Ecological Niche Modeling and Genetic Structure of Brown Bear (*Ursus arctos*) in Türkiye

by

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Koç University

Graduate School of Sciences and Engineering

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ABSTRACT

Türkiye, with its rich biodiversity and unique climatic/topographic characteristics, serves as a land bridge between Asia and Europe. Brown bear (*Ursus arctos*) is the largest carnivore species in Anatolia. Unfortunately, due to climate change and landscape transformation, brown bear habitats are fragmenting and becoming increasingly isolated, posing a significant conservation concern for the species' future. This thesis comprises the chapters examining the various ecological facets of brown bears across Türkiye. Considering bioclimatic, topographic, and anthropogenic environmental variables, the distribution of brown bears across the country was estimated using an ensemble modeling approach. Potential habitat suitability under different climate change scenarios was also investigated. The results indicate bears are primarily distributed in the Euro-Siberian biogeographic region, followed by Irano-Turanian, and Mediterranean. Climate change is expected to lead to a substantial loss of brown bear habitats. Additionally, it is projected that established protected areas might become insufficient to safeguard the species in the face of future habitat loss, leading to a conservation gap. I modeled the structural connectivity of brown bear habitats across the country, identified priority linkages and core patches, and discussed the potential impact of climate change on the ecological network of brown bears across Türkiye. Ultimately, the Western Black Sea and Eastern Anatolia core patches exhibited a relatively intact structure, while the Mediterranean region was identified as critical in terms of habitat configuration and fragmentation. Climate change is predicted to have significant impacts on brown bear ecological network. Then, I analyzed the spatiotemporal dynamics of human-brown bear conflict across Türkiye. A conflict risk map was generated, and the role of protected areas in mitigating conflict was evaluated. The findings revealed significant variations in conflict frequency by years, seasons, bear seasons, and regions. Conflict risk was found to be particularly high along the Black Sea coast and Eastern Anatolia. The primary cause of human-bear conflicts was identified as the confinement of bears to areas, with limited resources, leading them to seek anthropogenic food alternatives. Additionally, the peripheries of protected areas represented hotspots for human-bear conflict. In the next chapter, I analyzed the population structure and genetic variation of brown bears across Middle East. Results indicated that the Sarıkamış population exhibited a more isolated pattern and lower genetic diversity compared to the Western, Eastern, and Iranian populations. However, high genetic variation was detected across the region. Furthermore, environmental heterogeneity and geographic distance were identified as significant patterns driving the genetic differentiation of populations. Lastly, considering the findings from all preceding chapters, I discuss pro-active wildlife management approaches that promote coexistence. This comprehensive study aims to provide a holistic conservation approach for brown bears by examining their suitable habitats, ecological connectivity, population structure, strategies to mitigate human-bear conflict, and climate adaptation strategies. My results highlight the urgent need for effective conservation measures to safeguard Türkiye’s brown bears in the face of climate change, habitat loss, and human-bear conflict.

ÖZETÇE

Türkiye zengin biyoçeşitliliği ve barındırdığı klimatik/topografik özellikleriyle Asya ve Avrupa arasında önemli bir kara köprüsüdür. Bozayılar (*Ursus arctos*) Türkiye boyunca dağılım gösteren en büyük karnivorlardır. Ne yazık ki iklim değişikliği ve arazi dönüşümü nedeniyle bozayıların habitatları günden güne parçalanarak izole hale gelmekte ve bu durum türün geleceği açısından önemli bir koruma endişesi yaratmaktadır. Bu tez, Türkiye genelindeki bozayıların çeşitli ekolojik yönlerini inceleyen farklı bölümlerden oluşmaktadır. İlk kısımda, biyoklimatik, topografik ve antropojenik değişkenler kullanılarak bozayıların ülke boyuncaki dağılımları ekolojik niş modellemesi yaklaşımıyla modellenmiş ve çeşitli iklim değişikliği senaryoları kullanılarak gelecekteki potansiyel habitat uygunlukları incelenmiştir. Buna göre, en yaygın dağılım, sırasıyla, Avrupa-Sibirya, Iran-Turan ve Akdeniz biyocoğrafik bölgelerinde görülürken, iklim değişikliğinin bozayı habitatlarında önemli bir kayba yol açacağı tahminlenmiştir. Dahası, mevcut korunan alanların ise gelecekteki habitat kaybı göz önünde bulundurulduğunda yetersiz kalarak bir koruma boşluğuna yol açacağı öngörülmüştür. İkinci kısımda, ekolojik niş modelleme çıktıları kullanarak bozayı habitatlarının ülke boyuncaki yapısal bağlantısallığı modellenmiş, öncelikli koridor ve çekirdek habitatlar tespit edilmiştir. Ek olarak, iklim değişikliğinin yakın gelecekte bozayıların Türkiye boyuncaki ekolojik ağına potansiyel etkisi tartışılmıştır. Nihayetinde, Batı Karadeniz ve Doğu Anadolu çekirdek habitatları görece bütünlüklü bir yapı sergilerken Akdeniz bölgesinin özellikle yapısal bağlantısallık açısından durumunun kritik olduğu ve iklim değişikliğinin yakın gelecekte bozayıların ekolojik bağlantısallığı üzerine önemli etkileri olacağı tahminlenmiştir. Tezin bir diğer bölümünde ise, ülke boyuncaki insan-bozayı çatışmasının zamansal ve mekansal dinamikleri incelenerek, çatışma risk haritası çıkarılmış, bu bağlamda korunan alanların rolü değerlendirilmiştir. Sonuçlara göre, çatışma frekansları yıllara, mevsimlere, ayı periyotlarına ve bölgelere göre anlamlı farklılıklar sergilerken, çatışma yoğunluğunun ise özellikle Karadeniz sahilleri ve Doğu Anadolu boyunca arttığı tespit edilmiştir. İnsan-bozayı çatışmalarının altında yatan temel faktörün ise bozayıların yetersiz kaynak içeren sınırlı alanlara hapsolması sonucu insan ilişkili besin arayışına girmesi olduğu görülmüş ve korunan alanların etraflarının insan-bozayı çatışması açısından sıcak noktaları temsil ettiği bulgulanmıştır. Bir sonraki bölümde, Orta Doğu'daki bozayıların popülasyon yapısı ve genetik çeşitliliği analiz edilmiştir. Sonuçlara göre, Sarıkamış populasyonunun, Batı, Doğu ve İran populasyonlarına kıyasla her ne kadar daha izole bir patern ve düşük genetik çeşitlilik sergilediği görülse de, bölge boyunca genetik varyasyonun yüksek olduğu tespit edilmiştir. Dahası, çevresel heterojenite ve coğrafik uzaklığın populasyonların genetik farklılaşmasında anlamlı rolleri olduğu tespit edilmiştir. Tez çalışmasının son bölümünde ise tüm bu edinilen veriler ışığında, birlikte yaşamı destekleyecek proaktif yaban hayat yönetim yaklaşımları tartışılmıştır. Sonuç olarak, bu çalışma bozayıların uygun habitatlarını, ekolojik bağlantısallığını, populasyon yapısını, insan-bozayı çatışmasını hafifletme yollarını ve iklimsel uyum stratejilerini tartışarak bütünlüklü bir koruma yaklaşımı sunmayı amaçlamıştır. Çalışma bozayıların iklim değişikliği, habitat kaybı ve insan-ayı çatışmasına karşı etkili koruma önlemlerine ihtiyaç olduğunu vurgulamaktadır.

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ABBREVIATIONS

ANGSD	Analysis of Next Generation Sequencing Data
ANN	Artificial Neural Network
AUC	Area Under the Curve
CNRM-CM6-1	Coupled Climate Model of the Centre National de Recherches Météorologiques, Phase 6, Version 1
CT	Circuit Theory
CTA	Classification Tree Analysis
CwD	Cost-weighted Distance
d2Farmland	Distance to Farmland
d2Forest	Distance to Forest
d2PA	Distance to Protected Areas
d2Road	Distance to Road
d2Villages	Distance to Villages/human settlements
d2Water	Distance to Water
ENM	Ecological Niche Modeling
EucD	Euclidean Distance
FDA	Flexible Discriminant Analysis
F_{ST}	Allele Frequency Differentiation
GAM	Generalized Additive Model
GBM	Generalized Boosting Model
GCM	General Circulation Model
GEA	Genotype – Environment Association
GLM	Generalized Linear Model
HBC	Human-Brown Bear Conflicts
HFI	Human Footprint Index
IBD	Isolation by distance
IBE	Isolation by environment
IPCC	Intergovernmental Panel on Climate Change
LCP	Least Cost Path

LULC	Land Use/Land Cover
MARS	Multiple Adaptive Regression Splines
MIROC6	Model for Interdisciplinary Research on Climate, Version 6
MPI-ESM1-2-LR	Max Planck Institute for Meteorology Earth System Model, Version 1.0, Subversion 2.0, Lower Resolution
NPP	Net Primary Productivity
PA	Protected Area
PCA	Principal Component Analysis
PopDen	Population Density
$\hat{R}$	Effective Resistance
RAD-Seq	Restriction Site Associated DNA Sequencing
RCP	Representative Concentration Pathway
RF	Random Forest
SDM	Species Distribution Modeling
SFS	Site Frequency Spectrum
SRE	Surface Response Envelope
SSP	Shared Socio-economic Pathway
TSS	True Skill Statistics
XGBOOST	eXtreme Gradient Boosting Training
Θw	Watterson's Theta
π	Pairwise nucleotide differences

Chapter 1

1. General Introduction

Brown bear (Ursidae, Carnivora) is one of the most widely distributed terrestrial carnivores throughout Europe, Asia, and North America. Their number worldwide is estimated to be more than 200,000 individuals (McLellan et al., 2017). Brown bear is a generalist species. This opportunistic omnivore has high dietary plasticity (Trujillo et al., 2022), and a flexible trophic niche. Plant roots, grasses, leaves, fleshy fruits, hard mast, insects, fish, birds, reptiles, and mammals comprise their diet, but they Falso feed on carrion (Penteriani & Melletti, 2020). They have no natural non-human predators except in specific incidental cases. Brown bears prey on many species and keep some of these prey populations in check (Niedziałkowska et al., 2019), so they provide important indirect ecosystem functions (Diserens et al., 2020). In addition to that, they provide many other ecosystem services such as seed dispersal, and ecosystem engineering (García-Rodríguez et al., 2021; Zyśk-Gorczyńska et al., 2015). They have large area requirements that cover the home ranges of many other species, so brown bears are also defined as an umbrella species (Linnell et al., 2000). They have adapted to very different climates and topographic features. Throughout their distributional range, they can live in a diversity of biomes such as forests, shrublands, tundra, grasslands, and deserts (McLellan et al., 2017). They are distributed from sea level to altitudes above 5,000 meters (Garshelis, 2022). Furthermore, these iconic species are also flagships for conservation efforts due to their ecological importance and charisma (Ashrafzadeh et al., 2019). However, brown bears' slow population growth makes their populations highly vulnerable to long-term changes in environmental conditions (Ripple et al., 2014).

Rapid industrialization, urbanization, and continuous population growth present two of the most formidable challenges to our planet: climate change and biodiversity crisis (Bellard et al., 2012; Şekercioğlu et al., 2011a; Urban, 2015). It is estimated that a large proportion of plant and animal species will face serious range shifts and global extinctions if the temperature

increases continue to rise at their current rates that are substantially higher compared to pre-industrial levels (IPCC, 2014). Simultaneously, extensive human land use practices are causing substantial changes in land cover and resulting in significant habitat loss (Powers and Jetz, 2019). Anthropogenic factors such as deforestation are the main drivers of the destruction of habitats (Pecl et al., 2017; Tucker et al., 2018). These two major forces, climate change and landscape transformation, often disrupt critical aspects of a species' viability, such as feeding, denning, and reproductive areas (González-Bernardo et al., 2020a; Penteriani et al., 2019). The changes in a species' behavior and distribution, have profound effects on entire ecosystems (Dar et al., 2021; Martínez Cano et al., 2016; Zarzo-Arias et al., 2019). Consequently, brown bears suffer from these changing conditions. For these reasons, it is estimated that brown bears, which have already lost a large part of global their distribution in the last 150 years (Servheen, 1990), will experience serious range contractions in the future as well (Su et al., 2018; Dai et al., 2021a; Ashrafzadeh et al., 2022; Dai et al., 2019a; Dar et al., 2021; Penteriani et al., 2019; Mohammadi et al., 2021). This habitat fragmentation also disrupts the connectivity between suitable habitats. However, landscape connectivity is highly important for wildlife (Crooks et al., 2011). Connectivity between different core patches means high gene flow, which promotes genetic diversity, enhancing the adaptation ability of populations, dispersal, colonization success, and chances of long-term survival (Mohammadi et al., 2021; Calderón et al., 2024; Benazzo et al., 2017; Smith et al., 2020). However, it should be noted that despite all the mentioned threats, brown bear has high ecological flexibility and they often develop behaviorally plastic responses to human impact (Martin et al., 2010). However, disappearing suitable habitats and natural resources force brown bears to adapt to new areas, most of which are severely modified by people, making human-brown bear conflict (HBC) inevitable. The accessibility and abundance of anthropogenic food sources, such as open landfills, orchards, and beehives, exacerbate this problem even further. In addition to increasing brown bears' vulnerability to anthropogenic and natural environmental changes, this predicament also fosters negative attitudes toward their conservation. Therefore, determining the factors contributing to HBCs and improving conservation strategies geared towards fostering co-existence are critical for the persistence of brown bear populations and healthy ecosystems.

In order to plan effective wildlife management strategies, it is crucial to thoroughly understand the habitat suitability dynamics of brown bears and the factors influencing their ecology, both presently and under changing conditions. It also requires insights into the

ecological networks of the species and the identification of priority areas for their conservation. Additionally, comprehending the spatiotemporal dynamics of human-bear conflicts is essential for devising effective conservation plans. Therefore, this thesis aims to investigate the various aspects of the interactions between this charismatic species, human activities, and the changing environment within the unique ecosystems of Türkiye, which are facing a severe biodiversity crisis (Şekercioğlu et al., 2011a, b), compounded by the impacts of climate change.

1.1. Aim and Rationale of The Thesis

The core of this thesis is based on a field research on brown bears across Türkiye. The six separate chapters include ecological niche modeling, connectivity modeling, the assessment of human-brown bear conflict, population genetics, and the conservation implications of my findings.

In Chapter 2, I conducted ecological niche modeling of brown bears across Türkiye using occurrence records obtained from fieldwork. With the ensemble modeling approach, I estimated the current potential distribution of brown bear using bioclimatic, topographic, and anthropogenic variables, and discussed the roles of these predictors. Furthermore, I projected the potential habitat suitability of brown bear in the near future, taking into account different climate change scenarios, and examined the effectiveness of established protected areas in terms of habitat suitability of brown bear.

In Chapter 3, I modeled the structural connectivity of brown bears across the country by combining ecological niche modeling and connectivity modeling. While the quality of core patches and their linkages and prioritized conservation areas were determined, the impacts of climate change on bears' future ecological network were examined.

The focus of Chapter 4 is human-brown bear conflict in Türkiye. News media articles between 2017 and 2023 were compiled and the spatiotemporal dynamics of HBCs were discussed. Furthermore, conflict risk modeling across the country was performed using conflict event locations and bioclimatic and anthropogenic variables that have the potential to direct HBCs.

In Chapter 5, RAD-Seq was performed with the DNA samples extracted from scats, bloods and tissues of brown bears throughout Anatolia and Iran, and the population structure,

genetic diversity and isolation patterns were examined with this genome-wide data. This chapter provides preliminary insights into the population genetics of brown bears across Southwest Asia.

In Chapter 6, I discussed the conservation implications in light of the findings, made suggestions for the future, and addressed the main points of effective wildlife management for brown bears.

1.2. Study Area

As a mountainous country in southwestern Asia, Türkiye (35-42° N and 25-45° E) plays a pivotal role as a vast land bridge connecting the Eastern Palearctic to Europe. Türkiye covers 783,562 km^2, 97% of its surface area in Asia and 3% in Europe. The country has two main montane belts, including North Anatolian mountain chains and the Taurus mountains south of the study area. They represent big barriers and separate the inner and coastal parts of the country. The topographic surface of it is highly rugged with the altitude ranging from -2 m to 5,137 m a.s.l. (mean 1,130 m).

The country's diverse range of geology, plant communities, and climatic zones provides critical habitats for various animal species. Türkiye encompasses three of the world's thirty-six biodiversity hotspots: Caucasus, Irano-Anatolian, and Mediterranean basin (Şekercioğlu et al., 2011; Noroozi et al., 2019; Gür, 2022). The country hosts more than 20,000 animal species and ~11,000 vascular plants, one-third of which are endemic (Ergüner et al., 2019; https://www.iucn.org/content/biodiversity-turkey). Türkiye is also covered by three different biogeographic regions, Euro-Siberian, Irano-Turanian, and Mediterranean, which differ from each other due to their climatic and topographic properties (Noroozi et al., 2019). Although there are transition zones between them, each region has different vegetation regimes, geographical characteristics, and human usage patterns (Noroozi et al., 2019). Climate change is expected to affect each region differently (Ozturk et al., 2015; Demircan et al., 2017). Türkiye's climate regimes contain temperate, continental, and Mediterranean climates in northern, central, and southern parts, respectively (Akman & Ketenoğlu, 1986). While annual precipitation varies highly among the regions, the average precipitation is 618.9 mm (MGM, 2022). The region with the highest precipitation is Eastern Black Sea, and the region with the least precipitation is Southeastern Anatolia. Between 1970-2022, the annual average minimum

temperature was 7.9 ^{o}C, and the average maximum temperature was 19.2 ^{o}C (MGM, 2022). Unfortunately, Türkiye is estimated to experience a temperature increase of 0.5 to 1.5 ^{o}C in the by 2037 (Dalfes et al., 2007) and is seriously affected by climate change (Ozturk et al., 2015; Newbold et al., 2020).

Mediterranean climate prevails in the Mediterranean biogeographic region. It is characterized by dry summers, warm and rainy winters, and irregular precipitations. According to the Köppen Climate Classification, while *Csa* (Hot-Summer Mediterranean) and locally *Csb* (Warm-Summer Mediterranean) climate classes are common throughout Western Anatolia, *Dsa* (Hot-Summer Mediterranean Continental) climate class can be seen throughout the southern regions. From sea level to higher elevations, macquis and Turkish pine forests (*Pinus brutia* Ten.) give way to black pine (*Pinus nigra*) and cedar forests (*Cedrus libani* A. Rich.), respectively. Apart from them, pine (*Pinus pinea* L.), Taurus fir (*Abies cilicica* Carr), Mediterranean cypress (*Cupressus sempervirens* L.), junipers (*Juniperus* L.), common yew (*Taxus baccata* L.), hawthorn (*Crataegus* L.), Taurus fir (*Abies cilicica*), and oak (*Quercus* L.) species comprise the other members of the tree community. At higher altitudes, tree-line gives way to alpine meadows. Apart from brown bears, other mammalian carnivorous species, including gray wolf (*Canis lupus*), golden jackal (*Canis aureus*), Eurasian lynx (*Lynx lynx*), caracal (*Caracal caracal*), red fox (*Vulpes vulpes*), wild cat (*Felis silvestris*), jungle cat (*Felis chaus*), beech marten (*Martes foina*) and marbled polecat (*Vormela peregusna*) live in the Mediterranean basin. Additionally, ungulate species such as fallow deer (*Dama dama*), red deer (*Cervus elephus*), roe deer (*Capreolus capreolus*), wild boar (*Sus scrofa*), wild goat (*Capra aegagrus*) are also important components of the mammal community.

