

KARADENİZ TECHNICAL UNIVERSITY
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCE

DEPARTMENT OF FOREST ENGINEERING

**PREDICTION OF POTENTIAL DISTRIBUTION OF SELECTED TREE
SPECIES UNDER SSP CLIMATE CHANGE SCENARIOS, IN KASTAMONU,
TÜRKİYE**

MASTER THESIS

Mulugeta Siyoum MOLLA

MARCH 2024
TRABZON



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FOREWORD

This study was conducted within the framework of the Erasmus Mundus MEDfOR Program, financed by the Erasmus+ Programme of the European Union. The program was coordinated by the Instituto de Agronomia, University of Lisbon, Portugal, in collaboration with the University of Padova, Italy, and Karadeniz Technical University, Türkiye. I extend my sincere gratitude to the Erasmus+ Programme of the European Union and the MEDfOR Secretariat for their generous financial support, as well as to all the hosting universities that accommodated me during the entire duration of this study. Special appreciation goes to the General Directorate of Forestry for their generosity in sharing valuable data and resources, significantly enhancing the depth and reliability of this thesis. The meticulous organization and presentation of this data played a pivotal role in the overall success of the research.

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Mulugeta Siyoum MOLLA

Trabzon, 2024

THESIS STATEMENT

I, Mulugeta Siyoum MOLLA, pledge on my honor that this work entitle “Prediction of potential distribution of selected tree species under SSP climate change scenarios in Kastamonu, Türkiye” is the result of my own work under the supervision of Assoc. Prof. Uzay KARAHALİL in accordance with scientific research and ethical rules. I personally organize and analyzed data from the forest directorate stand type map and from previous related studies. To the best of my knowledge, it contains no material previously published by another person without citing the source. I also confirm that I have completely recognized and referred to all the material and results that are not originating from this work. In case the opposite interest arises, I declare that I accept the legal results. 28/03/2024

Mulugeta Siyoum MOLLA
Trabzon, 2024

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SUMMARY

Master Thesis

PREDICTION OF SPECIES DISTRIBUTION OF SELECTED TREE SPECIES UNDER CLIMATE CHANGE SCENARIO IN KASTAMONU, TÜRKİYE

Mulugeta Siyoum MOLLA

Karadeniz Technical University
The graduate School of Natural and Applied Sciences
Department of Forest Engineering
Supervisor: Assoc. Prof. Uzay KARAHALİL
2024, 98 pages

This study undertakes a comprehensive analysis of current predictions and future projections of species distribution for key tree species in Kastamonu province, Türkiye, under SSP2 and SSP5 climate change scenarios using the MaxEnt model. By investigating the intricate dynamics of changing habitat suitability, the study underscores the profound implications for tree species composition within forest ecosystems. The findings reveal that both biotic and abiotic factors, with climate change as a pivotal driver, significantly influence the distribution of tree species. Notably, temperature-related predictors consistently play a critical role, emphasizing their significance in species distribution modeling. Future projections unveil a nuanced landscape, delineating winners and losers based on habitat suitability changes, thereby highlighting the complexity of climate change impacts on various species. Specifically, *Pinus sylvestris*, *Pinus nigra*, *Fagus orientalis*, and *Abies nordmanniana* subsp. *equi-trojani* are projected to face challenges whereas, *Pinus brutia* displays a short-term decrease but a long-term increase in suitability, suggesting potential adaptive responses. The study provides valuable insights that can significantly enhance conservation strategies, fostering adaptability and effectiveness in the face of ongoing climate change impacts.

Key words: Habitat suitability; Maximum Entropy; Climate Change; Shared Socioeconomic Pathways; Kastamonu

ÖZET

Yüksek Lisans Tezi

SEÇİLEN ASLİ AĞAÇ TÜRLERİNİN SPP İKLİM DEĞİŞİKLİĞİ SENARYOLARINA GÖRE KASTAMONU, TÜRKİYE’DE TÜR DAĞILIMLARININ TAHMİN EDİLMESİ

Mulugeta Siyoum MOLLA

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Bu çalışma, MaxEnt modelini kullanarak çeşitli iklim değişikliği senaryoları altında Türkiye'nin Kastamonu ilindeki önemli ağaç türlerinin tür dağılımına ilişkin mevcut tahminlerin ve gelecekteki projeksiyonların kapsamlı bir analizini gerçekleştirmektedir. Değişen habitat uygunluğunun karmaşık dinamiklerini araştıran çalışma, orman ekosistemlerindeki ağaç türlerinin kompozisyonu üzerindeki derin etkilerin altını çizmektedir. Bulgular, iklim değişikliğinin temel etken olduğu hem biyotik hem de abiyotik faktörlerin ağaç türlerinin dağılımını önemli ölçüde etkilediğini ortaya koymaktadır. Özellikle sıcaklıkla ilgili belirleyiciler sürekli kritik rol oynamakta ve bunların tür dağılım modellemesindeki önemini vurgulamaktadır. Geleceğe yönelik projeksiyonlar, habitat uygunluğu değişikliklerine göre kazananları ve kaybedenleri tasvir eden, böylece iklim değişikliğinin çeşitli türler üzerindeki karmaşıklığını vurgulayan incelikli bir manzara ortaya koymaktadır. Özellikle *Pinus sylvestris*, *Pinus nigra*, *Fagus orientalis* ve *Abies nordmanniana* subsp. *Equi-trojani*'nin zorluklarla karşılaşacağı tahmin edilirken, *Pinus brutia*'nın uygunluğunda kısa vadeli bir düşüş ancak uzun vadeli bir artış görülüyor ve bu da potansiyel uyarlanabilir tepkiler olduğunu gösteriyor. Çalışma, devam eden iklim değişikliği etkileri karşısında koruma stratejilerini önemli ölçüde geliştirebilecek, uyarlanabilirliği ve etkililiği teşvik edebilecek değerli bilgiler sağlamaktadır.

Anahtar kelimeler: Habitat uygunluğu; Maksimum Entropi; İklim değişikliği; SSP scenarios; Kastamonu

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ACRONYMS OR ABBREVIATIONS

ANN	Artificial Neural Network
ASCII	American Standard Coder for Information Interchange
AUC – ROC	Area Under Curve Receiver Operating Characteristics
BIOCLIM	Bilclimate Analysis and Prediction System
BIOD	Biodiversity and Non-Wood Forest products Database
CLIMEX	Climate Change Experiment
CMIP	Coupled Model Intercomparison Project
CSV	Comma Delimited Value
CVH	Chinese Virtual Herbarium
DOMAIN	Domain Analysis
ENFA	Ecological Niche Factor Analysis
ENM	Ecological Niche Modeling
EUFORGEN	European Forest Genetic Resource Program
FAO	Food and Agricultural Organization
GARP	Genetic Algorithm for Rule-set Production
GBIF	Global Biodiversity Information Facility
GCM	General Circulation Model
GHG	Green House Gas
GIS	Geographical Information System
HSM	Habitat Suitability Modeling
IPCC	Intergovernmental Pannel on Climate Change
IUCN	International Union for Conservation of Nature
RCP	Representative Concentration Scenarios
SDM	Species Distribution Modeling
SRES	Special Report Emissions Scenarios
SSP	Shared Socioeconomic Pathways
SVM	Support Vector Machine
TIFF	Tag Image File Format

UNFCC

United Nations Framework Convention on Climate Change

WEF

World Economic Forum



1. GENERAL INFORMATION

1.1. Introduction

Forests, integral to our planet's ecosystems, provide essential services crucial for the well-being of both humans and the environment. Playing a pivotal role in the global carbon cycle, forests act as a substantial carbon sink, storing approximately 650 gigatons of carbon globally, twice the amount in the atmosphere (Mitchell and Pleeck, 2022). This carbon sequestration is vital for mitigating climate change, a significant global challenge. Additionally, forests contribute to climate regulation by releasing oxygen through photosynthesis, balancing greenhouse gas levels. They also regulate the water cycle, supporting ecosystems, agriculture, and providing drinking water. Acting as natural filters, forests improve air and water quality while fostering biodiversity by offering habitats for diverse plant and animal species (Gamfeldt *et al.*, 2014; Mori, 2017).

Beyond their environmental contributions, forests serve as a cornerstone for livelihoods, offering essential products such as timber, non-timber forest products, and medicinal plants. Roughly 1.6 billion people globally depend on forests for their livelihoods, contributing an estimated \$150 trillion to the global economy (IUCN, 2021; WEF, 2022). However, forests face escalating threats, including deforestation, forest degradation, and biodiversity loss, which are further exacerbated by climate change-induced phenomena such as rising temperatures, shifting precipitation patterns, and increased extreme weather events (FAO, 2020).

Climate change stands as one of the foremost environmental challenges confronting the world today, and its impact on forest ecosystems and biodiversity are of paramount concern (Dawson *et al.*, 2011). The changing climate presents a significant threat to forests, causing noticeable changes in the distribution patterns of many tree species. The anticipated trajectory of climate change indicates a forthcoming impact on the distribution of forest tree species in the coming decades, with the relentless progression of temperature, precipitation, and other climate variables on a global scale (IPCC, 2022).

It is evident that as temperatures continue to rise, optimal growing conditions for many species are anticipated to shift, prompting alterations in their geographic distribution. Concurrently, changes in precipitation patterns, including more frequent droughts or floods, are likely to further impact the distribution of tree species. The sensitivity of plant species to climate change is evident, as they either migrate, adapt, or face extinction in response to changed climate conditions (Bartesaghi-Koç *et al.*, 2018; Kelly and Goulden, 2008). In regions like Greece, climate change has led to some tree species respond positively and are being classified as "winners," expanding their distribution areas, while others respond negatively are termed "losers," projecting shrinkages in habitat suitability (Fyllas *et al.*, 2022; Dyderski *et al.*, 2018; Liu *et al.*, 2021). The impacts vary, with some species unable to survive in their current ranges due to exceeding physiological limits, while others might expand into previously inhospitable areas (IPCC, 2021). Similarly, other studies also indicated that while some tree species are expanding their distribution, climate change combined with habitat loss could reduce species occupancies (García-Valdés *et al.*, 2015). For instance, research on future prediction of selected Oak species in Marmara, Türkiye suggests that certain species will experience an increase, while the others are expected to decline under the future climate condition (Fosso *et al.*, 2023).

In the Mediterranean region, tree species face vulnerability to climate change, with the determinants being site climate marginality and adaptation to site conditions rather than species-specific factors (Dorado-Liñán *et al.*, 2019). The seasonal timing of climate and precipitation changes resulting in drought events poses a threat to the coexistence of Mediterranean tree species (Granda *et al.*, 2013). Temperature rises and changed precipitation patterns over the past decades are evident, and predictions suggest a potential shift in the distribution of forest trees throughout Europe, from high altitude to low altitude and vice versa (Beniston *et al.*, 2007; Spinoni *et al.*, 2018). Additionally, temperate or cold-adapted tree communities are expected to decline while Mediterranean tree communities grow significantly (Ruiz-Labourdette *et al.*, 2013). It is imperative that management plans consider the impact of climate change on species distribution, with predictions indicating a significant decrease in the potential range of cork oak, a basic species in many Mediterranean landscapes (Vessella *et al.*, 2017). Forests of Mediterranean species generally suffered a smaller overall reduction in area occupied than any other forest type. Despite a loss of present habitat, they will survive if they can colonize similar

habitats created by climate change mainly in areas that are currently sub-mediterranean (Benito-Garzon *et al.*, 2008).

Türkiye, in the Mediterranean region, faces substantial impacts from climate change, particularly in the distribution of its forest tree species. Yılmaz and Tolunay (2012) developed maps illustrating Türkiye's plant hardiness and heat zones, revealing distinct distributions of crucial forest tree species across these zones. Examining the potential distribution of Türkiye oak in the Sütçüler district under current and changing climates, Mert *et al.* (2016) utilized the classification and regression tree technique. Their findings indicated an anticipated alteration in the potential distribution of Türkiye oak as a consequence of climate change. Türkiye's oak woodland vegetation exhibits compositional diversity, encompassing xerophytic evergreen woodlands to mesophytic deciduous forests (Uğurlu *et al.*, 2012). Furthermore, the impact of climate change on Türkiye's main forest tree species in the region are likely to struggle to adapt to changing climatic conditions. They anticipate contractions in the ranges of these species, with some facing the imminent threat of extinction (Uzun and Sarikaya, 2021).

Climate change modify the ecological conditions in forests, causing tree migration from the Mediterranean to temperate areas and from temperate to boreal areas. Due to global warming, distribution ranges of temperate tree species are shifting northwards and upslope to cooler areas. Shifts in distribution first occur in response to changes in climate suitability, leading to the migration of certain species into new habitats and the decline of others (Axer *et al.*, 2021). The rate of projected climate change is unprecedented and is expected to be 10 to 100 times faster than the ability of trees to migrate, resulting in impacts on forest health and productivity. Climate conditions have already shifted, affecting the distribution of certain tree species in Canada. In the last 50 years, changes have occurred in plant hardiness zones. The climate in an area where a tree species currently lives and reproduces is likely to shift to new locations. Some tree species may not be able to migrate or adapt fast enough to a rapidly changing climate, resulting in impacts on forest health. Forest management needs to take into account shifting climate suitability zones. Careful selection of seed sources and species can contribute to maintaining healthy and productive trees in this changing environment. These changes in tree species distribution are important as they shape forest composition and affect ecosystem processes and wood supply. Tree species differ in the way they interact with their

environment, and changes in species composition may affect several ecosystem properties (FAO, 2013; URL-1).

Climate change is significantly impacting forest management in the Mediterranean region, not only affecting species distribution but also causing a range of negative effects on forest health, biodiversity, and ecosystem services. The consequences encompass increased aridity, alterations in land use, and the proliferation of pests and invasive species (Peñuelas *et al.*, 2017; Solomou *et al.*, 2017; Nunes *et al.*, 2021). These changes lead to modifications in forest structure and function, resulting in a diminished capacity to provide essential services (Peñuelas *et al.*, 2017).

In Turkey, a country with a Mediterranean climate, the impact of climate change is pronounced, causing various adverse effects, including a reduction in water supplies, an increase in forest fires, a decline in water levels, and an elevated mortality rate of livestock and wild animals (Bagdatli and Belliturk, 2016). Additionally, climate change has increased the frequency of extreme weather events in Turkey, such as heatwaves, droughts, and floods, with serious implications for agriculture, water resources, and biodiversity (Bagdatli and Belliturk, 2016). The changing climate has also led to a decline in rainfall, resulting in more frequent and intense droughts, as well as a reduction in water availability, impacting groundwater, wetlands, and water storage systems (Bagdatli and Belliturk, 2016). Studies have demonstrated that forest storm damage in Turkey is influenced by environmental factors and forest management practices, with windstorms causing significant destruction in the northern forests of the country (Torun and Altuniel, 2020). The impact of climate change on Turkey's forests is further exacerbated by the country's vulnerability to wildfires and flooding, expected to become more regular occurrences due to rising temperatures, decreased rainfall, and increased rainfall variability.

Nevertheless, sustainable forest management practices, such as those enhancing carbon sequestration, can help mitigate these adverse effects (Ruiz-Peinado *et al.*, 2017). Thus, there is a pressing need for continued monitoring and research, coupled with the implementation of adaptive management strategies to preserve Mediterranean habitats (Solomou *et al.*, 2017; Nunes, 2021). Baskent (2019) emphasizes the importance of forest management scenarios in mitigating the effects of climate change, with high-intensity management showing promise in maintaining ecosystem services.

Incorporating different future climate scenarios into forest management is crucial for providing alternatives and making informed decisions (Fosso, 2021; Yousefpour *et al.*, 2017). This can be achieved through a combination of qualitative scenario planning and quantitative simulation modeling, which helps identify key uncertainties and potential impacts (Symstad *et al.*, 2017). The use of forest decision support systems further enhances this process by assessing the impacts of different management models on ecosystem services (Nordström *et al.*, 2019). The pertinence of different adaptation strategies, such as reactive, active, and robust, should also be evaluated in the context of forest management under climate change (Yousefpour *et al.*, 2017).

The use of ecological niche modeling (ENM) or species distribution modeling (SDM) to quantify the relationship between species' presences and environmental conditions (Peterson and Soberón, 2012) has increased with the rapid development of GIS techniques and the accumulation and digitization of museum specimens. SDM is a numerical tool that combines observations of species occurrence or abundance with environmental estimates to predict species distribution across landscapes. SDMs have gained significant interest in the last two decades, and recent advances in SDMs allow us to potentially forecast anthropogenic effects on patterns of biodiversity at different spatial scales (Guisan and Thuiller, 2005). SDMs are now widely used across terrestrial, freshwater, and marine realms, and differences in methods between disciplines reflect both differences in species mobility and in "established use" (Elith and Leathwick, 2009).

Several modeling algorithms have emerged in the field of species distribution modeling (SDM), each presenting unique strengths and applications. These include the Climate Change Experiment (CLIMEX), recognized for simulating species distribution under present and future climate scenarios (Lanoiselet *et al.*, 2002), the Bioclimate Analysis and Prediction System (BIOCLIM), which identifies essential environmental factors in defining species distribution modeling (Busby, 1991), Domain analysis (DOMAIN) based on bioclimatic data (Carpenter *et al.*, 1993), and the Genetic Algorithm for Rule-set Production (GARP), acknowledged for its effectiveness in handling presence/pseudo-absence data (Stockwell, 1999), as well as Ecological-Niche Factor Analysis (ENFA) (Hirzel *et al.*, 2002). Additionally, Generalized Linear Models (GLM) and Generalized Additive Models (GAM) represent traditional statistical models, providing insights into relationships between species occurrence and environmental

variables (Li and Wang, 2012). Other machine learning approaches, such as the Maximum Entropy Species Prediction Model (MaxEnt), recognized for its proficiency in handling presence-only data in SDM (Phillips *et al.*, 2004), along with Artificial Neural Networks (ANN), Booster Regression Trees (BRT), renowned for their capability to navigate complex, non-linear relationships in the data, making them suitable for modeling species distributions, and Support Vector Machines (SVM) find application in SDM due to their expertise in handling high-dimensional data and classifying intricate patterns (Elith and Leathwick, 2009). These diverse algorithms collectively contribute to modeling the intricate relationship between species occurrence and environmental variables, facilitating precise predictions of species distributions under both current and future climate scenarios.

In recent times, MaxEnt has gained significant popularity as widely employed ecological modeling software (Phillips *et al.*, 2017). Utilizing a maximum entropy approach, MaxEnt models species distributions by leveraging presence-only data and environmental variables to predict the probability of species occurrence in a designated area (Phillips *et al.*, 2006). MaxEnt excels in forecasting and delineating current geographical regions for a given species while assessing the impacts of anticipated environmental changes and potential niche shifts based on future projections (Khan *et al.*, 2022). MaxEnt proves to be effective for SDM due to several key reasons. Firstly, it is specifically tailored to handle presence-only data, which is commonplace in ecological studies, presenting a significant advantage as many species' occurrence records rely on such data (Lisovsky and Dudov 2021; Valavi *et al.*, 2021). Secondly, MaxEnt produces distribution maps of comparable accuracy to ensemble methods, rendering it a pragmatic and reliable method for predicting species distributions (Kaky *et al.*, 2020). Moreover, MaxEnt consistently yields reproducible results when the input data are complete and proficiently addresses spatial bias in the input data, thereby enhancing the predictive performance of SDMs (Phillips *et al.*, 2017). The combination of MaxEnt's capability to handle presence-only data, its reliability in producing accurate distribution maps, and its effectiveness in addressing spatial bias positions it as a valuable and widely utilized tool in species distribution modeling.

MaxEnt has emerged as a pivotal tool for comprehending the intricate dynamics of climate change on species distributions and abundance. The imperative for precise climate projections in this realm has spurred an increased reliance on global climate model (GCM) outputs as

predictive variables. Researchers are increasingly turning to MaxEnt, leveraging its capacity to effectively model the potential distribution areas of species across different climatic scenarios, ranging from paleoclimate to current and future climate backgrounds (Lissovsky and Dudov, 2021; Liu *et al.*, 2019; Philips *et al.*, 2017).

Climate scenarios are integral tools employed in examining the potential effects of various driving factors, including demographic change, socioeconomic development, and technological advancements, on future greenhouse gas emissions and their impact on the climate. Among the latest scenarios guiding projections of global socioeconomic changes up to 2100 are the Shared Socioeconomic Pathways (SSPs). These pathways are crucial in developing greenhouse gas emissions scenarios that consider different climate policies and are central to the UN climate reports produced by the Intergovernmental Panel on Climate (IPCC) (O'Neill *et al.*, 2017; Riahi *et al.*, 2017).

Offering narratives that outline alternative socioeconomic developments, the SSPs provide a qualitative description of the logical relationships among narrative elements. Additionally, they include data accompanying the scenarios, offering insights into national population, development, and income growth. The most recent scenarios, featured in the IPCC Sixth Assessment Report and used in CMIP6, are built upon the SSPs and Representative Concentration Scenarios (RCP). These scenarios play a pivotal role in enhancing our understanding of the potential trajectories of future climate change and guiding policy decisions for mitigation and adaptation strategies (Meinshausen *et al.*, 2020; O'Neill *et al.*, 2017).

In Türkiye, numerous studies have been conducted on the distribution of tree species under future climate conditions and scenarios. These studies play crucial roles in forest management, including restoration programs, timber production, and other ecosystem services (Fosso and Karahalil, 2020; Pecchi *et al.*, 2019; Yilmaz *et al.*, 2017). While there have been some studies on pure and mixed stands of various species such as *Pinus sylvestris*, *Carpinus orientalis*, *Alnus orientalis*, *Abies nordmanniana* subsp. *equi-trojani*, *Fagus orientalis*, *Picea orientalis*, and *Quercus* spp. in Trabzon and Antalya region (Fosso, 2021), as well as *Quercus* spp. in Marmara region (Fosso *et al.*, 2023), most existing research has focused on predicting the distribution of either a single species or a few species (Mert *et al.*, 2016; Uğurlu *et al.*, 2012; Özdemir *et al.*, 2020; Topaçoğlu *et al.*, 2017; Bartesaghi-Koç *et al.*, 2018).

