14.5 meters. We estimated the area occupied by trees in their respective stands by determining the basal area of these stands. This examination resulted in an average of 25.90 m²/ha, with a distribution range from 6.51 to 63.15 m²/ha, thus illustrating the spatial distribution of trees and their arrangement.

We assessed stand density by calculating the number of trees per hectare for each tree species. We observed that tree density ranged from 217 to 1550 trees/ha, with a general average of 733 trees/ha. We also examined the Stand Density Index (SDI) to measure competition among trees within their respective stands. In the 46 natural mixed stands examined, the Stand Density Index was significant. The maximum (5194 trees/ha), minimum (104 trees/ha), and average (1032 trees/ha) SDI for *Pinus nigra* were higher than the maximum (4629 trees/ha), minimum (73 trees/ha), and average (799 trees/ha) SDI for *Pinus brutia*. We determined the wood volume in these mixed stands using single-entry volume equations (diameter at 1.30 m) specific to each species to estimate the total wood quantity in these stands. The volume equations used for these volumes were statistically significant ($p < 0.01$) and exhibited very high-performance characteristics for *Pinus nigra* ($R^2 = 0.992$; $SE = 0.033 \text{ m}^3$) and *Pinus brutia* ($R^2 = 0.994$; $SE = 0.308$), predicting their respective volumes based on tree diameter. The average wood volume in the stands was obtained at $182.87 \text{ m}^3/\text{ha}$, with a distribution range from $36.36 \text{ m}^3/\text{ha}$ to $478.51 \text{ m}^3/\text{ha}$. We studied the relative proportion of different tree species by calculating the mixture ratio based on the volume of each species present. This exercise revealed a dominance ratio between the species. *Pinus nigra* exhibited a ratio ranging from 52.4% to 89.9%. Additionally, internal variability was examined through tree diameter to highlight heterogeneity and diversity within the stands. This analysis of internal variability in the natural mixed forest stands of *Pinus nigra* and *Pinus brutia* indicated a high degree of heterogeneity (20-49%) in tree diameter. The analysis of this non-exhaustive set of parameters led to the validation of our hypothesis that the natural mixed forest stands of *Pinus nigra* and *Pinus brutia* in Türkiye exhibited specific and crucial characteristics, allowing for an understanding of their composition, dynamics, structure, evolution, and, in general, their current situation. In the second phase of our study, we precisely measured biomass and carbon storage capacity, taking into account each woody aboveground pool (individual tree, stem, branch, bark, and foliage), terrestrial pool (deadwood, litter, and herbaceous cover), and belowground pool (roots and soil organic matter) following the IPCC (2003) guidelines for best practices. Firstly, we dried the samples in an oven under recommended temperature and time conditions for each product. We determined the carbon content using the COSTECH Elemental Analyzer, based on three powder samples (0.6 to 1.0 mg) from each product.

Following this analysis, we found that carbon content varied in the tree stems (46.3-52.4%), branches (45.9-58.1%), leaves (36.2-53.9%), and bark (31.6-66.55%) for woody aboveground biomass, in litter (32.4-53.8%), deadwood (41.6-51.0%), and herbaceous cover (38.9-51.6%) for terrestrial biomass, and in roots (39.7-57.6%) and soil organic matter (0.07% to 0.12%) for belowground biomass. Initially, the volume of each *Pinus nigra* (68) and *Pinus brutia* (70) stem, as well as the volume of each of their branches and each cross-sectional segment sampled on each stem (138), were determined based on diameter and height measurements for trees, diameter at the top and length for branches, and thickness and axial diameter for stem sections. These volumes were used to estimate the biomass of each stem and its components. Consequently, the average biomass value for each individual tree and its components was determined for each species. For these trees, an individual biomass and carbon stock distribution diagram was conceptualized. We demonstrated that tree stems were the primary biomass reservoir, accounting for 64% (103.90 kg) and 66.42% (129.93 kg) relative to the total biomass of *Pinus nigra* (162.58 kg) and *Pinus brutia* (195.63 kg), respectively. Next, for both species (*P. nigra* and *P. brutia*), biomass was progressively observed in branches (20.63% and 19.65%), leaves (9.68% and 9.26%), and bark (8.52% and 6.66%), respectively. We also showed that the same trends were reflected in the distribution of carbon stock in each individual tree and its components. In *Pinus nigra*, stems represented 63.4% (51.16 kg) of the total tree carbon stock (80.72 kg), followed by branches at 18.5% (14.89 kg), leaves at 9.8% (7.92 kg), and bark at 8.5% (6.86 kg). In *Pinus brutia*, stems represented 65.5% (64.33 kg) of the total tree carbon stock (98.25 kg), followed by branches at 18.9% (18.66 kg), leaves at 9.1% (8.91 kg), and bark at 6.5% (6.35 kg). In this research project, we determined the biomass and carbon stocks of terrestrial pools (litter, deadwood, and herbaceous cover) to identify their individual capacity in terms of distribution per unit area. This examination highlighted the significance of these pools through the average values of their biomass, particularly in litter with 17443.99 kg/ha, deadwood (2328.00 kg/ha), and herbaceous cover (451.86 kg/ha), and carbon stocks which represented 44.5%, 47.7%, and 46.1% of their biomass, respectively. We analyzed the roots explicitly by carefully separating them by size, including fine roots (<2 mm), small roots (2-5 mm), and coarse roots (>5 mm). We meticulously examined their biomass and carbon stocks at different experimental depths (0-30 cm, 30-60 cm, and 60-90 cm) from the soil surface and per unit area to determine their individual responsibility in the distribution of biomass and carbon in the natural mixed forest ecosystems of *P. nigra* and *P. brutia*.

We considered the total experimental depth (0-90 cm) in all examined samples. This analysis led to the average values of fine root biomass (25.714 t/ha), small root biomass (5.45 t/ha), and coarse root biomass (24.98 t/ha), with their carbon storage capacity representing 48.1%, 48.5%, and 46.9% of their biomass, respectively. We examined the total capacity and distribution of root biomass stocks at each depth to demonstrate that average biomass stocks indeed varied between 0-30 cm (37.14 t/ha), 30-60 cm (15.316 t/ha), and 60-90 cm (7.38 t/ha). In this biomass distribution, carbon consistency represented 48.1%, 48.01%, and 47.8% of their respective biomass. We also analyzed the biomass concentration based on root category (fine, small, and coarse) to highlight the variation among their quantities. In the first depth (0-30 cm), the majority of biomass was concentrated in fine roots (46.3%), followed by coarse roots (43.9%), and finally small roots (9.8%). This trend was reflected in the variation in their carbon stock, showing 53.9%, 37.9%, and 8.17%, respectively. On the other hand, in the next depth (30-60 cm), biomass was concentrated in coarse roots (59.5%), followed by fine roots (31.4%), and finally small roots (9.1%). We showed that, in the same logic, carbon stock concentration was primarily in coarse roots (60%), followed by small roots (31%), and fine roots (9%). This same trend was highlighted in the final experimental depth (60-90 cm), where coarse root biomass was prominently represented (45%), followed by fine roots (29.1%), and finally small roots (25.9%). Corresponding carbon stocks were predominantly concentrated in coarse roots (45.01%), followed by fine roots (29.23%), and small roots (25.6%) of their biomass. We carefully examined the biomass contained in soil organic matter at distinct depths (0-10, 10-30, 30-50, 50-80, and 80-100 cm) to illustrate the precise distribution and individual capacity of this belowground pool to retain biomass per unit area. The average soil mass was recorded at 7560.87 t/ha, with its corresponding carbon stock accounting for 3.35% of this mass. Considering the analysis of the individual capacity of each of these aboveground and belowground biomass pools per unit area, it is evident that these different pools indeed constitute individual reservoirs that drive the dynamics and distribution of biomass in the natural mixed forest ecosystems of *Pinus nigra* and *Pinus brutia* in Türkiye. These clear observations led us to accept our hypothesis that aboveground biomass and corresponding carbon stocks are distributed in the natural forest ecosystems of *Pinus nigra* and *Pinus brutia* in Türkiye, in accordance with the various pools outlined in the IPCC (2023) Good Practice Guide for LULUCF. The biomass and carbon data collected in these analyses have enabled the development of predictive models for biomass and carbon in these ecosystems.