In the Euro-Siberan region, climate characteristics are complex and diverse. A transitional climate prevails in the parts of the region covering Marmara. In this region, the influence of the Mediterranean climate in the south decreases towards the north. The Euxinian climate, characterized by high precipitation during all months, is observed throughout the Black Sea region (Çolak & Rotherdam, 2006). Continental climate manifests itself in the inner parts of the mountain ranges that form a set parallel to the Black Sea coast. This region contains approximately one-third of Türkiye's forests and is the region with the most forests in the country. Broad-leaved forests extend along the Black Sea coast from the Istranca Mountains to the Georgia border. Beech (*Fagus* sp.), chestnut (*Castanea sativa*, Mill), linden (*Tilia* sp.), oaks

(*Quercus* sp.), maple (*Acer* L.), ash trees (*Fraxinus excelsior* L.), junipers (*Juniperus* L.), alder (*Alnus* sp.), hornbeam (*Carpinus betulus* L.), and poplar trees (*Populus* L.) are important members of the forest composition here. Furthermore, the coniferous members that exist in mixed forest at low altitudes and in coniferous forests at high altitudes are Turkish pine, black pine, oriental spruce (*Picea orientalis*), fir trees (*Abies nordmanniana*), and Scots pine (*Pinus sylvestris*). There is high food richness for bears in this region. Cherries (*Prunus* sp.), berries (*Fragaria vesca*), blackberries (*Rubus fruticosus*), chestnuts (*Castanea sativa*), cranberry (*Vaccinium* sp.), mulberry (*Morus* sp.), plums (*Prunus* sp.), hazelnuts (*Corylus avellana*), walnuts (*Juglans regia*), apples (*Malus domestica*), rosehips (*Rosa canina*), and many other fruits are part of the bears' diet. Apart from brown bears, large or meso carnivores such as gray wolf, golden jackal, lynx, wildcat, red fox and ungulate species including wild boar, red deer, roe deer, chamois (*Rupicapra rupicapra*), and wild goat live in the region.

The Irano-Turanian region covers Central and Eastern Anatolia. In this region with a high endemism rate (Noroozi et al., 2019), mostly continental climate prevails. It is characterized by low precipitation, hot and dry summers as well as cold winters and high diurnal temperature differences. However, it has substantial diversity at the micro-scale. For example, according to the Köppen Climate Classification, the mountainous regions of Eastern Anatolia have *Dsb* (Warm-Summer Mediterranean continental) climate class, while moving towards Northeastern Anatolia, the climate is mostly *Dfb* (Warm-Summer Humid continental), and *Dfc* (Subarctic) at higher altitudes. In the Southeastern Anatolia region and its surroundings, *Csa* climate class (Hot-Summer Mediterranean) prevails. The elevation dramatically increases from west to east in the region. Steppe plant communities mostly prevail in Central Anatolia. The forest cover in the region is quite low compared to the other two regions. Forests area mainly mixed and evergreen coniferous. Oak (*Quercus* sp), black pine (*Pinus nigra*), Scots pine (*Pinus sylvestris*), junipers (*Juniperus* sp.) and hornbeam (*Carpinus* sp.) are the main members of the tree community. At higher altitudes, there are large montane meadows.

Chapter 2

2. Ecological Niche Modeling of Brown Bears Across Türkiye

2.1. Introduction

Species occupy both geographical and environmental space, influenced by biotic and abiotic factors, as well as species inherent traits, such as adaptability and mobility (Soberon & Peterson, 2005). Species distribution modeling (SDM), also known as ecological niche modeling (ENM), is a critical tool to decipher how these factors shape species distribution patterns. ENM delineates environmental space using key environmental predictors, which are then projected onto geographical space (Sillero et al., 2021). It offers invaluable insights into habitat vulnerability, connectivity, and forecasting the impact of climate change (Penterani et al., 2019; Dar et al., 2021; Mohammadi et al., 2021). There are many definitions of ecological niche from past to present. While Grinnel defined the niches as a feature of the environment (Grinnel, 1917), Elton defined the niche as a feature of the ecosystem, taking into account bionomic variables (Elton, 1927). Hutchinson categorized the ecological niche, which he defined as a feature of species, into fundamental niche and realized niche, and stated it as n-dimensional hypervolume (Hutchinson, 1957). While Soberon & Peterson, (2005) define a niche by considering abiotic factors (e.g., climate, topography, soil characteristics, etc.), biotic factors (e.g., competition, parasitism, etc.), and the movement abilities of species, they have further clarified the difference between the fundamental and realized niche. Accordingly, while the fundamental niche is the entirety of the ideal living conditions of a species, the realized niche represents the area at the intersection of all three factors and provides a snapshot of the ecological and environmental conditions experienced by the species at any given time (Soberon & Peterson, 2005).

Although there are different ENM models such as mechanistic, correlative, and hybrid, the most frequently used ones to predict the realized niche are correlative models. Correlative models are divided into three main categories depending on the occurrence record type: i) presence-absence models, ii) presence-background models, and iii) presence-only models (Sillero et al., 2021). During fieldwork, the strategy for collecting data on the presence and

absence of the target species is essential. Mostly, only presence data is used in ENMs because it requires much more extensive observations to conclude that a species is absent from an area. This means much more time in the field and long-term monitoring efforts, and therefore more resources are needed. On the other hand, the discrimination capacity and model accuracy of presence-absence models between occupied and non-occupied areas depend on the absence records as well as the presence ones (van Proosdij et al., 2016). Thereby, artificial absence points are generated as a strategy. Presence-background models generate habitat suitability by comparing existing background with the environmental conditions in which the occurrence record was collected, and they do not require any absence data. Lastly, in presence-only models, only presence data is used (Sillero et al., 2021).

With their adaptability, omnivorous diet, and wide-ranging mobility, brown bears (*Ursus arctos*) inhabit diverse ecological niches across Türkiye. Their habitats span a wide range of elevations and include mixed shrublands, mixed and evergreen coniferous forests, broad-leaved forests, and open rocky areas (Ambarlı et al., 2016). Given their ecological significance and trophic role, brown bears serve as an ideal model for upscaling local habitat models (Scharf & Fernández, 2018). Unfortunately, brown bears, a species with slow population growth and large body size, are predicted to be highly sensitive to climate change in the future (Ashrafzadeh et al., 2022; Dai et al., 2021a; Dar et al., 2021; Penteriani et al., 2019; Su et al., 2018). Considering Türkiye's vulnerability to climate change (Ozturk et al., 2015), it can be expected that there will be a similar fate for Anatolian brown bears. In addition, human-brown bear conflict across the country has increased in recent years as a result of the growing human population and consumption, and the concomitant decrease in bear habitat size and quality (see Chapter 4). As they lose their favorable habitats, brown bears, which have relatively higher adaptability to human-related factors, wander around the areas close to human settlements, orchards, and pastures (Cozzi et al., 2016; Zarzo-Arias et al., 2021; Kemahlı et al., 2023). Until now, there has been limited ecological information available about brown bears in Türkiye (Can & Togan, 2004; Ambarlı, 2016; Ambarlı et al., 2016; Çilingir et al., 2016; Cozzi et al., 2016; Ambarlı et al., 2018; Suel, 2019; Tavşanoğlu et al., 2021; Dağtekin et al., 2023; Kemahlı et al., 2023), and no comprehensive data exists regarding their ecological niche throughout the country. For all these reasons, examining the current distribution of brown bears across the country and the effects of climate change on their habitat suitability is important to improve effective conservation strategies for the future.

This chapter aims to achieve three primary objectives: (1) determine the current potential distribution of brown bears across Türkiye; (2) project and assess potential habitat suitability under various CO_2 emission scenarios for both 2050 and 2070; (3) reevaluate the efficacy of established protected areas in light of the habitat suitability of brown bear habitats, considering both present day and future conditions.

2.2. Materials and Methods

2.2.1. Data Collection

The data obtained to perform ENM is of great importance for a good estimation. For instance, the sampling design should cover the entire study area, data acquisition should occur homogeneously, and there should be no bias in terms of the predictors to be used, such as habitat types, and climate conditions (Syfert et al., 2013; Inman et al., 2021). For this reason, it is important to know the ecology of the target species well before sampling. Between May 2020 and October 2021, I conducted extensive fieldwork with our research team to gather data on brown bear signs across Türkiye (Fig. 2.1). The data collection process involved a systematic random design, leading to the recording of 608 presence points (Fig. 2.2). The presence points were determined based on various signs such as footprints, rubbing tree, hair samples and scat samples (Fig. 2.1). To record the precise geographical coordinates of the occurrence records, we employed ArcGIS Survey123 (ESRI, USA).

Figure 2.1: Presence signs of brown bears including a rubbing tree, footprints, and scat samples.

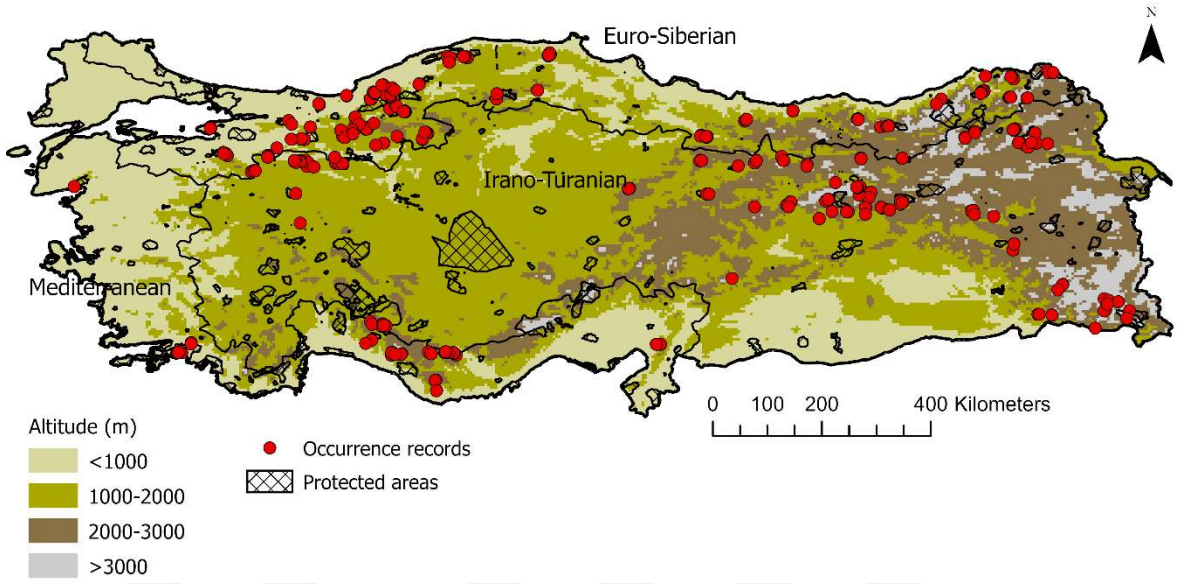

Figure 2.2: Occurrence records (n = 608) in the study area and the borders of the biogeographic regions.

In SDMs, the clustering level of occurrence points creates bias and causes noise in the model (Aiello-Lammens et al., 2015). To prevent this and to homogenize the species distribution, thinning approaches are applied (Naimi et al., 2014; Aiello-Lammens et al., 2015). This filtering can also be performed by taking environmental criteria into consideration and may give better results (Varela et al., 2014). Spatial autocorrelation (SA) is based on Tobler's Law (Tobler, 1970), which states that everything is related to everything else, and that nearby things are more closely related than distant things. Spatial autocorrelation can generate bias, causing over-fitting or inflated performance metrics (de Oliveira et al., 2014; Wenger & Olden, 2012). For all these reasons, to mitigate potential spatial clustering effects, I utilized the Mantel test, implemented using the *ecospat* package (Boavida et al., 2016; Broennimann et al., 2018). The spatial correlogram for environmental predictors reveals a positive autocorrelation in occurrence records extending up to 21.83 km (Fig. 2.3). Consequently, only 87 occurrence records were retained by considering the mentioned distance as the final dataset for the subsequent ENM (Fig. 2.4).

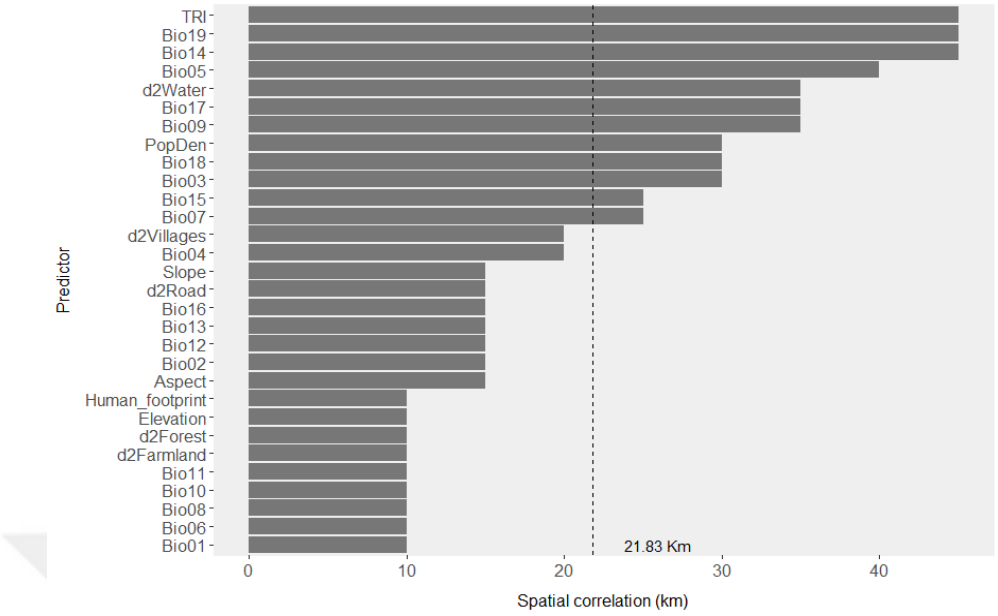

Figure 2.3: Minimum and average (dashed line) non-significant autocorrelated distances of variable predictors.

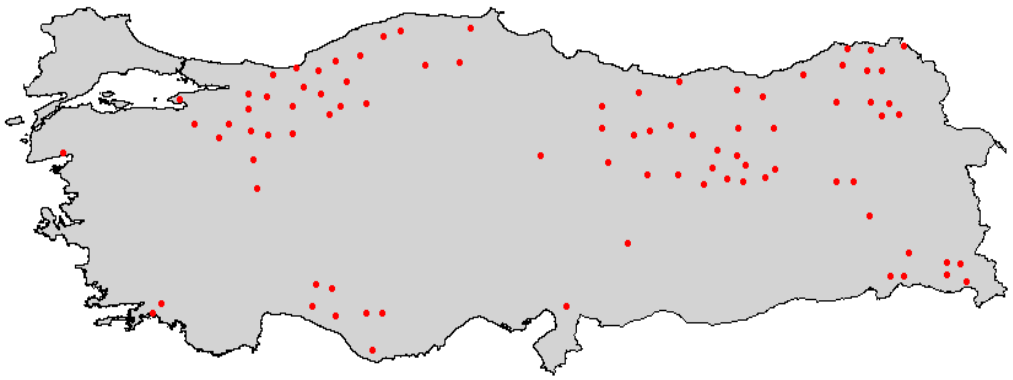

Figure 2.4: The presence records as a final dataset (n = 97) after spatial filtering.

2.2.2. Environmental Variables

Table 2.1: Environmental variables used for ecological niche modeling of brown bears in Türkiye. The bold variables were selected to run the final model.

Category	Database	Predictors	Unit	Source
Bioclimatic	Worldclim	**BIO1, Annual Mean Temperature**	°C	https://www.worldclim.org/data/cmip6/cmip6_clim2.5m.html
		BIO2, Mean Diurnal Range	°C	
		BIO3, Isothermality	-	
		BIO4, Temperature Seasonality	°C	
		BIO5, Max Temperature of Warmest Month	°C	
		BIO6, Min Temperature of Coldest Month	°C	
		BIO7, Temperature Annual Range	°C	
		BIO8, Mean Temperature of Wettest Quarter	°C	
		BIO9, Mean Temperature of Driest Quarter	°C	
		BIO10, Mean Temperature of Warmest Quarter	°C	
		BIO11, Mean Temperature of Coldest Quarter	°C	
		BIO12, Annual Precipitation	mm	
		BIO13, Precipitation of Wettest Month	mm	
		BIO14, Precipitation of Driest Month	mm	
		BIO15, Precipitation Seasonality	-	
		BIO16, Precipitation of Wettest Quarter	mm	
		BIO17, Precipitation of Driest Quarter	mm	
		BIO18, Precipitation of Warmest Quarter	mm	
		BIO19, Precipitation of Coldest Quarter	mm	
Topographic	SRTM	Elevation	m	https://www.worldclim.org/data/worldclim21.html
		Aspect	Radians	
		Slope	Radians	
		Terrain Ruggedness Index (TRI)	-	
Anthropogenic	Corine Land Use Land Cover 2018	**Distance to farmland**	km	https://land.copernicus.eu/pan-european/corine-land-cover/clc2018
		Distance to forest	km	
	Open Street Map	**Distance to road**	km	http://download.geofabrik.de/europe/turkey.html
	-	**Distance to villages**	km	
	HydroRIVERS - HydroSHEDS	**Distance to water**	km	https://www.hydrosheds.org/products/hydrorivers
	SEDAC	**Population Density**	No.of people/km2	https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11
		Human Footprint Index	HFI	https://sedac.ciesin.columbia.edu/data/set/wildareas-v3-2009-human-footprint

The ENM incorporated various environmental predictors including climatic, topographic, and anthropogenic variables (Table 2.1). I sourced 19 bioclimatic layers from the Worldclim database (Fick & Hijmans, 2017) with 2.5 arc-min resolution (approximately 4.6 km at the equator). It is known that the spatial resolution of environmental variables affects ENM performance (Wenger & Olden, 2012; Gillingham et al., 2012). This resolution was chosen considering the size of the study area and the dispersal ability of the brown bear, which is a generalist species with a relatively high adaptation to environmental change. Topographic variables, including Elevation, Slope, Aspect, and Terrain Ruggedness Index (TRI), were

derived from the Shuttle Radar Topography Mission (SRTM) elevation data (http://www.worldclim.org/). Due to the difference between Euclidean distance and arc distance, it is important to calculate topographic variables in the appropriate coordinate system (Sillero & Barbosa, 2021). Therefore, the Slope, Aspect, and TRI (Riley et al., 1999) rasters were derived after projecting to Lambert Azimuthal Equal-Area (ETRS 1989 LAEA), then projected again in WGS84.