To the knowledge of the researchers, the study area lacks a systematic evaluation of distribution modeling for several tree species, and the distribution of species included in the present study has not yet been examined or there is very limited information available. Moreover, rather than solely focusing on modeling the distribution of individual tree species, this study aims to predict stand composition with different tree species at the landscape level. Therefore, the primary objective of this study is to forecast the future distribution patterns of key forest tree species, considering a spectrum of climate scenarios. By addressing this existing knowledge gap, the study aspires to enhance understanding of the ecological consequences of climate change on forest ecosystems. Furthermore, the research aims to provide valuable insights essential for refining conservation strategies and implementing adaptive management practices in the face of evolving environmental conditions.

1.2. Objectives

The main objective of this study is to predict the future habitat suitability of selected tree species under different SSP climate scenarios. Specifically, the study aims;

- To predict the current potential distribution of selected key tree species in the study area
- To forecast the potential distribution variations of selected key species under proposed future climate change scenarios
- To assess the influence of key environmental variables for the species distribution modeling in the study area
- To investigate the spatiotemporal changes in habitat suitability of selected species

1.3. Climate Change and Climate Scenarios

1.3.1. Concepts and Definition of Climate Change

Climate change has become a focal point of attention in recent decades due to its potentially catastrophic effects on the environment and human societies. Essentially, climate

change refers to long-term shifts in Earth's climate patterns, encompassing alterations in temperature, precipitation, wind patterns, and other climatic variables (IPCC, 2014). The primary driving force behind these changes is the escalating concentration of greenhouse gases (GHGs) in the atmosphere, leading to global warming (IPCC, 2022).

While climate change has historical precedence in natural climate fluctuations, the contemporary era stands out for its unprecedented speed and magnitude, largely attributed to human activities accelerating GHG emissions since the industrial revolution (IPCC, 2018). IPCC defines climate change as a sustained alteration in climate properties persisting for decades or more (IPCC, 2014). Jackson (2021) echoes this definition, describing climate change as periodic modifications resulting from interactions within the Earth system.

Burning fossil fuels like coal, oil, and gas, along with deforestation and agriculture, are key contributors to increased GHG emissions, notably carbon dioxide (CO₂). Consequently, CO₂ levels in the atmosphere have surged by around 50% since pre-industrial times, causing a temperature rise of approximately 1.1°C (IPCC, 2021). The repercussions are already evident worldwide, with heightened occurrences of severe heatwaves, droughts, floods, and storms impacting human health, food security, infrastructure, and ecosystems.

The urgency to address climate change has prompted global collaboration through international agreements like the United Nations Framework Convention on Climate Change (UNFCCC) and the Paris Agreement. These initiatives aim to restrict global warming to below 2°C, with efforts to limit it to 1.5°C (IPCC, 2018; IPCC, 2022). Recent research underscores the interconnected nature of climate change with other global challenges such as biodiversity loss, food security, and social inequality. The IPCC's Sixth Assessment Report (AR6) from 2021 stresses that addressing the impacts of climate change requires a holistic approach, recognizing the intertwined relationship between climate change, natural systems, and human societies (IPCC, 2021).

1.3.2. The Shared Socioeconomic Pathway (SSP) Scenarios

The series of reports from the International Panel for Climate Change (IPCC) has consistently shown an increase in atmospheric greenhouse gas (GHG) concentrations, attributing the resulting climate change primarily to anthropogenic factors (IPCC, 2014; IPCC,

2018; IPCC, 2021). To advance climate change assessment, it is crucial to comprehend the potential range and nature of future scenarios. This involves evaluating risks to physical, natural, and human systems within various development pathways, as well as appraising options for mitigation and adaptation to address and manage those risks (O'Neill *et al.*, 2014). Despite the valuable insights gained from the Special Report on Emissions Scenarios (SRES) published in 2000, the SRES scenarios have lagged behind critical changes in society and the global economy over the past two decades. Demographic projections for mid- to late-century now differ, technological advancements for GHG emissions reduction are better understood, and Earth system models demand a broader range of input data, including details on air pollutants and land use.

In light of these advancements, the new scenario framework for climate change research seeks to integrate pathways of future radiative forcing and climate changes with alternative socioeconomic development pathways (O'Neill *et al.*, 2020). The Shared Socioeconomic Pathways (SSPs) play a pivotal role in this framework, serving as reference pathways that depict plausible societal and ecological evolution trends over a century-long timescale in the absence of climate change or policies. Given that climate change projections, impacts, and policy responses cannot be encapsulated within pathways describing radiative forcing or socioeconomic development, they are essential elements within the scenario matrix architecture, making the assumption of their exclusion unlikely (Kriegler *et al.*, 2012; O'Neill *et al.*, 2014; Riahi *et al.*, 2017).

The SSPs have been extensively utilized in climate change research and integrated into assessment models to examine the complex interactions among the economy, environment, and society (O'Neill *et al.*, 2017). Developed collaboratively with climate change researchers, economists, and social scientists, the SSPs capture a diverse range of possible socioeconomic futures, accounting for assumptions about population growth, economic development, and technological advancements. These scenarios, incorporating both socioeconomic and environmental factors, were integrated into the Coupled Model Intercomparison Project (CMIP6) alongside a set of new emission scenarios termed "Representative Concentration Pathways" (RCPs). The RCPs describe various levels of Greenhouse Gas and radiative forcing that could occur in the future, encompassing uncertainties in adaptation efforts to address and respond to climate changes and their impacts. Including a climate dimension with mitigation

targets and a baseline case, the SSPs provide a comprehensive framework with four main pathways (2.6, 4.5, 6.0, and 8.5 watts per square meter) and two additional scenarios (3.4 and 7.0 W/m²), covering a broad spectrum of forcing levels by 2100 (Fujimori *et al.*, 2017).

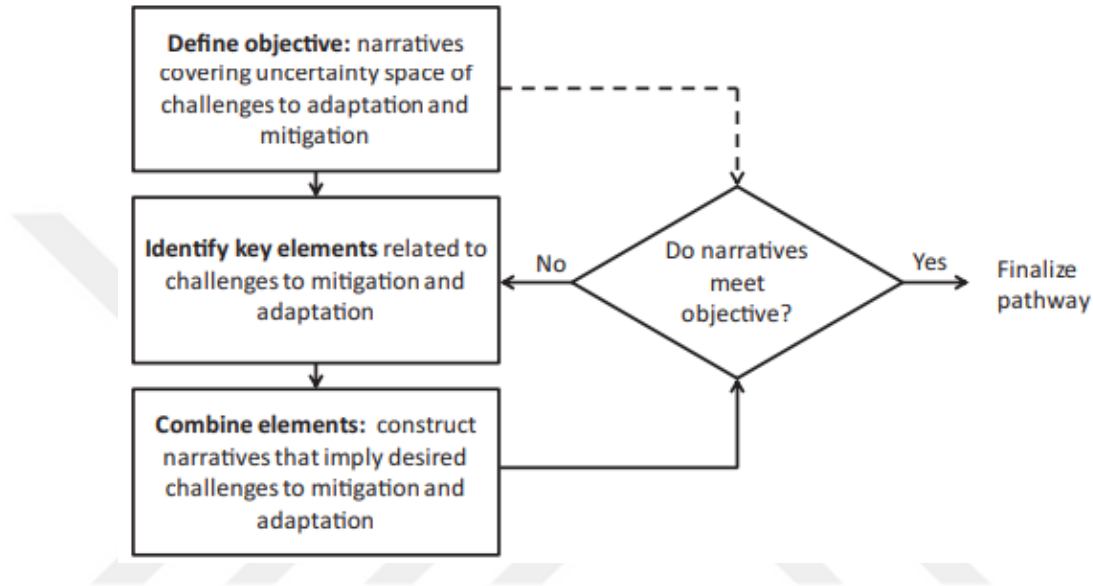


Figure 1. Flow diagram of process for developing the SSP narratives

Challenges in mitigation refer to factors and trends that contribute to the escalation of greenhouse gas emissions and hinder society's capacity to curtail them. These challenges encompass technological shortcomings, deficiencies in international decision-making institutions, and a lack of financial and other resources, such as political will, human and social capital, to support containment policies. Elevated emission levels can arise from diverse combinations, including high population growth, rapid economic expansion (often defined), energy-intensive economic systems, and a carbon-intensive energy supply, among others. It's important to note that not all factors need to align in the same direction to yield high (or low) emissions. On the other hand, socio-economic challenges impede adaptation efforts, intensifying the risks associated with climate change. These challenges involve issues like poverty and wealth distribution, ineffective national and international organizations, inadequate institutions and governance, restricted water and food security, a low level of education, and unplanned urbanization (O'Neil *et al.*, 2014).

The narratives within the socioeconomic dimension (SSP) are constructed through textual descriptions that outline potential future developments in broad societal trends. The primary objective is to establish an internally consistent logic for the main causal relationships, incorporating descriptions of trends that are often challenging to capture through modeling (O’Neil *et al.*, 2017). These narratives play a crucial role as a complement to quantitative model projections by detailing assumptions about demography, human development (such as health and education), economic growth, inequality, governance, technological change, and policy orientations among the SSPs. The selection of these variables is based on their common use as inputs to emission or impact models and their interrelationships (O’Neill *et al.*, 2020). The narratives are designed to cover a spectrum of outcomes in the future, illustrating the socioeconomic challenges they pose for both mitigating and adapting to climate change. These challenges encompass the underlying factors in each pathway that influence both adaptation and mitigation efforts (O’Neil *et al.*, 2017).

1.3.3. The Shared Socioeconomic Pathways (SSP) Narratives

The Shared Socioeconomic Pathways (SSPs) aim to depict scenarios where the challenges related to mitigation and adaptation range from low to very high. The baseline SSP scenarios operate on the assumption of an absence of climate policy, providing insights into how the underlying socioeconomic conditions would influence the implementation of climate policy. These pathways are constructed upon five narratives outlining diverse socioeconomic developments that could influence future societies in the absence of explicit additional policies or measures to limit climate forcing or enhance adaptive capacity. Their purpose is to facilitate climate research and policy analysis, encompassing a broad spectrum of challenges related to both mitigation and adaptation to climate change (Riahi *et al.*, 2017).

The scenarios encompass a world characterized by sustainable growth and development with a focus on equality (SSP1); a fragmented global landscape marked by a resurgence of nationalism and regional rivalry (SSP3); a world experiencing continual and escalating inequality (SSP4); a scenario of rapid and unrestricted growth in economic output and energy consumption driven by fossil fuels (SSP5); and a middle-of-the-road development world where

trends largely align with historical patterns (SSP2) (O'Neill *et al.*, 2017; Riahi *et al.*, 2017; Meinshausen *et al.*, 2020).

SSP1: Sustainability – Taking the Green Road

In a world gradually transitioning toward sustainability, there is a pervasive shift emphasizing inclusive development while respecting environmental boundaries. The change is driven by an increased awareness and acknowledgment of the social, cultural, and economic consequences associated with environmental degradation and inequality. Improved collaboration among diverse entities contributes to the gradual enhancement of global commons management. Investments in education and healthcare play a pivotal role in fostering a demographic transition, leading to a comparatively lower population. The emphasis on economic growth shifts towards prioritizing human well-being, even if it means accepting a somewhat slower economic growth rate. There is a commitment to development goals that effectively reduce inequality both across and within countries. Strategic investments in environmental technology and adjustments in tax structures bolster resource efficiency, curtail energy and resource consumption, and enhance overall environmental conditions. The appeal of renewable energy increases, and consumption patterns are geared towards achieving lower material growth and reduced resource intensity. This purposeful development, coupled with favorable conditions for renewable energy, fosters international cooperation and results in relatively minimal challenges for mitigation and adaptation (O'Neil *et al.*, 2017).

SSP2: Middle of the Road

In a scenario where global trends remain relatively consistent with historical patterns, social, economic, and technological developments proceed without significant shifts. Some countries make progress in development and income growth, while others fall short. Most economies maintain political stability, but globally connected markets operate imperfectly. Despite the endeavors of global and national institutions, the advancement toward achieving sustainable development goals remains sluggish. Technological progress persists without any groundbreaking innovations. Environmental systems undergo degradation, albeit with some

improvements, and there is an overall reduction in resource and energy consumption. The reliance on fossil fuels gradually diminishes, although unconventional fossil resources are still in use. Global population growth maintains a moderate pace, reaching a plateau in the latter part of the century as the demographic transition concludes. However, inadequate investments in education impede the shift towards lower fertility rates in low-income countries, sustaining population growth. Income inequality persists or improves at a slow pace, presenting challenges in reducing vulnerability to societal and environmental changes and impeding significant strides in sustainable development (O’Neil *et al.*, 2017).

SSP3: Regional Rivalry – A Rocky Road

The resurgence of nationalism, coupled with concerns about competitiveness, security, and regional conflicts, prompts countries to prioritize domestic or regional matters. This is exacerbated by the presence of limited and relatively weak global institutions, leading to uneven coordination in addressing worldwide issues. Policies gradually pivot towards national and regional security, giving rise to trade barriers, particularly in the energy and agriculture sectors. Nations prioritize achieving energy and food security within their regions, often embracing more authoritarian forms of government with regulated economies. Investments in education and technology decline, economic development lags, and consumption remains heavily reliant on material resources. Inequalities persist or worsen, especially in developing countries where extreme poverty coexists with pockets of moderate wealth. Limited international attention to environmental issues results in significant degradation in some regions, impeding progress toward sustainability. Population growth varies, presenting substantial challenges to mitigation due to increasing resource intensity and dependence on fossil fuels. Slow technological change and difficulties in international cooperation pose formidable challenges to adaptation (O’Neil *et al.*, 2017).

SSP4: Inequality – A Road Divided

Global and national inequalities are exacerbated by unequal investments in human capital, leading to disparities in economic opportunities and political influence. This results in a widening gap between a well-educated, globally-connected society engaged in knowledge- and

capital-intensive sectors and lower-income, poorly educated societies involved in labor-intensive, low-tech industries. A concentration of power occurs within a small political and business elite, even in democratic nations, leaving vulnerable groups with limited representation in national and global institutions. Industrialized and middle-income countries experience moderate economic growth, while low-income countries struggle to provide basic services such as water, sanitation, and healthcare. Social cohesion weakens, leading to increased conflict and unrest. High-tech sectors witness notable technological advancements, but uncertainty in fossil fuel markets leads to underinvestment in new resources in various regions. Energy companies diversify their sources, investing in both carbon-intensive and low-carbon options. Environmental policies predominantly address local issues around affluent areas. While the development of low-carbon options and a well-integrated international elite imply low challenges to mitigation, adaptation challenges are high for populations at lower development levels lacking effective institutions to cope with economic and environmental stresses (O’Neil et al., 2017).

SSP5: Fossil-fueled Development – Taking the Highway

In this economically prosperous world, driven by both industrialized and emerging economies, there is a growing reliance on competitive markets, innovation, and participatory societies for rapid technological progress and sustainable human capital development. Global markets integrate further, emphasizing competitiveness and removing barriers for disadvantaged populations. Significant investments in health, education, and institutions aim to enhance human and social capital. Economic and social development occurs alongside the exploitation of fossil fuels, resulting in rapid global economic growth. Despite addressing local environmental issues, there is limited effort to mitigate global environmental impacts, seen as a tradeoff with economic development. The global population peaks and declines, with developing countries experiencing swift fertility reduction, while high-income countries maintain relatively high fertility levels. Increased international mobility results from opening up labor markets. Heavy reliance on fossil fuels poses challenges to mitigation, but overall adaptation challenges are relatively low due to human development achievements, economic growth, and advanced infrastructure engineering (O’Neil et al., 2017).

1.3.4. Baseline CO₂ Emission under Different Scenarios

Global carbon dioxide (CO₂) emissions display considerable variability across different scenarios outlined in the Shared Socioeconomic Pathway (SSP) baselines. The SSP framework effectively highlights how baseline assumptions significantly impact emissions and temperatures (see Figure 2). In the SSP1, which emphasizes sustainability, emissions reach their peak between 2040 and 2060 without specific climate policies. They subsequently decline to around 22 to 48 gigatons of CO₂ (Gt CO₂) annually by 2100, leading to a temperature increase of 3-3.5°C. Conversely, the moderate SSP2 scenario sees emissions continue to rise until the end of the century, reaching between 65Gt CO₂ and 85Gt CO₂ and resulting in a warming of 3.8-4.2°C (Rao et al., 2016).

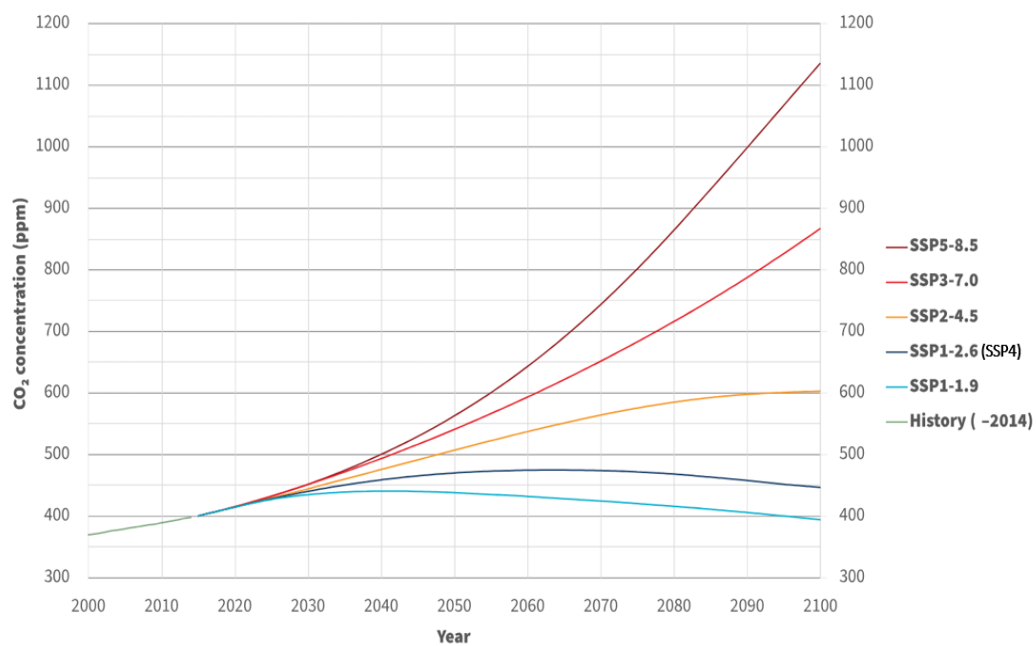


Figure 2. Predicted atmospheric CO₂ concentrations for different shared socioeconomic pathways (SSPs) across the 21st century

In the context of regional rivalry, SSP3 presents diverse baseline emission projections, with most models foreseeing increases up to approximately 76-86 Gt CO₂ by 2100. Notably, one model anticipates the highest emissions at 129 Gt CO₂ among all SSPs, primarily attributed to factors such as access to economically recoverable oil. The projected warming by 2100 under

SSP3 ranges from 3.9-4.6°C. In contrast, despite its marked inequality, SSP4 experiences relatively low emissions due to swift technological advancements in low-carbon energy sources. The emissions for SSP4 span from 34 Gt CO₂ to 45 Gt CO₂ by 2100, resulting in a warming of 3.5-3.8°C. Conversely, the high-growth, energy-intensive SSP5 exhibits the highest overall emissions among all SSPs, ranging from 104 Gt CO₂ to 126 Gt CO₂ by 2100, contributing to a warming of 4.7-5.1°C (Rao et al., 2016; Riahi et al., 2017).

1.4. Climate Change and Tree Species Distribution

Climate change is the most significant threats to biodiversity and predicting species distribution under climate change is an essential component of conservation and management planning. Climate is expected to continue changing worldwide with substantial implication for the composition and function of terrestrial ecosystems and will have a significant impact on the distribution of forest tree species in the coming decades (IPCC, 2021; Zhao *et al.*, 2022). The change in climate implies to the change in temperature, precipitation, wind pattern and other climatic variable which are essentials for the growth, reproduction and stability of the tree species. Therefore, the change in climate has direct and indirect significant impact on the habitat variation of species, plant phenology and even ecosystem stability.

As temperature rise continues, many species will experience a shift in their optimal growing conditions, resulting in changes in their geographic distribution typically, low altitude species will shift to the higher altitude in the potential distribution (Kamer, 2022; Fyllas *et al.*, 2022). Some species, for example, may no longer be able to survive in their current ranges as temperatures exceed their physiological limits, whereas others may be able to expand into previously inhospitable areas (Uzun and Sarikaya, 2021). In addition to temperature changes, precipitation patterns are likely to shift, with some areas experiencing more frequent droughts or floods, potentially altering tree species distribution. While, numerous studies have demonstrated the adverse effects of climate change on the distribution of tree species by reducing habitat suitability (Kamer, 2022), other studies have yielded contrasting results by indicating an increase in habitat suitability for certain tree species (Fosso and Karahlil, 2020; Fosso, 2021; Fosso *et al.*, 2023).

In addition to shift in species distribution, climate change has a wide range of impacts that are multifaceted. It increases the risk of forest fires in coastal areas and lowlands due to rising temperatures and drought. Additionally, trees at high altitudes are anticipated to have higher germination status and growth rate, which might heighten the risk of fire in these areas. Floods and storms can cause trees to fall, break or dry out, while water shortage in plantation forests may reduce the germination and survival of seedlings. Coastal forests are also threatened with extinction due to rising sea levels and salinization. Furthermore, hotter days and fewer cold days may increase pressure on insect populations and trees. Increasing CO₂ levels could require additional resources like water, nitrogen, phosphorus, and potassium for faster photosynthesis plants, which could potentially displace slower-acting plants.