A significant portion of our research has been dedicated to the development of allometric equations, allowing us to explore and unveil the intricate, subtle, and hidden mathematical relationships between structural variables such as diameter at 1.30 m, tree height, and stand-level parameters. These equations enable us to confidently predict biomass formation and carbon storage in individual trees, tree components, and mixed natural stands of *Pinus nigra* and *Pinus brutia* in Türkiye. To achieve this, we developed thirty prediction models, fifteen for biomass and fifteen for carbon storage. For each tree species, seven biomass prediction models and seven carbon storage prediction models were created. Among these prediction models, five for biomass and five for carbon were developed for each individual tree and its components (stem, branch, foliage, and bark) using nonlinear regression primarily employing tree diameter as the predictor (estimator). We also used these two predictors (d and h) to obtain biomass and carbon models using multiple linear regression (MLR) and an algorithm-based Multi-Layer Perceptron (MLP) approach from Artificial Neural Networks (ANN). At the stand level, we developed biomass and carbon storage prediction models using several stand parameters such as mean diameter, mean height, site productivity index, crown fence, and tree density. By considering these predictors, we employed the MLR method to develop biomass and carbon storage models. Similarly, the ANN method was employed to develop biomass and carbon models for the stands examined. The most performant models were selected based on performance criteria such as correlation, RMSE, F-test, and standard error. All biomass and carbon storage prediction models for individual trees and their components were statistically significant at 1% ($p < 0.01$). We demonstrated that among the multiple allometric equations developed in our work primarily using tree diameter as a predictor, the Power model was the best alternative, showing the high performance and best accuracy (R^2 ranging from 76.8 to 95.8%). We used the same principle to identify and select the best multiple linear regression equations using both diameter and height. Using the MLP-ANN method, we highlighted that diameter was the most important predictor in building each biomass and carbon storage model for individual trees in each species. In the case of biomass and carbon models for stands, we identified, with the help of MLP-ANN, the priority order and the contributive part of each predictor in building these intelligent models. In this regard, mean stand diameter was more important in the carbon model compared to the biomass model. We found that models based on MLP-ANN outperformed MLR models for predicting biomass and carbon for individual trees and forest stands.

Even though the coefficient of determination was similar, adjusting the number of hidden layers and neurons in MLP-ANN models improved their performance. By providing biomass and carbon prediction models based on diameter ($D_{1.30}$) alone or with height (H) for individual trees and their components, as well as stand parameters for stands, we demonstrated the existence of complex and intertwined relationships between these structural parameters and the variation in biomass and carbon storage. Our hypothesis that these structural parameters strongly and significantly influence biomass and carbon storage has proven practical. Furthermore, we meticulously analyzed the overall potential for aboveground and belowground biomass and carbon storage in these mixed forest ecosystems across the country. This exploration enabled us to better understand how these crucial elements (biomass and carbon) are distributed and stored within these unique environments and what they represent in the national potential of forest ecosystems in their roles in climate change mitigation. Indeed, we identified all mixed stands of *Pinus nigra* and *Pinus brutia* throughout all regional forest directorates in Türkiye. Their total area was approximately 79,207.44 ha, distributed unevenly across nearly 350 Forest Operations Departments belonging to about 113 Forest Management Directorates. We used the average data for each aboveground and belowground biomass pool and their average carbon stocks to calculate the biomass and carbon potential for each forested area containing these examined stands. We showed that all trees in these forests represented 9.09 Mt of biomass and stored 4.47 MtC. We also demonstrated that biomass potential was also significant in litter (1.38 Mt), deadwood (0.184 Mt), herbaceous cover (0.036 Mt). We considered a depth of 0-30 cm in belowground biomass and carbon estimates. We indicated that root biomass represented 2.94 Mt and a stock of 1.41 MtC, while soil mass represented 598.57 Mt and stored approximately 20.04 MtC. In 2021, General Directorate of Forestry (Türkiye) estimated that all forest ecosystems in the country stored about 1.99 GtC. According to our findings, carbon amount of the mixed forests of *Pinus nigra* with *Pinus brutia* represent 3.312% (0.066 GtC) of this national stock. By highlighting these valuable pieces of information, we demonstrated in this thesis project that, mixed forest ecosystems of *Pinus nigra* and *Pinus brutia* play a significant role in climate change mitigation, by store a significant carbon amount. Our observations confirm the hypothesis of unequal distribution of carbon quantities between aboveground and belowground components and the substantial contribution of this biomass and carbon potential in the broader context of forest ecosystems in Türkiye.

Finally, using a simple mapping method, we graphically depicted the quantities of biomass and carbon in these mixed forest ecosystems, shedding light on their preferential geographic distribution. We introduced vector spatial data (.shp) and Excel data (biomass and carbon) into ArcGIS 10.3 software to reveal the spatial distribution of the national biomass and carbon potential of mixed forest ecosystems of *Pinus nigra* and *Pinus brutia*. We showed that biomass and carbon of these types of forest stands were predominantly concentrated in the Aegean region (48.4%), followed by the Marmara (22.64%), Mediterranean (14.23%), Black Sea (14.04%), Southwest Anatolian region (4.21%), and Central Anatolia (2.26%). Through these observations, the hypothesis of preferential geographical distribution is evident for mixed stands of *Pinus nigra* and *Pinus brutia* in Türkiye. The results of this study offer a comprehensive view of these mixed forest ecosystems in Türkiye, providing invaluable insights for sustainable forest management and climate change mitigation. In this conclusion, we summarize the key findings of our research, emphasizing their importance for forestry science and the conservation of these exceptional ecosystems. This study makes a significant contribution in accordance with Target T4.1 (Target (T4.1): Research and development projects will be prepared and implemented to solve problems in the forestry field, to develop new techniques and to ensure effective governance) of the Strategic Goal G4 (To improve Institutional Capacity) of Türkiye's Forestry Strategic Plan 2019-2023. The biomass and carbon estimates of mixed natural forests of *Pinus nigra* with *Pinus brutia* constitute a scientific contribution to the Climate Change Action Plan of the Republic of Türkiye (2011-2023), particularly for the LULUCF sector (General Directorate of Forestry Strategy Plan, 2019).

6. RECOMMENDATIONS

At the conclusion of our study, several recommendations have been formulated and presented in this section. We recommend:

- ✓ Develop specific allometric equations: Continue to refine and develop specific allometric equations for estimating biomass and carbon storage in individual trees, with an emphasis on using diameter as a predictor.
- ✓ Incorporate tree height: In the development of allometric equations, consider tree height in addition to diameter to improve the accuracy of biomass and carbon estimation.
- ✓ Expand studies to other tree species: Expand your research to include other tree species, in addition to *Pinus nigra* and *Pinus brutia*, to obtain a more comprehensive picture of mixed forest ecosystems in Türkiye.
- ✓ Refine prediction models for tree components: Develop specific prediction models for individual tree components, such as the stem, branches, leaves, and bark, using diameter and height as predictors. Promote the use of artificial intelligence through the application of Artificial Neural Networks and the utilization of all other relevant algorithms in predicting forest biomass and carbon storage.
- ✓ Analyze roots at different depths: Continue to analyze roots at different soil depths to assess their contribution to carbon storage and biomass. Implement precise root sampling methods that maximize the extraction of coarse roots as well.
- ✓ Study the effects of climate change: Evaluate how mixed forest ecosystems of *Pinus nigra* and *Pinus brutia* may be affected by climate change and how this could influence biomass and carbon storage.
- ✓ Share allometric equations: Make the allometric equations developed in the course of this study available as open source so that other researchers can use and improve them.
- ✓ Collect large-scale monitoring data: Expand the collection of large-scale monitoring data to cover a broader range of mixed forest ecosystems in Türkiye.
- ✓ Explore Carbon Offset Programs: Investigate the possibility of participating in carbon offset programs to generate funding for the conservation of mixed forests.
- ✓ Support ongoing research: Allocate adequate resources and financial support for ongoing research on mixed forest ecosystems to deepen knowledge, improve management practices, and advance scientific progress.

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Annex 1. Sample Plot Inventory Field Report Card

[illegible]

Annex 2. Example of Sample Tree Inventory Field Report Card

ÖRNEK AĞAÇ ENVANTER KARNESİ

Bölge Müdürlüğü	Bursa	Örnek Ağaç No	293	Bölme No :	235
İşletme Müdürlüğü	Orhanlı	Örnek Ağaç Türü	Çe	X	674058
İşletme Şefliği	Meydan	Meşecere Tipi Sembolü	ÇkÇe b 3	Y	4397301

Seksiyon Ölçümleri		Dal Ölçümleri			Dal Ağırlığı (kg)	Gövde Ağırlığı (kg)	Seksiyon Çapları
Yükseklik	Çap	Dal No	d	h			
0,3	32,0	1	2,6	211	54		
1,3	32,5	2	6,6	402	55		
3,3	27,0	3	2,2	119	56		
5,3	27,6	4	2	109	57		
7,3	19,0	5	1,4	188	58		
9,3	15,1	6	4,4	213	59		
11,3	15,3	7	4,4	307	60		
13,3	4,1	8	4,4	180	61	4,5	
		9	4,2	294	62		
		10	5,2	274	63		
		11	3,2	240	64		
		12	3	211	65		
		13	4,1	295	66		
		14	4,4	304	67		
		15	6	360	68		
		16	5,5	292	69		
		17	2,6	186	70		
		18	3	152	71		
		19	5	191	72		
		20	2,9	193	73		
		21	6,7	177	74		
		22	2,2	154	75		
		23	2,4	121	76		
		24	1,6	115	77		
		25	2	189	78		
		26	2,4	178	79		
		27	2,4	130	80		
		28	2,4	120	81		
		29	2,6	93	82		
		30	1,5	80	83		
		31	1,7	76	84		
		32	1,5	65	85		
		33	2,1	101	86		
		34	1,8	75	87		
		35	2,6	126	88		
		36	2,7	176	89		
		37	1,9	104	90		
		38	3,9	210	91		
		39			92		
Örnek Dal No	1	40			93		
0,30'a Gelme Yaşı	6	41			94		
		42			95		
1,3' a Gelme Yaşı		43			96		
		44			97		
		45			98		
Uç Parça Uzunluğu	153	46			99		
		47			100		
Karbon Kesiti		48			101		
Yüksekliği	5,3	49			102		
Son Kesit Yükseliği	13,3	50			103		
		51			104		
Ağaç Boyu	14,83	52			105		
		53			106		