Anthropogenic factors that had the potential to influence the distribution of brown bears were also taken into account as distal variables. These included Distance to Farmland, Distance to Forest, Distance to Roads, Distance to Villages, and Distance to Water sources, as well as Population Density and the Human Footprint Index (HFI). I generated Forest and Farmland layers by using the Corine Land Use Land Cover 2018 Vector Dataset (CLC, 2018). To generate the Forest layer, I combined *Broad-leaved forest*, *Coniferous forest*, *Mixed forest*, and *Transitional woodland/shrub* attributes and extracted these layers. To generate the Farmland layer, I combined the attributes named *Non-irrigated arable land*, *Permanently irrigated land*, *Rice fields*, *Vineyards*, *Fruit trees and berry plantations*, *Olive groves*, *Pastures*, *Annual crops associated with permanent crops*, *Complex cultivation patterns*, *Land principally occupied by agriculture with significant areas of natural vegetation*, *Agro-forestry areas*, and extracted these layers. Then, I generated the proximity layers named Distance to Forest and Distance to Farmland using the Euclidean Distance Tool in ArcGIS by arranging their cell size and extent. I selected and extracted 1st to 4th "order river" attributes from the HydroRIVERS database (Lehner & Grill, 2013) since this vector layer appropriately covers all water sources across the country, from small springs in/around forests and agricultural fields to large rivers. I selected the *motorways*, *primary*, *secondary*, and *trunk* roads and their *linked roads* attributes from the Open Street Map. I generated the proximity layers named Distance to waters and Distance to roads by using the Euclidean Distance Tool in ArcGIS. I obtained the Population Density and the Human Footprint Index (HFI) rasters (Venter et al., 2016) from the Socioeconomic Data and Application Center (SEDAC) database. All variables were properly resampled, cropped, and masked based on the study area.

2.2.3. Multicollinearity

To account for multicollinearity among the occurrence data frame, data was analyzed using R (*version* 4.2.2). Variables exhibiting a correlation coefficient greater than 0.7 and a

variance inflation factor exceeding 10 were excluded from further analysis. This process was conducted using the *corrplot* (Wei & Simko, 2021) and *usdm* packages (Naimi,2023). Following this, sixteen variables were retained for subsequent modeling, including Distance to Forest, Distance to Farmland, Distance to Roads, Distance to Villages, Distance to Water, Population Density, Human Footprint, Aspect, Slope, TRI, Annual Mean Temperature (BIO1), Mean Diurnal Range (Mean of monthly (max temp - min temp)) (BIO2), Isothermality (BIO3), Mean Temperature of the Wettest Quarter (BIO8), Mean Temperature of the Driest Quarter (BIO9), and Annual Precipitation (BIO12).

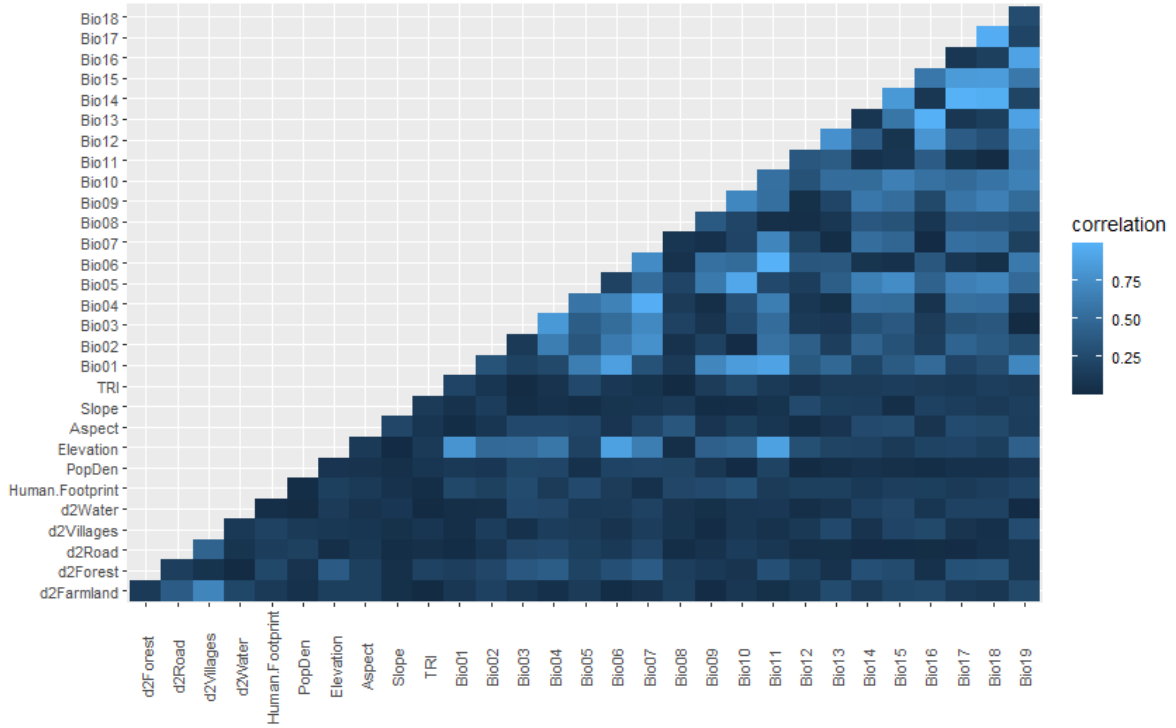

Figure 2.5: Correlation matrix of environmental predictors for ecological niche modeling.

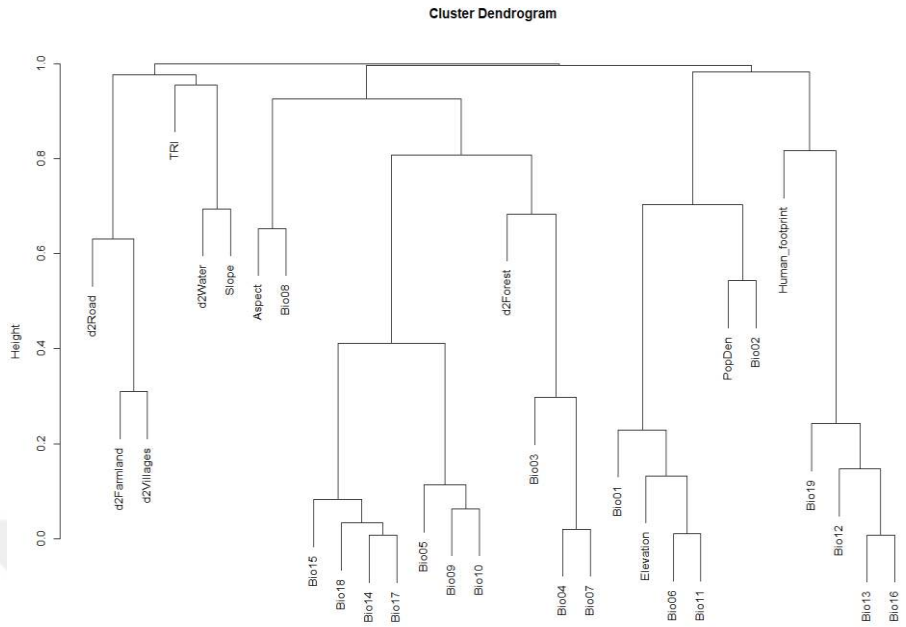

Figure 2.6: Cluster dendrogram of environmental predictors for ecological niche modeling.

2.2.4. Future Forecasting

ENM makes it possible to evaluate the potential ecological niche of the target species. For future projections, I downloaded bioclimatic variables with a resolution of 2.5 arc-minutes from WorldClim 2.1., based on the CMIP6 (Coupled Model Intercomparison Project Phase 6) data, as featured in the sixth assessment report (AR6) of the IPCC (IPCC, 2023). General circulation models (GCMs) are mathematical models generated by considering the dynamics of atmospheric and oceanic parameters across the planet and account for various energy sources, e.g., radiation, throught the Naiver-Stokes equations (Temam, 2024). These inputs are then used to simulate the Earth's atmosphere (Rogelj, 2013). In this part, I choose three widely used GCMs; MIROC6 (Watanabe et al., 2020), CNRM-CM6-1 (Voldoire et al., 2020), and MPI-ESM1-2-LR (Giorgetta et al., 2020) since they were already experienced to predict accurate ENMs across Europe in other studies (Canturk & Kulaç, 2021; Gür, 2022; Naimi et al., 2022). The main differences between these GCMs are their resolution, the numerical methods they use, and the climate parameters (IPCC, 2023). The mentioned GCMs simulate the atmosphere and ocean data and provide different resolutions in polar and equatorial regions.

For all three GCMs, I downloaded three different Shared Socio-economic Pathways/Representative Concentration Pathway climate change scenarios including

SSP1/RCP2.6 as an optimistic future, SSP3/RCP7.0 as a moderate future and SSP5/RCP8.5 as a pessimistic future for both 2050 (average for 2041-2060) and 2070 (average for 2061-2080) to project future habitat suitability. In the optimistic scenario based on lower emissions, average temperatures are expected to increase by 2 ºC by 2100, while in the pessimistic scenario based on the highest emissions, average temperatures are estimated to increase by 5.5 ºC by 2100 (Pant et al., 2021).

2.2.5. Ecological Niche Modeling

Species distribution modeling literature, which has been growing rapidly over the last decade in particular, offers a fairly wide range in the number of modeling techniques. However, the differences between models can be dramatic, depending on the technique being used. Therefore, choosing suitable models might be difficult. The ensemble approach significantly increases the prediction performance by combining results from different modeling techniques and thus presents the relationships that are aimed to be captured by the model by separating them from background noise (Hao et al., 2020). To predict both current and future potential distributions of brown bears across Türkiye, I employed an ensemble forecasting approach using the *biomod2* package in R *v4.2.2.* (Thuiller et al., 2009). *Biomod2* is a versatile modeling platform capable of integrating up to ten distinct modeling algorithms, resulting in an ensemble model. I applied statistical and machine learning models, including Generalized Linear Model (GLM) (McCullagh & Nelder, 1989), Generalized Additive Model (GAM) (Hastie & Tibshirani, 2017), Maximum Entropy (Maxent) (Phillips et al., 2017), Random Forest (RF) (Breiman, 2001), Artificial Neural Network (ANN) (Lek & Guégan, 1999), Multivariate Adaptive Regression Spline (MARS) (Leathwick et al., 2015), Generalized Boosted Model (GBM) (De'ath, 2007), Classification Tree Analyses (CTA) (Vayssières et al., 2000), Flexible Discriminant Analysis (FDA) (Hastie et al., 1994), and Surface Response Envelope (SRE) (Busby, 1991). While some of the algorithms are regression-based, some are machine learning-based. Reproducing ENM results is important and depends on the processing of occurrence data, environmental data and their processing, model calibration, and repeatability of model transfer processes (Feng et al., 2019). Therefore, the default settings of the algorithms were selected to simplify the interpretation and reproducibility of the results.

The modeling process began with the random generation of 1,000 pseudo-absence points (Pant et al., 2021). It is known that ENMs are affected by the number of pseudo-absences

(Barbet-Massin et al., 2012). There is an intense discussion on this issue in the literature (Barbet-Massin et al., 2012; Sillero et al., 2021; Kanagaraj et al., 2013; Wisz & Guisan, 2009; Papeş & Gaubert, 2007). There are some studies suggesting the use of varying numbers of pseudo-absence for regression and classification techniques (Franklin et al., 2010); therefore, there is no definitive rule (Wisz & Guisan, 2009). However, the pseudo-absence number depends on the extent of species distribution and it must capture environmental variability in the study area, especially for generalist species. Subsequently, the dataset was split into training (80%) and testing (20%) (Pant et al., 2021). I conducted three cross-validation iterations using a bootstrap approach for each model, and pseudo-absence points were generated three times to mitigate random bias (Thuiller et al., 2009). Although pseudo-absence points were randomly generated throughout the entire environmental space, this approach was used to prevent false-absence generation that affects model performance (Bedia et al., 2013).

The predictive performance of ENMs is evaluated by considering classification capacity, discrimination capacity, and calibration capacity (Sillero et al., 2021). Classification capacity, which is the ability of the model to correctly classify occupied areas and non-occupied areas by considering a threshold is measured by metrics such Cohen's Kappa and True Skill Statistics (TSS) (Allouche et al., 2006). To assess discriminatory capacity, I employed TSS, a prevalence-independent metric for species data (Allouche et al., 2006). TSS considers both omission and commission errors, yielding values between -1 (no better than random) and +1 (perfect agreement). Discrimination capacity, which measures the comparison of occupied vs. non-occupied areas, is evaluated by considering the Area Under the Curve (AUC) in the plot of Receiver Operating Characteristic (ROC). The AUC value has a range between 0.5 and 1. While a value of 0.5 indicates that the model does not give a better result than random chance, a closer value to 1 indicates a better model performance (Hosmer Jr. et al., 2013). *Biomod2* offers the opportunity to choose from individual models based on different algorithms (Hao et al., 2020). To reduce uncertainty and generate a final model, I selected models with TSS scores greater than 0.6, using a weighted average approach (Araújo and New, 2007; Thuiller et al., 2009). Subsequently, I produced 19 ensemble maps encompassing three distinct GCMs and scenarios for two time periods (i.e., 2050s and 2070s) in addition to the present day. Binary transformation was performed using a threshold that maximizes TSS to generate predictive outputs (Thuiller et al., 2019). The consensus method, based on the weighted approach, increases model accuracy (Marmion et al., 2009) and creates a binary map depicting occupied and non-occupied areas,

taking into account the threshold value (Thuiller et al., 2009). To analyze changes in the range size between current and future scenarios, I generated output rasters depicting gain (range expansion), stable (no change), no occupancy, and loss (range contraction) areas through a comparative analysis of binary maps.

To quantify the changes in habitat range by latitude, I utilized the top 65th percentile of probability maps for each scenario (average of three GCMs) for both 2050 and 2070. I converted these rasters to polygons, and I generated 500 random points within each polygon using the Create Spatially Balanced Points tool in ArcGIS, as well as occupied areas for the present day. I analyzed the mean values of the points for longitude and latitude to assess the spatial variance of suitable habitats. Additionally, I categorized suitable habitats into four elevational ranges: i) < 1000 m, ii) 1000-2000 m, iii) 2000 – 3000 m, iv) > 3000 m to investigate the altitude-related shifts in suitable patches.

Lastly, I evaluated the status of established protected areas for both current and future projections, based on an average of three GCMs. There are various PA classifications in Türkiye (Birben, 2020; NCNP, 2022). Therefore, I selected the related PA types in terms of their relevance for brown bear ecology and extracted them as follows: *National parks*, *Nature conservation areas*, *Special environment protection areas*, *Wildlife enhancement areas*, *Locally important wetlands*, *Nationally important wetlands*, *RAMSAR areas*, and *Protection forests*. These types represent 71% of the protected areas across Türkiye.

2.3. Results

2.3.1. Current Potential Distribution of Brown Bears

Ten ecological niche models evaluated varied in their predictive performance, with SRE, GAM, and CTA exhibiting the lowest AUC values, and SRE, GAM, and ANN demonstrating the lowest TSS values (Fig. 2.7). In contrast, GBM, RF, and GLM algorithms consistently exhibited the highest AUC and TSS values (Fig. 2.7). The ensemble model which combined the strengths of these algorithms, demonstrated excellent predictive ability, with an AUC of 0.92 and TSS of 0.71 (Fig. 2.7). The ensemble model's results indicated that approximately 20% of Türkiye's land area, totaling 156,712 square kilometers, is currently suitable for brown bear habitation. The most suitable habitats were predicted in the Euro-Siberian (47%), Irano-Turanian (43%), and Mediterranean (9%) biogeographic regions,

respectively (Fig. 2.8). Forests covered 49% of these suitable habitats, while farmlands comprised 17%.

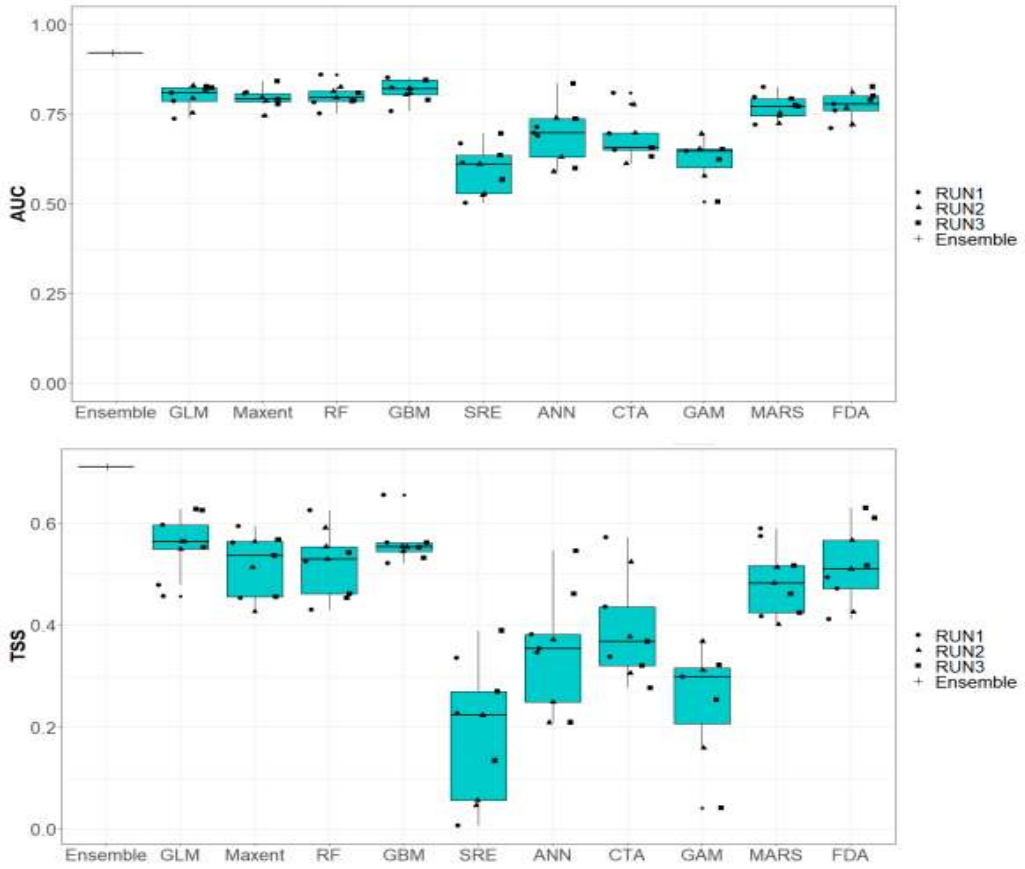

Figure 2.7: Receiver operating characteristic (ROC) area under the curve (AUC) (top) and True skill statistics (TSS) (bottom) values as the predictive performance of different modeling techniques used in the ecological niche modeling.