Consequently, it appears that the ecological response and behavior of plant species may vary depending on their specific environmental needs. Under future climate conditions, this could lead to significant changes in the geographic distribution and vegetation structure of plant species, with some seeking new habitats, others adapting to new conditions, and some facing the threat of extinction. To mitigate the impacts of climate change on the future distribution of forest tree species, it is essential that humans take action to reduce greenhouse gas emissions and slow the pace of global warming. This will help to minimize the extent of the changes that are likely to occur in the coming decades, and may allow some tree species to adapt to changing conditions.

1.5. Species Distribution Modelling

Species distribution modelling (SDM), also known as ecological niche modelling (ENM), is a technique used to predict the potential distribution of a species based on environmental variables (Guisan and Zimmermann, 2000). It involves the use of statistical models to relate species occurrence records to environmental variables, such as temperature, precipitation, and vegetation cover, and to use these relationships to predict the likelihood of occurrence of the species across a given area (Guisan and Thuiller, 2005; Elith *et al.*, 2011). SDM can be used to estimate the potential impact of environmental change on species ranges, to identify areas of high conservation value, and to inform management decisions aimed at protecting biodiversity (Pecchi *et al.*, 2019; Khan *et al.*, 2022). SDM is a useful tool for identifying potential

translocation sites and directing surveys for endangered species (Eyre *et al.*, 2022), as well as for informing transboundary conservation and management efforts under climate change (Blair *et al.*, 2022). SDM algorithms can also be used to identify regions in which species can grow in agroecological consortiums (Sasso and Costa, 2022). However, the choice of SDM framework can affect the predictive performance of the model, and different frameworks may be more appropriate for different research objectives (Waldock *et al.*, 2022).

Species distribution models rely significantly on the geographical coordinates of species locations. While some algorithms utilize presence-absence data, collecting reliable absence data is challenging and time-consuming, particularly for mobile species like birds that change locations seasonally and cover vast distances. Plants with infrequent sprouting intervals pose similar challenges, as the year of data collection may coincide with the plant's hibernation year, rendering absence data unreliable. Fortunately, various sources, including herbariums, natural history museums, and online databases, provide ample presence data, facilitating the creation of species distribution models. Elith *et al.* (2008) conducted a study comparing models that use presence-only data and presence-absence data, finding that presence-only data models, especially those employing machine-learning algorithms, are as predictive as their presence-absence counterparts.

There are numerous models used in the SDM process, and it is generally acknowledged that no single algorithm is ideal in every situation. In order to reduce the level of uncertainty in the model, it is essential to choose the appropriate algorithm. Various traits and grouping criteria can be used to divide the algorithms used in SDM computational steps into various groups (Jarnevich *et al.*, 2015; Koo *et al.*, 2017). Li and Wang, (2013), for instance, compared 11 well-known models, such as regression, classification, and complex models, and offered suggestions for model formulation, parameter estimation, and model selection.

1.5.1. Maximum Entropy (MaxEnt) Model Approach

The MaxEnt algorithm stands out as the most widely used and significant statistical method for predicting species distribution models (SDMs) (Philips *et al.*, 2017). It operates on the principle of maximum entropy, emphasizing the importance of representing a probability distribution with the greatest entropy based on precisely stated prior data. When applied to

SDMs, MaxEnt is implemented as a machine learning Java software, utilizing environmental grids (e.g., bioclimatic data) and georeferenced species occurrence data mediated by GBIF. This software builds a model expressing the probability distribution of habitat suitability for a given species across grid cells, incorporating both categorical and continuous variables (Baldwin, 2009).

MaxEnt produces output data in raw, cumulative, and logistic formats (Philips and Dudik, 2008). While raw data is the primary output, it can be challenging to interpret due to often small values for each data point. Cumulative data offers the probability of finding the species at each location on a scale of 0-100, facilitating interpretation in geographical information systems (GIS). However, the values in cumulative data are not proportional, impacting visualization in GIS programs. The logistic format accurately reflects differences in output values on a 0-1 scale, making it more useful for interpretation compared to other output formats (Baldwin, 2009).

MaxEnt provides the ability to assess the importance of variables in predicting species distribution through two methods. Firstly, the final MaxEnt model provides the percentage contribution of each variable, although correlations between variables may influence the results. The second method involves the jackknife approach, excluding one variable at a time during model runs, providing insights into the performance and importance of each variable in explaining species distribution (Baldwin, 2009).

An additional significant feature of MaxEnt is its ability to assess the significance of the model, a crucial element in any modeling approach. The evaluation of the model is commonly carried out by determining the area under the curve (AUC) of the receiver operating characteristic (ROC) produced by MaxEnt outcomes. The AUC scale spans from 0 to 1, where values near 0.5 suggest a fit no superior to random, and a value of 1.0 signifies a flawless fit (Baldwin, 2009).

MaxEnt software, being a powerful tool for SDMs, can handle complex data and produce accurate predictions with few assumptions. It employs a set of locations where species are observed, commonly referred to as presence-only data, along with environmental predictors (such as precipitation and temperature) distributed across a predefined landscape divided into grid cells. MaxEnt derives background locations from this landscape, comparing them to the known presence locations where the presence status is uncertain (Merow et al., 2013; Philips et al., 2006; Philips et al., 2017).

1.5.2. Presence or Occurrence Data

The reliability of the forecasted results is closely linked to the accuracy and dependability of the species location points in SDM. The occurrence data are derived from estimating the probable acceptable distribution under climate change scenarios (Braunisch and Suchant, 2010). In MaxEnt modelling occurrence data is one of the major required inputs and it refers to the locations where a species has been observed or known to exist within a specific area. This data is used to build a predictive model that estimates the probability of species occurrence across the landscape based on environmental variables such as climate, topography and land cover. MaxEnt uses presence-only data, meaning that the model is built solely from the observed locations of the species rather than absence data (Phillips *et al.*, 2006; Phillips *et al.*, 2017).

The occurrence data can be obtained from a variety of sources, including field surveys, museum collection, national forest inventories, forest stand type maps and species databases. It is possible to collect using one of the techniques or in combination. There are various databases that are open-sources and freely available on website at the global, regional and local levels. At the global level for instance, the Global Biodiversity Information Facility (GBIF, <http://www.gbif.org>), used in several studies (Kamer, 2022; Khan *et al.*, 2022). The EUFORGEN maps available on (<http://www.euforgen.org/species/>) can be considered as European distribution maps. This database was created by “Forest Genetic Resource Program” and consists of a series of Pan-European distribution maps for 45 different species, which are updated continuously. There are enormous online databases applicable at national or local level. For instance, the Chinese Virtual Herbarium (CVH) (<http://www.cvh.ac.cn/>) (Kamer, 2022) is among the various freely accessible from the online databases.

It is crucial to ensure that this data is representative of the species' distribution within the specific area and not biased towards certain areas or habitats. By using the occurrence data in combination with environmental variables, MaxEnt estimates the species' environmental requirements and predicts its potential distribution across the landscape. The model output is a probability surface that represents the predicted suitability of each location for the species.

1.5.3. Environmental Predictors

Environmental predictors play a crucial role in determining both current and future species distributions across temporal and spatial scales. Among these variables, bioclimatic factors such as temperature and precipitation serve as primary indicators influencing species distribution, significantly shaping the ranges in which species are found. Additionally, geographic data, including land cover and soil type, further characterize the habitat. Integrating these diverse data types allows for a comprehensive understanding of the habitat and the identification of environmental factors influencing species distribution (Elith *et al.*, 2011; Merow *et al.*, 2013).

With the increasing availability of climate information, several global datasets have gained popularity as valuable scientific references. Prominent among these datasets are WorldClim, CHELSA, CliMond, ecoClimate, ENVIREM, and MERRAclim. WorldClim, accessible at <http://www.worldclim.org>, stands out as the most widely utilized global dataset (Noce *et al.*, 2020). Its creation represents a significant advancement in the global understanding of environmental conditions (Hijmans *et al.*, 2005; Ramirez and Bueno, 2009). The initial version of WorldClim relied on long-term average monthly temperature and precipitation, boasting a high resolution of nearly 1 km² and drawing from historical records collected from weather stations worldwide. This dataset empowers researchers and scientists to analyze the intricate climatic patterns and conditions worldwide (Hijmans *et al.*, 2005).

Over the past decade, the number of climate stations providing data has increased, particularly in high latitudes and elevations. In 2016, the WorldClim dataset underwent refinement, and an extended version was released, encompassing numerous high-altitude and elevation climate stations. Unlike its predecessor, which included only monthly temperature and precipitation, the updated version incorporates critical variables such as solar radiation, windspeed, and vapor pressure, vital for modeling essential processes like plant growth. The recent version also allows downloads at a higher spatial resolution of up to 30 seconds (Fick and Hijmans, 2017; Wang *et al.*, 2017).

The WorldClim dataset, recently updated version 2.1 as of January 2020, offers 19 Bioclimatic Indicators (BioClimInd) with remarkably high spatial resolution (up to 30 arc-seconds, approximately 0.9 km at the equator). These indicators encompass both current climate conditions (1970-2000) and future projections (2021-2040, 2041-2060, 2061-2080, 2081-2100),

utilizing data from 9 General Circulation and Earth System Models (GCMs) from CMIP6. The climate time series have undergone downscaling and bias correction, covering the four Shared Socioeconomic Pathways (SSPs) that guide simulations for the IPCC's 6th Assessment Report (AR6) (URL-2).

Table 1. The 19 bioclimatic indicators in worldclim dataset *Hijmans et al. (2005)*

Code	Description
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp – min temp)
BIO3	Isothermality (BIO2/BIO7) (x100)
BIO4	Temperature Seasonality (standard deviation x100)
BIO5	Max Temperature of the warmest month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5 – BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

1.5.4. Advantages of MaxEnt Model

MaxEnt has several advantages over other models for species distribution modeling (SDM). It is a powerful tool for SDM due to its ability to handle complex relationships between environmental variables and species distributions. MaxEnt can simulate nonlinear relationships and interactions between variables, unlike other SDM methods that rely on linear relationships between species and environmental variables. In light of various environmental scenarios, this enables more precise predictions of species distributions. MaxEnt also has the capacity to deal with missing data, which is a benefit. There are gaps in the data for many species occurrence datasets, and some regions have no known species. MaxEnt can predict the likelihood of a

species' occurrence in these areas using environmental data from these regions to fill in the blanks (Elith *et al.*, 2006; Ghareghan *et al.*, 2020).

The goal of MaxEnt is to identify the most uniform and widely distributed probability distribution that is subject to known constraints and serves as the closest approximation to an unknown distribution. Additionally, MaxEnt creates and selects background "pseudo-absence" points as a presence-only model to describe uninhabited distribution areas for the target species. On the other hand, the MaxEnt model's machine-learning algorithm aids in determining approximate distributions and maximum entropy with greater accuracy. In ecology, conservation planning, and management, the maximum entropy (MaxEnt) method has long been used to predict the present and future geographic distribution of various animal and plant species (Elith *et al.*, 2011, Zhang and Wang, 2022).

1.5.5. Limitations of MaxEnt Model

Maxent modeling, while widely employed in species distribution modeling, encounters several limitations. The primary constraints of the MaxEnt model involve its assumption of systematic or random sampling across the entire study area, as highlighted by Royle *et al.* (2012). Criticisms of MaxEnt encompass its inclination to produce overly complex or simplistic models due to sampling bias. Issues such as underestimating the probability of species occurrence within known areas, overestimating occurrence beyond observed ranges, and overall probability overestimation have been raised (Morales *et al.*, 2017).

Despite these challenges, the MaxEnt technique offers the advantage of modeling using only relevant species' presence data and necessary environmental/spatial data. Its simplicity and ease of implementation are considered key advantages (Fitzpatric *et al.*, 2013). Additionally, the necessity for meticulous parameter configuration, especially with limited sample sizes, is emphasized by Merow *et al.* (2014) and Morales *et al.* (2017). Shcheglovitova and Anderson (2013) advocates a jackknife approach for refining model settings, particularly beneficial for datasets with sparse occurrence records. Phillips and Dudik (2008) introduces concepts like hinge features, a new logistic output format, and background sampling strategies to enhance predictive accuracy and running time.

However, MaxEnt is susceptible to overfitting, as noted by Lissovsky and Dudov (2021). Overfitting can compromise model transferability and accuracy, occurring when a model is overly intricate and closely fits the training set of data. On the positive side, MaxEnt considers interactions between environmental variables, accommodates both continuous and categorical data, and estimates optimal species distributions by linking various variables (Fois et al., 2018). Despite its drawbacks, this technique has demonstrated successful application, especially in extensive areas where the necessity for absence data is less critical (Wisz et al., 2013).



2. MATERIALS AND METHODS

2.1. Description of the Study Area

2.1.1. Geographical Location of Kastamonu

The study was conducted in the captivating the province of Kastamonu, which is located in the northern part of Türkiye and is positioned between the geographical coordinates of 41–42° north latitudes and 33–46° east longitudes (Figure 2). Covering a substantial area, this province encompasses approximately 13,108 square kilometers, making up about 1.7% of Türkiye's total landmass (Öztürk and Özdemir, 2013). It holds a unique place within the country's geography, situated at the heart of the Black Sea region and sharing its borders with the Euxine province of the Circumboreal phytogeographical region. It is bordered by Sinop to the east, Bartın to the west, Çankırı to the South, Çorum to the southeast and the north by the Black Sea.

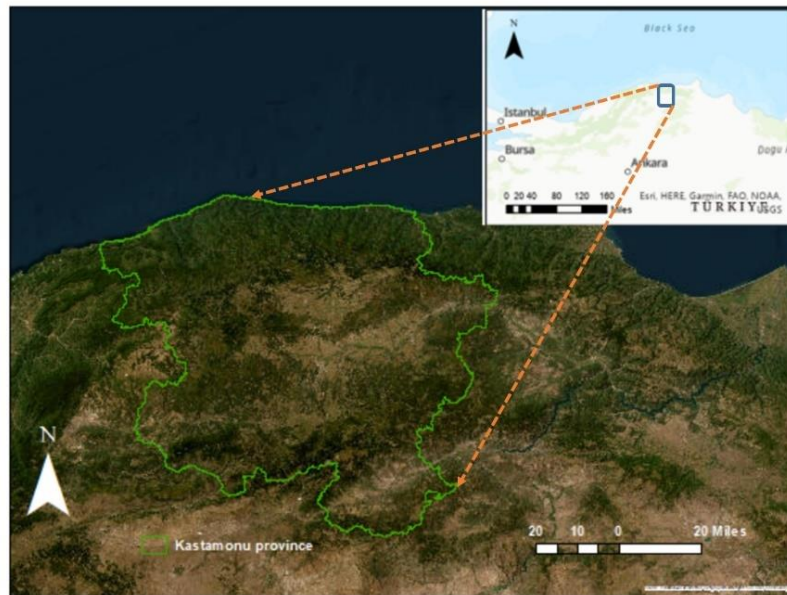


Figure 3. The geographical location map of Kastamonu Province

Kastamonu's exceptional landscape is a visual delight. It is surrounded by the imposing Isfendiyar (Küre) Mountains to the north and the formidable Ilgaz Mountains to the south, embracing the province with natural beauty. To the west, it extends along the Western Black Sea, boasting an impressive 170-kilometer coastline along this remarkable body of water. The Küre Mountains National Park and Ilgaz Mountain National Park are the two hotspot areas for biodiversity in Türkiye (Öztürk and Ayan, 2015).

2.1.2. Climate and Topography

Kastamonu is typically known by its rugged terrain, about 74.6% of the province's surface area is covered with mountainous, 21.6% with Plateaus and only 3.8% with plain landscape which spans a wide range of altitudes, varying from around 0 meter at the Black Sea to 2587 meters above sea level at Ilgaz Mountain. This diverse topography adds a unique charm to the area, providing a mix of rugged peaks and serene highlands (Baydil and İbret, 1999).

In terms of its climate, Kastamonu features a classic humid continental climate with distinct seasons. Winters are notably cold, often covered in a pristine blanket of snow, while summers bring warmth and a lush display of greenery. The annual climate variations vividly depict the weather patterns of the area, with an average annual temperature of 9.2 degrees Celsius. This temperature spectrum extends from the maximum temperature of 26.9 °C during the warmest month (August) and -6.54 °C in the coldest summer days of January (URL-3; URL-4).

Precipitation, a pivotal element in shaping Kastamonu's natural environment, follows its own seasonal rhythm. The province receives an annual dose of moisture that can fluctuate significantly, ranging from 450 to 1,215 millimeters. This variability results in an average annual precipitation of approximately 550 millimeters, influencing various aspects of the region, from the lushness of its forests to the flow of its rivers and streams. These climatic dynamics not only make Kastamonu an intriguing subject of study but also contribute to its exceptional ecological and geographical diversity (Baydil and İbret, 1999).

2.1.3. Soil and Vegetation Type

Kastamonu exhibits a remarkable diversity of soils, reflecting its geological history. Broadly it can be identified as sandy loams, clayey soils, and well-drained rocky outcrops coexist throughout the landscape. This diversity has given rise to a rich variety of vegetation types, ranging from temperate hardwood forests covered with oak, Beech, chestnut, hornbeam, and maple trees to lush, shaded understories teeming with ferns, mosses, and wildflowers. In addition to these natural marvels, the site also includes coniferous such as pine, fir as well as wetland patches that support cypress, tupelo, and various aquatic plant species.

Kastamonu province stands out as an exceptionally forest-rich region, with approximately 65% of its mountainous terrain covered by forests (Şen and Güngör, 2018). This percentage surpasses Türkiye's average forest coverage of 28.6%. Among Kastamonu's total forest area (876,314 ha) 79.4% (695,763 ha) are productive forests, while the remaining 20.6% (180,531 ha) are categorized as degraded forests (GDF, 2022). The dominant tree species found in Kastamonu province of Turkey include *Pinus nigra* subsp. *pallasiana*, *Pinus sylvestris* var. *hamata*, *Abies nordmanniana* subsp. *equi-trojani*, *Juniperus* spp. (*Juniperus communis* var. *saxatilis*, *Juniperus oxycedrus*), *Quercus* spp. (*Quercus petraea* subsp. *iberica*, *Quercus pubescens*, *Quercus cerris*, *Quercus macranthera* subsp. *sypirensis*), *Fagus orientalis*, *Carpinus betulus*, *Castanea sativa*, and *Populus tremula* (Karaköse and Terzioğlu, 2019). Additionally, Scots pine (*Pinus sylvestris* L.), Oriental Beech (*Fagus orientalis* L.), and *Juniperus* spp. (*Juniperus communis* var. *saxatilis*, *Juniperus oxycedrus*) are also among the main native tree species in northern Turkey covering the Kastamonu region (GDF, 2022).

2.1.4. Description of the Studied Tree Species

For this study, the tree species that are ecologically and economically important in the study area were selected in consultation with the main supervisor and experts from the regional forestry directorate based on available data on their distribution and abundance, as well as their ecological traits and significance for ecosystem functioning and services. Accordingly, five key tree species; namely, *Abies nordmanniana* subsp. *equi-trojani* (Trojan Fir), *Fagus orientalis* (Oriental Beech), *Pinus brutia* (Turkish Red Pine), *Pinus nigra* (Anatolian Black pine), and

Pinus sylvestris (Scots pine) were selected for current distribution and future prediction under different climate scenario. Their ecological description, distribution and uses are described below.

Abies nordmanniana subsp. *equi-trojani* (Trojan Fir)

Abies nordmanniana subsp. *equi-trojani*, commonly known as Nordmann fir, is an evergreen conifer species that can reach heights of up to 50 meters, featuring a straight trunk and initially pyramidal crown that later transforms into a flat-topped shape (Alizoti *et al.*, 2011). The *Abies* genus comprises over 50 species globally distributed, primarily in the northern hemisphere, including Africa and Asia. In Turkey, four naturally occurring *Abies* species are *Abies nordmanniana* subsp. *equi-trojani* subsp. *equi-trojani* in north-western part, *Abies nordmanniana* subsp. *equi-trojani* subsp. *nordmanniana* in the Eastern Black Sea region, and *Abies cilicica* in the Taurus Mountains. *Abies nordmanniana* subsp. *equi-trojani* is predominantly found in the Eastern Black Sea region of Turkey, thriving at altitudes ranging from 600 to 2000 meters. It prefers humid bioclimates, with certain taxa extending into sub-humid regions (Yener, 2012).

Fir wood, often considered less technically valuable than pine wood, is commonly used in carpentry due to its softness and workability. It serves various purposes in general construction, paper production, the manufacturing of glued and composite wood products, veneer, plywood, panels, poles, and as a source of fuel wood. Notably, the bark, buds, and cones of *Abies nordmanniana* subsp. *equi-trojani* may contain a significant amount of fine, highly resinous turpentine (Alizoti *et al.*, 2011).

Fagus orientalis (Oriental Beech)

Fagus orientalis, commonly called the oriental Beech, belongs to the *Fagaceae* family and thrives in temperate climates. Its natural habitat includes Türkiye, the Caucasus, northern Iran, and parts of southeastern Europe, with a distribution extending from the Bulgarian-Turkish border to the Black Sea coastline and the Crimean Peninsula, mainly in the Northern Anatolian Mountains (Atalay, 1992). In Türkiye, the oriental Beech is widespread in northern Thrace,

south of the Marmara Sea, and throughout the Black Sea Region, occurring both in pure stands and mixed environments with conifers and other deciduous trees. There are also isolated populations in the Murat Mountains in the inner Aegean Region and the Amanos Mountains in the eastern Mediterranean Region (Atalay, 1992; Cansaran, 2012). Thriving at elevations between 700 and 1200 meters, facing northern to northeastern aspects with a moderate slope, the oriental Beech is sensitive to extreme temperatures, especially dry summers and early or late frost. Classified as a medium-density hardwood with robust properties, it is primarily used as fuel but has applications in various industries, such as particleboard production, furniture manufacturing, flooring veneer, mining poles, railway ties, and paper production (Atalay, 1992; Kandemir and Kaya, 2009).