Taksitör :	Moussa M. M. M.
Tarih :	16.07.2020
İmza :	

Annex 3. Example of Tree Profile Analysis Report Card

Bölge Müdürlüğü		Ağaç Bayı		24.53	
İşletme Müdürlüğü		Son Kesit Yüksekliği		23.30	
İşletme Şefliği		Ağaçın Yaşı		189	
Bölme No		Ağaç Türü		Çek	
Mescere Tipi					
Örnek Alan No					
Ağaç No		2000023			
Kesit no	Kesit Yüksekliği (m)	Kesit Yılı	Kesit Alanı (m ²)	Kesit Alanı (m ²)	Kesit Alanı (m ²)
1	0.3	183	6	10	32
2	1.3	174	15	12	16
3	3.3	160	29	13	12
4	5.3	150	39	10	9
5	7.3	140	49	8	6
6	9.3	132	57	7	7
7	11.3	124	65	7	7
8	13.3	110	79	7	7
9	15.3	96	93	7	7
10	17.3	91	98	7	7
11	19.3	80	109	7	7
12	21.3	52	137	7	7
13	23.3	9	180	7	7
14	25.3			7	7
15	27.3			7	7
16	29.3			7	7
17	30.3			7	7
18	31.3			7	7

Kesim Tarihi : 21.08.2020	
Ölçümü Yapan : KAYSAR HANCI	

Yaslar	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yüksekliği (m)	3	10	32	31	58	40	87	114	61	138	160	191	238	281	318	356	394	432	470
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	189
Yas	10	20	30	40	50	60	70	80	90										

* Karbon hesit : 11.30

Annex 4. Example of Elemental Analysis Report

09.11.2020 08:14

Chromatogram C:\EAS Clarity\TOVAG_11803111\Data\bos_14-Eki-2020_682.PRM

Page 1 of 7

KTÜ Orman Fakültesi Elementel Analiz Raporu

		Sample	Sample Weight [mg]	Nitrogen				Carbon			
				Reten. Time	Response	Weight [mg]	Weight [%]	Reten. Time	Response	Weight [mg]	Weight [%]
d-cz-137-2_27-E	Signal 1	d-cz-137-2	0,774	2,447	73,415	0,008	1,0	3,640	2966,597	0,371	47,9
d-cz-137-1_27-E	Signal 1	d-cz-137-1	0,835	2,420	86,367	0,012	1,5	3,620	3224,186	0,405	48,4
d-cz-136-2_27-E	Signal 1	d-cz-136-2	0,893	2,450	77,742	0,009	1,0	3,623	3469,310	0,436	48,9
d-cz-136-1_27-E	Signal 1	d-cz-136-1	0,954	2,420	72,246	0,007	0,8	3,617	3644,027	0,459	48,1
d-cz-135-2_27-E	Signal 1	d-cz-135-2	0,664	1,987	0,979	N/A	N/A	3,633	2572,620	0,320	48,1
d-cz-135-1_27-E	Signal 1	d-cz-135-1	0,592	2,423	71,604	0,007	1,2	3,640	2320,399	0,287	48,4
d-ck-135-2_27-E	Signal 1	d-ck-135-2	0,777	2,460	74,170	0,008	1,0	3,617	3251,310	0,408	52,5
d-ck-135-1_27-E	Signal 1	d-ck-135-1	0,721	2,467	75,877	0,009	1,2	3,623	2926,242	0,366	50,7
d-cz-134-2_27-E	Signal 1	d-cz-134-2	0,683	2,433	63,321	0,004	0,6	3,637	2632,494	0,327	47,9
d-cz-134-1_27-E	Signal 1	d-cz-134-1	0,876	2,470	75,399	0,008	1,0	3,623	3321,647	0,417	47,6
d-ck-134-2_27-E	Signal 1	d-ck-134-2	0,831	2,433	69,857	0,006	0,8	3,623	3344,439	0,420	50,6
d-ck-134-1_27-E	Signal 1	d-ck-134-1	0,876	2,443	71,355	0,007	0,8	3,617	3704,594	0,467	53,3
d-ck-133-2_27-E	Signal 1	d-ck-133-2	0,907	2,440	69,596	0,006	0,7	3,607	3705,893	0,467	51,5
d-ck-133-1_27-E	Signal 1	d-ck-133-1	0,949	2,463	74,192	0,008	0,8	3,610	3852,611	0,486	51,2
d-cz-138-2_27-E	Signal 1	d-cz-138-2	0,918	2,390	89,541	0,013	1,5	3,623	3518,930	0,443	48,2
d-cz-138-1_27-E	Signal 1	d-cz-138-1	0,924	2,380	87,139	0,013	1,4	3,620	3518,240	0,443	47,9
d-ck-138-2_27-E	Signal 1	d-ck-138-2	0,870	2,603	226,123	0,062	7,1	3,607	3599,168	0,453	52,1
d-ck-138-1_27-E	Signal 1	d-ck-138-1	0,609	2,457	59,949	0,003	0,5	3,637	2498,570	0,310	50,9
d-ck-137-2_27-E	Signal 1	d-ck-137-2	0,754	2,500	75,942	0,009	1,1	3,633	2812,154	0,351	46,5
d-ck-137-1_27-E	Signal 1	d-ck-137-1	0,695	2,457	60,074	0,003	0,4	3,630	2727,469	0,340	48,9
d-ck-136-2_27-E	Signal 1	d-ck-136-2	0,675	2,477	66,216	0,005	0,8	3,620	2932,128	0,366	54,3
d-ck-136-1_27-E	Signal 1	d-ck-136-1	0,814	2,480	74,096	0,008	1,0	3,623	3318,376	0,417	51,2
d-cz-139-2_27-E	Signal 1	d-cz-139-2	0,905	2,393	89,190	0,013	1,5	3,613	3559,297	0,448	49,5
d-cz-139-1_27-E	Signal 1	d-cz-139-1	0,940	2,390	92,590	0,015	1,5	3,617	3624,271	0,457	48,6
d-ck-139-2_27-E	Signal 1	d-ck-139-2	0,846	2,450	61,979	0,004	0,4	3,610	3275,126	0,411	48,6
d-ck-139-1_27-E	Signal 1	d-ck-139-1	0,802	2,450	73,546	0,008	1,0	3,637	3069,666	0,384	47,9
bos_27-EW-202	Signal 1	bos	0,765	2,483	73,310	0,008	1,0				
d-cz-133-2_27-E	Signal 1	d-cz-133-2	0,765	2,440	73,241	0,008	1,0	3,630	2785,879	0,347	45,4
d-cz-133-1_27-E	Signal 1	d-cz-133-1	0,766	2,440	77,031	0,009	1,2	3,627	2923,336	0,365	47,7
d-ck-132-2_27-E	Signal 1	d-ck-132-2	0,805	2,443	74,895	0,008	1,0	3,620	3272,998	0,411	51,0
d-ck-132-1_27-E	Signal 1	d-ck-132-1	0,719	2,463	70,323	0,007	0,9	3,630	2890,181	0,361	50,2
d-cz-132-2_27-E	Signal 1	d-cz-132-2	0,784	2,473	62,028	0,004	0,5	3,623	2982,320	0,373	47,6
d-cz-132-1_27-E	Signal 1	d-cz-132-1	0,620	2,463	65,280	0,005	0,8	3,640	2355,010	0,291	47,0
d-ck-131-2_27-E	Signal 1	d-ck-131-2	0,933	2,463	70,559	0,007	0,7	3,600	3740,861	0,472	50,6
d-ck-131-1_27-E	Signal 1	d-ck-131-1	0,606	2,497	62,751	0,004	0,7	3,627	2376,773	0,294	48,5
d-ck-126-2_27-E	Signal 1	d-ck-126-2	0,699	2,433	56,728	0,002	0,3	3,623	2684,462	0,334	47,8
d-ck-126-1_27-E	Signal 1	d-ck-126-1	0,930	2,470	73,511	0,008	0,8	3,603	3622,116	0,456	49,1
d-ck-125-2_27-E	Signal 1	d-ck-125-2	0,954	2,430	63,356	0,004	0,4	3,610	3850,881	0,486	51,0
d-ck-125-1_27-E	Signal 1	d-ck-125-1	0,759	2,453	69,905	0,007	0,9	3,633	3101,300	0,389	51,2
d-ck-124-2_27-E	Signal 1	d-ck-124-2	0,804	2,493	71,655	0,007	0,9	3,620	3279,716	0,412	51,2
d-ck-124-1_27-E	Signal 1	d-ck-124-1	0,850	2,443	61,173	0,003	0,4	3,610	3360,982	0,422	49,7
d-ck-122-2_27-E	Signal 1	d-ck-122-2	0,875	2,443	68,838	0,006	0,7	3,617	3534,936	0,445	50,9
d-ck-122-1_27-E	Signal 1	d-ck-122-1	0,760	2,463	57,762	0,002	0,3	3,630	3048,625	0,382	50,2
d-ck-123-2_27-E	Signal 1	d-ck-123-2	0,857	2,483	66,785	0,005	0,6	3,627	3398,558	0,427	49,9
d-ck-123-1_27-E	Signal 1	d-ck-123-1	0,839	2,470	80,237	0,010	1,2	3,630	3394,215	0,427	50,9
d-ck-127-2_27-E	Signal 1	d-ck-127-2	0,813	2,457	69,347	0,006	0,8	3,617	3265,545	0,410	50,4
d-ck-127-1_27-E	Signal 1	d-ck-127-1	0,746	2,470	61,080	0,003	0,5	3,617	3014,225	0,377	50,6
d-ck-129-2_27-E	Signal 1	d-ck-129-2	0,725	2,460	59,991	0,003	0,4	3,623	2941,869	0,368	50,7
d-ck-129-1_27-E	Signal 1	d-ck-129-1	0,670	2,480	65,588	0,005	0,7	3,627	2712,340	0,338	50,4
d-ck-128-2_27-E	Signal 1	d-ck-128-2	0,816	2,453	67,429	0,006	0,7	3,610	3285,101	0,412	50,5
d-ck-128-1_27-E	Signal 1	d-ck-128-1	0,839	2,450	62,876	0,004	0,5	3,613	3441,960	0,433	51,6
d-ck-130-2_27-E	Signal 1	d-ck-130-2	0,551	2,457	56,152	0,002	0,3	3,627	2094,021	0,257	46,7
d-ck-130-1_27-E	Signal 1	d-ck-130-1	0,946	2,470	68,045	0,006	0,6	3,603	3577,009	0,450	47,6
d-cz-131-2_27-E	Signal 1	d-cz-131-2	0,812	2,433	70,038	0,007	0,8	3,617	3001,629	0,376	46,2
d-cz-131-1_27-E	Signal 1	d-cz-131-1	0,708	2,460	78,174	0,009	1,3	3,627	2598,825	0,323	45,6
bos_27-EW-202	Signal 1	bos	0,708	2,487	81,375	0,011	1,5				
d-ck-94-3_26-EW	Signal 1	d-ck-94-3	0,663	2,483	69,810	0,006	1,0	3,637	2792,337	0,348	52,5