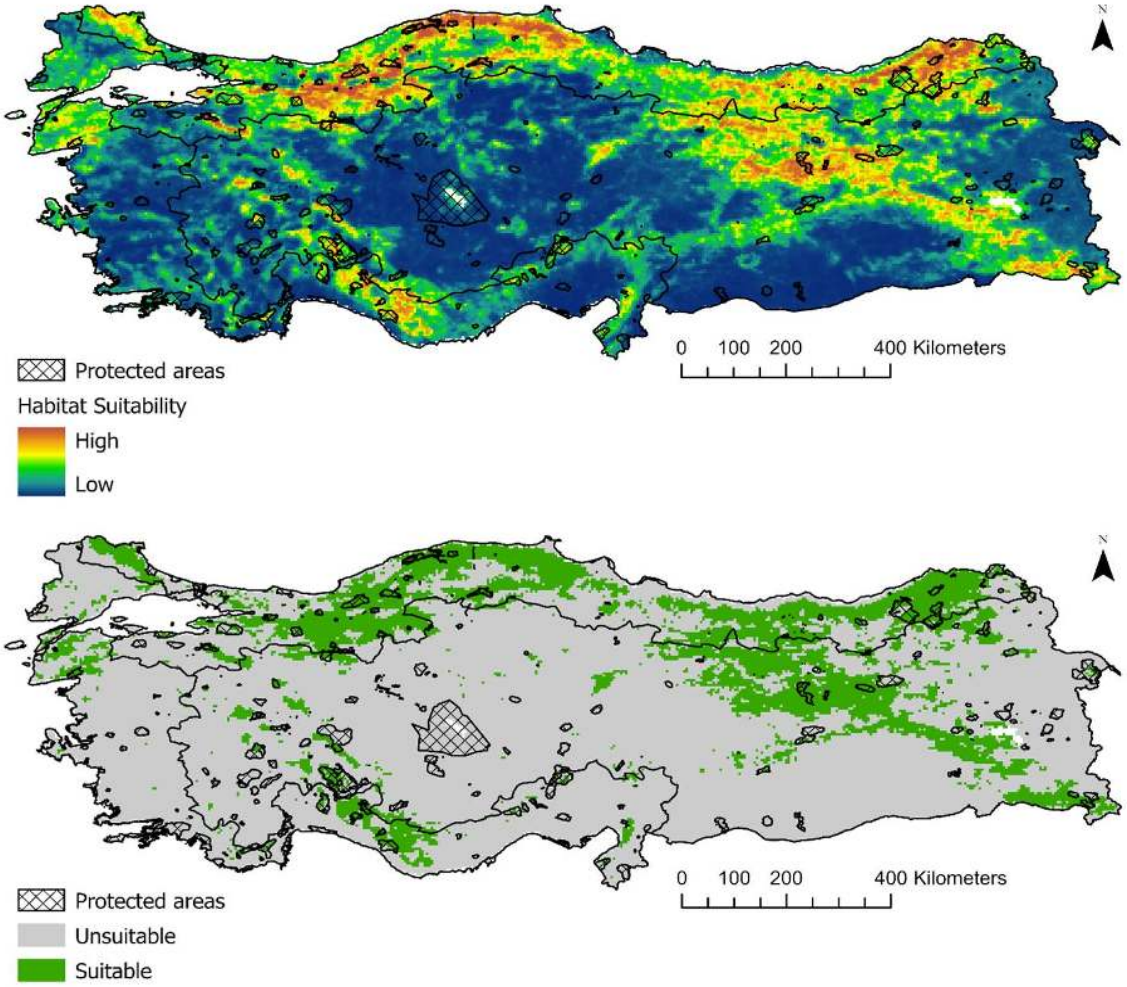

Figure 2.8: The potential current distribution of brown bears across Türkiye derived from the ensemble model (top); the binary map based on the current ensemble model for Türkiye (bottom).

Environmental variables played varying roles in the models. The Distance to Forest was the most influential variable, contributing 27%, followed by the Mean Diurnal Range (BIO2) at 17%, and Annual Mean Temperature (BIO1) and Isothermality (BIO3) at 10% each (Fig. 2.9). Brown bear presence probability decreased with increasing distance to forests (Fig. 2.10). Additionally, as human population density (1%) increased, bear presence probability decreased, aligning with expectations (Fig. 2.10). However, the Distance to Water (%2) and Distance to Villages (%0.2) had relatively lower importance (Fig. 2.9). The importance of Distance to Roads was 3%, and the Human Footprint was 1% (Fig. 2.9). Topographic variables including Aspect, TRI and Slope had the lowest importance (Fig. 2.9). Among bioclimatic variables, Isothermality (BIO3) (10%), Mean Temperature of the Wettest Quarter (BIO8) (5%), and Mean Temperature of the Driest Quarter (BIO9) (2%) negatively influenced brown bear presence

probability. Interestingly, Annual Mean Temperature (BIO1) and Mean Diurnal Range (BIO2) showed optimum values for brown bear presence probability at around 7°C and ~9°C, respectively (Fig. 2.10).

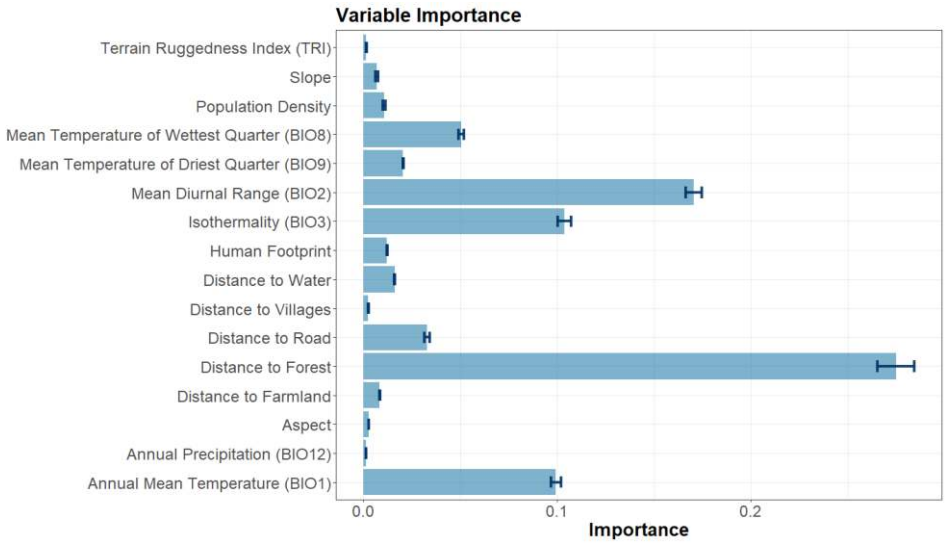

Figure 2.9: Percent contribution of environmental predictors to the final ensemble model for ecological niche modeling of brown bears across Türkiye.

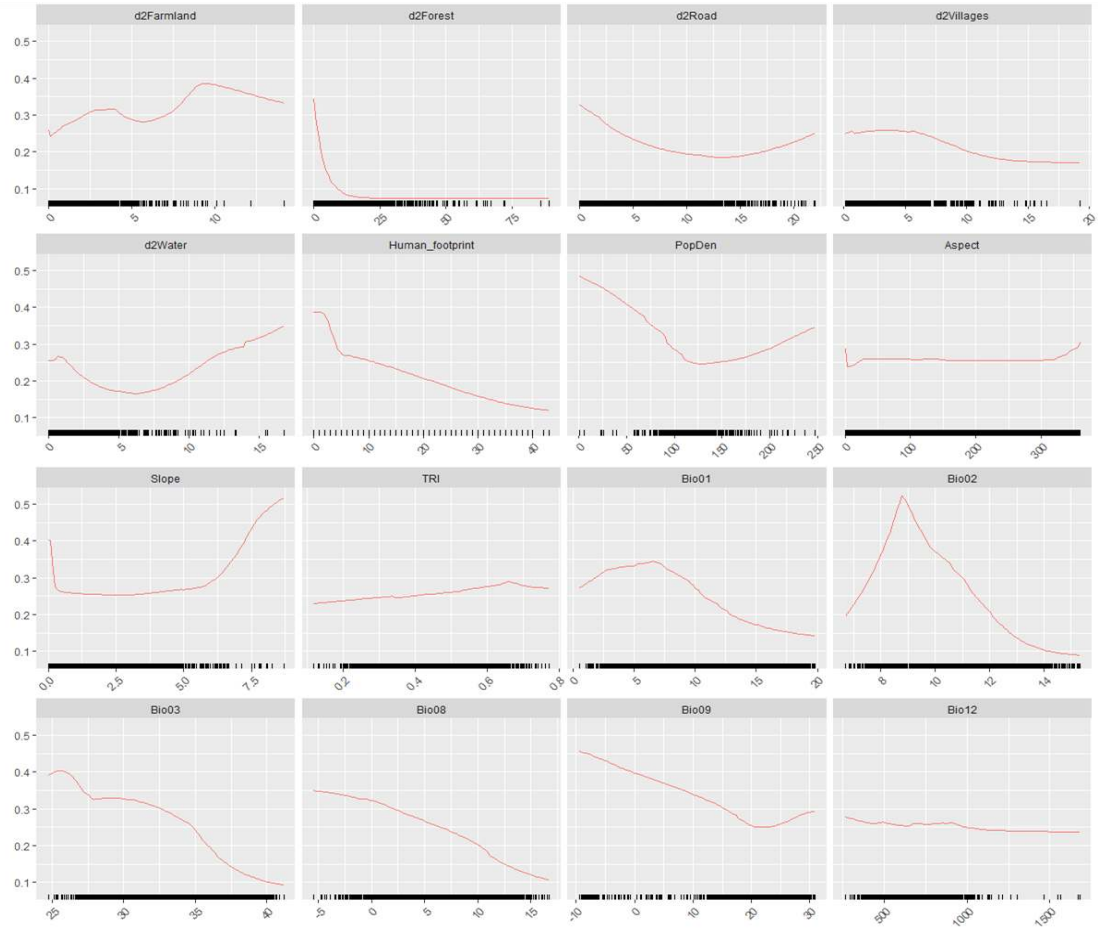

Figure 2.10: Response curves of the environmental predictors in the ensemble model for ecological niche modeling of brown bears across Türkiye.

To predict the potential distribution of brown bear for present day, firstly, I used the static anthropogenic predictors in addition to dynamic bioclimatic variables. However, this could have led to more conservative estimates. Therefore, I decided to improve another ensemble model by using only bioclimatic variables. While doing this, I kept all model settings and package versions the same. While this *bioclimatic ensemble model* showed a much more optimistic estimate (Fig. 2.11), it offered much lower model accuracy metrics compared to the previous model involving anthropogenic variables. For instance, the AUC and TSS values of the previous ensemble model were 0.92 and 0.71, respectively, while the AUC and TSS values of the *bioclimatic ensemble model* were 0.84 and 0.58, respectively. While the *bioclimatic ensemble model* included the BIO15 (Precipitation Seasonality) variable in addition to the ones of the previous model, the importance of the variables also differed (Fig. 2.12). While the ensemble model, including anthropogenic variables, emphasized that ~20% of the country represents the suitable habitat for brown bears, this ratio increased to 27% of the country in the

bioclimatic ensemble model (Fig. 2.11). Therefore, the rest of the discussion is based on the ensemble model, in which anthropogenic variables were included, as it provides more robust predictions, and the outputs of this ensemble model will be used as input in the next chapter of the thesis.

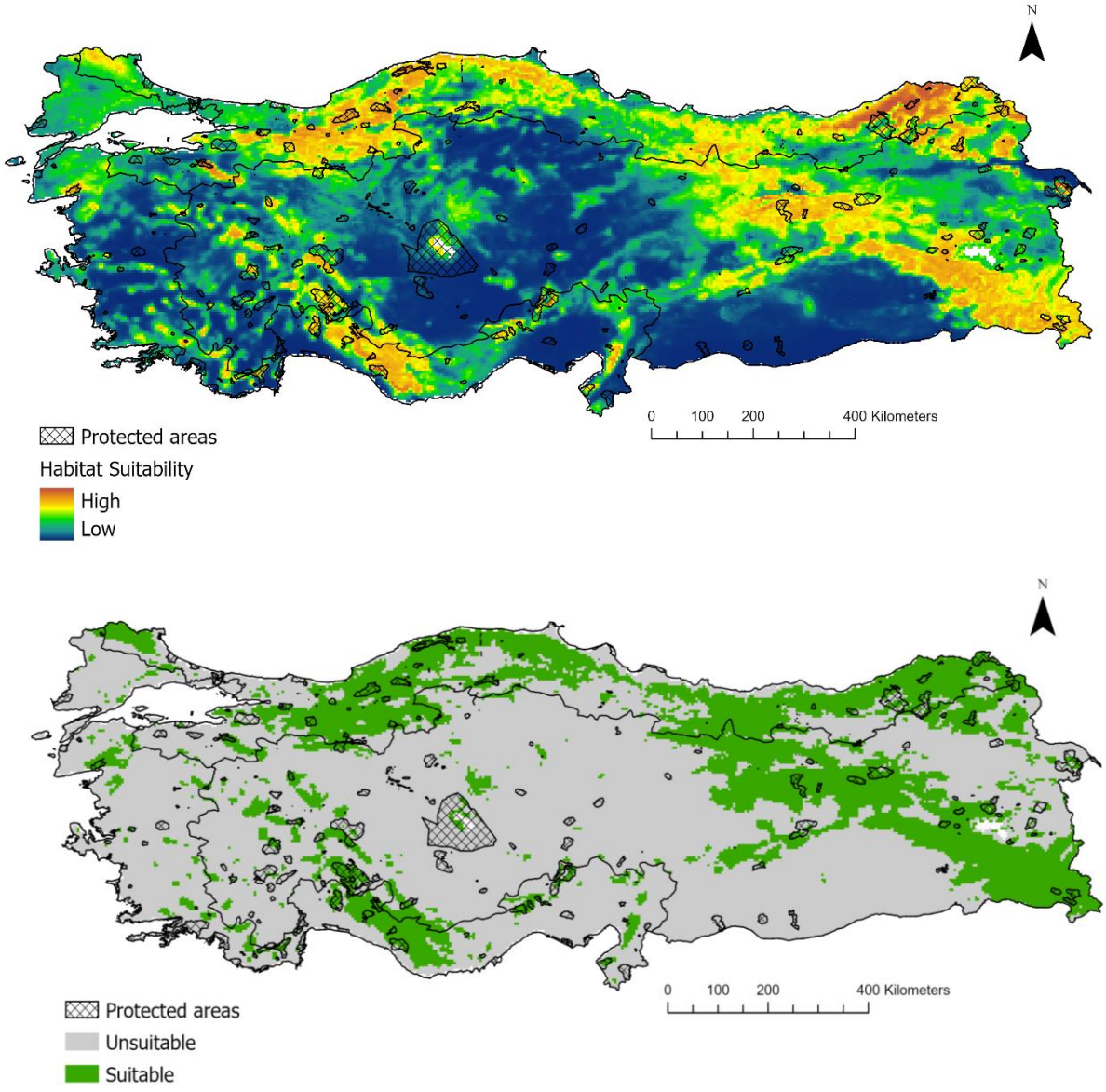

Figure 2.11: The potential current distribution of brown bears across Türkiye derived from the bioclimatic ensemble model (top); the binary map based on the bioclimatic ensemble model for Türkiye (bottom).

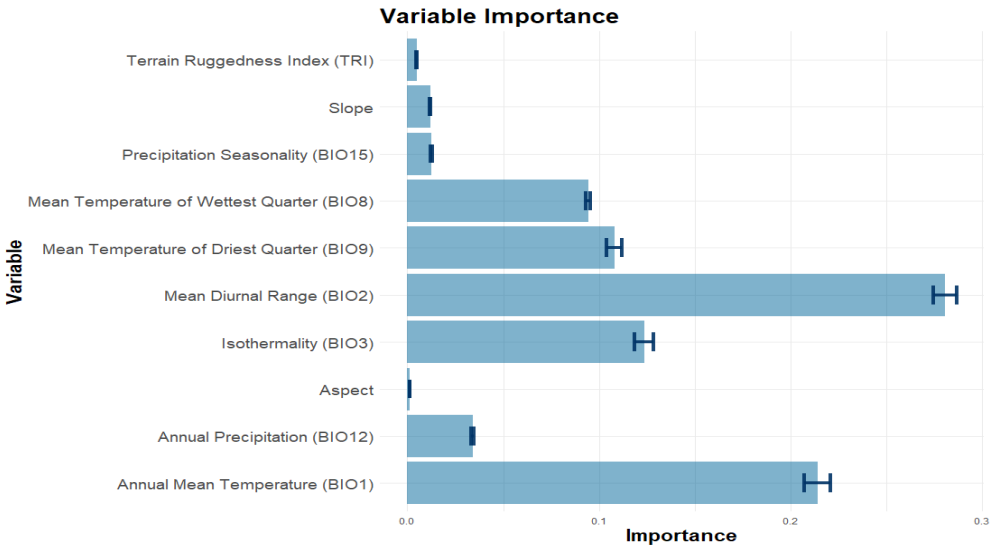

Figure 2.11: Percent contribution of bioclimatic predictors to the bioclimatic ensemble model.