Pinus brutia (Turkish Red Pine)

The Turkish Red Pine, scientifically known as *Pinus brutia*, is a fast-growing tree species primarily distributed in the Eastern Mediterranean region, spanning Türkiye, Greece, Cyprus, Syria, Lebanon, Iran, and Iraq. Variants of this species are also found in Ukraine, around the Black Sea, and in the Caucasus. Adaptability to diverse substrates and Mediterranean bioclimates characterizes *Pinus brutia* forests. In Türkiye, these forests are expansive, particularly in regions with a Mediterranean climate and higher rainfall. Thriving in a broad temperature range, Turkish pine plays a vital role as a major source of wood and forest cover in many Mediterranean countries, notably in Türkiye where it holds economic significance. The wood serves various purposes, from construction to industry, carpentry, firewood, and pulp production, while the seeds are used in pastry making. The total forest cover exceeds 4 million hectares, with a substantial portion situated in Türkiye. *Pinus brutia* is crucial for the region's economy and holds paramount importance as the most significant conifer species in Türkiye (Boydak and Caliskan, 2006; Fady *et al.*, 2003).

Pinus nigra subsp. *pallasiana* (Anatolian Black Pine)

The Anatolia Black Pine, scientifically known as *Pinus nigra* Arnold, is a wind-pollinated conifer reaching up to 30 meters in height. Recognizable by its bark ranging from light grey to

dark grey-brown and deeply furrowed patterns, the tree's crown shifts from broadly conical to umbrella-shaped, especially in rocky terrain. Thriving mainly in Mediterranean-type climates, it displays adaptability to diverse bioclimatic conditions, from humid to semi-arid. The species grows optimally at altitudes between 800 and 1500 m but exhibits variation in different regions. Noteworthy for its versatility on various substrates, including limestone and acidic soils, the black pine holds economic significance due to its fast growth, durable wood, and ease of processing (Isajev *et al.*, 2004).

Pinus sylvestris (Scots Pine)

Scots pine (*Pinus sylvestris* L.) is a resilient pioneer species with a notable ability to regenerate following natural or human disturbances, provided there is minimal competition from weeds and grazing pressure is low. Typically found in pure and fairly even-aged stands, Scots pine thrives on poorer, sandy soils, rocky outcrops, peat bogs, or in proximity to forest limits. Fertile sites, however, see Scots pine being outcompeted by other tree species like spruce or broad-leaved varieties. Its extensive distribution spans the entire Eurasian continent, surviving in conditions ranging from the boreal forest limit with minimal frost-free days to the steppe plains of Central Asia, limited by drought periods. In southern Europe and Asia Minor, isolated occurrences are confined to montane zones at altitudes up to 2200 m. Valued for its easily workable wood with good mechanical properties, Scots pine holds commercial importance in Europe, primarily serving as construction timber and pulpwood (Mátyás *et al.*, 2003).

2.2. Methods

2.2.1. Data Collection and Preparation

To build species distribution models within MaxEnt, two essential types of input data are required: species presence/absence data and raster-formatted GIS datasets encompassing environmental variables. This section outlines the procedures for acquiring and preparing the data utilized in these models. All data processing was conducted using ArcGIS version 10.8.

Species Presence Data

Species presence data refers to specific point locations defined by their longitudinal (X) and latitudinal (Y) coordinates, which demarcate the geographical distribution of a species (Philips *et al.*, 2017). For the purposes of this study, the presence or occurrence data were obtained from the forest management plan's stand type map, as provided by the General Directorate of Forestry, Türkiye, derived from the 2020 dataset.

In order to establish the precise coordinates for each presence point using the global positioning system, latitude and longitude data were generated for the selected species. This process involved geoprocessing, employing the coordinate then 'features to points' function within ArcGIS 10.8. Subsequently, attribute tables for the generated feature points of each selected species were exported as table databases, further refined in Microsoft Excel, and organized under three column headings: "Species," "Longitude," and "Latitude." The data was then saved as a Comma Delimited (*.CSV) file, as required by the MaxEnt software.

Number of Presence Data and Spatial Auto-correlation Correction

The number of sample presence point data for each species is presented in Table 2. These presence data points were chosen from the stand type map, with the specific aim of ensuring their spatial independence. This strategic approach was adopted to avoid spatial autocorrelation issues and to enhance the model's overall performance. Eliminating spatial clusters of locations is imperative during model calibration and assessment. The presence of such clusters often leads to models being excessively influenced by environmental biases, which in turn diminishes their capacity to predict data that is spatially independent, ultimately resulting in overestimation of model performance (Boria *et al.*, 2014; (Lissovsky and Dudov, 2020).

The presence of spatial autocorrelation among species occurrences can disrupt the desired independence between training and test datasets when employing a random division (Lissovsky and Dudov, 2020). To address this concern, the Spatially Rarefy Occurrence Data Tool, available in the ArcGIS 10.8 SDM toolbox, was utilized. This tool effectively filtered out multiple occurrence points within the same 1 km² grid, preserving only one representative point.

Consequently, a combined total of 783 presence points were used in both the current and future distribution modeling for all the considered species.

Table 2. Number of presence points for each species included in this study

No.	Species	Number of points
1	<i>Abies nordmanniana</i> subsp. <i>equi-trojani</i>	145
2	<i>Fagus orientalis</i>	132
3	<i>Pinus brutia</i>	86
4	<i>Pinus nigra</i>	117
5	<i>Pinus sylvestris</i>	303

Environmental Predictors

Environmental predictors play a pivotal role in determining current and future species distributions, both in terms of time and space. In this study, various environmental predictors, encompassing bioclimatic, topographic, and soil were harnessed from diverse sources to model the current and future distribution of species.

To predict the future distribution of tree species, this study relied on the Shared Socioeconomic Pathways (SSP) scenarios, encompassing diverse future climate conditions based on socio-economic and greenhouse gas emissions scenarios. This involved projecting future scenarios for the 2050s (2041 to 2060) and 2090s (2081 to 2100), with a specific focus on two climate change scenarios: SSP2-45 (Middle of the Road), intermediate challenges to adaptation and mitigation and SSP5-85 (Fossil Fuel Development – Taking the Highway). The third Hadley Centre Global Environmental Model (HadGEM3-GC31-LL) in the Global Coupled configuration 3.1 from CMIP6 was specifically employed for running future projections in species distribution modeling.

In addition to the nineteen bioclimatic variables, three topographic variables; slope, elevation, and aspect were incorporated as predictor variables in the Species Distribution Model (SDM). The dataset also included soil variables such as soil pH, soil organic carbon, and soil cation exchange capacity, which were sourced from the ISRIC Global Soil Information database (<https://www.isric.org/explore/soilgrids>). These soil variables were used to simulate the current

potential distribution of the species, as there is no mechanism to track changes in soil properties over time.

To ensure compatibility with the presence data coordinates, all environmental variables were harmonized in terms of geographical extent and projections. Subsequently, each variable was clipped to the study area's extent using ArcGIS 10.8 software and saved in the required ASCII file format for compatibility with MaxEnt (Dormann *et al.*, 2013).

To address potential issues arising from spatial auto-correlation between predictor variables, a thorough multicollinearity assessment identified thirteen variables with multicollinearity problems. To mitigate these issues and improve model performance, the Variance Inflation Factor (VIF) was employed to filter out variables displaying high correlation and retaining those less correlated. This strategic reduction aimed to produce more reliable results, enhancing the predictive accuracy of the model (Girma *et al.*, 2015).

Multicollinearity, arising from significant correlations among predictor variables, has the potential to undermine the stability and reliability of the model. To mitigate this issue, a systematic approach was employed, involving the removal of variables with a VIF exceeding 5, indicating substantial correlation with other variables. This careful selection process led to the inclusion of fifteen variables (eight bioclimatic, two topographic, and five soil variables) for the conclusive modeling using the MaxEnt software, enabling comprehensive modeling of both current and future distributions (see table 3).

Table 3. List of Environmental variables used in MaxEnt

Code	Description	Database source	Unit
BIO1	Annual Mean Temperature	Worldclim	⁰ C
BIO3	Isothermality (BIO2/BIO7) (x100)	Worldclim	⁰ C
BIO7	Temperature Annual Range (BIO5 – BIO6)	Worldclim	⁰ C
BIO8	Mean Temperature of Wettest Quarter	Worldclim	⁰ C
BIO12	Annual Precipitation	Worldclim	mm
BIO15	Precipitation Seasonality (Coefficient of Variation)	Worldclim	mm
BIO16	Precipitation of Wettest Quarter	Worldclim	mm
BIO17	Precipitation of Driest Quarter	Worldclim	mm
Soil_cec	Soil cation exchange capacity	SoilGrids	
Soil_pH	Soil pH	SoilGrids	
Soil_omc	Soil organic carbon	SoilGrids	
Aspect	Aspect	SRTM DEM Global	Degree
Slope	Slope	SRTM DEM Global	Degree

2.3. Setting MaxEnt Run

To commence a MaxEnt modeling session, initiate the setup by configuring essential files and directories. This involves supplying a CSV file with presence sample locations (latitude and longitude) and specifying a dedicated directory for environmental variables. All of the 13 environmental variables are continuous variables. Once the setup is complete, load environmental layers, and the MaxEnt model's training progress is displayed, presenting a step-by-step analysis of species and environmental parameters. Proficiency in ecology and Geographic Information Systems (GIS), with a particular focus on ESRI products like ArcGIS, is crucial for effectively utilizing MaxEnt. The software is available as an open-source download, and to initiate a run, input a file with presence data, assign a directory for environmental variables, and specify an output directory. Running a session generates multiple output files, including an HTML file showcasing diverse outputs, accessible for viewing in image processing software. The resulting images, formatted as PNG files, are systematically stored in the "plots" directory, facilitating further examination and in-depth analysis of the results (Philips *et al.*, 2017).

2.3.1. MaxEnt Output

The algorithm produces varied outcomes, including a raster layer indicating species presence in each cell (species.asc), a file with key calculation results (maxentResults.csv), a file outlining λ coefficients and the minimum/maximum values of all feature layers in the analysis (species.lambdas), a file detailing distribution curve shapes and the proportion of inaccurately predicted occurrences (species_omission.csv), and visual representations like a gradient-filled "range map." The application of calculated thresholds converts the probabilistic model into a binary form (1 representing presence, 0 for absence). Spatial outputs exhibit variation but maintain a monotonous correlation. The raw outcome signifies the relative likelihood of species

presence, normalized into cumulative, logistic, and cloglog representations, each serving specific purposes. MaxEnt offers four output formats: raw, cumulative, logistic, and cloglog. The raw output reflects the MaxEnt exponential model, while cumulative values denote the percentage of distribution where raw values exhibit maximum correlation. Logistic and cloglog values involve computations based on raw values and serve specific functions. Although these formats are monotonically linked, they differ in scaling and interpretation, necessitating statistical analyses to extract predictions for species distribution or habitat suitability. This analytical approach aids in identifying crucial environmental variables contributing significantly to the model.

2.3.2. Statistical Analysis

In this context, MaxEnt is employed to model habitat suitability for specific tree species, identifying the influence of environmental variables on the model. The objective of Habitat Suitability Models (HSM) is to define the spatial range limits of chosen species by linking their current distributions to prevailing environments and projecting future biogeographical ranges under different environmental change scenarios. Crucial environmental variables include factors affecting eco-physiology, disturbances, and resource availability. The software is run separately for various tree species, generating output maps to assess future mixture options. Model performance is evaluated using species response curves derived from model output, and the calibration involves training and test sets (80% of the total occurrence data) and test (20% of the total occurrence data) for design assessment.

The Receiver Operating Characteristic Curve's Area under the Curve (AUC of ROC) functions as an indicator of model performance, ranging between 0 and 1. An AUC < 0.5 signifies models performing worse than chance, while an AUC of 0.5 suggests pure guessing. Model performance is classified as failing (0.5 to 0.6), bad (0.6 to 0.7), reasonable (0.7 to 0.8), good (0.8 to 0.9), or great (0.9 to 1) (Swets, 1988). The jackknife test is employed to evaluate prominent environmental variables influencing species potential distribution. Species response curves elucidate the relationship between habitat suitability and environmental factors, and the resulting species distribution chart is categorized into high (>0.6), good (0.4 to 0.6), moderate (0.2 to 0.4), and low (<0.2) potential. MaxEnt outputs encompass JPEG images, ASCII files for

subsequent GIS analysis, response curves, jackknife variable importance images, and an HTML file summarizing and detailing the analysis.

2.4. Habitat Suitability Classification and Species Composition Mapping

The ASCII files from each MaxEnt run were imported into ArcGIS 10.8™ and transformed into raster TIFF format. Subsequent processing involved multiplication by 100, rounding down, and a series of steps, including duplicating the raster dataset, establishing a raster attribute table, converting the raster into a polygon vector, dissolving by grid code, and finally, clipping the boundaries. Following these steps, pixel values were categorized into different levels of habitat suitability: 0 to 25 represented unsuitable habitats, 25 to 50 indicated less suitable areas, 50 to 75 denoted moderately suitable habitats, and 75 to 100 signified highly suitable environments. These suitability levels were then assigned numerical values: “1” for unsuitable, “2” for less suitable, “3” for moderately suitable, and “4” for highly suitable. Accordingly, habitat suitability values of “1” and “2” were considered unsuitable areas, while values of “3” and “4” were considered to be suitable.

To illustrate the composition of forest stands, the species distribution map for all species was intersected to identify stand types under different climate scenarios and time periods. The intersection operation involved selecting suitability classes of each polygon from the attribute table. Stands with a single species exhibiting suitability classes of either “3” and/or “4” were categorized as dominance of that particular species. If two or more species displayed suitability classes of “3” and/or “4,” the polygon was considered a “mixed” stand. In cases where there were no habitat suitability classes of “3” and/or “4,” the area was labeled as “unsuitable”.

Furthermore, the spatial change analysis was executed to determine changed in the study area over various scenarios and time periods, resulting in producing of maps depicting both the modified areas and those that remained unchanged.

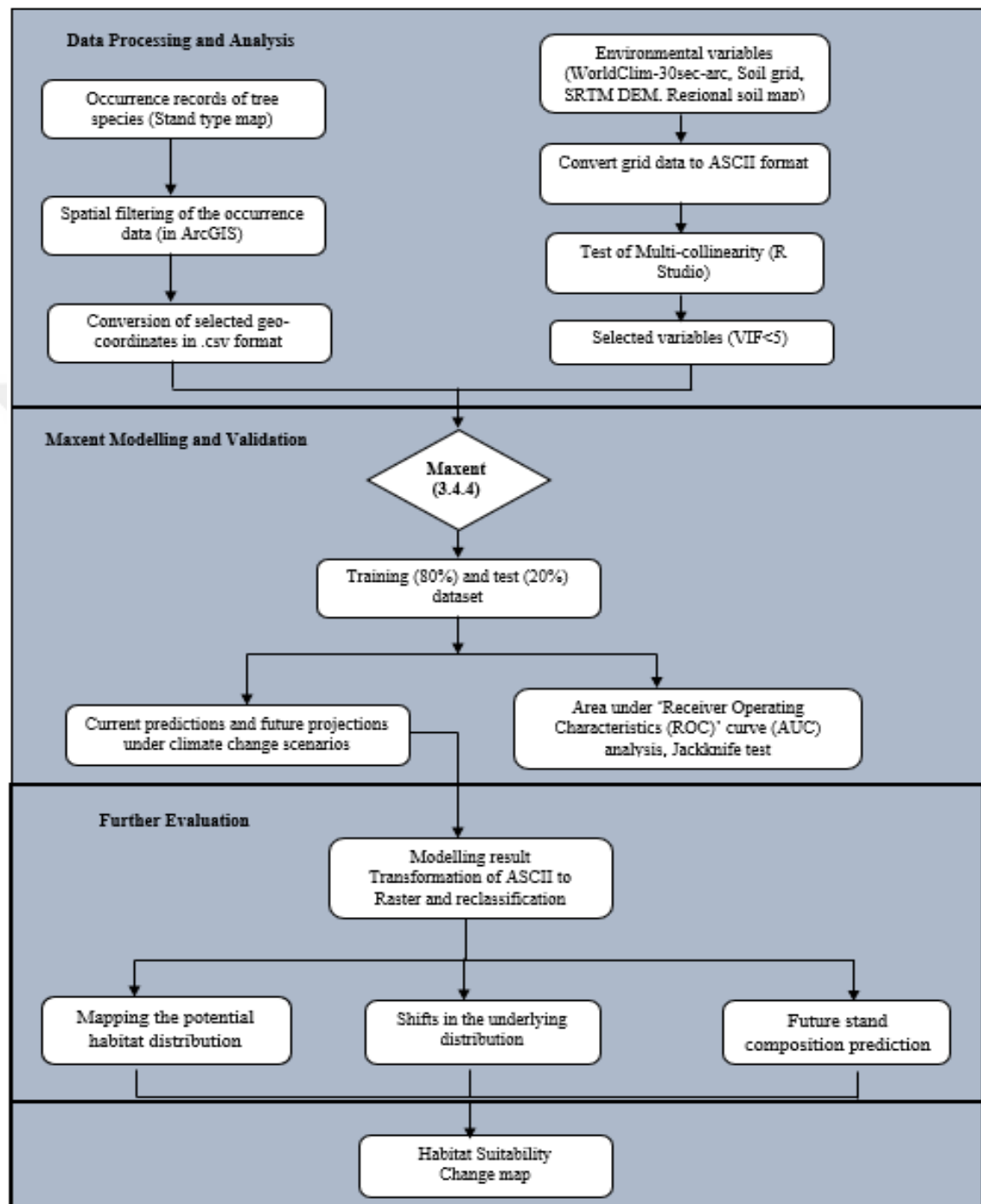


Figure 4. Flow chart of modeling process in this study

3. RESULTS

This chapter is comprised of three sections. The first section describes evaluation of models and analysis of variable contribution for the MaxEnt model. The second section focuses on describing mapping the current and future species distribution of selected key species in the study area. The final section presents future habitat suitability mapping of species in pure as well as mixed stand with change maps under the changed climate scenarios in the study area.

3.1. Species Distribution Model Prediction

3.1.1. Evaluation of Model Performance

The MaxEnt algorithm, implemented in the MaxEnt software, plays an important role in forecasting the potential niche range and distribution patterns of species under current and projected climate change scenarios. This modeling approach is based on a set of environmental variables, including bioclimatic factors such as temperature and precipitation, topographic variables encompassing slope, elevation, and aspect, as well as soil-related variables like soil pH, cation exchange capacity, and organic matter content. To address multicollinearity, a test was conducted, leading to the exclusion of thirteen out of the initial twenty-five environmental variables from the analysis.

The accuracy of the MaxEnt model's forecasts is assessed through the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) for the test data. This measurement assesses the model's fit and predictive reliability. Table 4, presents the training and test AUC values of the predicted distribution of tree species in the study area. Notably, the AUC values for some species within the model demonstrate significant predictive accuracy, except in the case of *Pinus nigra*, where the model performed less optimally during omission testing. The AUC values revealed that variations existed in model performance. Under current climate predictions, the test AUC values range from 0.62 to 0.96, with *Pinus brutia* (Çz) exhibiting the highest AUC value and *Pinus nigra* (Çk) the lowest. This indicates that the predictive capability

of the models varies among species, with some demonstrating more robust and reliable distribution predictions than others. It is crucial to note that AUC values typically exhibit higher values for species with more limited ranges compared to the study area outlined by the environmental data (Philips et al., 2017)

Table 4. MaxEnt model evaluation for current distribution of the studied species

No	Tree species (Scientific name)	Symbols in Türkiye	Test AUC
1	<i>Abies nordmanniana</i> subsp. <i>equi-trojani</i>	G	0.77
2	<i>Fagus orientalis</i>	Kn	0.80
3	<i>Pinus brutia</i>	Çz	0.62
4	<i>Pinus nigra</i>	Çk	0.62
5	<i>Pinus sylvestris</i>	Çs	0.80

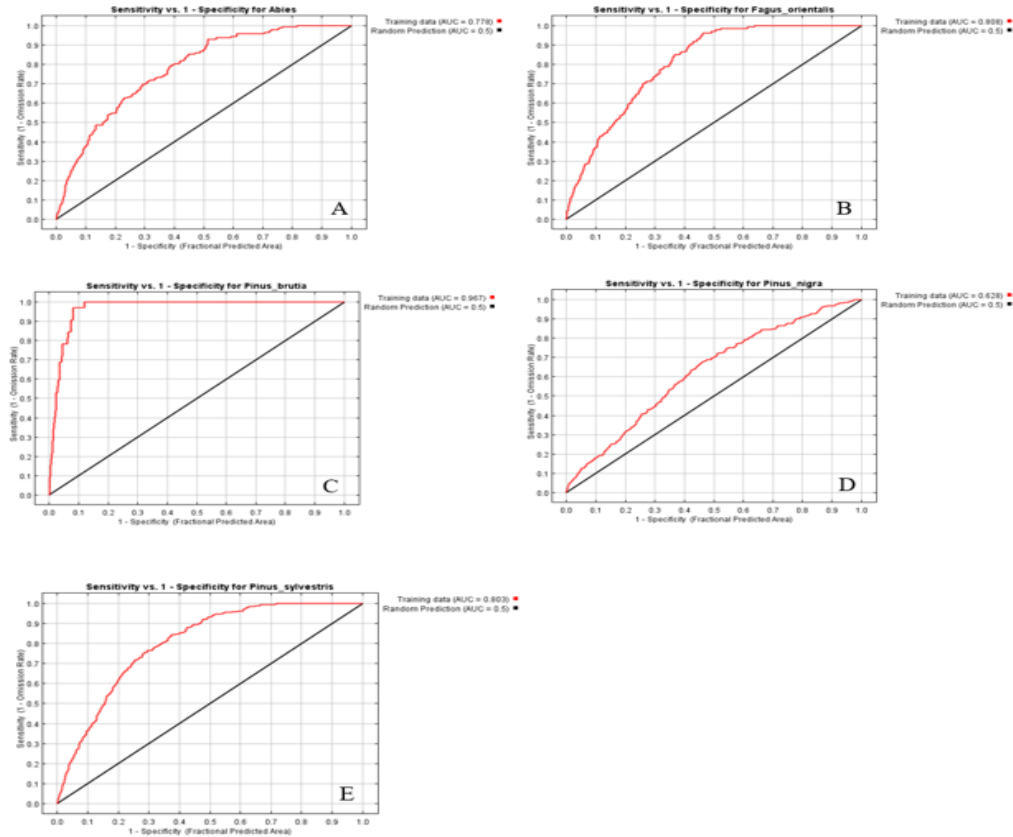


Figure 5. Area under the curve from the MaxEnt model (A = *Abies nordmanniana* subsp. *equi-trojani*; B = *Fagus orientalis*; C = *Pinus brutia*; D = *Pinus nigra*; E = *Pinus sylvestris*)

3.1.2. Analysis of Variable Importance

Analysis of variable importance is an estimate of the relative contribution of environmental variables to the MaxEnt models (Philips *et al.*, 2017). The top-three contributors of predictor variables to the current distribution of the tree species in this study are summarized in Table 5. Several environmental variables contributed to the MaxEnt model prediction for the current distribution of the selected species differently (see the full tables and jackknife in appendix 2 and 3). The result depicted that, isothermality, annual mean temperature and slope are the most frequently appeared variable, influencing the distribution of majority of the studied species.