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File	Edit	Format	View	Help						
_05-Eki-2022_1079	Signal 1	2021-dal-284-a	0,766	0,116	15,2	0,354	46,5			
_05-Eki-2022_1078	Signal 1	2021-dal-308-a	0,489	0,117	23,9	0,222	45,4			
_05-Eki-2022_1077	Signal 1	2021-dal-288-a	0,819	0,086	10,5	0,374	45,7			
_05-Eki-2022_1076	Signal 1	2021-dal-279-a	0,684	0,093	13,6	0,325	47,5			
_05-Eki-2022_1075	Signal 1	2021-dal-277-a	0,582	0,080	13,8	0,365	62,8			
_05-Eki-2022_1074	Signal 1	2021-dal-292-a	0,513	0,065	12,7	0,236	46,0			
_05-Eki-2022_1073	Signal 1	2021-dal-283-a	0,703	0,071	10,1	0,339	48,3			
_05-Eki-2022_1072	Signal 1	2021-dal-306-2	0,717	0,064	9,0	0,354	49,4			
_05-Eki-2022_1071	Signal 1	2021-dal-306-1	0,551	0,060	10,8	0,267	48,5			
_05-Eki-2022_1070	Signal 1	2021-kst-279-a	0,614	0,037	6,1	0,275	44,8			
_05-Eki-2022_1069	Signal 1	2021-kst-283-a	0,552	0,052	9,4	0,249	45,0			
_05-Eki-2022_1068	Signal 1	2021-kst-299-a	0,790	0,057	7,2	0,359	45,5			
_05-Eki-2022_1067	Signal 1	2021-kst-294-a	0,721	0,060	8,3	0,329	45,6			
_05-Eki-2022_1066	Signal 1	2021-kst-292-a	0,642	0,052	8,1	0,288	44,9			
_05-Eki-2022_1065	Signal 1	2021-kst-308-a	0,493	0,057	11,6	0,223	45,2			
_05-Eki-2022_1064	Signal 1	2021-kst-297-a	0,820	0,065	7,9	0,380	46,3			
_05-Eki-2022_1063	Signal 1	2021-kst-281-a	0,773	0,067	8,6	0,355	45,9			
_05-Eki-2022_1062	Signal 1	2021-kst-304-a	0,489	0,067	13,7	0,228	46,7			
_05-Eki-2022_1061	Signal 1	2021-kst-288-a	0,523	0,074	14,2	0,246	47,1			
_05-Eki-2022_1060	Signal 1	2021-kst-301-2	0,727	0,028	3,8	0,321	44,2			
_05-Eki-2022_1059	Signal 1	2021-kst-301-1	0,627	0,068	10,9	0,281	44,9			
_04-Eki-2022_1058	Signal 1	2021-kst-277-a	0,473	0,058	12,3	0,219	46,2			
_04-Eki-2022_1057	Signal 1	2021-kst-295-a	0,587	0,057	9,7	0,269	45,7			
_04-Eki-2022_1056	Signal 1	2021-kst-306-a	0,411	0,072	17,5	0,195	47,6			
_04-Eki-2022_1055	Signal 1	2021-kst-284-2	0,420	0,015	3,5	0,190	45,2			
_04-Eki-2022_1054	Signal 1	2021-kst-284-1	0,579	0,062	10,8	0,278	48,0			
_04-Eki-2022_1053	Signal 1	2021-do-111-a-tekrar	0,663	0,067	10,1	0,000	0,0			
_04-Eki-2022_1052	Signal 1	2021-do-111-a	0,663	0,065	9,8	0,254	38,2			
_04-Eki-2022_1051	Signal 1	2021-do-91-a	0,769	0,066	8,6	0,334	43,4			
_04-Eki-2022_1050	Signal 1	2021-do-104-a	0,516	0,066	12,9	0,223	43,3			
_04-Eki-2022_1049	Signal 1	2021-do-86-a	0,712	0,061	8,6	0,273	38,3			
_04-Eki-2022_1048	Signal 1	2021-do-90-a	0,549	0,062	11,3	0,252	46,0			
_04-Eki-2022_1047	Signal 1	2021-do-87-a	0,773	0,058	7,5	0,338	43,7			
_04-Eki-2022_1046	Signal 1	2021-do-97-a	0,561	0,062	11,1	0,250	44,5			
_04-Eki-2022_1045	Signal 1	2021-do-100-a	0,756	0,067	8,8	0,329	43,5			
_04-Eki-2022_1044	Signal 1	2021-do-93-a	0,665	0,063	9,5	0,297	44,7			
_04-Eki-2022_1043	Signal 1	2021-do-99-a	0,506	0,068	13,5	0,223	44,1			
_04-Eki-2022_1042	Signal 1	2021-do-110-a	0,704	0,061	8,6	0,307	43,6			
_04-Eki-2022_1041	Signal 1	2021-do-95-a	0,552	0,055	9,9	0,244	44,1			
_04-Eki-2022_1040	Signal 1	2021-do-94-a	0,400	0,064	16,0	0,187	46,7			
_04-Eki-2022_1039	Signal 1	2021-do-92-a	0,770	0,058	7,5	0,359	46,6			
_04-Eki-2022_1038	Signal 1	2021-do-103-a	0,596	0,065	10,8	0,244	41,0			
_04-Eki-2022_1037	Signal 1	2021-do-88-a	0,387	0,060	15,5	0,165	42,6			
_04-Eki-2022_1036	Signal 1	2021-do-89-a	0,693	0,064	9,3	0,276	39,9			
_04-Eki-2022_1035	Signal 1	2021-do-112-2	0,640	0,062	9,7	0,289	45,1			
_04-Eki-2022_1034	Signal 1	2021-do-112-1	0,656	0,063	9,6	0,303	46,2			
_04-Eki-2022_1033	Signal 1	2021-do-113-a	0,707	0,065	9,2	0,305	43,1			
_04-Eki-2022_1032	Signal 1	2021-do-109-a	0,606	0,066	10,9	0,272	44,9			
_04-Eki-2022_1031	Signal 1	2021-do-96-a	0,772	0,028	3,6	0,351	45,5			
_04-Eki-2022_1030	Signal 1	2021-do-114-a-tekrar	0,544	0,021	3,9	0,231	42,4			
_04-Eki-2022_1029	Signal 1	bos	0,544	0,030	5,6	0,000	0,0			