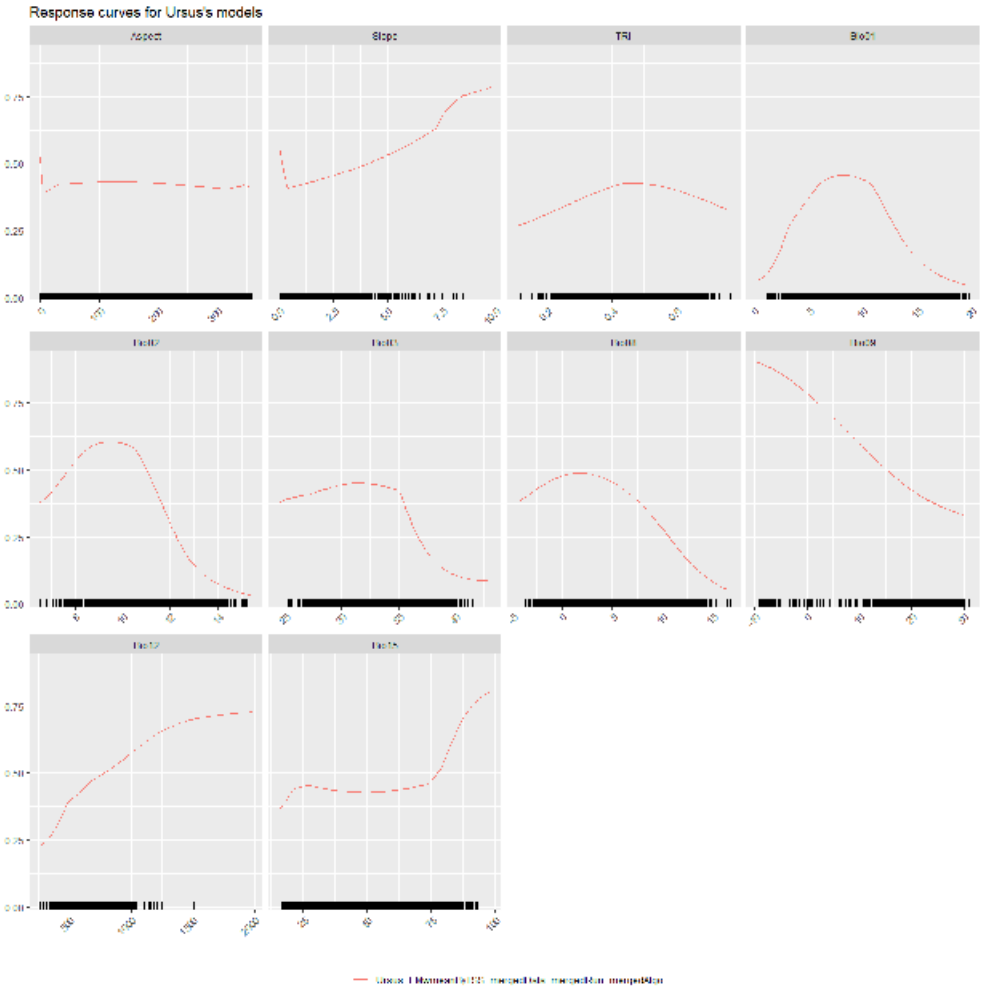

Figure 2.12: Response curves of the environmental predictors in the bioclimatic ensemble model.

2.3.2. Potential Future Habitat Suitability for Brown Bears

These findings suggest that brown bears' suitable habitats face considerable vulnerability to climate change. The most susceptible predictions among GCMs in terms of potential habitat suitability of brown bears in 2050 and 2070 were MIROC6, CNRM-CM6-1, and MPI-ESM1-2-LR models, respectively (Fig. 2.13, Fig. 2.14). Under an optimistic scenario, habitat loss in 2050 ranged from 30% (MPI-ESM1-2-LR) to 56% (MIROC6), while in the pessimistic scenario, it ranged from 37% (MPI-ESM1- 2-LR) to 65% (MIROC6) (Fig. 2.14, Table 2.2). The situation worsened in 2070, with habitat loss ranging from 50% (MPI-ESM1-2-LR) to 82% (MIROC6) under the pessimistic scenario (Fig. 2.13, Fig. 2.14, Table 2.2). However, the rate of range expansion remained relatively low, with habitat gain ranging from 0.2% to 1% in 2050 (Table 2.2). In 2070, while the percentage of gain areas increased slightly under the optimistic and moderate scenarios, it remained low in the pessimistic scenario (Table 2.2). Despite some potential for habitat gain, the overall outlook indicated a significant range contraction in all scenarios.

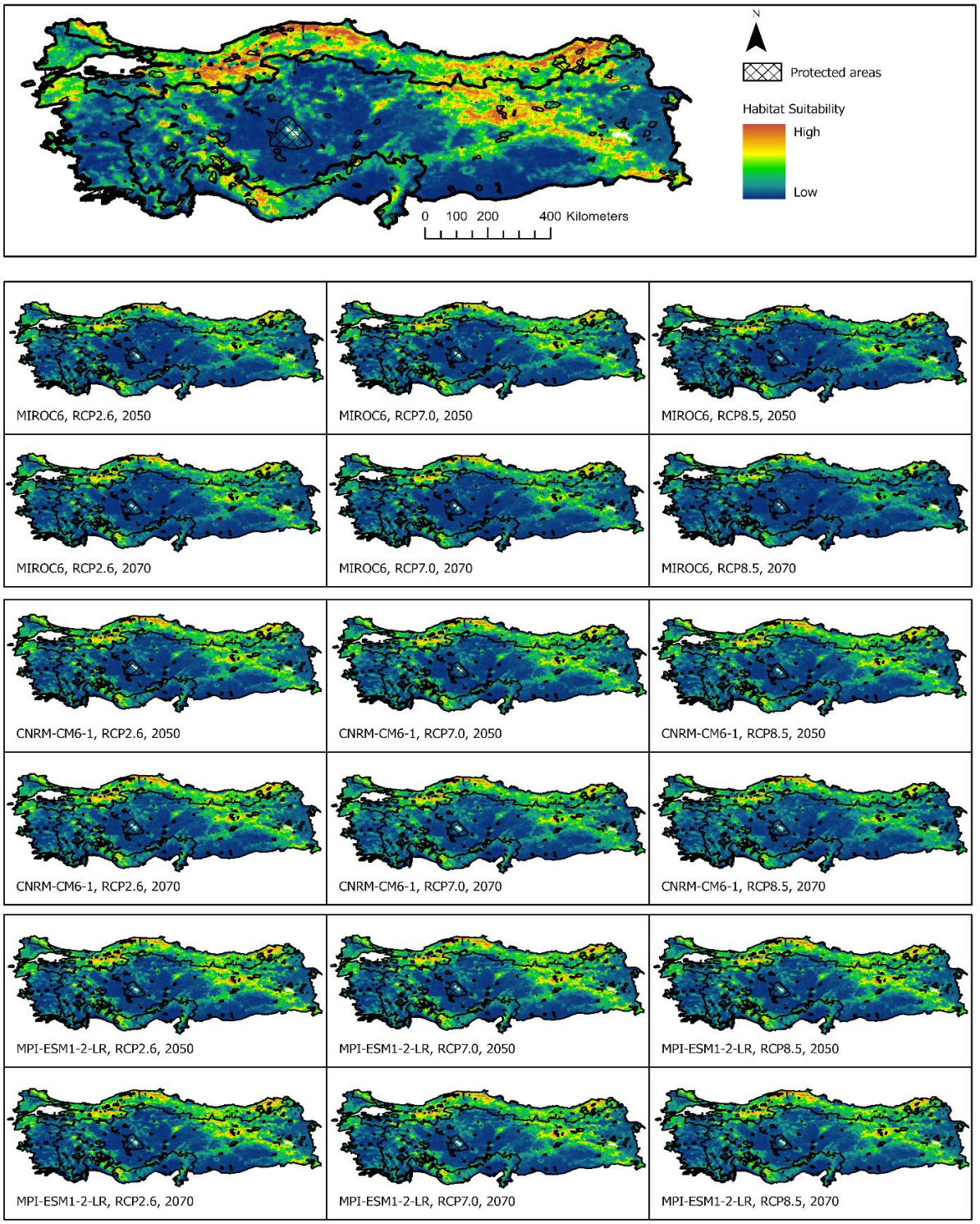

Figure 2.13: Habitat suitability maps of brown bears in Türkiye derived from MIROC6, CNRM-CM6-1, and MPI-ESM1-2-LR GCMs by considering the optimistic (RCP 2.6), moderate (RCP 7.0), and pessimistic (RCP 8.5) future scenarios for 2050 and 2070.

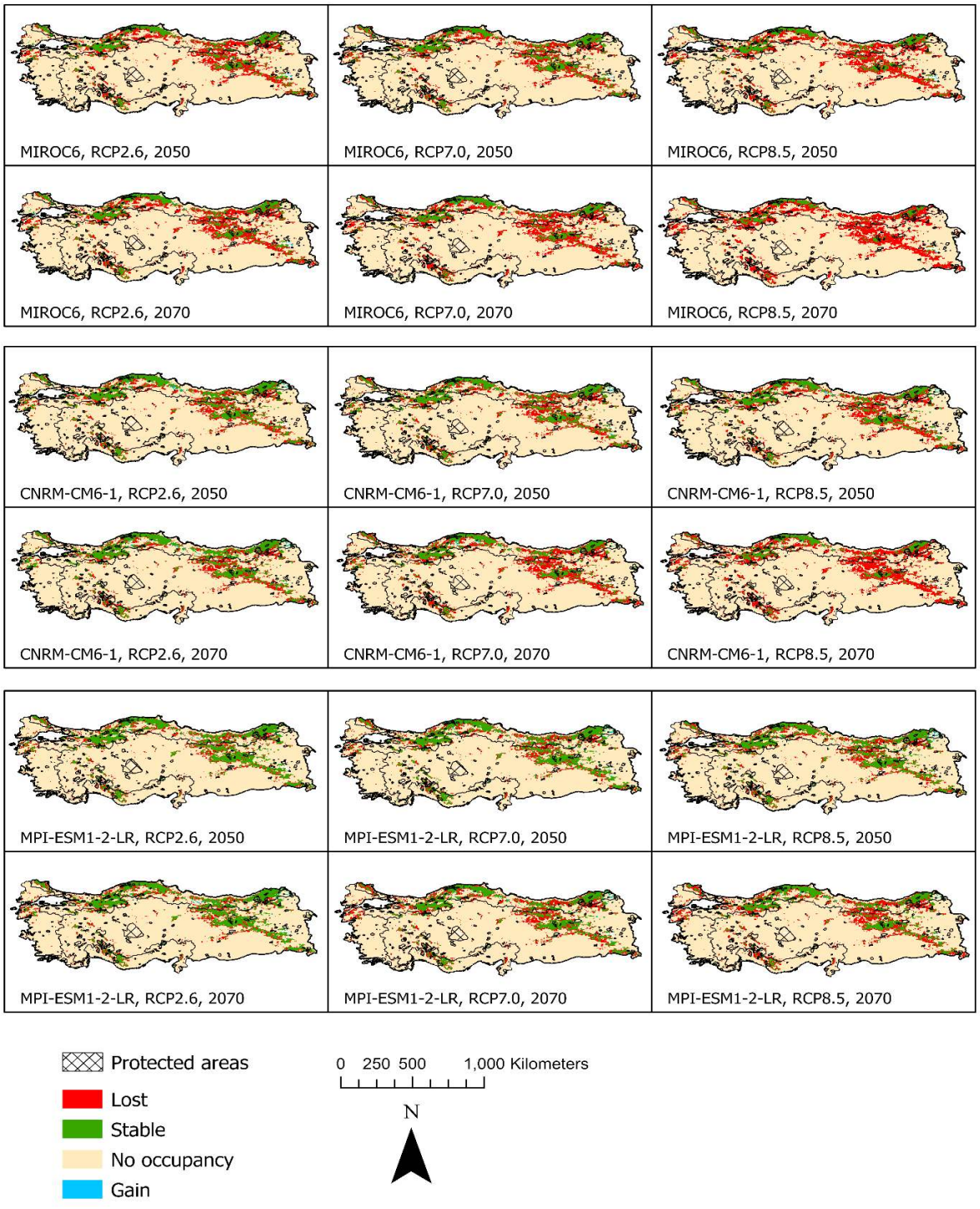

Figure 2.14: Ensemble forecasting of the future range change by considering optimistic (RCP 2.6), moderate (RCP 7.0), and pessimistic (RCP 8.5) scenarios for brown bears of Türkiye in both 2050 and 2070 based on MIROC6, CNRM-CM6-1, and MPI-ESM1-2-LR GCMs.

Table 2.2: Future potential habitat suitability in the whole country for three different GCMs by considering optimistic (RCP 2.6), moderate (RCP 7.0) and pessimistic (RCP 8.5) scenarios.

		MIROC6				CNRM-CM6-1				MPI-ESM1-2-LR			
Time	**Scenario**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**
2050	RCP 2.6	56.79	0.30	42.92	-56.49	42.20	0.97	56.83	-41.23	30.66	0.51	68.84	-30.15
	RCP 7.0	51.01	0.16	48.84	-50.85	45.64	0.73	53.64	-44.91	34.24	1.30	64.47	-32.94
	RCP 8.5	65.29	0.21	34.50	-65.08	50.92	0.67	48.40	-50.25	38.28	0.89	60.83	-37.40
2070	RCP 2.6	58.82	0.44	40.74	-58.38	39.63	1.04	59.33	-38.59	31.76	0.97	67.27	-30.80
	RCP 7.0	63.63	0.28	36.08	-63.35	55.64	0.72	43.64	-54.92	43.59	1.00	55.41	-42.59
	RCP 8.5	82.33	0.06	17.61	-82.26	70.77	0.16	29.07	-70.62	50.33	0.62	49.05	-49.71

Table 2.3: Future potential habitat suitability in three biogeographic regions of Türkiye for both 2050 and 2070 by considering optimistic (RCP 2.6), moderate (RCP 7.0) and pessimistic (RCP 8.5) scenarios.

2050		**Euro-Siberian**				**Irano-Turanian**				**Mediterranean**			
GCM	**Scenario**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**
CNRM-CM6-1	**RCP 2.6**	32.80	1.80	65.4	-31.00	51.57	0.22	48.22	-51.35	46.56	0.22	53.11	-46.34
	RCP 7.0	37.40	1.18	61.42	-36.22	54.21	0.34	45.45	-53.86	47.89	0.22	51.88	-47.67
	RCP 8.5	41.27	1.16	57.58	-40.11	60.73	0.27	39.00	-60.47	54.66	0.11	45.23	-54.55
MPI-ESM1-2-LR	**RCP 2.6**	25.84	0.78	73.38	-25.07	32.30	0.29	67.41	-32.01	47.34	0.11	52.55	-47.23
	RCP 7.0	30.04	1.89	68.07	-28.16	35.92	0.86	63.23	-35.06	47.56	0.33	52.11	-47.23
	RCP 8.5	32.02	1.36	66.62	-30.67	41.42	0.51	58.07	-40.91	55.32	0.22	44.46	-55.10
MIROC6	**RCP 2.6**	47.47	0.16	52.38	-47.31	66.50	0.29	33.20	-66.21	59.20	0.89	39.91	-58.31
	RCP 7.0	43.40	0.16	56.44	-43.24	58.44	0.17	41.39	-58.26	55.32	0.11	44.57	-55.21
	RCP 8.5	53.58	0.09	46.33	-53.49	77.09	0.29	22.62	-76.80	70.18	0.33	29.49	-69.85
2070		**Euro-Siberian**				**Irano-Turanian**				**Mediterranean**			
GCM	**Scenario**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**	**Loss (%)**	**Gain (%)**	**Stable (%)**	**Range Change (%)**
CNRM-CM6-1	**RCP 2.6**	27.93	1.91	70.16	-26.02	51.37	0.29	48.34	-51.08	44.68	0.11	55.21	-44.57
	RCP 7.0	43.02	1.18	55.80	-41.84	68.51	0.29	31.20	-68.22	60.20	0.22	39.58	-59.98
	RCP 8.5	57.24	0.31	42.45	-56.93	83.91	0	16.09	-83.91	78.71	0.11	21.18	-78.60
MPI-ESM1-2-LR	**RCP 2.6**	26.36	1.49	72.16	-24.87	33.99	0.59	65.43	-33.40	48.78	0.11	51.11	-48.67
	RCP 7.0	37.04	1.36	61.60	-35.69	47.48	0.78	51.74	-46.70	58.65	0.22	41.13	-58.43
	RCP 8.5	39.62	1.00	59.38	-38.62	57.41	0.34	42.25	-57.07	71.62	0.00	28.38	-71.62
MIROC6	**RCP 2.6**	48.11	0.24	51.65	-47.87	69.83	0.39	29.78	-69.44	62.31	1.55	36.14	-60.75
	RCP 7.0	50.64	0.49	48.87	-50.16	75.38	0.05	24.57	-75.33	75.17	0.22	24.61	-74.95
	RCP 8.5	71.82	0.00	28.18	-71.82	92.67	0.15	7.19	-92.52	87.92	0.00	12.08	-87.92

Table 2.4: The average range change of three different GCMs for each biogeographic region of Türkiye for both 2050 and 2070 by considering optimistic (RCP 2.6), moderate (RCP 7.0) and pessimistic (RCP 8.5) scenarios.

2050			
Scenario	**Euro-Siberian**	**Irano-Turanian**	**Mediterranean**
RCP 2.6	-34.46	-49.85	-50.63
RCP 7.0	-35.87	-49.06	-50.04
RCP 8.5	-41.42	-59.39	-59.83
2070			
RCP 2.6	-32.92	-51.30	-51.33
RCP 7.0	-42.56	-63.41	-64.45
RCP 8.5	-55.79	-77.83	-79.38

The gain areas in both future time points were primarily in the Euro-Siberian region, whereas the Mediterranean and Irano-Turanian regions showed lower gains (Table 2.3). On average across the three climate models, the Mediterranean, Irano-Turanian, and Euro-Siberian regions were projected to experience the most habitat loss for both 2050 and 2070, respectively (Fig. 2.15 & Table 2.3). Specifically, range contraction estimates for 2050 ranged from 34% to 41% for Euro-Siberian, 49% to 59% for Irano-Turanian, and 51% to 60% for the Mediterranean biogeographic regions depending on the scenario (Fig. 2.14, Table 2.3). In 2070, the situation was projected to be even more dire, with range contraction estimates of 32% to 56% for Euro-Siberian, 51% to 78% for Irano-Turanian, and 51% to 79% for Mediterranean regions of Türkiye (Fig. 2.14, Table 2.3). This implies that large portions of brown bear's suitable habitats, primarily in the Mediterranean and Irano-Turanian regions, are at risk of being lost in the near future.

The model revealed an interesting relationship between elevational ranges and potential habitat suitability, both in the present and the near future. Currently, 16% of suitable areas were below 1000 m, while 39% were found in each of the 1000-2000 m and 2000-3000 m elevational ranges, and 6% were above 3000 m (Fig. 2.15a). However, the proportion of suitable areas within these elevational ranges varied, with 11% below 1000 m, 17% in the 1000-2000 m range, 37% in the 2000- 3000 m range, and 27% above 3000 m currently representing suitable patches (Fig. 2.15a). Future projections based on the average of three GCMs suggested that potential habitat loss by 2050 will range from 46% to 71% for elevations below 1000 m, from 46% to 52% for the 1000-2000 m range, from 44% to 54% for the 2000-3000 m range, and from 32% to 41% for elevations above 3000 m, depending on the scenario (Fig. 2.15b). By 2070, the

potential habitat loss is expected to be even higher, with estimates ranging from 50% to 75% for elevations below 1000 m, from 47% to 63% for the 1000-2000 m range, from 46% to 75% for the 2000-3000 m range, and from 37% to 62% for elevations above 3000 m, depending on the scenario (Fig. 2.15b). These findings indicate that climate change will significantly affect brown bear habitat suitability at different elevational ranges. Moreover, the range shift of potentially suitable habitats suggests that climate change will alter the habitat suitability of brown bears by altitude (Fig. 2.15c), with a clear northward shift and to higher elevations in response to climate change effects (Fig. 2.16).