According to variable analysis result (Table 5), the principal contributor for the model prediction of *Abies nordmanniana* subsp. *equi-trojani* (G), are isothermality (bio3), accounting for 66.8% of its distribution pattern, followed by slope (8.8%) and aspect (16.9%). Similarly, the current distribution model prediction of *Fagus orientalis* (Kn), are influenced by temperature annual range (bio7) with 65.8%, followed by isothermality (17.2%) and precipitation seasonality (bio15) by 9.3%.

Table 5. Top three dominant factors affecting the current distribution tree species in Kastamonu

Species	Variables	Description of variables	Percent Contribution
<i>Abies nordmanniana</i> subsp. <i>equi-trojan</i>	bio_3	Isothermality	66.8
	slope	Slope	8.9
	aspect	Aspect	8.3
<i>Fagus orientalis</i>	bio_7	Temperature Annual Range	45.8
	bio_3	Isothermality	17.2
	bio15	Precipitation Seasonality	9.0
<i>Pinus brutia</i>	bio_1	Annual Mean Temperature	70.8
	bio_17	Precipitation of Driest Quarter	8.6
	Bio_15	Precipitation Seasonality	8.0
<i>Pinus nigra</i>	Slope	Slope	43.5
	bio_1	Annual Mean Temperature	19.7
	bio_3	Isothermality	9.2
<i>Pinus sylvestris</i>	bio_1	Annual Mean Temperature	63.7
	bio_16	Precipitation of Wettest Quarter	8.8
	bio_3	Isothermality	8.3

Furthermore, the distribution of *Pinus nigra* (Çk) is influenced by a combination of topographic and climatic variables, specifically slope, bio1, and bio3, contributing 43.5%, 19.7%, and 9.2%, respectively. The topographic variables in model distribution of *P. nigra* (Çk) are highly important. For *Pinus sylvestris* (Çs) the most contributor variable for the model prediction was annual mean temperature (bio1), which contributes about 42.9%, followed by precipitation of wettest quarter (8.8%) and isothermality (bio3) 8.3%. Likewise, the model prediction of *Pinus brutia* (Çz), was substantially influenced by isothermality (70.8%), precipitation of driest quarter (8.6%), and precipitation of driest quarter (8%).

3.1.3. Current Distribution and extent of occurrence

The current distribution of selected tree species within the region is represented in Figure 6A-E. The result obtained from MaxEnt modeling revealed that *Abies nordmanniana* subsp. *equi-trojani* (G) shows remarkable adaptability across a wide altitudinal range. This adaptability encompasses regions of varying altitudes, ranging from mid-altitude along coastline of the Black Sea to the elevated mountainous terrain of Ilgaz mountain in the south, where altitudes exceed 2000 meters above sea level (figure 6A). Notably, this species does not exist in the lowlands of Araç, Kastamonu center, Taşköprü, and Tosya (refer from figure 6H). Similarly, *Pinus nigra* (Çk) exhibit a comparable distribution pattern, spreading throughout all regions within the study area and encompassing more extensive altitudinal ranges. As shown in Figure 6D, although it spreads throughout the regions, they are particularly well-suited in northern parts along the Black Sea coastline, as well as in the southwestern region, mainly within low to mid-altitude zones.

Figure 6B provides an insight into the potential distribution of *Fagus orientalis* (Kn). The prediction of its current distribution indicates that *Fagus orientalis* (Kn) ranges a broad altitudinal range, covering the lowlands along the Black Sea coastline and mid-altitudes in both the northwestern and southeastern parts of the study area. In contrast, the current distribution of *Pinus brutia* follows a more confined distribution pattern, primarily concentrated at lower altitudes within the study area.

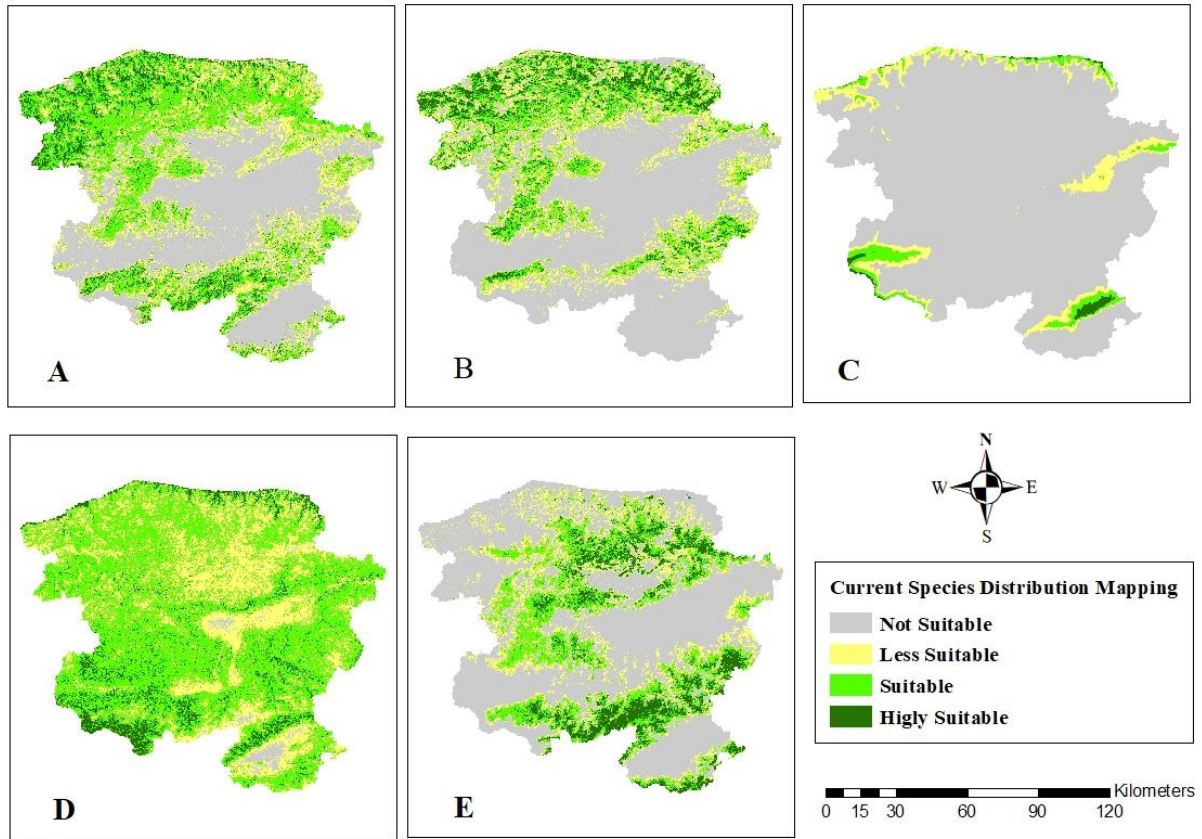


Figure 6. Current distribution prediction of tree species (A = *Abies nordmanniana* subsp. *equi-trojani*; B = *Fagus orientalis*; C = *Pinus brutia*; D = *Pinus nigra*; E = *Pinus sylvestris*)

As depicted in Figures 6C, *Pinus brutia* (Çz) displays a fragmented distribution along the Black Sea Coastline, and highly suitable areas in the southern and southwestern lowlands. From an ecological perspective, it can be inferred that *Pinus brutia* exhibit a preference for lowland climates. Furthermore, *Pinus sylvestris* (Çs) demonstrates a more limited altitudinal distribution range, primarily concentrated in the higher altitudes of Ilgaz Mountain in the south, as well as the northeastern and central highlands of the study area.

3.1.4. Future Prediction of Species Distribution Under Climate Scenarios

The future forecast for *Abies nordmanniana* subsp. *equi-trojani* (G) is presented in Appendix 1 and summarized in Table 6. A key result from this prediction is the widespread

decrease in habitat suitability for *Abies nordmanniana* subsp. *equi-trojani* (G) under both the SSP2 and SSP5 climate scenarios for both the 2050 and 2090 time periods. The shift in suitability classes follows a distinct pattern, marked by a more substantial decline of 49.66% and 46.45% in the 2050 time period under both the SSP2 and SSP5 climate scenarios, respectively. Notably, the magnitude of the change differs as the suitable area is projected to decrease further from 2020 to 2090 under both scenarios. While, there is a marginal increase in the suitable habitat area from 2050 to 2090, the overall suitable area is expected to decrease by the end of the century.

The suitability classes also showed that suitable and highly suitable areas are expected to shift into less suitable and not suitable areas in significant amount, an estimate of 150,048 ha of highly suitable areas of *Abies nordmanniana* subsp. *equi-trojani* which is 95% of the total highly suitable area is expected to shrink from the current (2020) to 2050 with a gradual decrease from time to time and across periods.

The prospective prediction for *Fagus orientalis* (Kn) illustrates a transformation from suitable to unsuitable across future climate scenarios and periods, each with varying magnitudes (Table 6). The prediction result indicates a decrease in distribution by 25.8% from 2020 to 2050, 24.5% from 2020 to 2090 under the SSP2 climate scenario. Similarly, under the SSP5 scenario, future habitat suitability is anticipated to decrease of 28.1% from 2020 to 2050, succeeded by an increase of 29.62% from 2020 to 2090 time period. In summary, the future potential habitat suitability is expected to decline under both climate scenarios and substantially shrinks under SSP5 by the end of the century.

In contrast, the future projection for *Pinus nigra* (Çk), unveiled a reduction in highly suitable and less suitable classes, coupled with an increase in suitable and unsuitable classes under both climate scenarios and future periods. Consequently, the future forecast anticipates a 49.66% increase in total suitability for the period 2050 under SSP2 followed by a subsequent decrease of 47.77% in 2090 under the same scenario. Additionally, SSP5 scenario indicates a decrease of 49.39% and 46.45% in suitability area in 2050 and 2090 time periods respectively.

Table 6. Species distribution shift under different climate scenarios and time periods (in ha)

Climate Scenarios and Periods	Suitable Area of Tree Species in hectare (ha)				
	Ck	Cs	Cz	G	Kn
Current (2020)	472,247	332,620	57,135.6	834,509	365,478
SSP2_2050	322,198.9	246,644	56,278.6	420,035.6	266,963.8
Rate of change (%)	-31.77	-25.84	-1.49	-49.66	-26.95
SSP2_2090	334,538.5	250,971	56,053.5	435,812.2	235,728.8
Rate of change (%)	-29.16	-24.54	-1.89	-47.77	-35.50
SSP5_2050	331,081.2	239,122.9	61,822.3	422,342	250,898.7
Rate of change (%)	-29.89	-28.89	8.20	-49.39	-31.35
SSP2_2050	324,451.5	234,080.6	60,300.9	446,859.3	250,511.7
Rate of change (%)	-31.29	-29.62	5.53	-46.45	-31.45

The percent change is calculated by subtracting the area of habitat suitability of the current (2020) from each scenario habitat suitability. The positive (+) sign indicates a positive change, representing an increase in area. Conversely, the negative (-) sign indicates a reduction in suitability area compared to the base distribution prediction.

Furthermore, the future prediction for *Pinus sylvestris* (Çs), anticipates a shift in habitat suitability, transitioning from the unsuitable and highly suitable categories to less suitable and suitable classes under both climate scenarios for the future periods. This transition results in an overall reduction in habitat suitability by 49.66% and 47.77% in 2050 and 2090 under SSP2 climate scenario, respectively. Similarly, the prediction under SSP5 exhibits a decrease of 49.3% in 2050 followed by a decrease of 46.45% in 2090.

Unlike the other species, the future estimation for *Pinus brutia* (Çz) indicates an expected increase in suitability area by 8.2% and 5.53% under both climate scenarios and 2090 periods. SSP5 in 2050 and 3.61% under SSP5 in 2090. Contrarily, a considerable decrease of 1.49% and 1.89% is expected under both climate scenarios and 2050 period.

3.2. Forest Stand Composition Under Climate Change Scenarios and Periods

Anticipated changes in habitat suitability for the studied tree species are expected to influence the composition of forest stands and the overall landscape pattern in response to climate change. The analysis of these forest stand compositions is conducted with a focus on regional dominance. The forest stands composition maps, presented below are generated by intersecting maps of individual tree species. The determination of stand types involves identifying the habitat suitability classes of each polygon within the dataset. Specifically, stands characterized by a single species with suitability classes “3” and/or “4” are categorized as dominance, denoted as pure stands of that particular species. In cases where two or more species exhibit suitability classes of “3” and/or “4,” the polygon is classified as a “mixed” stand. Conversely, areas lacking habitat suitability classes of “3” and/or “4” are designated as “unsuitable”. This analytical approach provides insight into how changes in habitat suitability may shape the composition and structure of forest stands in response to climate-induced alterations.

The stand composition of the forest area is presented in Figure 7. From the figure, it is evident that the areas dominantly suitable for pure stands of *Pinus nigra* (Çk), *Fagus orientalis* (Kn), and mixed stand areas will significantly decrease from current (2020) to 2050 and 2090 periods under both climate scenarios. Conversely, pure stands of *Pinus brutia* (Çz), *Pinus sylvestris* (Çs), and not suitable area will expand from 2020 to 2050 and 2090 periods under both scenarios. The results of composition of species suitability maps from 2020 to 2090 under the SSP2 climate scenario, revealed that most species exhibit similar trends in changes in their composition of habitat suitability maps although, the magnitude of these changes varies. Notably, *Abies nordmanniana* subsp. *equi-trojani* (G) stands out by increasing its suitability area from 2020 to 2090 (Figure 7A). Additionally, the areas suitable for mixed stands changes under the influence of other species. In habitat suitability change from the period 2050 to 2090 under the SSP2 climate scenario, most species display consistent trends with those observed in the shift from 2020 to 2050 under the SSP2 climate scenario. However, there are exceptions in the case of *Pinus sylvestris* (Çs), and *Pinus brutia* (Çz) which exhibit inconsistent pattern in

suitability change from 2020 to 2090 under the SSP5 scenario. Likewise, the areas suitable for mixed stands decrease in 2050 and 2090 periods under both climate scenarios.

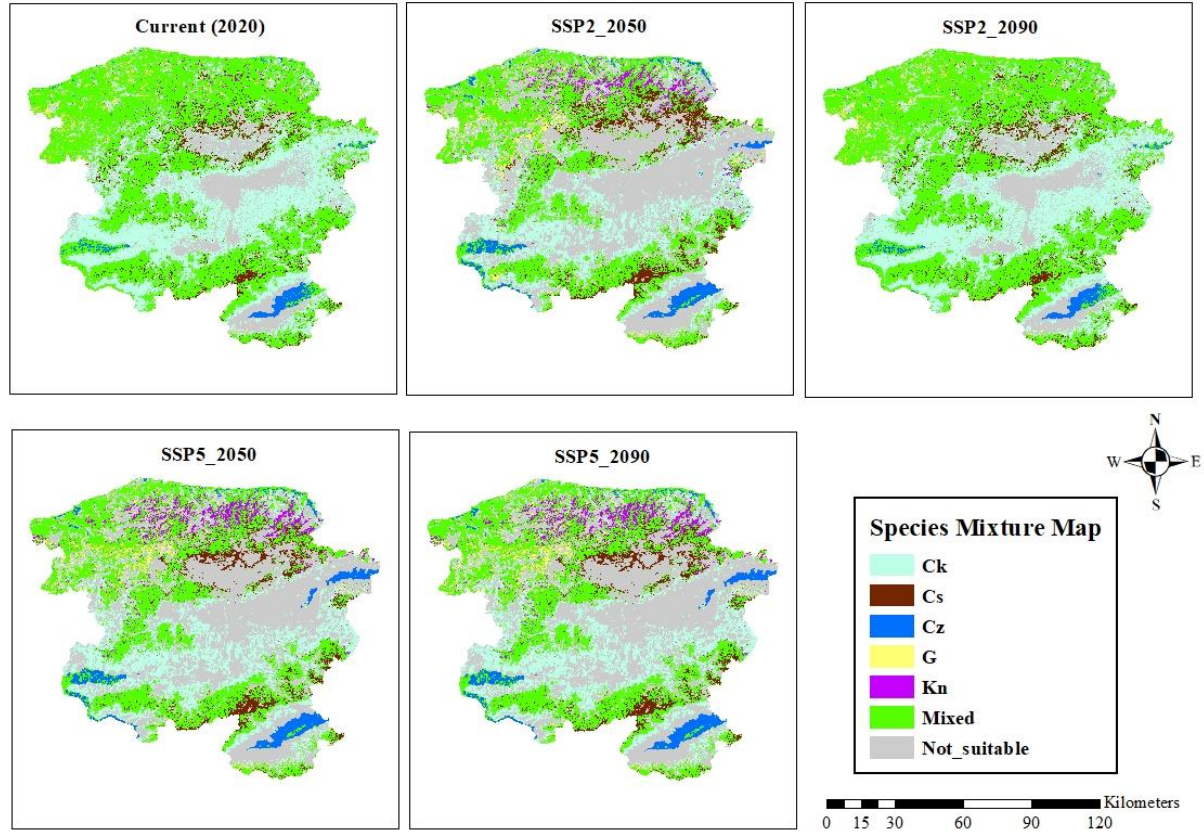


Figure 7. Mixed forest stand map under different scenarios and periods

3.2.1. Potential Distribution Change Analysis Under Different Climate Scenarios

In this section, the results concerning the evolution of habitat suitability for key species across three periods under two climate scenarios are presented. The analysis explores the magnitude of shifts in habitat suitability, providing insights into changes in the dominance of specific species or stand types within the landscape.

3.2.2. Potential Distribution Change from 2020 to 2050 Under SSP2 Scenario

Table 7 summarizes the change in suitable area for tree species from 2020 to 2050 under the SSP2 climate scenario. According to the results, *Pinus nigra* (Çk), shedding light on the impact of the SSP2 climate scenario from 2020 to 2050. Notably, *Pinus nigra* (Çk) exhibits a decline with suitability from 381,824 ha to 218,307 ha. This expansion encroaches upon mixed forests (66,730 ha) and areas that were previously unsuitable (14,397 ha). Similarly, the suitability for species distribution for mixed stands diminishes from 599,404 ha to 388,079 ha, by encroaching significant area from *Pinus sylvestris* and *Abies nordmanniana* (G) areas estimated about 17,598 ha and 6,866 ha respectively.

Table 7. Change matrix from 2020 to 2050 under SSP2 in Kastamonu Regional Forest

SSP2_2020	Area (ha)	SSP2_2050							
		Çk	Çs	Çz	G	Kn	Mixed	Not_suit	Grand Total
	Çk	129194	576		2806	357	3892	245014	381842
	Çs	6383	24266		1678	239	17598	12822	62989
	Çz			17185			2220		19406
	G	1299	191		7085	541	6866	11687	27673
	Kn	301	16		96	2728	1855	1392	6392
	Mixed	66730	47302	18581	25432	37810	354624	48930	599411
	Not_suit	14397	199		1677	378	1021	197596	215271
	Grand Total	218307	72552	35767	38777	42056	388079	517444	1312986

On the contrary, dominant *Pinus sylvestris* (Çs) and *Pinus brutia* (Çs) experiences a significant expansion, increasing from 19,406 ha to 35,767 ha. Similarly, *Fagus orientalis* (Kn) and *Abies nordmanniana* subsp. *equi-trojani* (G) also exhibit an increase in their suitability area. Furthermore, around 211,325 ha of currently suitable area is anticipated to become suitable for various dominant species.

3.2.3. Potential Distribution Change from 2050 to 2090 Under SSP2 Scenario

Table 8 presents the shifts in habitat suitability of tree species from 2050 to 2090 under the SSP2 climate scenario. The result revealed that slight increases in the suitability area of

Abies nordmanniana subsp. *equi-trojani* (G), expanding from 38,782 ha to 42,401 ha. This expansion is mainly by taking from the mixed stands and previously unsuitable areas. Likewise, *Pinus nigra* (Çk), and *Pinus brutia* (Çz), experience minor increases from 2050 to 2090 under the SSP2 climate scenario. In contrast, *Pinus sylvestris* (Çs), and *Fagus orientalis* (Kn) witness a decrease in suitability. Consequently, the habitat suitability for areas previously unsuitable show a slight increase.