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Sample ID	Sample	Sample Weight [mg]	Weight [mg]	Weight [%]	Nitrogen Weight [%]	Nitrogen	Nitrogen	Carbon	Carbon
_15-Haz-2022_1540	Signal 1	2020-dal-133-a	0,599	1,698	283,4	0,222	37,0		
_15-Haz-2022_1539	Signal 1	2020-dal-137-a	0,432	1,249	289,2	0,318	73,5		
_15-Haz-2022_1538	Signal 1	2020-dal-132-a	0,711	0,950	133,6	0,362	50,9		
_15-Haz-2022_1537	Signal 1	2020-dal-136-a	0,667	0,729	109,2	0,328	49,2		
_15-Haz-2022_1536	Signal 1	2020-dal-140-a	0,441	0,559	126,7	0,227	51,5		
_15-Haz-2022_1535	Signal 1	2020-dal-121-a	0,484	0,347	71,6	0,262	54,1		
_15-Haz-2022_1534	Signal 1	2020-dal-120-a	0,492	0,127	25,8	0,250	50,7		
_15-Haz-2022_1533	Signal 1	2020-dal-97-a	0,859	0,112	13,1	0,444	51,7		
_14-Haz-2022_1532	Signal 1	2020-dal-107-a	0,783	0,452	57,7	0,423	54,1		
_14-Haz-2022_1531	Signal 1	2020-dal-134-a	0,531	0,222	41,9	0,268	50,5		
_14-Haz-2022_1530	Signal 1	2020-dal-63-a	0,613	0,184	30,1	0,339	55,3		
_14-Haz-2022_1529	Signal 1	2020-dal-98-a	0,514	0,124	24,2	0,283	55,1		
_14-Haz-2022_1528	Signal 1	2020-dal-138-a	0,676	0,132	19,6	0,373	55,1		
_14-Haz-2022_1527	Signal 1	2020-dal-135-a	0,653	0,133	20,3	0,341	52,2		
_14-Haz-2022_1526	Signal 1	2020-dal-131-a	0,640	0,115	17,9	0,336	52,6		
_14-Haz-2022_1525	Signal 1	2020-dal-123-a	0,695	0,097	14,0	0,362	52,0		
_14-Haz-2022_1524	Signal 1	2020-dal-139-a	0,622	0,112	18,0	0,328	52,8		
_14-Haz-2022_1523	Signal 1	2020-dal-125-a	0,555	0,107	19,3	0,298	53,6		
_14-Haz-2022_1522	Signal 1	2020-dal-129-a	0,561	0,108	19,3	0,300	53,5		
_14-Haz-2022_1521	Signal 1	2020-dal-111-a	0,799	0,104	13,0	0,407	50,9		
_14-Haz-2022_1520	Signal 1	2020-dal-130-a	0,540	0,106	19,7	0,315	58,3		
_14-Haz-2022_1519	Signal 1	2020-dal-104-a	0,600	0,069	11,5	0,307	51,1		
_14-Haz-2022_1518	Signal 1	2020-dal-122-a	0,625	0,097	15,5	0,329	52,6		
_14-Haz-2022_1517	Signal 1	2020-dal-110-a	0,404	0,159	39,4	0,218	54,0		
_14-Haz-2022_1516	Signal 1	2020-dal-108-a	0,539	0,121	22,5	0,282	52,4		
_14-Haz-2022_1515	Signal 1	2020-dal-105-a	0,721	0,038	5,3	0,377	52,3		
_14-Haz-2022_1514	Signal 1	2020-dal-109-a	0,740	0,042	5,7	0,365	49,4		
_14-Haz-2022_1513	Signal 1	2020-dal-124-a	0,595	0,045	7,6	0,298	50,0		
_14-Haz-2022_1512	Signal 1	2020-dal-58-a	0,427	0,138	32,3	0,234	54,9		
_14-Haz-2022_1511	Signal 1	2020-dal-57-a	0,477	0,153	32,1	0,254	53,2		
_14-Haz-2022_1510	Signal 1	2020-dal-40-a	0,643	0,070	10,9	0,331	51,5		
_14-Haz-2022_1509	Signal 1	2020-dal-96-a	0,728	0,181	24,9	0,395	54,2		
_14-Haz-2022_1508	Signal 1	2020-dal-103-a	0,407	0,106	26,0	0,214	52,6		
_14-Haz-2022_1507	Signal 1	2020-dal-126-a	0,788	0,117	14,9	0,411	52,2		
_14-Haz-2022_1506	Signal 1	2020-dal-127-a	0,526	0,186	35,3	0,280	53,2		
_14-Haz-2022_1505	Signal 1	2020-dal-99-a	0,599	0,126	21,1	0,328	54,7		
_14-Haz-2022_1504	Signal 1	2020-dal-52-a	0,798	0,122	15,3	0,393	49,2		
_14-Haz-2022_1503	Signal 1	2020-dal-39-a	0,616	0,080	13,0	0,329	53,5		
_14-Haz-2022_1502	Signal 1	2020-dal-59-2	0,607	0,102	16,8	0,316	52,0		
_14-Haz-2022_1501	Signal 1	2020-dal-59-1	0,460	0,152	33,0	0,240	52,1		

Annex 5. Tree Data (Volume and Biomass)