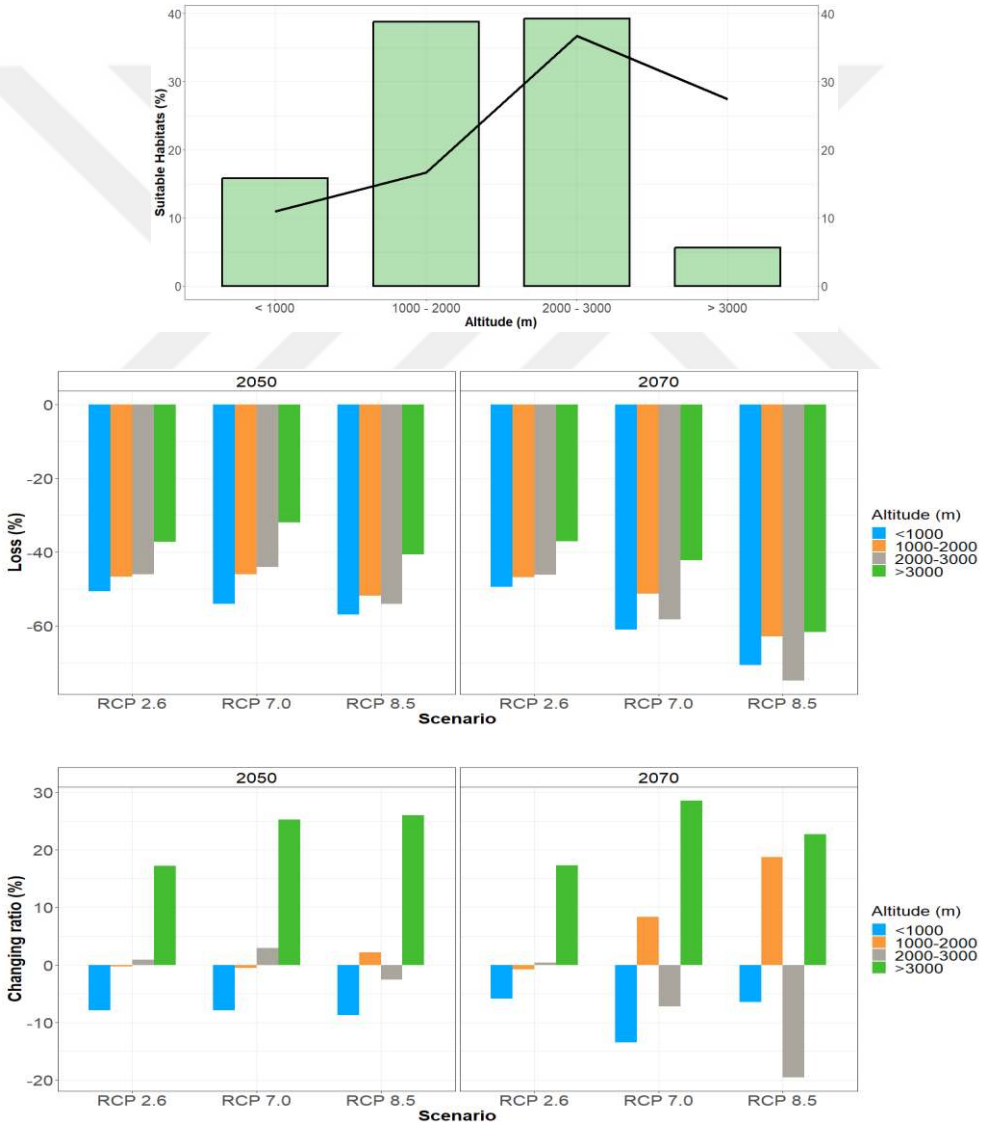

Figure 2.15: a) The ratio of various elevational ranges in suitable habitats (bar), and the ratio of suitable patches in various elevational ranges (line) for present day (top); b) the range contraction (-%) by altitude in future projections (mid); c) potential shifts (%) in suitable habitats by altitude for both 2050 and 2070 (bottom).

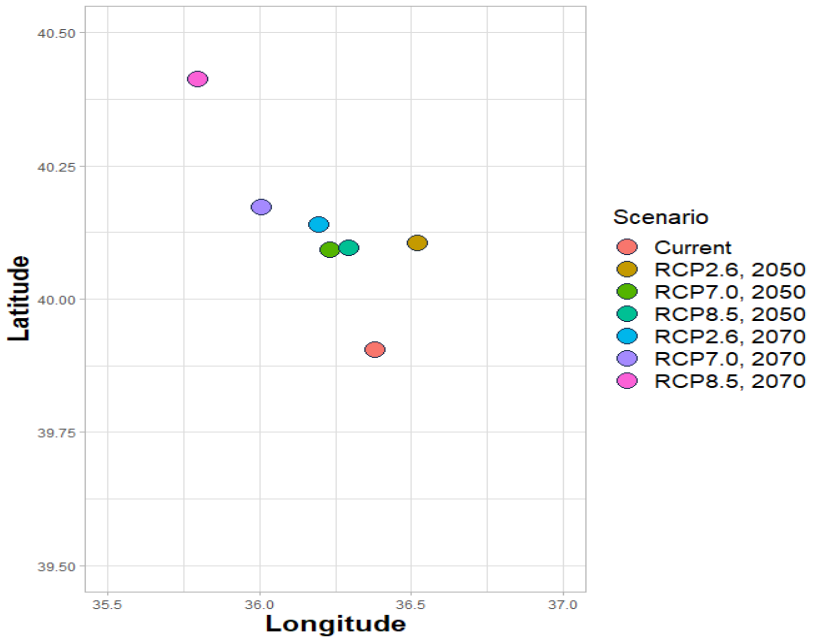

Figure 2.16: The spatial variation of the range in Türkiye of brown bears by considering current and different future scenarios. The distribution of brown bears exhibited a north shift in Türkiye under future projections.

2.3.3. Potential Habitat Suitability and Protected Areas

Currently, 25.27% of all suitable patches were within selected protected areas, but this overlapping proportion is expected to decrease in the future, varying between 16.94% - 17.14% in 2050 and 11.31% - 16.75% in 2070, depending on the scenario (Fig. 2.17a). Similarly, 6.99% of the selected protected areas in Türkiye are currently suitable for brown bears, but this ratio is projected to decrease from 4.34% to 4.74% in 2050 and from 3.13% to 4.63% in 2070 under different scenarios (Fig. 2.17b). These findings indicate that a conservation gap in the future will occur for suitable habitats of brown bears.

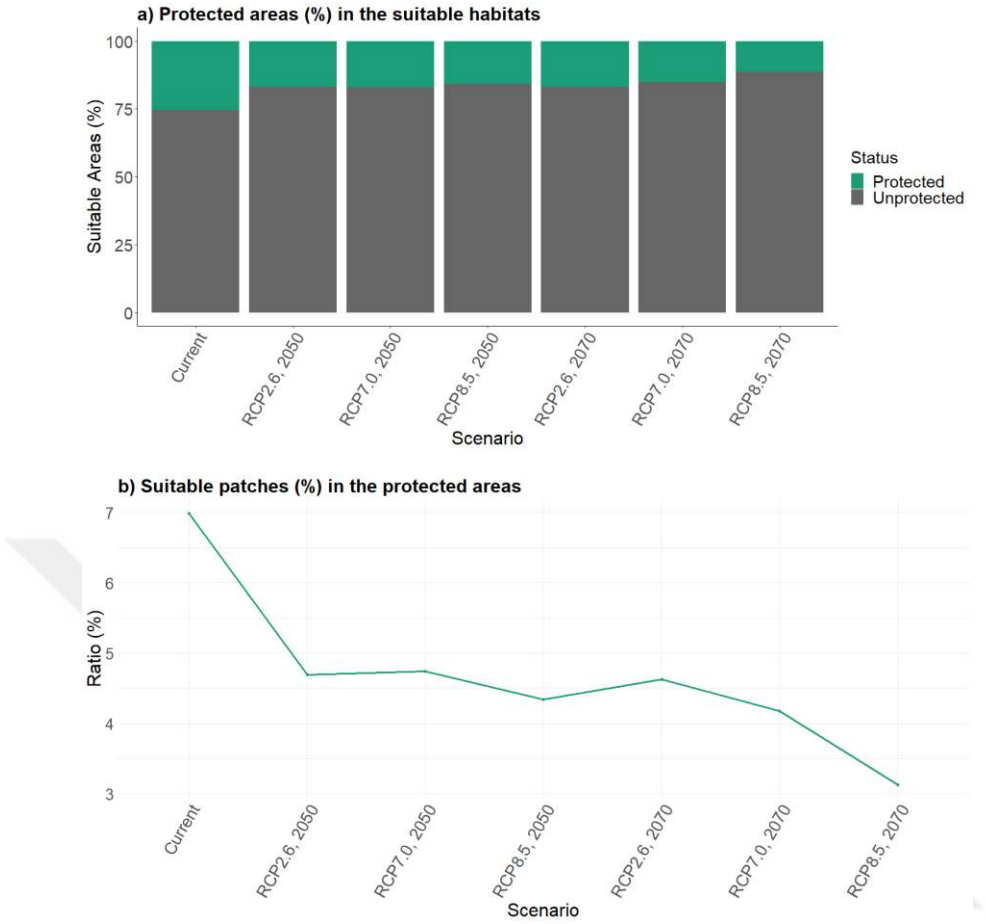

Figure 2.17: a) The protected area ratio in suitable habitats for both present day and future projections. b) Suitable habitats ratio in the selected established protected areas across the country for present day and future scenarios.

2.4. Discussion

Identifying the present and future distributions of species is critical to figuring out their interactions with the environment. In this way, we can learn the needs of species and understand their landscape responses to climate change and anthropogenic factors. In this study, I evaluated the distribution of brown bears in Türkiye with a high agreement using an ensemble model. While doing this, I used climatic, topographic, and human-related variables because these factors are important in evaluating the habitat condition of brown bears (Mateo- Sánchez et al., 2014; Dai et al., 2019a; Mohammadi et al., 2021; Dar et al., 2021). The ensemble model suggested that approximately 20% of Türkiye's land area is currently suitable for brown bear habitation. This estimate aligns with the findings of previous studies that utilized different methodologies and data sources. For instance, Ambarlı et al. (2016) and McLellan et al. (2017) suggested that brown bears could inhabit 20-30% of Türkiye's land area, primarily in the

northern and eastern parts of the country, with suitable habitats in the southern regions are fragmented. My model also identified the Euro-Siberian, Irano-Turanian, and Mediterranean biogeographic regions as the most suitable for brown bears, respectively, in agreement with previous research.

Performing the assessment vulnerability of brown bears provides an important baseline to know how their response to climate change and land use land cover (LUCC) change. In this context, ENM as an ecological tool not only provides us with information on suitable areas by considering the changing predictors but also shows thoroughly the effects of these predictors on the brown bears. Thus, it is quite useful in terms of conservation biology and wildlife management. Contrary to GCMs, future simulations of LULC involve much more uncertainty in predicting the future situation. The anthropogenic factors I used in the model were static. However, as previously emphasized, combining static variables with high driving potential with dynamic climatic variables yields much better results than excluding them altogether (Stanton et al., 2012). I confirmed these insights with the improved model, demonstrating that combining static anthropogenic predictors with dynamic bioclimatic variables provided better estimates.

Human dominance in pristine areas is increasing every year, and interventions to LULC are significantly accelerating the fragmentation process today (Mantyka-Pringle, 2015; Santos et al., 2021). Indeed, land cover and human-related variables were found key factors in my ensemble model. Distance to Forest emerged as the most influential variable affecting brown bear presence probability. This result is consistent with the species' reliance on forested habitats for sheltering, foraging, and denning (Recio et al., 2021; Ziółkowska et al., 2016). The negative relationship between bear presence probability and distance to forests suggests that brown bears prefer areas closer to forests, highlighting the importance of maintaining and connecting forested landscapes for brown bear conservation.

Temperature-related variables, such as Mean Diurnal Range (BIO2) and Annual Mean Temperature (BIO1), were significant predictors, with brown bears exhibiting an optimum presence probability at specific temperature ranges. This finding underscores the importance of climate in shaping brown bear distribution patterns. However, the model predicted that brown bears living in Türkiye will experience warmer annual mean temperatures in the future than present day, indicating that bears have to cope with impacts associated with rising temperatures (Fig. 2.18). Increased temperatures can cause thermal stress on brown bears by altering their

thermoregulatory behavioral responses (Sawaya et al., 2017). For instance, brown bears can exhibit more nocturnal activities in this case (McLellan & McLellan, 2015). Furthermore, the most crucial factor in managing the denning entry/exit time of brown bears is the ambient temperature (Evans et al., 2016), and long-term changing temperatures lead to shorter periods of denning, which modulates the bears' energy budget (González-Bernardo et al., 2020a). The denning activity of bears can vary depending on the spatial features, and brown bears in the Mediterranean region, in particular, may not hibernate every year due to rising temperatures and low snow cover (personal communication). Regular monitoring of the habitats and behavior of brown bears is a critical necessity to understand their responses to climate change. All mentioned factors may significantly decrease cub survival rates (Pigeon et al., 2016) and may negatively affect population viability.

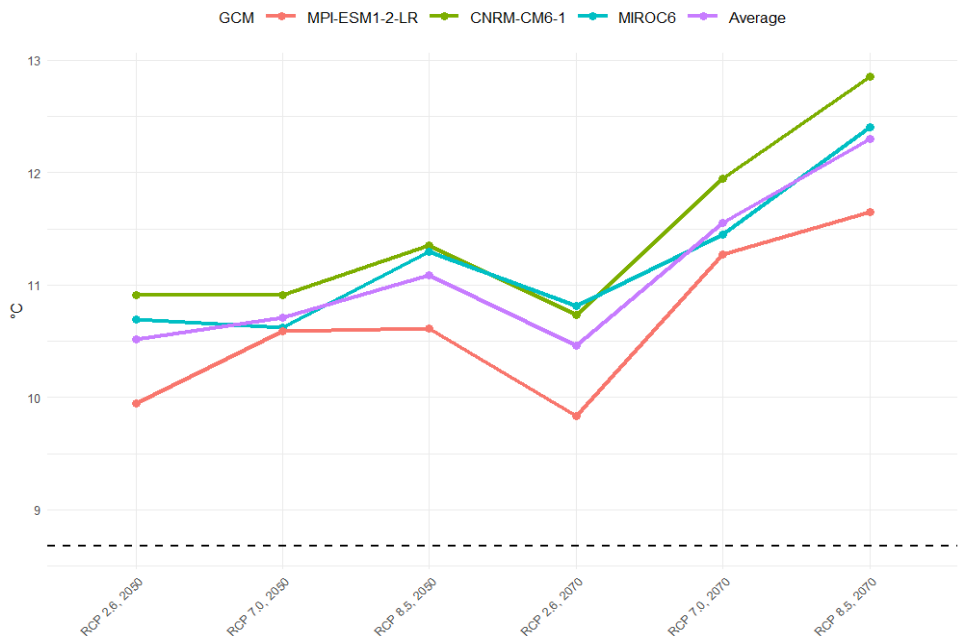

Figure 2.18: The average values for Annual Mean Temperature (BIO1) in the potential suitable habitat patches for each GCMs in the future based on binary products of the ensemble model. The black-dashed line represents the average value for the present day.

On the other hand, bears may choose more rugged areas or higher altitudes to avoid human impact (Goldstein et al., 2010; Piédallu et al., 2019; Suel, 2019; Zarzo-Arias et al., 2019). These areas represent low-risk high- quality habitats by providing food and shelter. However, increasing road access to pristine areas has become one of the most significant issues in recent years across Türkiye (Bilici & Akay, 2021). The increased road network in pristine

areas means an increasing human footprint and an accelerated fragmentation process (Cushman et al., 2013; Kimmig et al.,2020; Lecis et al., 2022). In the model, unexpectedly, I determined that the presence probability of bears decreased as the distance to road increased; however, its contribution was low (3%). This pattern means that the roads may represent an ecological trap for the brown bears (Lamb et al., 2017). Brown bears frequently use the roads for their traveling to their feeding and reproduction areas. Although the main highways represent an ecological barrier to bear movement, it has been shown that the roads with less traffic, such as secondary roads, can support bear movement (Northrup et al., 2012; Skuban et al., 2017). Furthermore, increased road density at lower altitudes, coupled with factors like human presence, is known to increase the risk of mortality for brown bears (Parsons et al., 2023). Road density, affecting individual circadian behavior (Ordiz et al., 2014), can act as a barrier influencing connectivity (Epps & Keyghobadi, 2015; Karamanlidis et al., 2012), leading to negative effects at the population level. In the densely populated Western Black Sea region with a high bear population, it was shown that bears utilize habitats with higher risks compared to other wild mammals (Dagtekin et al., 2023). The pursuit of anthropogenic food sources, such as garbage dumps (Cozzi et al., 2016), can alter the seasonal habitat use patterns of bears (Dagtekin et al., 2023) and result in demographic consequences (Kemahlı et al., 2023). Lastly, the model indicated that as population density and HFI increase, the presence probability of brown bears decreases (Fig. 2.10). There was a significant decrease in the presence probability of bears in the moderate and high-level patches in terms of HFI. Hence, it is important that human activity should not be enhanced in areas with an HFI value < 5. (Venter et al., 2016).

The results of the future habitat suitability projections indicate that brown bears in Türkiye face substantial challenges due to climate change. Under both optimistic and pessimistic scenarios, brown bear habitat is projected to contract, with the Mediterranean and Irano-Turanian regions experiencing the most significant losses. This is concerning, as these regions currently support a considerable portion of the brown bear population in Türkiye. The magnitude of habitat loss by 2070 under the pessimistic scenario, with estimates ranging from 50% to 82%, highlights the urgency of conservation efforts to mitigate the impacts of climate change on brown bear populations. Additionally, the limited potential for range expansion in the future indicates that brown bears may face difficulties in finding new suitable habitats to compensate for the losses. In recent years, deforestation in Türkiye has been rapidly increasing, and the density of aged forests, especially in core habitats, is decreasing daily (TOD, 2022).

This situation not only disrupts the habitat of many species throughout the forest ecosystem but also leads to various indirect effects on brown bears. Although brown bears have developed various adaptations, such as changing the time periods in which they use young and aged forest areas, to avoid overheating, such patterns have gender differences (Stewart et al., 2013). As forest degradation increases and habitat quality are disrupted, it may lead to additional stresses for the species, such as infanticide and overheating (Nellemann et al., 2007; Rogers et al., 2021; Ordiz et al., 2017).