Table 8. Change matrix from 2050 to 2090 under SSP2 in Kastamonu Regional Forest

	Area (ha)	SSP2_2090							
		Çk	Çs	Çz	G	Kn	Mixed	Not_suit	Grand Total
SSP2_2050	Çk	193171	645	28	479	127	11061	12810	218323
	Çs	527	46563		4220	499	10856	9905	72573
	Çz	104		29979	10	0	905	4782	35783
	G	654	242	5	24057	325	10035	3461	38782
	Kn	352	637	28	470	26263	11984	2320	42057
	Mixed	25944	13751	696	9512	7042	329118	2088	388154
	Not_suit	18917	5915	6430	3649	2141	1991	478266	517312
	Grand Total	239670	67754	37169	42401	36401	375953	513635	1312986

3.2.4. Potential Distribution Change from 2020 to 2090 Under SSP2 Scenario

Table 9 summarizes the shifts in habitat suitability for various species from 2020 to 2090 under the SSP2 climate scenario. The suitability area for *Fagus orientalis* (Kn) widens from 6,392 ha to 36,401 ha, primarily at the expense of mixed forests (32,0522 ha). Similarly, *Pinus brutia* (Çz) undergoes a substantial increase, expanding from 19,405 ha to 37,153 ha during the same period by taking significant suitability area from mixed stand and *Pinus nigra* (Çk). Moreover, *Pinus sylvestris* (Çs) and *Abies nordmanniana* subsp. *equi-trojani* (G) show a minor increase in suitability. In contrast, the suitability areas of *Pinus nigra* (Çk) decrease under the same period and climate scenario.

Table 9. Change matrix from 2020 to 2090 under SSP2 in Kastamonu Regional Forest

SSP2_2020	Area (ha)	SSP2_2090							
		Çk	Çs	Çz	G	Kn	Mixed	Not_suit	Grand Total
	Çk	133434	1484	3891	1782	293	3702	237253	381843
	Çs	6473	22652		2064	481	16250	15068	62991
	Çz	113		15658	8	0	2003	1621	19405
	G	1369	221	47	6688	566	7394	11383	27673
	Kn	358	42	9	94	2612	1799	1475	6392
	Mixed	82473	42725	15319	30576	32052	343683	52576	599407
	Not_suit	15429	611	2226	1181	394	1047	194381	215272
	Grand Total	239653	67737	37153	42397	36401	375880	513762	1312986

3.2.5. Potential Distribution Change from 2020 to 2050 Under SSP5 Scenario

Table 10 summarizes the change in habitat suitability of tree species from 2020 to 2050 under the SSP5 climate scenario. According to the results, *Abies normanniana* (G) experiences significant increase in suitability from 2020 to 2050 under the SSP5 climate scenario, primarily at the expense of mixed forests. Similarly, *Fagus orientalis* (Kn), and *Pinus brutia* (Çz) exhibit slight increases in suitability area. However, *Pinus nigra* (Çs) notably showed their suitability areas are projected to be decline under the same climate scenario and period. Furthermore, significant area of mixed stand will be changed to be suitable for other species, while there will be an increase in unsuitable areas.

Table 10. Change matrix from 2020 to 2050 under SSP5 in Kastamonu Regional Forest

SSP5_2020	Area (ha)	SSP5_2050							
		Çk	Çs	Çz	G	Kn	Mixed	Not_suit	Grand Total
	Çk	132375	924	3649	1724	191	3706	239272	381844
	Çs	6565	24592		1246	425	15790	14369	62990
	Çz	40		16552	6	0	1944	861	19405
	G	1345	165	7	7932	565	6282	11375	27673
	Kn	324	19	1	127	2837	1648	1433	6392
	Mixed	73299	36715	17263	28208	46236	344174	53511	599409
	Not_suit	16298	401	3944	1172	250	892	192310	215270
	Grand Total	230250	62818	41419	40419	50505	374439	513133	1312986

3.2.6. Potential Distribution Change from 2050 to 2090 under SSP5 Scenario

Table 11 illustrates the changes in habitat suitability for tree species from 2050 to 2090 under the SSP5 climate scenario. It is evident that the habitat suitability areas of *Pinus sylvestris* (Çs), and *Pinus brutia* (Çz), undergo a significant decrease in this time period and under the same climate scenario. According to the change matrix result, *Fagus orientalis* (Kn) showed differ from the trends noted from the previous predictions that will not appear as a dominant species in 2090 periods under SSP5 climate scenario. On the contrary, *Pinus nigra* (Çz) exhibit an expanding pattern of suitability from 2050 to 2090. This expansion extends into mixed stands and previously unsuitable areas, covering approximately 18,053 ha and 21,673 ha, respectively. Similarly, *Abies nordmanniana* subsp. *equi-trojani* (G), also experiences an increase in suitability area, gaining additional suitable habitat primarily from *Fagus orientalis* (Kn), mixed stands, with estimates of 31,722 ha and 19,994 ha respectively, under the same climate scenario and over the specified time periods.

Table 11. Change matrix from 2050 to 2090 under SSP5 in Kastamonu Regional Forest

SSP5_2050	Area (ha)	SSP5_2090						
		Çk	Çs	Çz	G	Mixed	Not_suit	Grand Total
	Çk	197116	184	210	523	13652	19064	230752
	Çs	663	44759		591	11614	5633	63262
	Çz	30		33200	4	1282	7372	41890
	G	1193	449	9	22571	11253	5194	40671
	Kn	518	245	7	31772	15190	2844	50579
	Mixed	18053	12951	1661	19994	320894	3322	376877
	Not_suit	21673	4071	3148	7785	2838	469435	508952
	Grand Total	239249	62662	38237	83243	376727	512867	1312986

3.2.7. Potential Distribution Change from 2020 to 2090 under SSP5 Scenario

Table 12 summarizes the changes in habitat suitability for tree species from 2020 to 2090 under the SSP5 climate scenario. The change in suitability area for *Pinus brutia* (Çz), *Abies nordmanniana* subsp. *equi-trojani* (G) show consistent suitability change as observed from 2020 to 2050, despite with varying magnitudes. Similarly, unsuitable areas also experience a significant expansion estimated about (215,272 ha to 517,097 ha) from previously suitable for

mixed stand and other dominant species in the same period and under the same climate scenario. On the contrary, Pine species (*P. brutia* and *P. sylvestris*) exhibit a significant decline in habitat suitability from 2020 to 2090 under the SSP5 climate scenario.

Table 12. Change matrix from 2020 to 2090 under SSP5 in Kastamonu Regional Forest

SSP5_2020	Area (ha)	SSP5_2090						
		Çk	Çs	Çz	G	Mixed	Not_suit	Grand Total
	Çk	131056	865	1076	1570	3123	244151	381843
	Çs	7118	22682		1580	17660	13949	62990
	Çz	23		16870	3	2202	306	19405
	G	1762	170	102	7546	7138	10953	27673
	Kn	299	11	3	3170	1557	1349	6392
	Mixed	81712	38104	18368	67770	341699	51752	599407
	Not_suit	16691	341	1365	1400	836	194637	215273
	Grand Total	238664	62176	37787	83042	374218	517098	1312986

3.3. Potential Species Distribution Change Map

The habitat suitability change map provides a detailed visualization of how the suitability of the environment for specific species or multiple species has evolved over time. The figures below offer a clear depiction of the anticipated climate sensitivity within the region. Analyzing the map reveals that the central part of the region is particularly vulnerable to the effects of climate change in the foreseeable future. This heightened sensitivity is most pronounced in the central and northeastern parts of the region, which predominantly include areas at mid to low altitudes.

In these areas, climatic shifts and alterations are projected to have a more significant impact. This underscores the critical importance of addressing and mitigating the potential challenges these regions may face as they adapt to changing environmental conditions. Notably, the changes in habitat suitability are more substantial under both scenario for both the periods of 2050 and 2090 compared to the current period. In contrast, the changes under the SSP5 climate scenario are less remarkable. The variations in habitat suitability across these scenarios are evident, highlighting the considerable differences in the magnitude of change projected under different climate pathways.

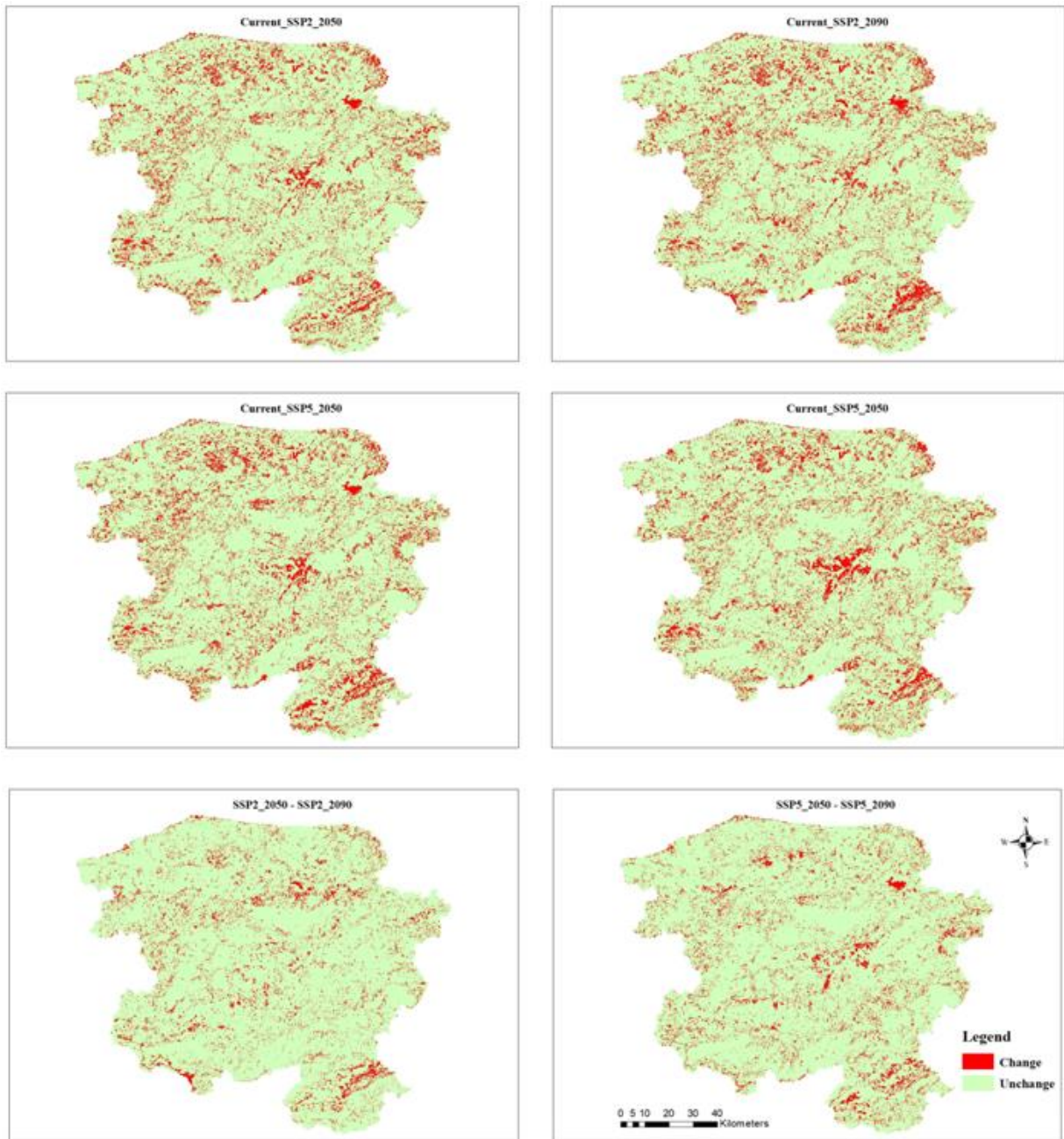


Figure 8. Habitat suitability change maps in Kastamonu regional forests under climate change scenarios and time periods

The map serves as an essential tool for understanding how climate change may influence habitat suitability, aiding in the development of effective conservation strategies. By identifying areas most at risk, stakeholders can prioritize efforts to enhance resilience and adaptive capacity in these vulnerable regions. The data emphasizes the need for proactive measures to address the impacts of climate change, particularly in the central and northeastern parts of the region, where mid to low altitude areas are expected to experience the most significant transformations. The insights gained from this map can inform policy decisions and guide resource allocation to ensure the sustainability of species and ecosystems in the face of climate change.



4. DISCUSSION

4.1. Current Species Distribution Modeling and Variable Contribution

The results presented in this chapter provide valuable insights into the habitat suitability and distribution of key tree species in Kastamonu region, both under current climate conditions and in projected future scenarios. The following discussion will highlight the key findings and their implications.

The MaxEnt model was employed to predict the potential niche range and distribution patterns of species, using a range of environmental variables (Elith *et al.*, 2011, Philips *et al.*, 2006). The model's performance was assessed through the AUC-ROC for test data. The AUC values indicated variations in the model's performance, with some species demonstrating more robust AUC value than others. These variations revealed that different species respond differently to the environmental factors considered in the modeling predictions. Notably, AUC values typically show higher values for species with narrower ranges concerning the study area defined by environmental data. In a similar vein, Philips and Dudik (2008) have noted that AUC values are inclined to be higher for species with narrow ranges in relation to the study area outlined by environmental data. However, it is crucial to note that higher AUC values do not necessarily indicate better models; this pattern is an inherent characteristic of the AUC statistic itself (Philips *et al.*, 2017). Despite being widely used as a standard measure for evaluating predictive model accuracy, there remains ongoing debate about the appropriateness of AUC (Jiménez-Valverde, 2012). Lobo *et al.* (2008) have argued that AUC can be misleading as a measure of model performance since it overlooks predicted probability values and model goodness-of-fit, assumes equal costs for commission and omission errors, and is sensitive and positively correlated with the spatial extent under consideration.

4.2. Environmental Factors Affecting Tree Species Distribution

Tree species distribution is influenced by a combination of various biotic and abiotic factors, encompassing environment conditions and competitive interactions, with climate change significantly impacting their geographical ranges. The variable importance analysis revealed that various environmental variables contributed differently to the MaxEnt model's predictions for the current distribution of tree species included in this study. Studies including Khan *et al.* (2022), have emphasized the significant role of environmental variables, such as temperature, precipitation, topography and soil in shaping the distribution patterns of tree species. Different species exhibited diverse responses to these environmental variables (Liu *et al.*, 2021). Notably, climate, especially at the regional scale emerged as a pivotal factor influencing the distribution of tree species (Lin *et al.*, 2020).

The major determinants influencing habitat suitability for most tree species were temperature-related predictors, with specific variables varying among them, encompassing bio1, bio3, bio7, bio8, and bio17. In particular, annual mean temperature (bio1) and isothermality (bio3) were the most important climatic predictors that appeared frequently in most of the species. These variables were appeared as influencing variables in the distribution of all species included in this study except *Pinus nigra* (Çk). This is because temperature variables play a crucial role in species distribution modeling (SDM) due to their significant impact on species' reproductive success and range delimitation (Bykova *et al.*, 2012). In line with this finding, Xiong *et al.* (2019) found that temperature plays a key role in driving the distribution of *Abies taxa*.

In addition to climate variables, soil pH and soil organic carbon are the other determinant variables for the prediction of current distribution of *Abies nordmanniana* subsp. *equi-trojani* (G), *Fagus orientalis* (Kn), *Juniperus* spp. (Ar), *Pinus nigra* (Çk) and *Pinus sylvestris* (Çs). In line with this finding, there are various studies that supports soil pH exerts a significant impact on its biological, chemical, and physical characteristics, influencing processes that directly impact the presence and growth of plants. Similarly, soil organic carbon plays a crucial role in preserving soil quality by enhancing soil nutrition. Numerous studies have corroborated this discovery, highlighting the importance of temperature and soil variables in determining the potential distribution of *Abies nordmanniana* subsp. *equi-trojani* (Naudiyal *et al.*, 2021).

Another study was also found that humidity and topographic parameters were important variables for the potential distribution of *Abies nordmanniana* subsp. *equi-trojani* in Caucasus (Pshegusov *et al.*, 2021).

4.3. Potential Species Distribution Under the Future Climate Scenarios

The future predictions for species distribution under different climate scenarios and time periods provide insights into how these key species may respond to climate change. Broadly speaking, certain species can be categorized as winners when they extend their range, while others are considered losers when their habitat suitability is expected to decrease (Dyderski *et al.*, 2018). This distinction applies to various species, with specific geographical trends observed in mountainous Mediterranean tree species and temperate tree species located at the rear edge, as both are anticipated to experience habitat area reductions (Ruiz-Labourdette *et al.*, 2012; Ruiz-Labourdette *et al.*, 2013).

The key findings in this study depicted that a potential reduction in suitable habitat area of *Abies nordmanniana* subsp. *equi-trojani* (G) in the future under both climate scenario. Climate change will intensify summer droughts, posing a significant threat to fir forests. This is likely to escalate the occurrence and scale of wildfires, profoundly impacting the survival, reproduction, and regeneration of fir trees (Alizoti *et al.*, 2011). The future changed climate condition with subsequent extreme weather conditions will lead to a wider range of temperature and precipitation fluctuations are likely to loss of its habitat suitability. In line with these findings, Beridze *et al.* (2021) indicates that future climate changes, including reduced precipitation and overall warming, may put the remnant populations of *Abies* spp. at risk of decline. The vegetation in the region, including *Abies* spp., will be strongly impacted by global warming and a drier climate, leading to shifts in distribution areas and a decrease in evergreen coniferous forests (Sano *et al.*, 2018). Bartesaghi-Koç *et al.* (2018) also highlights the vulnerability of *Abies cilicica* and suggests that rising temperatures in the eastern Mediterranean basin may impact its distribution. Similarly, Fosso (2021), highlighted that the future climate change will affect the habitat suitability of *Abies nordmanniana* in the Trabzon, Black Sea region.

The future distribution of *Pinus nigra* (Çk) depicted that the future climate change will affect the future distribution of this species. Climate change can alter the timing of seasonal events, such as flowering, migration and reproduction. Species that are not able to adjust their phenology in response to changing climate condition may face challenge in maintaining suitable habitat. Various studies support these findings for instance, Fyllas *et al.* (2022) reported that *Pinus nigra* (Çk) would suffer significant area loss due to the future climate change in Greece. Candel-Pérez (2012) analyzes the growth patterns of *Pinus nigra* (Çk) under different climate change scenarios, and Majeed *et al.*, (2023) explores the climate signal in sub-annual width measurements of *Pinus nigra* (Çk) tree rings. They highlight the vulnerability of certain populations to climate change, with some populations projected to decline or face potential extinction. Similarly, Arslan and Örüçü (2019) also indicated that there will be a significant loss of suitability in the future climate for *Pinus nigra*.

In the contrary, there are others studies that highlight the future climate may improve the growth potential of the species (Dyderski *et al.*, 2018). For instance, Usta (2021) the current and future prediction of *Anatolia Pine* in Uludag and Kazdagi conservation areas was evaluated. The result showed that these areas remain suitable for *Anatolia Pine* under both present and anticipated future climate scenarios. Likewise, the suitable area will increase under the future climate scenario in *Antalya* (Fosso, 2021).

The future distribution of *Pinus brutia* (Çz) is projected to decline in future periods under changing climate scenarios. As global temperatures rise, the physiological tolerance of species is affected, causing some to find their current habitats becoming too warm, while others may benefit from expanded suitable areas. This finding is consistent with several other studies. For instance, Fosso (2021) examined the impact of climate change on the potential distribution of *Pinus brutia* in Antalya and found that this species is poorly adapted and very susceptible to future climate conditions. Similarly, Bede-Fazekas *et al.* (2013) studied the impact of climate change on the potential distribution of Mediterranean pines, including *Pinus brutia* (Çz), and identified a potential shift in distribution for this species. Additionally, Semra (2012) predicted the future distribution potential of Turkish pine and concluded that it will shift to the higher altitudinal ranges. Topaçoğlu *et al.* (2017) investigated the geographic variation patterns of *Pinus brutia* (Çz) populations in southern Türkiye, highlighting the importance of these patterns for afforestation and reforestation programs.

The study also evaluated the projected impact of future climate change on *Fagus orientalis* (Kn), predicting a significant reduction in its distribution within the study area. Climate change can alter species interactions, influencing factors such as competition for resources and symbiotic associations, which in turn affect species distributions. This finding is consistent with various studies.

For example, Ayan et al. (2022) foresees population contractions of Oriental Beech in specific regions of Türkiye under future climate scenarios, particularly on the southern slopes of the North Anatolian Mountains and in the transition zone of Central Anatolia. Dagtekin et al. (2020) corroborate this perspective by identifying major refugia for Oriental Beech in northern Iran and the Caucasus region. These outcomes highlight the importance of genetic conservation programs for the species.

Moreover, Sari and Kandemir (2020), along with Demir and Kandemir (2022), explore the prospective distributions of other plant species in Türkiye, emphasizing the need to understand and monitor habitat suitability and potential shifts induced by climate change. Additionally, Fosso (2021) emphasizes the vulnerability of *Fagus orientalis* in Trabzon due to anticipated climate impacts. Semra (2012) also highlighted that the potential distribution area of Oriental Beech will diminish, with the overall distribution expected to become narrower.

The results for *Pinus sylvestris* (Çs) indicate a decrease in habitat suitability under future climate scenarios and periods, attributed to its limited ability to adapt to changing environmental conditions. Climate change may lead to unfavorable conditions, such as increased temperatures, altered precipitation patterns, and extreme weather events, which can reduce habitat suitability. However, over the long term, some species may exhibit adaptive responses or migrate to more suitable areas as ecosystems adjust to new climate norms. This finding aligns partially with the study conducted by Benito-Garzon et al. (2008), which predicts a rapid decrease in the distribution of *Pinus sylvestris* (Çs) in the Iberian Peninsula, with populations becoming restricted to higher altitudes in the north. Similarly, García-López (2012) reports a reduction in the distribution area of *Pinus sylvestris* (Çs) in Spain, particularly in the southern half of the country. Additionally, Arslan and Örüçü (2019) evaluated the potential distribution of *Pinus sylvestris* and predicted significant losses in its distribution areas in the future.

4.4. Forest Stand Composition Under the Future Climate

The study explored the intricate dynamics of how changes in habitat suitability could influence the composition of tree species within the forest area. Notably, it revealed a multifaceted scenario where certain tree species stand to benefit amid future climate change, while others might suffer due to diminishing habitat suitability in response to the changing climate. This duality underscores the emergence of 'winners' among species whose distribution is expanding and 'losers' among those grappling with shrinking habitat suitability, an intricately linked phenomenon to the consequences of climate change (Dyderski *et al.*, 2018).