N ^o	D _{1.30}	H _{Çk}	V _{tree}	B _{stem}	B _{bran}	B _{fol}	B _{bark}	N ^o	D _{1.30}	H _{Çz}	V _{tree}	B _{stem}	B _{bran}	B _{fol}	B _{bark}
Data of Anatolian Black Pine (<i>Pinus nigra</i>)								Data of Turkish Red Pine (<i>Pinus nigra</i>)							
1	12,0	7,5	0,049	16,04	2,42	2,43	2,57	1	13,0	7,7	0,053	17,04	5,59	3,21	2,14
2	12,0	7,5	0,048	11,18	1,38	2,55	3,01	2	10,0	7,7	0,029	10,75	1,97	0,81	2,02
3	10,0	6,2	0,033	9,85	2,00	0,76	2,23	3	9,0	5,7	0,024	6,03	0,99	0,60	1,85
4	14,0	10,5	0,095	19,58	4,93	4,99	7,91	4	23,0	13,1	0,347	99,78	7,44	4,98	8,93
5	24,0	12,1	0,256	86,00	15,10	17,97	12,58	5	20,0	11,7	0,217	53,18	19,40	13,65	4,26
6	13,0	6,0	0,053	21,26	15,18	3,19	2,66	6	15,0	8,4	0,093	26,94	4,31	1,86	6,60
7	20,0	12,8	0,230	73,20	5,23	2,59	11,74	7	19,0	8,8	0,169	52,49	20,09	9,44	6,74
8	17,0	7,8	0,116	34,02	6,01	4,95	5,04	8	11,0	5,9	0,041	16,01	2,64	2,18	1,90
9	7,0	6,7	0,015	5,06	2,29	1,37	1,17	9	10,0	7,1	0,034	10,52	5,46	2,60	2,09
10	20,0	9,2	0,142	32,31	7,81	6,90	8,50	10	26,0	13,9	0,304	96,62	19,94	3,00	15,65
11	21,5	7,1	0,158	60,20	23,04	9,30	5,03	11	24,7	9,4	0,226	106,29	54,29	23,56	11,67
12	22,0	12,9	0,247	74,79	11,55	15,06	13,95	12	24,7	9,2	0,245	83,57	54,77	7,30	14,83
13	19,0	9,2	0,179	54,03	33,77	12,39	9,72	13	19,0	13,9	0,122	38,28	4,86	1,53	5,03
14	18,0	8,9	0,116	33,39	12,44	16,70	6,46	14	18,0	10,8	0,128	43,17	10,11	6,82	5,07
15	22,0	12,9	0,250	78,13	8,36	2,10	19,30	15	30,0	14,4	0,453	179,62	25,65	18,48	13,18
16	18,0	10,3	0,120	34,96	6,89	3,42	8,21	16	15,0	8,8	0,074	29,99	4,94	3,11	3,82
17	32,4	17,6	0,651	391,88	91,10	31,18	32,34	17	36,6	17,1	0,934	368,02	96,29	23,36	24,27
18	20,5	11,6	0,208	71,99	13,85	5,99	9,68	18	26,9	13,9	0,367	148,23	64,14	11,61	14,25
19	21,2	9,8	0,214	77,56	23,94	4,59	10,09	19	28,9	14,5	0,516	195,79	61,29	10,60	31,94
20	21,1	11,7	0,267	89,01	35,31	18,85	11,37	20	25,1	12,0	0,327	118,95	72,95	24,92	14,92
21	25,6	13,7	0,375	145,55	58,61	19,69	19,51	21	32,5	15,0	0,742	247,54	172,52	25,80	17,90
22	16,7	8,9	0,113	35,94	15,13	10,43	7,39	22	14,3	9,2	0,068	22,60	15,39	6,21	2,77
23	8,1	5,3	0,018	4,37	1,95	0,96	1,31	23	14,4	9,2	0,090	27,78	11,34	3,94	5,76
24	13,5	8,6	0,065	27,40	10,18	7,95	4,09	24	21,6	13,4	0,256	81,02	61,94	25,65	5,58
25	16,8	10,0	0,140	41,55	20,27	14,16	7,41	25	23,3	15,8	0,298	114,64	33,45	17,98	9,99
26	7,5	6,2	0,017	5,97	3,23	0,87	1,28	26	27,0	18,4	0,584	235,80	51,47	6,25	25,20
27	25,6	12,8	0,385	140,07	32,01	22,80	47,30	27	28,9	15,0	0,397	132,50	77,63	54,38	12,10
28	12,0	10,5	0,062	18,88	8,92	6,61	0,63	28	14,5	8,6	0,082	30,07	14,57	12,86	2,97
29	24,8	10,6	0,271	101,93	62,15	20,01	11,82	29	19,5	9,9	0,156	69,36	28,20	12,50	6,72
30	26,4	14,0	0,384	116,08	55,95	16,81	9,91	30	19,1	9,3	0,141	48,01	31,21	13,39	7,50
31	10,3	7,9	0,048	13,84	14,74	6,80	1,98	31	10,9	6,5	0,039	14,54	6,47	2,97	2,91
32	20,2	8,8	0,193	69,00	45,85	15,47	8,94	32	14,3	11,2	0,079	32,63	5,19	1,78	4,01
33	13,0	6,9	0,056	20,17	11,75	9,62	3,68	33	15,7	9,3	0,082	18,08	12,57	7,09	1,70
34	14,7	5,6	0,038	12,82	4,39	4,15	3,05	34	15,0	10,2	0,090	36,55	8,77	2,49	2,92
35	15,0	6,8	0,075	20,77	14,94	11,21	3,14	35	20,6	11,5	0,195	74,38	34,04	36,31	5,95
36	12,1	7,3	0,049	16,65	5,07	5,12	4,61	36	15,5	7,2	0,072	26,57	9,87	2,85	2,98
37	10,8	5,7	0,035	9,73	6,71	9,71	2,40	37	30,5	14,8	0,506	184,24	15,38	13,71	16,28
38	27,2	14,4	0,443	150,09	24,32	3,90	18,93	38	23,0	12,8	0,287	135,01	8,85	4,66	15,83
39	31,7	21,1	1,059	415,71	78,63	44,65	49,29	39	29,5	16,7	0,602	212,14	83,92	24,59	26,71
40	22,9	18,3	0,424	177,08	19,35	9,00	21,68	40	23,0	14,2	0,437	171,42	41,55	10,79	12,46
41	17,1	14,5	0,194	74,85	26,69	15,91	8,03	41	29,2	17,0	0,576	236,48	74,25	12,18	26,43
42	27,3	17,5	0,576	214,47	28,41	24,69	26,70	42	24,5	13,7	0,329	131,54	33,15	45,20	14,50
43	21,1	14,8	0,308	115,77	46,75	30,49	11,26	43	31,0	15,7	0,513	174,88	46,67	41,94	50,13
44	21,4	14,4	0,318	122,49	24,82	13,80	18,15	44	27,2	15,0	0,524	228,01	31,13	74,61	22,40
45	20,4	12,1	0,259	110,39	38,74	21,29	14,90	45	23,2	14,8	0,350	152,33	31,74	39,53	24,67
46	20,6	14,8	0,344	131,20	50,41	16,44	12,90	46	25,6	14,4	0,418	175,83	39,10	24,43	11,78
47	23,8	16,1	0,397	145,86	22,61	5,27	21,66	47	26,7	12,1	0,446	122,32	56,84	27,61	23,64
48	25,5	15,1	0,504	122,77	79,15	35,66	19,85	48	24,3	14,8	0,343	146,67	23,74	9,77	8,16
49	24,5	15,1	0,431	139,21	40,37	17,05	21,49	49	29,0	17,3	0,549	214,25	41,81	7,89	17,46
50	23,5	15,2	0,421	153,84	47,84	17,79	15,45	50	21,3	14,4	0,296	153,06	25,04	15,54	10,11
51	20,4	14,3	0,256	91,58	20,01	3,54	13,41	51	26,3	17,8	0,427	177,57	24,26	14,64	14,25
52	18,1	14,8	0,217	84,78	12,23	11,61	15,71	52	24,1	15,4	0,325	152,41	37,95	41,85	9,07
53	30,8	14,5	0,578	169,95	35,60	19,71	36,63	53	18,7	17,4	0,232	101,85	12,99	30,70	9,22
54	25,8	11,8	0,398	92,49	72,48	82,05	17,40	54	13,2	14,2	0,102	45,88	3,35	3,55	3,68
55	23,1	8,9	0,215	73,97	21,90	21,92	12,06	55	25,2	13,8	0,347	139,31	33,65	18,55	8,03
56	17,9	9,3	0,144	13,56	14,50	12,09	3,63	56	26,9	13,0	0,351	163,31	31,88	7,03	14,14
57	17,6	12,6	0,203	64,90	21,50	20,20	8,43	57	21,8	8,6	0,191	81,13	18,14	24,98	12,43
58	34,3	14,8	0,556	383,26	76,42	72,04	29,98	58	22,0	10,6	0,222	92,25	19,69	18,74	23,14
59	31,7	13,6	0,478	220,94	53,91	51,80	13,43	59	34,5	18,0	0,794	71,12	161,01	4,47	7,77
60	38,2	21,1	1,323	616,12	82,50	24,85	57,20	60	35,8	16,9	0,688	346,39	106,84	66,54	21,67
61	29,0	14,8	0,549	230,93	76,91	29,23	17,41	61	30,8	18,5	0,739	308,43	207,84	96,80	19,39
62	36,9	22,3	1,250	408,22	125,72	48,54	48,08	62	32,2	16,0	0,734	300,85	66,12	13,03	19,01
63	20,3	12,4	0,225	92,49	16,96	10,39	11,08	63	42,9	23,1	1,650	328,40	121,42	39,66	46,85
64	18,4	12,0	0,203	68,96	20,87	8,51	11,62	64	22,1	16,4	0,303	642,91	15,40	56,66	29,42
65	27,9	8,8	0,454	153,90	85,45	28,05	23,89	65	24,6	12,6	0,289	196,54	22,05	6,16	13,81
66	21,7	12,0	0,229	89,33	21,52	12,36	10,52	66	29,6	12,2	0,436	114,32	38,64	4,12	13,50
67	18,9	10,4	0,195	61,00	11,96	6,94	14,80	67	27,5	12,1	0,446	167,64	71,74	13,81	29,67
68	1,1	0,7	10 ⁻⁴	0,04	0,07	0,12	/	68	22,8	12,6	0,215	131,09	27,08	35,98	12,72
/	/	/	/	/	/	/	/	69	21,7	12,0	0,209	181,85	5,39	12,10	15,73
/	/	/	/	/	/	/	/	70	2,7	1,0	0,001	0,11	0,19	0,20	0,04