In Türkiye, brown bears use various vegetation types, and their diets are largely composed of plants rather than livestock (Ambarlı, 2016). However, climate change will impact the brown bears and their food resources by either changing their shifts or reducing their abundance (Penteriani et al., 2019; Pérez- Girón et al., 2024). Furthermore, climate change will compel bears to seek alternative food sources by altering the ripening times of the fruits they commonly feed on during the hyperphagic period (Pérez- Girón et al., 2022). This will lead bears to forage for anthropogenic food sources more frequently, indicating an increasing human-wildlife conflict (see Chapter 4). Especially in geographies with scattered settlements, such as the Euro-Siberian region, this will result in increased crop damage, house break-ins, and damage to beehives (Ambarlı & Bilgin, 2008; Dai et al., 2019b; see Chapter 4) while in areas like the Irano-Turanian region including wide pastures, it may lead to increased livestock predation (Kusak & Şekercioglu, 2021, see Chapter 4). On the other hand, brown bears will face various risks in foraging available food resources by making large seasonal movements (Penteriani et al., 2019). Brown bears play crucial roles as providers of important ecosystem services, such as seed dispersal, contributing to the distribution of seeds over long distances (García-Rodríguez et al., 2021). However, several studies predict that these reciprocal interactions between brown bears and their food sources might be disrupted due to climate change (Pérez-Girón et al., 2024).

According to my findings, brown bears seem to be stuck in fragmented areas of the Mediterranean compared with Euro-Siberian and Irano-Turanian regions. For instance, the Northwest Mediterranean (e.g., around of Mount Ida), the southwest Mediterranean, including Muğla's forests, and the Western Taurus Mountains, were manifested as fragmented areas. Moreover, the southernmost population of brown bears in the world is in the Turkish pine forests of the west Mediterranean (Soyumert et al., 2020) and these areas are particularly

susceptible to climate change (Dalfes et al., 2007). The Mediterranean region of Türkiye is often exposed to severe wildfires, many of which are human-induced (Tavsanoglu & Pausas, 2022). Major habitat losses caused by such fires may affect microevolutionary processes (Harris et al., 2023). Hence, wildfires that seriously threaten the core habitats of brown bears in this region may have more dramatic effects on the current and future distributions of bears than initially perceived (Cunningham & Ballard, 2004; Khosravi et al., 2022). There is a need for additional preventive and deterrent measures to conserve the natural areas in this region. In the Mediterranean, determining the variables driving the movement ability of bears at a fine scale by conducting monitoring with camera traps and developing conservation strategies to support coexistence are of urgent importance.

There are similar habitat loss and range shift risks not only for brown bears but also for the future of other species in Türkiye. For example, it has been determined that the broad-leaf forest species beech (*Fagus orientalis*), which is included in a significant part of brown bear suitable habitats, will also show a northward shift (Dagtekin et al., 2020) and substantial range contractions in the future (Ayan et al., 2022). A similar trend has been shown for *Carpinus betulus* (Varol et al., 2022). For another mammal species, Anatolian ground squirrels, it has been predicted that climate change and human dominance will cause habitat loss of up to 77% in their existing habitats, including Anatolia (Gür, 2022). Additionally, habitat loss and range shift risk for brown bears due to climate change are not limited to Türkiye. The suitable areas of brown bears only within protected areas in Central Asia are predicted to decrease by 1,103,912 km^2 in the near future (Su et al., 2018). Similarly, it has been shown that the amount of suitable habitat for *Ursus arctos pruinosus* and *Ursus arctos isabellinus* in the Hindi Kush Himalayan region will decrease significantly due to climate change and will shift to higher altitudes (Dai et al., 2021a). In the Chaharmahal and Bakhtiari regions, which have a significant brown bear population in Iran, it has been predicted that up to 45% of suitable habitats loss will be experienced in the pessimistic scenario until 2050 (Ashrafzadeh et al., 2022). It is thought that there will be a habitat decline of up to 91% in 2070 for bears in Sanjiangyuan National Park in China (Dai et al., 2019a). Similarly, in the Western Himalayas, brown bears are predicted to face a dramatic habitat loss (> 90%) in case of a pessimistic future, while less than quarter of the area (< 23%) would be lost in the low emission scenarios, and there would be a range shift to higher altitude (Dar et al., 2021). The global distribution of brown bears and their densities have constantly decreased by more than 50% since the 1850s (Servheen, 1990). All

these projections have indicated the increasing vulnerability of brown bears to climate change globally and the need for urgent and transboundary conservation actions (Almasieh et al., 2019; Kopatz et al., 2021; Reljic et al., 2018).

Elevation-based analysis revealed that climate change will affect brown bear habitat suitability at different elevations. Although brown bears are typically a high altitude species, their habitat preferences can be influenced by human land usage or the shifting of natural food sources (Lamamy et al., 2019; Penteriani et al., 2019; Schrag et al., 2008). Lower elevations below 1000 m are projected to experience the highest potential habitat loss, while higher elevations above 3000 m are expected to be less affected. It should be noted that deforestation rates in the lowlands <1000 m are too high because of forest conversion to human settlements and agricultural areas. Besides, since the pastoralist lifestyle is common in Türkiye's higher altitudes, the undisturbed habitats in the 1000-3000m elevational range are at risk of human activities. According to my results, the potential distribution of brown bears in Türkiye will shift northward because of climate change in the near future. The northward shift and the shift of suitable habitats by altitudes suggest that brown bears may need to adapt to changing elevation zones to cope with climate change effects. This highlights the importance of maintaining landscape connectivity to facilitate brown bear movement across elevational gradients and core patches.

The decline in habitat overlap with Türkiye's protected areas is a significant concern for brown bear conservation. Protected areas play a crucial role in conserving biodiversity and providing refuge for species threatened by habitat loss. Ecological processes have spatial and temporal dynamics. Therefore, the status of protected areas should be planned by considering the changing climate and land use/land cover. The PAs in Türkiye are greatly inadequate in coverage and are under serious anthropogenic threats (Şekercioğlu et al., 2011a,b; Birben, 2020; Atmiş et al., 2018). In chapter four, of this thesis, I examine of Human – Brown bear conflicts across the country, showing that the areas around PAs in Türkiye are hotspots for human-bear conflicts. Similar conservation gaps have been estimated in other regions (Mukherjee et al., 2021; Su et al., 2018). The projected decrease in habitat overlap with protected areas underscores the need for adaptive management strategies that consider the changing distribution of brown bear habitats and the potential need for new protected areas or adjustments to established ones.

There are some limitations to this study. Although the study area is extensive, the presence data obtained has good spatial coverage. However, considering the habitat use flexibility of brown bears, generating a better dataset covering the whole country would strengthen the accuracy of the models. In this context, the importance of actively developing public databases with the contributions of official institutions and citizen science observations is critical (Tiago et al., 2017; Adler et al., 2020). The anthropogenic variables I used were not considered for future projections, which in some cases may be substantial. Thus, these results may offer a more conservative projection for the future. The patches considered as core habitats were binary map products based on the ensemble model and should be thoroughly re-evaluated by expert opinion during the planning of conservation strategies. In this model, biotic interactions were not considered. Vegetation covers may change drastically due to climate change (Kelly & Goulden, 2008; McKenney et al., 2007), while plant species and the natural prey of bears may also exhibit range shifts (Ali et al., 2021; Khosravi et al., 2021). Therefore, joint effects of biotic interactions should also be considered in future projections (Lucas et al., 2023). Lastly, the models were carried out at a coarse, country scale, but fine-scale studies are essential to understand the effects of climate change and anthropogenic interactions and to improve landscape-specific conservation strategies.

2.5. Conclusion

In this chapater, I performed the ensemble approach by using the *biomod2* package to evaluate the current species distribution and future habitat suitability of brown bears across Türkiye. To do this, I used bioclimatic, topographic, and anthropogenic variables that shape the distribution of bears. While brown bears are distributed in three different biogeographic regions of Türkiye, they are primarily found in the Euro-Siberian, Irano-Turanian regions, with the Mediterranean region a distant third. The variables that most contributed to the model were Distance to Forest, Mean Diurnal Range (BIO2), Annual Mean Temperature (BIO1), and Isothermality (BIO3), in that order. I projected potential habitat suitability for both 2050 and 2070 by considering three different climate change scenarios, which were optimistic, moderate, and pessimistic. I found that climate change would lead to a serious loss in the potential habitats of brown bears in the near future. Accordingly, the Mediterranean, Irano-Turanian, and Euro-Siberian were the regions where this loss would be the highest, in that oder. Furthermore, I have shown that brown bears will exhibit a northward shift under climate change and that their range

contraction varies based on elevation. Both the future range shift of brown bears and the decreasing ratio of suitable patches indicated that evaluating the status of core habitats and protected areas is a necessity. Ultimately, identifying vulnerable habitats by using current and future projections; and modeling of the wildlife corridors to enhance the connectivity among the suitable patches is an urgent issue for the conservation of brown bears across the country. The results emphasize the importance of proactive conservation measures, including habitat protection, restoration, and climate adaptation strategies, to ensure the long-term survival of brown bear populations in Türkiye. Additionally, my findings can inform conservation planning and policy development to mitigate the impacts of climate change on this iconic species.

Chapter 3

3. Structural Connectivity of Brown Bear Habitats Across Türkiye

3.1. Introduction

As human dominance globally increases, the fragmentation of natural habitats has greatly accelerated (Haddad et al., 2015). Human land use changes land cover, and it causes the degradation of suitable habitats for many species and loss of biodiversity by generating anthropized areas (Crooks et al., 2017). Altering habitat configuration also exacarbates climate change effects (Elsen et al., 2020). While fluctuations in bioclimatic variables affect habitat quality, it forces species to range shift by modulating their dispersal patterns (Pecl et al., 2017; Chapter 2). Large carnivores are one of the most vulnerable species against all mentioned factors because of their large body sizes, low reproduction rates, slow population growth, and low density (Ripple et al., 2014; Di Minin et al., 2016). They are keystone species that require large, integrated protected areas to meet their ecological needs. Therefore, identifying suitable habitats for species under different future projections by considering the synergistic effects of anthropogenic and climatic predictors allows us to determine key corridors and vulnerable habitats, helps understand species' responses against climate change, and improve effective conservation strategies (Mohammadi et al., 2021; Dai et al., 2021a; Dar et al., 2022). Furthermore, one of the Aichi Biodiversity Targets is to facilitate movement among metapopulations (CBD, 2022: Target 11).

Evaluating broad-scale landscape connectivity is very important to cope with the adverse effects of habitat loss and fragmentation on wildlife (Crooks et al., 2011). Maintaining connectedness is important as the restoration and preservation of suitable habitats for the long-term conservation of large carnivores because the viability of populations requires ecological linkages between their core habitats (Fletcher et al., 2016). Connectivity is the degree to which landscape facilitates or impedes movement, a necessary conservation element for population persistence, range expansion, prey-predator dynamics, genetic diversity, and demographic exchange among populations (Littlefield et al., 2019; Baggio et al., 2011; Cushman et al., 2018). Landscape connectivity can be classified as structural and functional connectivity (Liang et al.,

2022). While functional connectivity considers the behavioral responses of species to landscape features (Fletcher et al., 2016), structural connectivity focuses on the analysis and configuration of the landscape structure (Rodrigues et al., 2022; Vlková et al., 2024). Connectivity among habitat patches is greatly affected by anthropogenic activities such as deforestation and urbanization (Olsoy et al., 2016). Therefore, detecting such spatial areas for target species is critical for effective species conservation. Species distribution modeling is one of the essential ecological tools to determine species-specific needs under climate change and landscape transformation (Chapter 2; Austin & Van Niel, 2011). Identifying the locations that support the ecological network of species by using the results of species distribution models as input for connectivity analysis and removing the anthropogenic factors that can represent the barrier to conservation management in those locations help the persistence of species (Mohammadi et al., 2021; Mateo-Sánchez et al., 2015a). Hence, landscape connectivity models are a practical tool for prioritizing critical habitats and linkages to improve the movement capability of species.

Furthermore, increased human activity in fragmented bear habitats accelerates human-bear conflicts (HBCs) and leads people to take a negative attitude toward conservation efforts as a challenge to co-existence (Morales-Gonzallez et al., 2020; Dai et al., 2021b). I showed in Chapter 2 that when the suitable habitats of Anatolian brown bears and established protected areas are evaluated, a conservation gap will occur in the near future. In addition, protected areas across Türkiye are already under human pressure and represent a hotspot for HBCs (Atmiş et al., 2018, Chapter 4). As an umbrella species, conserving suitable habitats for brown bears is crucial to healthy ecosystem function (Morales-González et al., 2020). Habitat connectivity of brown bears is one of the research questions that has not yet been studied in Türkiye. For all these reasons, the main motivations of this chapter were to determine the ecological network of brown bears across Türkiye and to evaluate structural connectivity among the patches, and to examine climate change effects on brown bear ecological network to help strengthen the linkage among core habitats.

3.2. Materials and Methods

3.2.1. Resistance Surfaces

Landscape resistance surfaces reflect the local cost of movement of a species through an environment (i.e. cost-map) and represent landscape permeability (Zeller et al., 2012). To generate resistance surfaces, I used habitat suitability maps from the ensemble model in Chapter

2 to generate resistance surfaces for evaluating the connectivity network. For the future projections, I obtained different probability maps for each scenario from each GCM. To avoid uncertainty among the GCMs, I took the mean value of three different GCMs after I rescaled the rasters for each scenario by using the linear method in Rescale by Function Tool in ArcGIS. Then, I selected the top 65^{th} percentile of the rasters as suitable habitats to generate binary maps. Since many carnivore species exhibit male-biased dispersal (Peck et al., 2017; Shirane et al., 2019), I determined the area of the patches, then excluded the areas lower than 83 km^2, based on the mean size of male brown bears' home ranges in northeastern Türkiye (Ambarlı et al., 2016). These habitat patches represent the nodes in the context of circuit theory. I transformed habitat suitability values from average habitat suitability maps of three GCMs for each scenario into resistance rasters (Keeley et al., 2016). To do this, I carried out a transformation function as follows:

$$100 - 99 \times ((1 - \exp(-c \times h)) / (1 - \exp(-c)))$$

where *h* is the habitat suitability value in a cell and *c* is a constant that governs the shape of the function (Trainor et al., 2013). Since bears have high movement capability and can move even in less suitable habitats, the relationship between habitat suitability and resistance is not strictly linear, so I set *c* to 4 (Shokri et al., 2021). I rescaled the resistance values to range between 1 and 1000 by linear interpolation, which states that the cells that had higher values have higher resistance, and vice versa (Fig. 3.1). All maps used in the connectivity analysis were projected to Lambert Azimuthal Equal-Area (ETRS 1989 LAEA), and all resistance surfaces were resampled at 1x1 km spatial resolution.

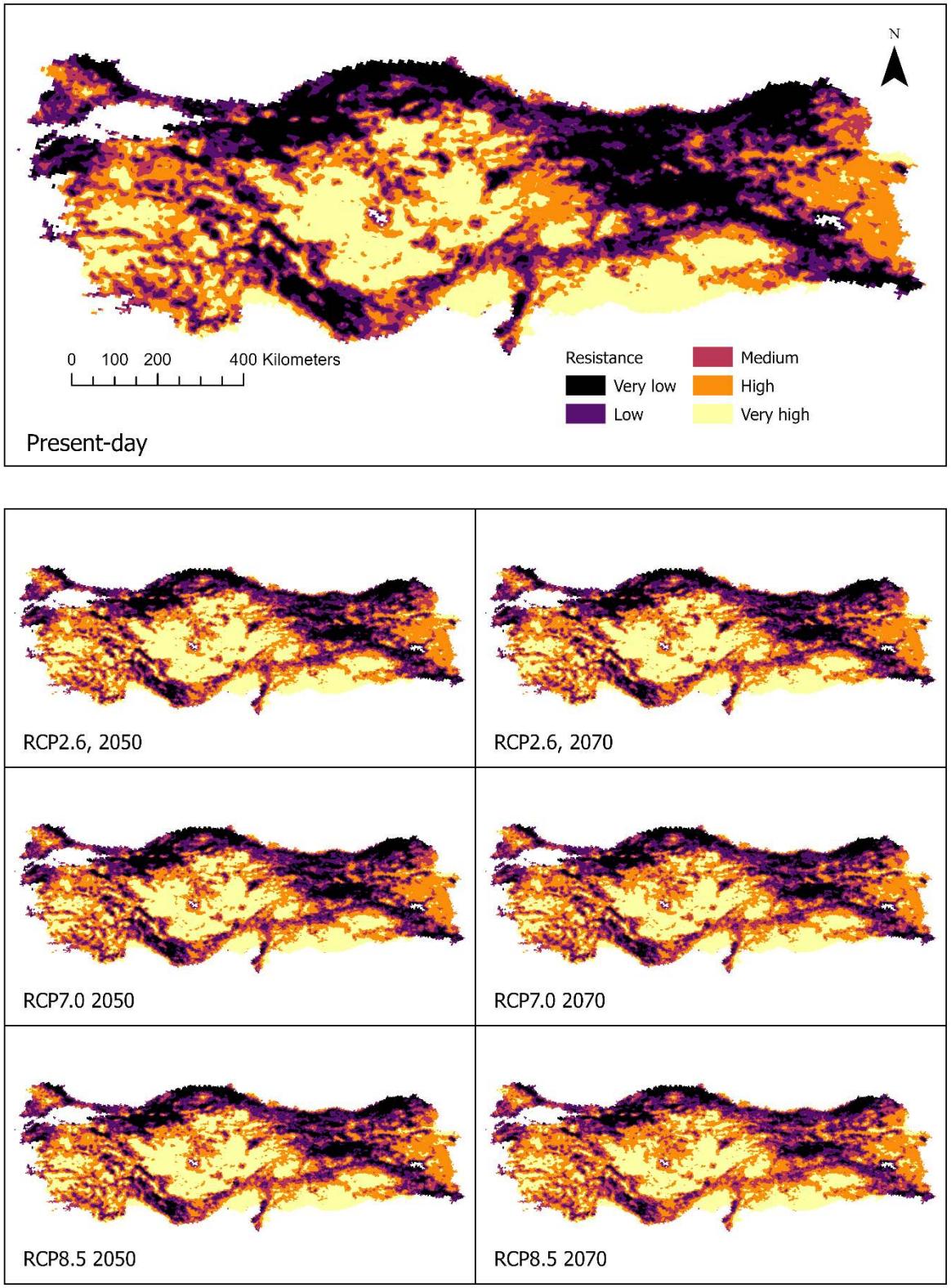

Figure 3.1: Resistance surfaces used for the connectivity modeling.