The most compelling findings of this study have disclosed that regions conducive to specific species are anticipated to diminish, signifying potential challenges in conserving these particular habitats. Furthermore, the overall unsuitable area demonstrates a similar trend, suggesting that the altered area may become suitable for other species. Conversely, the habitat suitability of certain species, including areas suitable for mixed-stand forests, is expected to expand, providing insights into preserving species diversity within these ecosystems. This shift implies that climate change may instigate significant transformations in forest composition and diversity, a development of paramount importance in the context of future climate change.

As habitat suitability undergoes changes, certain species may find previously inhospitable areas more conducive for growth, expanding their ranges into newly suitable habitats. Climate change is a key driver of these shifts, with observable changes in distribution ranges and regeneration dynamics (Axer 2021). Conversely, species once well-adapted to a specific area may contract their ranges if the habitat becomes less suitable. Alterations in habitat suitability can reshape the competitive dynamics among tree species, potentially leading to shifts in dominance within the forest and consequent changes in its overall structure and composition. Numerous studies, such as Buras and Menzel (2019) aligns with these findings, projecting changes in forest species composition and abundance under extreme climate change scenarios.

One of remarkable findings in this study is the anticipated dominance of *Pinus nigra* (Çk) in habitat suitability over other pure stands in the future climate projection. In line with this finding, both Fyllas *et al.*, (2022) and Vayreda *et al.* (2016) highlight the significance of a species' capacity to endure drought and respond to disturbances. Drought-tolerant species and broadleaf species are more likely to prevail under warmer and drier conditions. Xu *et al.*, (2012)

adds that the relative importance of competition and colonization in driving these changes can vary over time, with competition playing a more crucial role in the short term and colonization becoming more dominant in the long term. Buras and Menzel (2019) further emphasizes the potential for significant shifts in tree species composition, predicting a decline in abundance for some species and an increase for others, ultimately resulting in changes in species diversity.

Furthermore, the suitability areas of mixed stands are expected to increase in future climates. Mixed-species forest stands contribute to structurally more complex stand formations (Juchheim *et al.*, 2020), a finding supported by several studies. For instance, Sebald *et al.* (2021) emphasizes that increasing tree species diversity within and between stands enhances forest resistance and resilience to disturbances under climate change. Noce *et al.* (2017) suggests diverse impacts of climate change on forest species suitability in Southern Europe across different forest categories. Kabrick *et al.* (2017) found that certain mixed hardwood-softwood stands had better compatibility and adaptability scores for projected future climates compared to pure stands. Moreover, managing mixed stands or converting to mixed stand management, as proposed by Jourdan *et al.* (2021), could mitigate the adverse effects of climate change on forest productivity and wood production. Aldea *et al.* (2022) discovered that mixed stands, especially those with Scots pine, exhibited higher drought resistance compared to pure stands, though the advantage decreased with longer drought durations.

Under future climate conditions, managing mixed species forests can yield positive outcomes. As suggested by Creutzburg *et al.*, (2017), climate change is projected to enhance forest productivity by 30-41% and elevate total ecosystem carbon storage by 11-15% over the coming century. Similarly, research by Pretsch *et al.*, (2015) indicates that mixed stands comprising various tree species exhibit greater productivity compared to adjacent pure stands. Vacek *et al.* (2021) illustrate that mixed mountain forests, particularly those with a higher proportion of European Beech, can not only enhance timber production but also contribute to greater structural diversity compared to monospecific forests in the context of climate change. Bauer *et al.* (2016) further corroborate these findings, showing that future climate change scenarios may lead to an increase in tree species richness and significant shifts in species composition, resulting in heightened diversity, especially in the northern regions of the United States.

5. CONCLUSION AND RECOMMENDATIONS

This study systematically examines the current prediction and future projection of species distribution for selected key tree species in Kastamonu province, Türkiye, under two climate change scenarios (SSP2 – Intermediate and SSP5 – Extreme) using the MaxEnt model. The intricate dynamics of changing habitat suitability and its profound implications for the composition of tree species within forest ecosystems are investigated. The distribution of tree species is influenced by a combination of biotic and abiotic factors, with climate change playing a profound role. The variable importance analysis highlights the diverse contributions of environmental variables, with temperature and precipitation as well as topographic soil related predictors emerging as key factors affecting habitat suitability.

Temperature-related predictors, such as annual mean temperature (bio1) and isothermality (bio3), consistently influence habitat suitability across various species, emphasizing their critical role in species distribution modeling. Additionally, soil pH and soil organic carbon prove to be crucial determinants for specific species. These findings contribute valuable insights into the complex interplay of environmental factors shaping the current distribution patterns of the studied tree species.

The future projections for tree species distribution under diverse climate scenarios present a nuanced landscape, with winners and losers emerging based on habitat suitability changes. The intricate pattern of change, observed over different periods and scenarios, underscores the complexity of the impact of climate change on various species. *Fagus orientalis* (Kn) faces challenges, with potential habitat reduction and increased vulnerability to the extreme scenarios which may lead to extinction, emphasizing the urgency of genetic conservation programs. Similarly, *Pinus* species (*P. brutia*, *P. nigra* and *Pinus sylvestris*) are projected to undergo significant area loss, highlighting difficulties in adapting to shifting climate conditions. Moreover, *Abies nordmanniana* subsp. *equi-trojani* faces a substantial reduction.

In this complex situation, where climate change serves as a catalyst, it leads to both beneficiaries and disadvantaged tree species, emphasizing the possibility of significant changes in the composition and diversity of forests. As habitat suitability undergoes alterations, some

species may take advantage of newly suitable areas, expanding their territories, while others, previously well-adapted, might reduce their ranges due to less suitable environments. These shifts in habitat suitability have the potential to reshape competitive interactions, potentially changing dominance patterns within the forest and impacting its overall structure and composition.

Based on the findings of this study several recommendations can be done to improve our understanding and approach to tree species conservation within the context of climate change. Firstly, it suggests that managing mixed-species forests can yield positive outcomes, enhancing forest productivity and structural diversity the forest ecosystem. These findings provide valuable insights for forest management strategies under future climate conditions, highlighting the potential benefits of mixed-species stands in mitigating the adverse effects of climate change on forest ecosystems. Additionally, there is a call for more comprehensive studies encompassing a diverse range of tree species, enabling a holistic assessment of their responses to changing environmental conditions. Furthermore, expanding the range of climate scenarios considered in future research can contribute to a more robust understanding of potential impacts, facilitating the development of adaptive management strategies. Implementing these recommendations in future research and management initiatives can significantly enhance the effectiveness and adaptability of conservation strategies in the face of ongoing climate change impacts.

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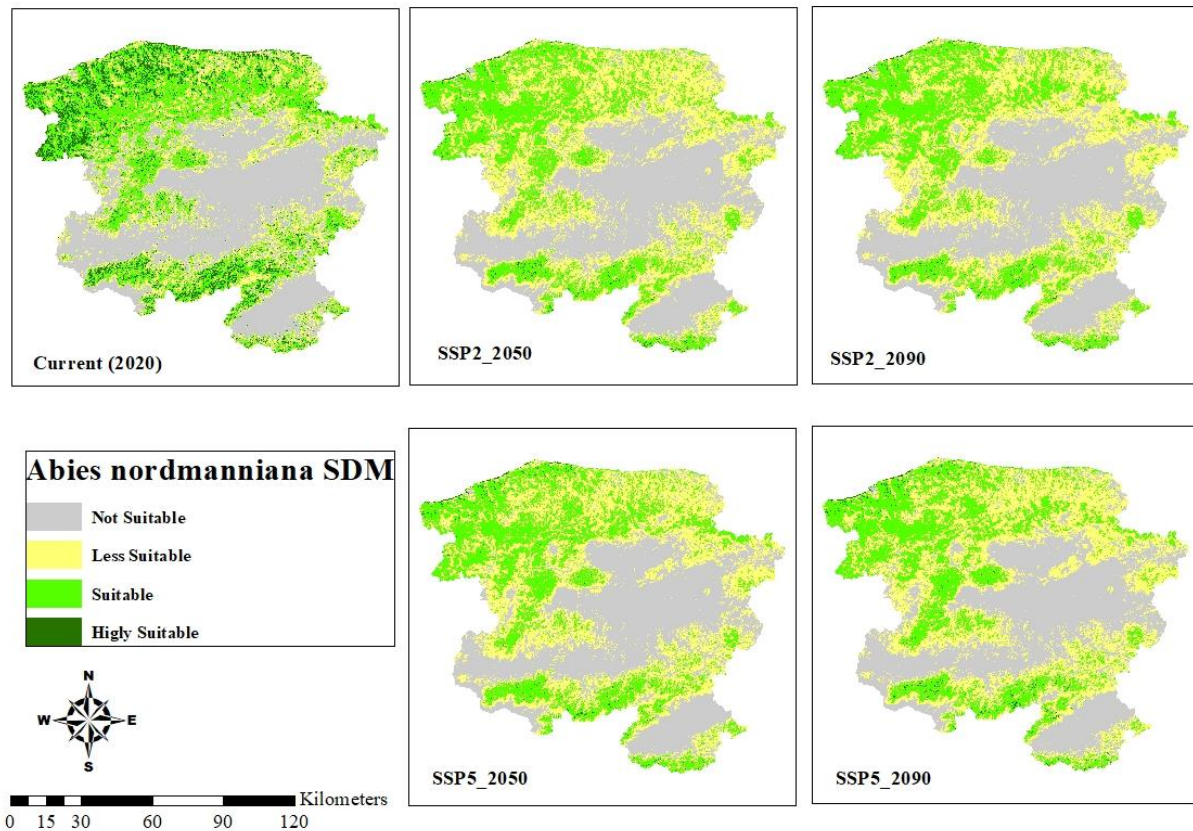
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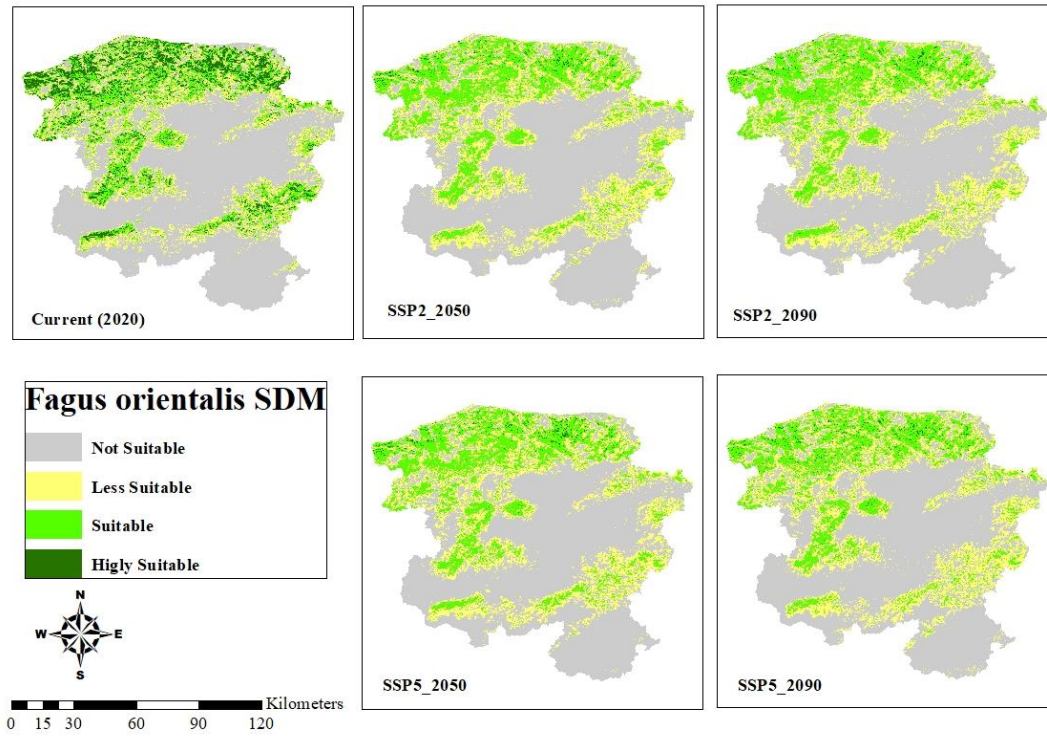
7. APPENDICES

Appendix 1: Future Habitat Suitability Projection of studied tree species

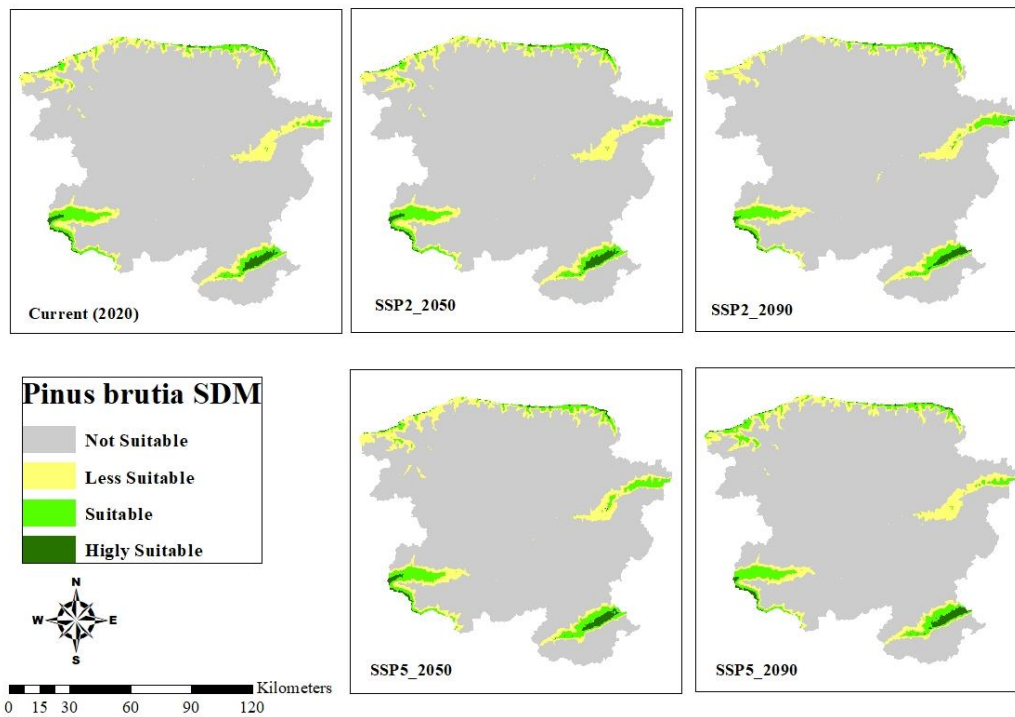
Appendix 1A: Future Potential Distribution Projection of *Abies nordmanniana* subsp. *equi-trojani*



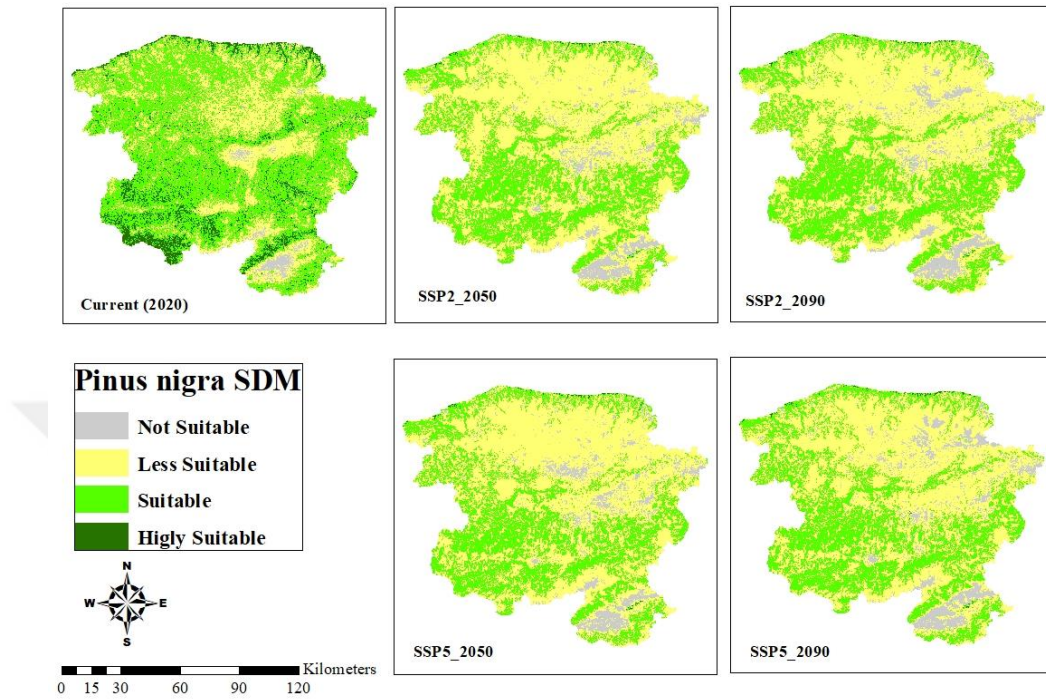
Appendix 1B: Future Potential Distribution Projection of *Fagus orientalis*



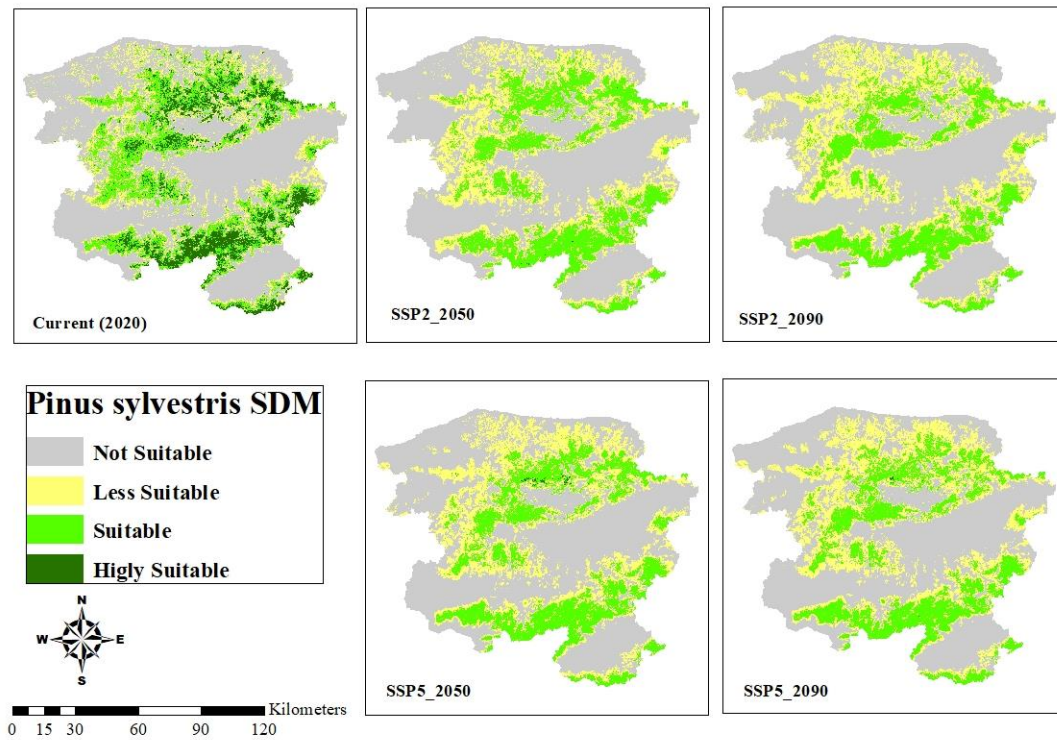
Appendix 1C: Future Potential Distribution Projection of *Pinus brutia*