No	Meydane	CC	SI	Alan m ²	Stand Parameters										Ölül Örtü		Ölül Ödün		Diri Örtü	
					N	A	D _m	H _m	H ₁₀₀	G	D _q	V _{stand}	B _{litter}	C _{litter}	B _{litter}	C _{litter}	B _{litter}	C _{litter}	B _{litter}	C _{litter}
/	/	/	/	/	Ades/ha	sil	cm	m	m	m ³ /ha	cm	m ³ /ha	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha
1	ÇKÇebc1	1	3	600	333	2	14,45	8,51	10,22	6,51	15,77	2,18	17805,6	7834,5	2341,9	1117,1	452,0	207,9		
2	ÇKÇab3	3	4	400	1550	2	16,95	15,08	15,83	39,97	18,12	10,09	9552,0	3639,3	2580,0	1256,5	496,2	214,0		
3	ÇKÇad2	2	4	400	725	2	27,15	15,61	16,85	48,18	28,60	15,06	9360,0	4071,6	5045,0	2376,2	501,0	213,1		
4	ÇKÇad3	3	4	400	575	3	28,22	16,39	17,37	41,32	29,61	12,99	14496,0	6479,7	6035,0	2845,5	495,0	217,4		
5	ÇKÇebc2	2	2	600	867	5	19,60	14,52	15,61	30,55	21,19	13,08	17248,0	7813,3	1040,0	487,8	144,0	65,7		
6	ÇKÇac2	2	4	600	700	5	23,91	14,38	16,66	29,93	23,33	13,37	10704,0	5127,2	935,0	437,6	852,0	381,7		
7	ÇKÇac3	3	2	400	1275	4	20,57	13,73	15,52	49,80	22,30	14,55	15904,0	7808,9	114,0	54,0	625,0	263,4		
8	ÇKÇad3	3	3	400	800	6	19,41	19,80	21,11	32,30	22,67	10,91	8520,0	3731,8	2395,0	1124,2	125,0	48,6		
9	ÇKÇac3	3	3	600	433	3	19,86	18,96	23,70	17,21	22,48	7,82	25176,0	11278,8	2706,0	1267,2	59,0	26,3		
10	ÇKÇad2	2	3	600	600	5	23,19	22,66	23,07	31,16	25,71	15,92	51488,0	22603,2	4422,0	2048,7	33,0	15,4		
11	ÇKÇac1	1	3	600	383	5	22,71	14,39	16,39	17,06	23,81	7,34	23288,0	10828,9	2672,0	1234,5	89,0	39,5		
12	ÇKÇac2	2	4	600	483	5	21,93	12,10	12,20	20,44	23,21	9,11	22040,0	10072,3	990,0	411,8	1425,0	689,7		
13	ÇKÇad2	2	5	600	933	3	14,85	10,46	12,11	18,95	15,64	6,77	20976,0	8138,7	2460,0	1144,6	1116,0	525,6		
14	ÇKÇad2	2	4	600	433	6	23,10	12,30	12,62	21,08	24,88	10,35	22832,0	9566,6	5972,0	2750,7	87,0	39,8		
15	ÇKÇac2	2	4	600	467	4	18,60	11,22	12,00	14,04	19,57	5,92	64168,0	31185,6	3322,0	1546,7	462,5	195,3		
16	ÇKÇab3	3	4	400	1075	4	17,89	14,29	15,86	28,70	18,44	7,05	24768,0	10724,5	2654,0	1340,3	456,5	187,6		
17	ÇKÇac2	2	4	600	950	5	16,39	9,00	9,75	24,11	17,97	9,23	8336,0	4020,5	4044,0	1912,8	60,0	25,3		
18	ÇKÇab3	3	3	400	1000	1	9,70	6,22	7,58	7,81	9,97	1,89	12958,8	4704,0	981,7	450,6	854,7	413,2		
19	ÇKÇab3	3	3	400	1375	1	8,55	6,28	7,72	9,48	9,37	2,59	9007,2	3985,7	673,8	319,7	2959,2	1447,0		
20	ÇKÇab3	3	3	400	1325	1	9,30	4,56	6,33	9,55	9,58	2,40	12348,0	4488,5	947,8	476,3	353,5	171,2		
21	ÇKÇab2	2	3	400	850	3	24,44	11,31	15,25	44,19	25,73	11,36	10860,8	5370,7	759,3	340,5	75,5	29,6		
22	ÇKÇab3	3	2	400	825	3	28,27	12,15	15,53	57,09	29,68	16,42	9346,0	4542,2	2227,7	1069,3	61,2	27,9		
23	ÇKÇab3	3	4	400	1325	1	12,04	6,86	9,70	16,45	12,57	3,43	4731,6	1859,5	2848,0	1374,2	775,1	398,4		
24	ÇKÇab3	3	4	400	1075	3	23,21	13,05	15,43	48,84	24,05	11,75	23150,8	11401,8	1530,8	780,7	126,3	61,7		
25	ÇKÇab3	3	4	400	1375	2	11,61	7,08	10,63	19,75	13,52	4,52	16034,8	6943,1	1113,6	549,0	104,3	53,8		
26	ÇKÇab3	3	3	400	1450	1	9,25	7,82	13,63	12,60	10,71	3,18	10244,0	4932,5	860,7	421,3	144,1	73,7		
27	ÇKÇab3	3	4	600	800	4	30,28	14,19	17,53	58,41	30,49	16,76	30175,4	9761,7	1239,3	632,0	76,1	37,9		
28	ÇKÇad2	2	4	400	800	4	30,34	15,50	19,00	63,15	31,70	19,14	23046,8	10855,0	760,5	366,6	47,6	21,1		
29	ÇKÇac2	2	3	400	800	4	23,50	15,55	21,83	39,75	25,15	10,74	7199,2	3736,4	1591,4	746,4	88,4	41,1		
30	ÇKÇad3	3	4	400	825	4	26,70	14,37	16,78	48,82	27,45	12,67	26821,2	12901,0	4211,5	2082,6	110,4	52,9		
31	ÇKÇad3	3	4	400	800	4	29,66	15,47	20,53	58,53	30,52	16,51	29720,8	15127,9	7106,8	3411,3	187,8	91,6		
32	ÇKÇac1	1	5	600	517	6	17,38	7,94	7,94	20,20	21,31	9,03	7512,0	2888,4	2462,0	1242,1	489,1	222,1		
33	ÇKÇab2	2	4	600	550	3	23,44	13,96	13,96	25,93	24,50	11,48	14496,0	5812,9	923,0	444,9	448,0	206,1		
34	ÇKÇab2	2	4	600	217	6	24,24	12,21	12,21	10,93	25,34	4,42	26280,8	11484,7	1865,0	893,3	501,0	223,9		
35	ÇKÇab2	2	4	600	250	5	24,23	12,24	14,20	12,13	24,85	5,32	11400,0	5426,4	1868,0	922,8	397,0	185,0		
36	ÇKÇac2	2	4	600	417	4	26,68	13,39	15,30	20,47	25,01	8,47	24768,0	10922,7	2003,0	969,5	435,0	194,4		
37	ÇKÇab2	2	5	600	550	5	12,52	9,60	10,30	9,59	14,90	3,96	9080,0	4195,0	771,0	362,4	435,0	203,1		
38	ÇKÇab2	2	5	600	617	5	10,73	10,62	12,30	7,94	12,80	3,04	11776,0	3862,5	1295,0	607,4	707,0	311,8		
39	ÇKÇac2	2	5	600	417	5	17,08	13,24	15,10	11,54	18,78	4,93	8832,0	4115,7	2490,0	1257,5	414,0	188,4		
40	ÇKÇac2	2	4	600	267	3	23,99	13,49	16,40	12,71	24,63	5,60	7024,0	3778,9	2381,0	1140,5	403,0	179,3		
41	ÇKÇac2	2	4	600	217	4	27,26	13,22	18,40	13,09	27,74	5,78	11816,0	4785,5	2281,0	1085,8	649,0	293,3		
42	ÇKÇab2	2	4	600	817	6	15,38	14,48	15,00	16,83	16,20	6,25	6840,0	3249,0	2138,0	981,3	586,0	258,4		
43	ÇKÇab2	2	4	600	283	4	16,75	10,32	13,80	7,66	18,55	3,43	22696,0	10508,2	2628,0	1190,5	85,0	37,0		
44	ÇKÇab1	1	4	800	300	3	16,60	8,37	9,88	7,26	17,56	3,69	17842,4	7904,2	1925,4	926,1	491,0	220,5		
45	ÇKÇab1	1	4	600	633	4	19,02	7,46	9,30	21,17	20,63	8,44	17832,8	8078,3	1917,9	957,0	494,3	223,4		
46	ÇKÇad3	3	3	400	450	5	23,54	17,30	18,92	27,16	27,72	9,77	11720,0	4559,1	3559,0	1676,3	809,0	359,2		