Appendix 1D: Future Potential Distribution Projection of *Pinus nigra*

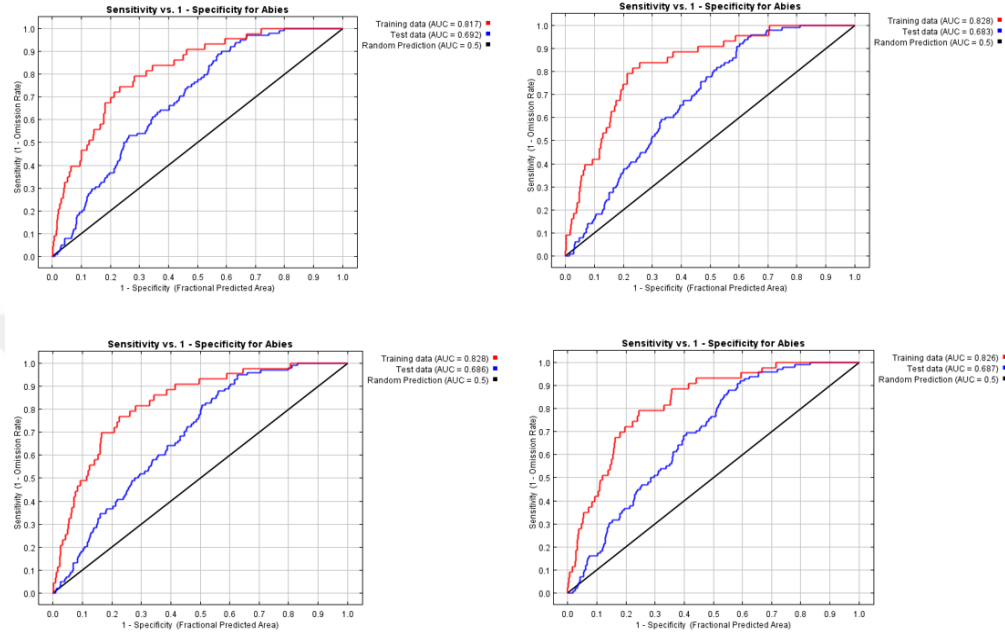


Appendix 1E: Future Potential Distribution Projection of *Pinus sylvestris*

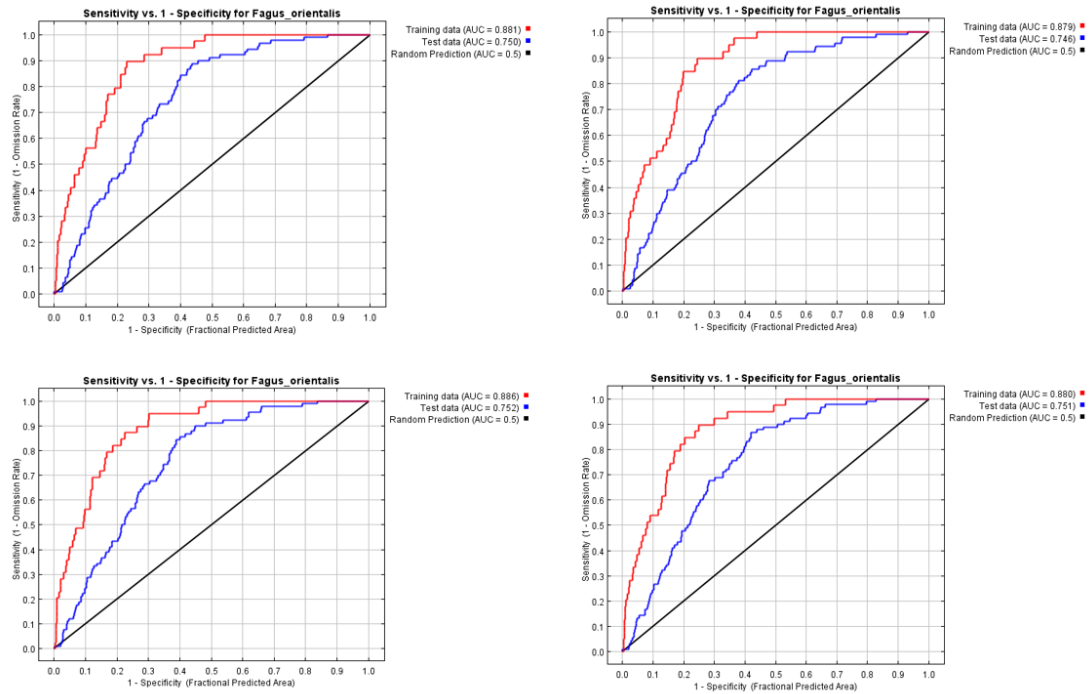


Appendix 2: Area Under the Curve (AUC) of MaxEnt models of studied species

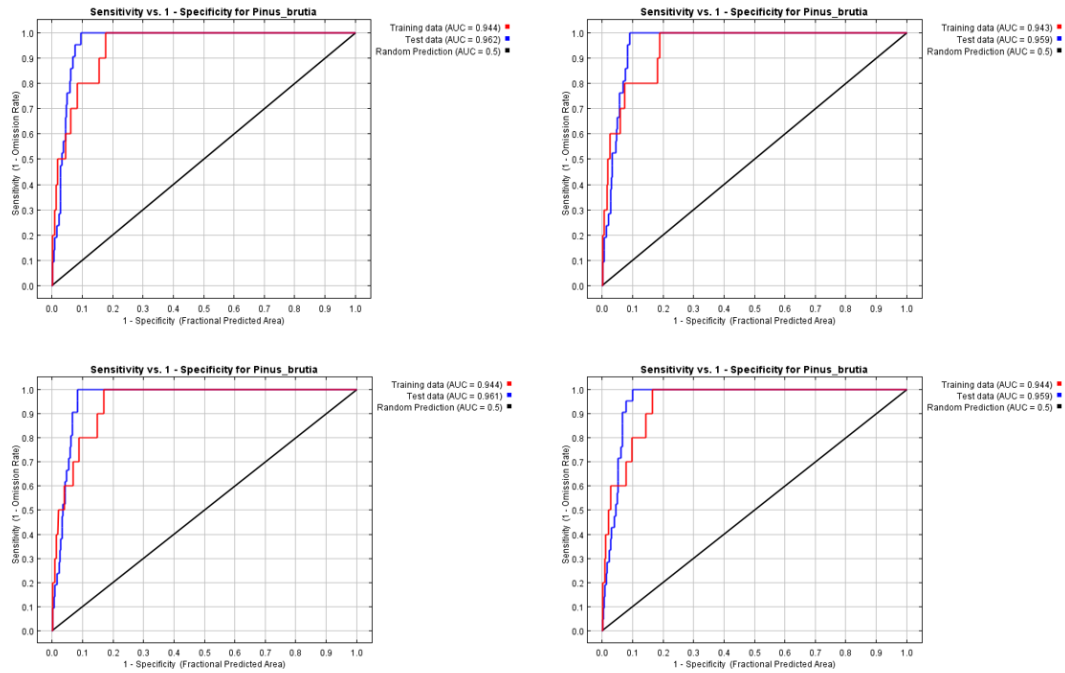
Appendix 2A: AUC of MaxEnt models for *Abies nordmanniana* subsp. *equi-trojani*



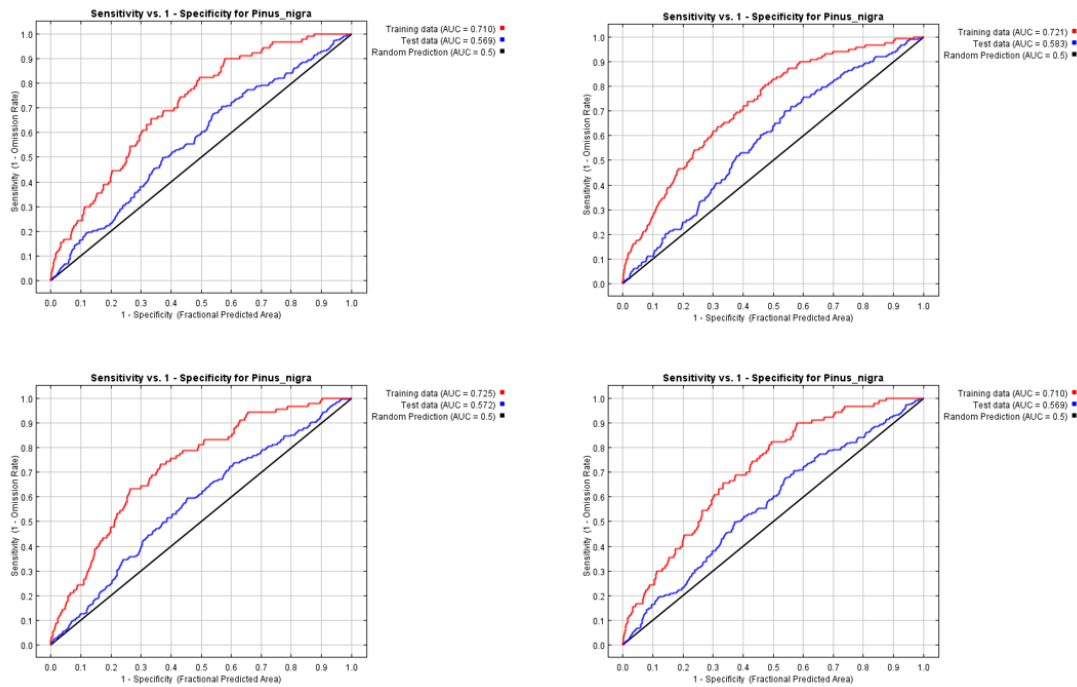
Appendix 2B: AUC of MaxEnt models for *Fagus orientalis*



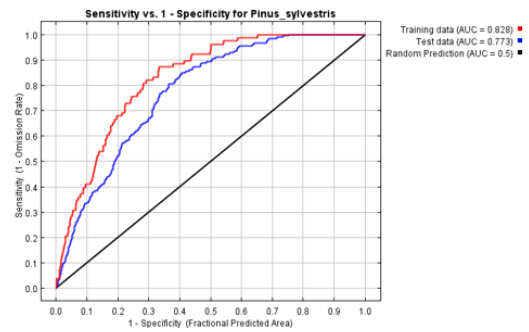
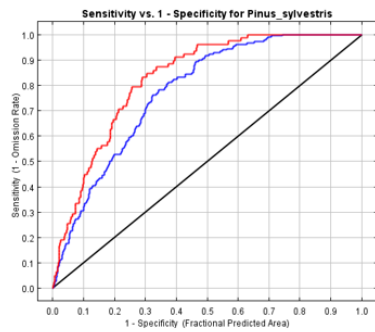
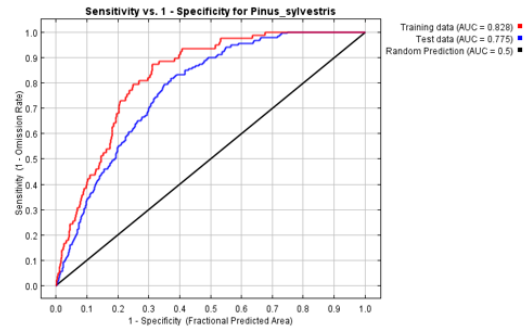
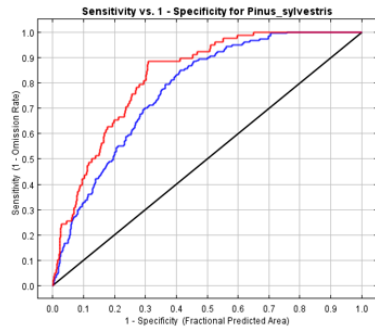
Appendix 2C: AUC of MaxEnt models for *Pinus brutia*



Appendix 2D: AUC of MaxEnt models for *Pinus nigra*

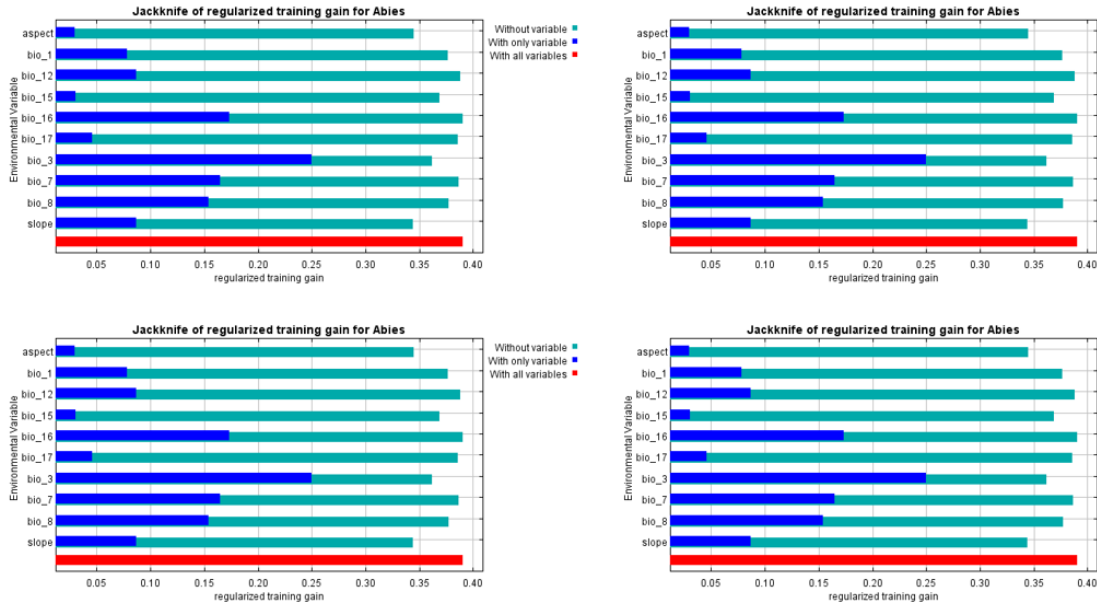


Appendix 2E: AUC of MaxEnt models for *Pinus sylvestris*

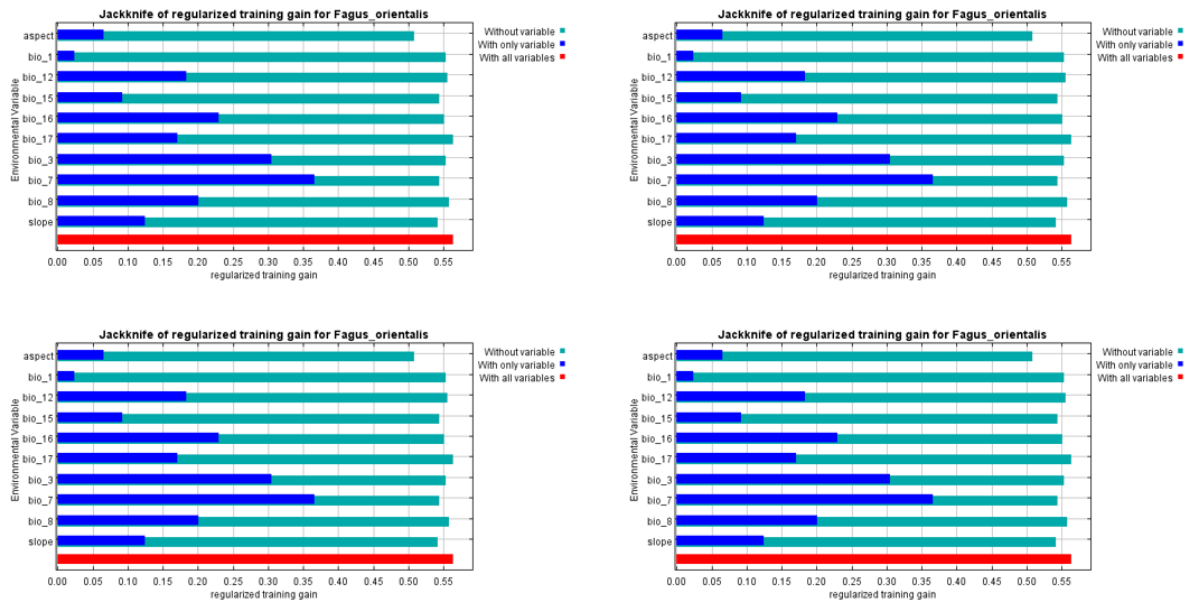


Appendix 3: Jackknife of regularized training gain for the studied tree species

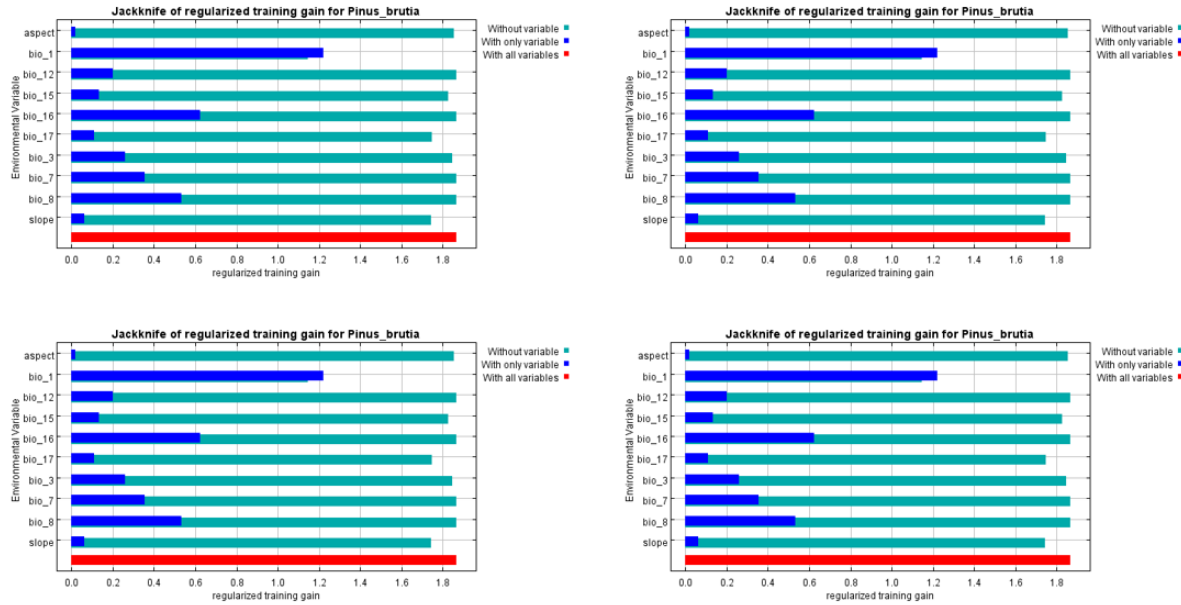
Appendix 3A: Jackknife of regularized training gain for *Abies nordmanniana*



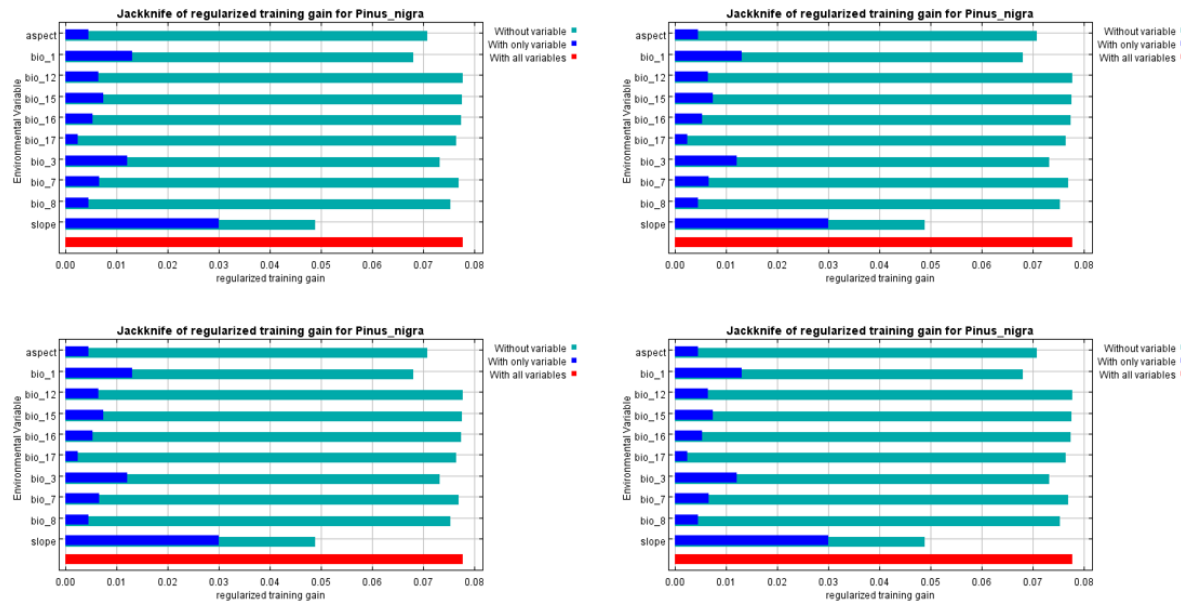
Appendix 3B: Jackknife of regularized training gain for *Fagus orientalis*



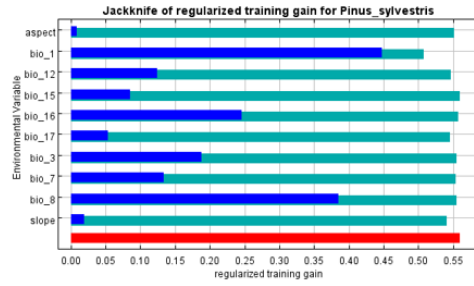
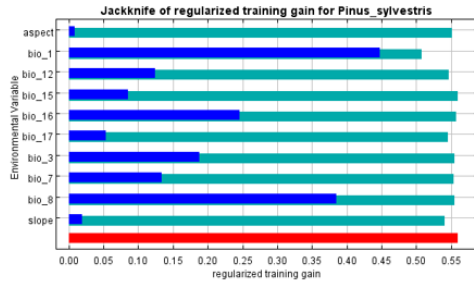
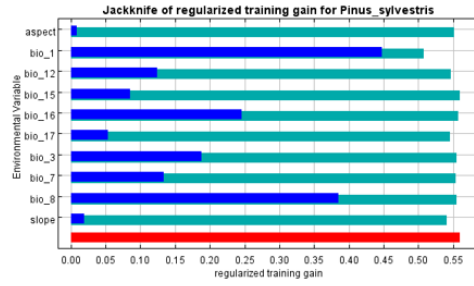
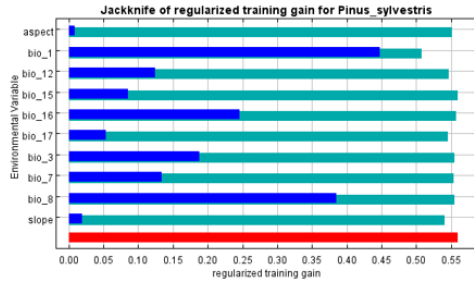
Appendix 3C: Jackknife of regularized training gain for *Pinus brutia*



Appendix 3D: Jackknife of regularized training gain for *Pinus nigra*



Appendix 3E: Jackknife of regularized training gain for *Pinus sylvestris*



Resume

Mulugeta Siyoum Molla is an Ethiopian forestry professional with a strong academic background and extensive research experience. He obtained his Bachelor in General Forestry from Wondo Genet College of Forestry, Hawassa University, Ethiopia, in 2010. Following this, he embarked on a career in research, serving as a Junior Researcher at the Ethiopian Institute of Agricultural Research from 2010 to 2014. Driven by a passion for academia and a commitment to furthering his expertise, he pursued higher education and obtained a Master of Science (MSc) in Natural Resource Economics and Policy from the same University in 2016. His dedication to academia was further demonstrated by his involvement as an Assistant Researcher at the Ethiopian Environment and Forest Research Institute until 2017. Since October, 2017, he has been engaged in a new career as a Lecturer at Wollo University. He has awarded the Erasmus Mundus Joint Master's 10th Edition, Mediterranean Forest and Natural Resources (MEDfOR) Scholarship Program in 2021. This esteemed scholarship allowed him to undertake a comprehensive study program across renowned European universities. He completed his first year of study at the University of Lisbon, followed by his second year at the University of Padova. Finally, he successfully conducted his thesis research at Karadeniz Technical University.