No	0-30				30-60		60-90		Mass of Soil Organic Matter										
	B_Kilcal	B_Ince	B_Kalin	B_Fine	B_Small	B_coarse	B_fine	B_small	B_coarse	B_0-10	B_10-30	B_30-50	B_50-80	B_80-100					
	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha	kg/ha	ton/ha	ton/ha	ton/ha	ton/ha	ton/ha					
1	22769,7	13226,6	9465,4	6185,9	1150,1	8579,4	1492,1	1274,5	2207,0	781,9	1571,7	1287,6	1939,9	1026,1					
2	45228,6	1795,2	8066,5							854,3	1879,6								
3	16475,0	1802,9	279,8	3388,3		1740,8	1461,0	870,4		766,5	1484,1	1619,4	2352,7	1026,1					
4	11656,9	1189,0	955,9							380,0	715,0								
5	36058,5	1523,2	13055,7	9947,2	870,4	2207,0				577,3	903,8	1314,0	1673,2						
6	41032,1	2020,5	5284,4	2424,6	777,1		9947,2	1865,1		638,6	682,4	1017,0	1595,3	850,3					
7	37612,8	497,4	1243,4	2797,6	310,8			2175,9		516,1	1125,2	1611,0	1751,1	850,3					
8	12434,0	5750,7	45384,0	7491,5	2859,8	2735,5	1088,0	652,8	1492,1	746,9	1571,7	1287,6	1939,9	1026,1					
9	33571,7	2331,4	590,6	9947,2	2797,6	7149,5	12123,1	3636,9	1958,4	742,1	1383,1	1340,9	1806,0	693,5					
10	16785,9	1554,2		3388,3	373,0	258,0	5284,4	2082,7	11501,4	724,2	1581,6	1465,0	1224,1	808,5					
11	14609,9	1119,1	901,5	4072,1	746,0					671,2	919,9	1103,7	1338,1	1199,2					
12	19583,5	2409,1		5595,3	1212,3	5875,1				463,9	951,0	891,3	392,1						
13	19583,5	2393,5		5595,3	1523,2	5875,1													
14	12123,1	901,5	7149,5	2393,5	1119,1					693,1	1193,7	927,9	2930,4						
15	12123,1	901,5	7149,5	2393,5	497,4														
16	30152,4	1305,6	1119,1	4227,6	373,0	1429,9	2424,6			664,3	573,8	397,1	1481,3	1676,3					
17	16164,2	3947,8	2642,2	3326,1	1212,3		3046,3			463,7	687,2	1327,4	1354,8	657,3					
18	15075,0	4197,5	46550,0	4375,0	1172,5	23645,0	1137,5	2925,0	7659,3	928,5	3218,5	2856,4	4273,9	3565,9					
19	13725,0	2752,5	12487,5	4818,2	550,0	12450,0	330,0	2505,0	1389,3	1045,4	2633,6	2972,2	3150,5	3150,5					
20	21025,0	4472,5	25352,5	4500,0	2775,0	11500,0	1165,0	1542,5	4158,3	1060,8	2615,3	3607,2	3041,5	2712,4					
21	5925,0	2277,5	30817,5	3000,0	1550,0	25825,0	127,5	2479,2	7605,5	1429,0	2667,8	2900,6	3147,7						
22	3825,0	765,0	48885,0	2250,0	2400,0	7475,0	412,5	2647,5	8176,0	1433,8	3759,2	3133,4	4825,4	3228,5					
23	23360,8	5965,0	15210,0	4850,0	1022,5	18312,5	527,5	2472,5	5113,3	1077,3	2753,0	2382,9	1905,5	1905,5					
24	38650,0	5080,0	26265,0	4250,0	1825,0	18000,0	552,5	2225,0	5485,0	769,7	2156,9	2024,8	2975,2	2606,6					
25	19075,0	5105,2	10395,0	3550,0	1677,5	13147,5	722,5	2935,0	3431,0	887,1	2042,0	2178,4	2178,4	2010,1					
26	20566,2	2622,5	16682,5	5200,0	1395,0	14672,5	502,5	3207,5	2396,5	744,0	2088,1	1675,5	4354,5	2085,3					
27	13000,0	1850,0	11350,0	1400,0	2127,5	16375,0	817,5	1532,5	4127,5	945,6	1575,6	1488,9	1752,7						
28	5806,1	2047,5	18347,5	3325,0	242,5	17180,0	1215,0	1302,5	3962,8	835,2	1502,4	1653,6	2150,4	1436,4					
29	9250,0	5747,5	43607,5	6725,0	1070,0	34605,0	1057,5	4150,0	4077,5	1087,8	1971,5	2649,5	2629,0	2480,0					
30	6180,4	1325,0	39032,5	4725,0	1976,4	19145,0	655,0	2707,5	3601,3	769,1	2110,8	2804,7	4887,4	3350,6					
31	20544,6	2377,5	39297,5	15425,0	1675,0	15450,0	750,0	2077,5	4181,8	832,0	1781,7	2944,0	3201,8						
32	23571,8	3710,0								791,9	1571,7								
33	40410,4	3419,3	30463,3	4662,7	1834,0	2828,7				593,8	1739,2	1386,6	2697,1						
34	30618,7	2144,9	16848,0	4507,3	1740,8	8424,0	994,7	1740,8	4693,8	767,6	1856,9	1415,5	2580,4	2337,0					
35	30618,7																		
36	20826,9	870,4	3323,8	4351,9	2890,9	13988,2	2611,1			941,4	1974,7	1444,3	2463,7	1602,3					
37	6442,4	963,6	8392,9	4849,3	1492,1	9232,2	994,7	1740,8	4693,8	750,0	1071,9	1697,2	2979,3	2337,0					
38	6527,8																		
39	7126,2	1088,0	8392,9	4662,7	1068,0	6621,1	4103,2	1647,5	808,2	750,0	1071,9	1320,4	1656,0	1186,5					
40	21409,8	4149,8	8626,1	4631,7	1958,4	6434,6	4010,0	1554,2	901,5	906,4	2078,2	1312,2	1630,5	1154,3					
41	21363,1	2455,7	8346,3	4724,9	1150,1	6558,9	3885,6	1678,6	746,0	906,4	1571,7	1291,6	1665,3	1149,5					
42	21448,6	11796,7	4196,5																
43	17019,0	2746,7	4451,1	4849,3	1482,1	9234,2	994,7	1740,8	4693,8	694,1	556,6	1697,2	2979,3	2337,0					
44	15122,8																		
45	15223,9	2724,3	4439,1	4849,3	1502,1	9230,2													
46	30960,6	2984,2	36058,5							914,5	1326,2	1244,6							

Annex 6. Summary of Activation Function in ANN

Activation Function	Formula	Common Applications	Advantages	Disadvantages
Linear	$f(x) = x$	Rarely used in modern neural networks	None	Does not introduce non-linearity
Binary	$f(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$	Classification tasks with binary output	Simple and efficient	Limited to binary classification tasks
Sigmoid	$f(x) = \frac{1}{1 + e^{-x}}$	Classification tasks	Output can be interpreted as probability	Saturates for large positive or negative inputs; not zero-centered
Tanh	$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	Classification tasks	Zero-centered; does not saturate for large positive or negative inputs	None
ReLU	$f(x) = \max(0, x)$	Widely used in modern neural networks	Simple and efficient; does not saturate for large inputs	Can suffer from "dying ReLU" problem; not zero-centered
Softmax	$f(x)_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$	Classification tasks with multiple classes	Outputs probability distribution over classes	None

Source: Baheti (2023)

Annex 7. Universal Carbon Terms and Units

Carbon Pool

A system that has the capacity to accumulate or release carbon.

Carbon Stock

The quantity of carbon in a pool, reported as a measure of mass or weight.

Carbon is measured and reported at different scales and units.

1 metric ton = 1 tonne = 1.102 short tons = 1,000 kg = 2,204.62 lbs

The carbon in a country is often reported in million metric tons or megatons:

1 million metric tons (MMT) = 1 megaton (Mt) = 1 teragram (Tg) = 1x10¹² grams (g)

Global measures of carbon are usually reported in billion metric tons or gigatons:

1 billion metric tons (BMT) = 1 gigaton (Gt) = 1 petagram (Pg) = 1x10¹⁵ grams (g)

Carbon Flux

A measure of the amount of carbon transferred between different pools in a specified time period.

1 million metric ton (MMT) / year = 1 teragram (Tg) / year

1 billion metric ton (BMT) / year = 1 petagram (Pg) / year

Carbon Density

A measure of the weight of carbon per a unit of area.

10 tons / hectare (ha) = 1 megagram (Mg) / ha = 1 kilogram (kg) / m²

1 hectare = 2.47 acres

1 ton of carbon is equivalent to 3.67 tons of carbon dioxide, or CO₂ = C*3.67

Sources: CRS, adapted from Maria Janowiak et al., Considering Forest and Grassland Carbon in Land Management, U.S. Department of Agriculture (USDA) Forest Service, GTR-WO-95, June 2017, p. 4 (Hoover and Riddle, 2020). Forest Carbon Primer.

Annex 8. Some reference photos in the laboratory and in forest.



CURRICULUM VITAE

Moussa Beau-Gars MBOHOU Kouffen, Foumban Arrondissement, West Region of Cameroon. He commenced his primary education at Njintout Public School and continued his secondary education at Bilingual Sultan Ibrahim NJOYA High School in Foumban, where he earned his Scientific Baccalaureate in 2008. Moussa successfully passed the national entrance examination for the Faculty of Agronomy and Agricultural Sciences at the University of Dschang for the academic year 2008-2009, where he pursued studies in Forest Engineering. He successfully completed his Master's Degree, presenting a thesis titled "Relative Tree Positioning Method during Geo-Referenced Logging Inventories in Cameroon according to the APV-FLEGT (European Union)," earning a degree in Water, Forests, and Wildlife Engineering in 2014. In 2016, Moussa was selected for the International Scholarship Program of the Republic of Türkiye (YTB Scholarships) for a Doctoral Program in Forest Management at the Faculty of Forest Engineering, Graduate School of Natural and Applied Sciences at Karadeniz Technical University. Subsequently, in 2019, he was appointed as a Researcher by the Minister of Civil Service and Administrative Reform on behalf of the Ministry of Scientific Research and Innovation of Cameroon.