3.2.2. Habitat Connectivity

There are different methods to evaluate landscape connectivity, such as least-cost path (Adriaensen et al., 2003), resistance kernels (Compton et al., 2007, Cushman & Landguth, 2012), circuit theory (Dickson et al., 2019), centrality analyses (Estrada & Bodin, 2008), and factorial least-cost path (Cushman et al., 2009). In this study, I simulated the potential dispersal of brown bears across Türkiye for current and future conditions by combining the circuit and graph theories. First, I calculated least-cost paths (LCP) using resistance surface and core habitats as input for each scenario via the Linkage Mapper Tool (McRae and Kavanagh, 2011). Linkage Mapper maps least-cost paths connecting adjacent core patches by considering resistance surface, and LCP follows a route with minimum cost-weighted distance (CWD), meaning the least energy cost for dispersal movement. On the other hand, Circuit Theory (CT) combines the circuits with movement ecology. It considers the landscape to predict the movement patterns of a random walker between sources, which are nodes, or are core patches in this case, and target cells (McRae et al., 2008). According to CT modeling, if the patches are in an unfamiliar landscape, the cells providing proper ecological requirements have low resistance values. The patches that hinder ecological processes have high resistance values, so higher current densities indicate increased movement probability. While LCP gives a single optimal path among the patches, CT calculates multiple paths since it assumes that animals can decide for each cell. Briefly, LCPs analysis produces vector corridors between pairwise nodes and ignores strength, thus providing insights into landscape configuration (Wang et al., 2022). To estimate current flow centrality metrics and determine pinch-points within LCPs, I used Circuitscape implemented through Linkage Mapper (McRae et al., 2014). Pinchpoint analysis identifies the bottlenecked areas on the landscape for connectivity and indicates the areas for conservation priority since there is no alternative dispersal path to them (Dutta et al., 2016). I used the Pinchpoint Mapper Tool in Linkage Mapper to identify these areas by experimenting with a 200 cost-weighted km width. In addition, I used Centrality Mapper tools to identify the most critical core patches and corridors. Centrality Mapper was utilized to assess the significance of core habitat areas and the least-cost corridors in maintaining a connected network. Raster centrality using Circuitscape was calculated with the all-to-one method. Current flow centrality measures the importance of a link or core area for maintaining connectivity across the network. This involved a precise calculation of the flow of a 1-amp current across all pairs within the corridor network, with the cost-weighted distance of the least-

cost corridor acting as the resistance between core areas (Suksavate et al., 2019). In other words, this measurement assigns a higher centrality score to a patch where many paths in the network pass through, compared to a patch where a few paths pass through. Moreover, I divided the centrality values by core patch size to obtain the area-corrected centrality score, which emphasizes the importance of small patches that aid connectivity (Mallory & Boyce, 2019; Greenspan et al., 2021). Lastly, I used the Barrier Mapper Tool to detect the barrier areas for connecting the suitable patches with detection radiuses ranging from 5 to 10 km and a radius step value of 1 km.

3.3. Results

3.3.1. Current Ecological Network of Brown Bears Across Türkiye

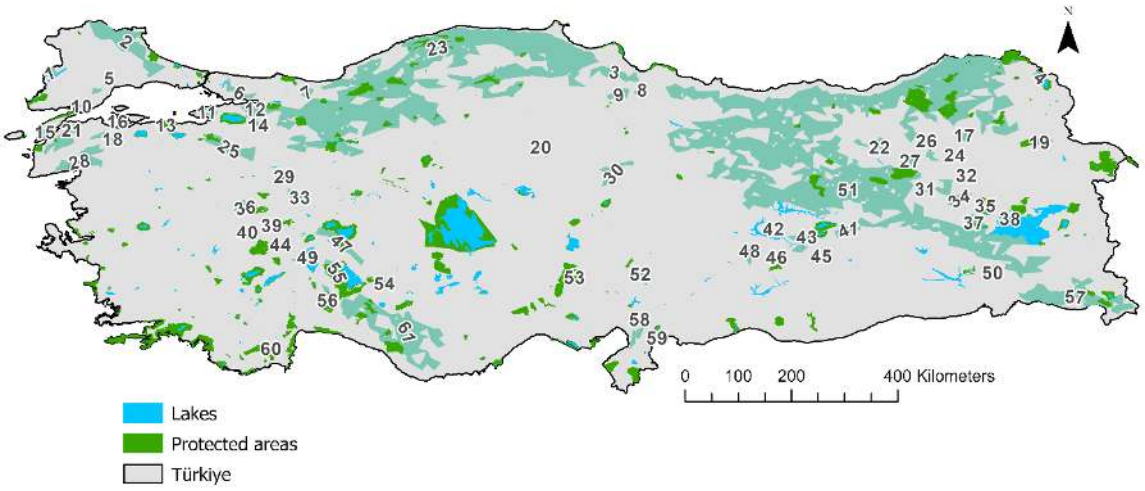

Figure 3.2: Brown bears' core habitat patches acros the country.

I identified 61 core habitats with an area ranging from 86.83 to 64,215 km^2 for present day across the country (Fig. 3.2, Table 3.1). The total area of core habitats was 134,885 km^2, which was 13.9% less than the total area of suitable patches for living brown bears in Türkiye (156,712 km^2, Chapter 2) since I removed the suitable patches smaller than male bears' home range size as core habitats. I determined that while there are only five core patches with a total area of 3,579 km^2 in Thrace, there are 56 core patches with a total area of 131,306 km^2 in Anatolia (Fig. 3.2). Corridor mapping identified 106 LCPs to connect the core habitats for present day (Table 3.2). Mean Euclidean distance (EucD) (the straight-line distance from one node's edge to another) between the core habitats was 45 km (SD = 48, range = 1 – 228 km); mean cost-weighted distance (CwD) (the cumulative cost incurred while traversing the LCPs)

was 19,161 weighted km (SD= 26,729, range = 197.5 – 163,100 km); and mean LCP length (actual distance traveled walking along the LCP) was 53 km (SD = 56, range = 1 – 260 km) (Fig. 3.4, Table 3.2).

Table 3.1: Detailed information about the 61 core habitat patches across Türkiye.

core_ID	Area (km2)	Current centrality (amps)	Area-corrected current centrality
Meriç (1)	200.85	98.37	0.49
Istranca Mountains (2)	2986.58	231.31	0.08
Samsun (3)	957.14	891.94	0.93
Çıldır (4)	209.59	60	0.29
Ganos Mountains (5)	114.67	135.72	1.18
Kocaeli Hills (6)	505.5	284	0.56
Akçakoca Mountains (7)	234.59	60	0.26
Taşova (8)	153.51	516.65	3.37
Akdağ (Ladik) (9)	390.7	266.66	0.68
Gelibolu (10)	94.32	83.6	0.89
Samanlı Mountains (11)	321.79	158.36	0.49
Kartepe (12)	166.82	349.96	2.1
Karacabey (13)	104.85	171.12	1.63
Uludağ (14)	86.83	253.26	2.92
Eceabat (15)	182.5	60	0.33
Biga (16)	216.61	168.02	0.78
Tortum (17)	117.78	92.03	0.78
Karlık Mountain (18)	107.99	200.11	1.85
Kağızman (19)	344.7	72.87	0.21
Boğazkale (20)	121.94	134.84	1.11
Biga Mountains (21)	1052.56	131.2	0.12
Kop Mountain (22)	676.49	87.08	0.13
Western Black Sea block (23)	37323.68	1112.56	0.03
Pasinler (24)	182.79	124.43	0.68
Yirce Mountains (25)	1276.37	671.6	0.53
Palandöken Mountain (26)	178.06	134.88	0.76
Çat (27)	158.01	141.64	0.9
Mount Ida (28)	1550.56	220.25	0.14
Türkmenbaba Mountain (29)	255.28	455.54	1.78
Akdağmadeni (30)	884.64	199.96	0.23
Varto (Akdoğan Mountains) (31)	172.11	199.98	1.16
Hınıs (Akdoğan Mountains) (32)	462.31	194.08	0.42
Odunpazarı (33)	482.93	354.97	0.74
Karaçoban (Akdoğan M.) (34)	283.63	112.37	0.4
Bulanık (Akdoğan M.) (35)	98.11	98.54	1
Murat Mountain (36)	561.04	359.08	0.64
Karaçavuş Mountains (37)	156.67	143.8	0.92
Ahlat (38)	336.69	77.56	0.23

Ahır Mountain (39)	152.76	314.93	2.06
Bulkaz Mountain (40)	95.12	168.68	1.77
Bingöl Mountains (41)	305.17	339.34	1.11
Hasan Mountain (42)	108.15	169.05	1.56
Karaoğlan Mountain (43)	113.44	237.2	2.09
Çivril (Akdağ) (44)	162.63	171.42	1.05
Şakşak Mountain (45)	219.69	246.22	1.12
Nemrut Mountain (46)	110.5	177.52	1.61
Sultan Mountains (47)	1007.52	279.2	0.28
Yeşilyurt (48)	319.76	214.97	0.67
Eğirdir (49)	480.29	290.1	0.6
Yazlıca Mountain (50)	158.9	60	0.38
Eastern Anatolia block (51)	64215.1	1168.31	0.02
Sarımsak Mountain (52)	232.52	238.63	1.03
Aladağlar (53)	137.13	247.64	1.81
Loras Mountain (54)	109.2	89.42	0.82
Kızıldağ (55)	957.98	256.61	0.27
Bozburun Mountain (56)	313.08	144.15	0.46
Hakkari Mountains (57)	4104.74	60	0.01
Zorkun Upland (58)	153.32	152.26	0.99
Amanos Mountains (59)	353.63	60	0.17
Beydağları (60)	102.37	62.95	0.61
Geyik Mountains (61)	7252.1	250.46	0.03

Table 3.2: Detailed information about 106 mapped linkages between core habitats across Türkiye.

From_Core	To_Core	Euclidean distance (km)	Cost-weighted distance (km)	Least-cost path (LCP, km)	Absolute distance (CwD:EucD)	Absolute resistance (CwD:LCP)	Current flow centrality	Effective resistance (R̂)	CwD:R̂
Meriç (1)	Istranca Mountains (2)	83.25	33251.48	92.05	399.44	361.22	66.11	9406.61	3.53
Meriç (1)	Ganos M. (5)	56.95	18505.66	65.53	324.97	282.42	33.19	4355.31	4.25
Meriç (1)	Gelibolu (10)	60.31	17956.31	66.33	297.75	270.73	37.44	3200.04	5.61
Istranca Mountains (2)	Ganos M. (5)	67.62	20249.49	75.64	299.48	267.71	108.5	8848.96	2.29
Istranca Mountains (2)	Kocaeli Hills (6)	88.41	26226.81	95.63	296.65	274.26	228	11883.4	2.21
Samsun (3)	Taşova (8)	11.41	2432.45	12.73	213.13	191.12	295.9	623.92	3.9
Samsun (3)	Akdağ (Ladik) (9)	10.28	2158.17	12.41	210.04	173.85	221.19	398.81	5.41
Samsun (3)	Western Black Sea block (23)	8.14	1429.78	9.49	175.74	150.74	843.45	341.27	4.19
Samsun (3)	Eastern Anatolia block (51)	38.74	9638.83	47.8	248.84	201.66	363.34	1754	5.5
Çıldır (4)	Eastern Anatolia block (51)	25.19	5841.09	30.14	231.91	193.79	60	2606.41	2.24
Ganos M. (5)	Gelibolu (10)	5.18	2674.94	9.07	516.3	294.89	69.75	782.01	3.42
Kocaeli Hills (6)	Western Black Sea block (23)	14.55	3607.44	15.83	247.92	227.92	280	2811.16	1.28
Akçakoca Mountains (7)	Western Black Sea block (23)	5.08	1167.92	6.24	229.95	187.11	60	158.09	7.39
Taşova (8)	Akdağ (Ladik) (9)	6.72	1587.5	8	236.2	198.44	211.99	205.71	7.72
Taşova (8)	Eastern Anatolia block (51)	29.25	6220.8	33.97	212.69	183.13	465.41	1256.71	4.95
Akdağ (Ladik) (9)	Boğazkale (20)	129.9	75114.94	156.1	578.27	481.21	40.13	26354	2.85
Samanlı Mountains (11)	İznik (12)	17.6	2524.97	20.41	143.46	123.69	147.8	1220.28	2.07
Samanlı Mountains (11)	Yirce Mountains (25)	32.64	14978.99	49.56	458.89	302.26	108.92	9215.5	1.63
İznik (12)	Uludağ (14)	4.41	1641.45	5.83	372.04	281.65	36.57	518.9	3.16
İznik (12)	Western Black Sea block (23)	2.49	601.04	2.83	241.48	212.53	310.62	223.23	2.69
İznik (12)	Yirce Mountains (25)	38.01	12172.14	41.97	320.23	290.02	144.94	3005.67	4.05
Karacabey (13)	Biga (16)	74.75	31451.32	85.43	420.76	368.17	68.31	12648.4	2.49
Karacabey (13)	Karlık Mountain (18)	65.05	30879.62	78.11	474.72	395.32	68.73	12645.7	2.44
Karacabey (13)	Yirce Mountains (25)	49.78	24440.52	58.46	490.93	418.11	145.2	12317.7	1.98
Uludağ (14)	Western Black Sea block (23)	3.46	785.18	5.41	226.93	145.03	224.52	121.9	6.44
Uludağ (14)	Yirce Mountains (25)	37.65	9571.51	43.14	254.21	221.86	185.44	2714.86	3.53
Eceabat (15)	Biga Mountains (21)	10.57	2451.27	12.31	231.89	199.08	60	536.31	4.57
Biga (16)	Karlık Mountain (18)	1	497.83	2.41	497.83	206.23	96.63	145.65	3.42
Biga (16)	Biga Mountains (21)	19.79	4102.28	22.73	207.34	180.5	67.56	699.29	5.87
Biga (16)	Mount Ida (28)	10.79	2258.44	11.83	209.25	190.94	43.53	339.03	6.66
Tortum (17)	Pasinler (24)	24.38	12163.83	33.49	498.99	363.26	44.61	10833.8	1.12
Tortum (17)	Eastern Anatolia block (51)	10.61	4108.97	14.9	387.24	275.79	79.45	1276.28	3.22
Karlık Mountain (18)	Yirce Mountains (25)	129.11	54170.71	142.5	419.57	380.15	90.75	32150.9	1.68

Karlık Mountain (18)	Mount Ida (28)	5.9	1284.17	8.66	217.84	148.36	84.1	326.14	3.94
Kağızman (19)	Pasinler (24)	89.55	31741.89	119.91	354.46	264.71	25.42	9869	3.22
Kağızman (19)	Eastern Anatolia block (51)	23.7	9147.38	25.8	386.03	354.58	60.33	1796.97	5.09
Boğazkale (20)	Western Black Sea block (23)	90.72	60061.57	100.85	662.06	595.54	67.95	16277.2	3.69
Boğazkale (20)	Akdağmadeni (30)	86.33	56242.41	113.27	651.51	496.55	60.24	14492.4	3.88
Boğazkale (20)	Aladağlar (53)	228.03	163100	248.56	715.36	656.25	41.35	71267.4	2.29
Biga Mountains (21)	Mount Ida (28)	17.35	3594.26	21.73	207.2	165.43	74.83	964.01	3.73
Kop M. (22)	Çat (27)	29.88	9380.38	33.83	313.92	277.3	43.28	1080.73	8.68
Kop M. (22)	Eastern Anatolia block (51)	17.27	4405.8	23.38	255.13	188.41	70.89	1033.63	4.26
Western Black Sea block (23)	Yirce Mountains (25)	43.27	11687.04	50.63	270.08	230.85	162.56	1213.11	9.63
Western Black Sea block (23)	Türkmenbaba Mountain (29)	44.73	21353.58	47.41	477.43	450.36	216.03	20790.6	1.03
Pasinler (24)	Palandöken Mountain (26)	11.58	2257.69	13.24	194.98	170.49	78.49	1229.34	1.84
Pasinler (24)	Hınıs (Akdoğan Mountain) (32)	42.82	13613.44	51.46	317.95	264.57	40.36	5382.98	2.53
Yirce Mountains (25)	Mount Ida (28)	145.69	56696.78	160.47	389.16	353.32	87.2	32842.4	1.73
Yirce Mountains (25)	Türkmenbaba Mountain (29)	42.54	14759.75	46.14	346.95	319.88	224.93	8238.23	1.79
Yirce Mountains (25)	Murat Mountain (36)	72.63	39112.51	100.01	538.55	391.08	133.26	12002.4	3.26
Palandöken Mountain (26)	Çat (27)	13.01	2891.95	15.9	222.35	181.89	90.76	823.87	3.51
Palandöken Mountain (26)	Hınıs (Akdoğan M.) (32)	35.01	13170.93	41.53	376.23	317.17	40.51	2413.71	5.46
Çat (27)	Eastern Anatolia block (51)	14.95	4712.46	17.9	315.28	263.28	89.24	918.84	5.13
Mount Ida (28)	Murat M. (36)	208.69	94466.05	257.89	452.65	366.3	90.84	45696.8	2.07
Türkmenbaba Mountain (29)	Odunpazarı (33)	12.44	3560.16	15.73	286.19	226.37	326.62	1043.32	3.41
Türkmenbaba Mountain (29)	Murat M. (36)	50.89	28690.2	58.53	563.81	490.21	83.5	8488.04	3.38
Akdağmadeni (30)	Eastern Anatolia block (51)	61.92	19489.65	69.67	314.73	279.75	165.43	4986.22	3.91
Akdağmadeni (30)	Sarımsak Mountain (52)	165.64	103300	184.52	623.34	559.56	53.87	22726.1	4.54
Akdağmadeni (30)	Aladağlar (53)	166.19	105900	178.94	637.32	591.91	60.39	82759.5	1.28
Varto (Akdoğan M.) (31)	Hınıs (Akdoğan M.) (32)	3.42	518	5	151.68	103.6	153.67	76.44	6.78
Varto (Akdoğan M.) (31)	Eastern Anatolia block (51)	5.54	1051.5	7	189.84	150.21	186.29	312.26	3.37
Hınıs Akdoğan M.) (32)	Karaçoban (Akdoğan M.) (34)	5.68	1120.5	9	197.2	124.5	93.61	884.11	1.27
Odunpazarı (33)	Murat M. (36)	49.16	28050.78	57.94	570.58	484.13	54.37	12320	2.28
Odunpazarı (33)	Ahır Mountain (39)	45.29	22912.02	55.14	505.91	415.51	97.13	7027.45	3.26
Odunpazarı (33)	Sultan Mountains (47)	47.04	20391.45	52.77	433.45	386.43	171.82	5495.06	3.71
Karaçoban (Akdoğan M.) (34)	Bulanık (Akdoğan M.) (35)	22.22	8702.14	24.9	391.62	349.5	39.35	6084.59	1.43
Karaçoban (Akdoğan M.) (34)	Karaçavuş M. (37)	28.2	7813.79	31.9	277.06	244.95	31.78	2690.65	2.9
Bulanık (Akdoğan M.) (35)	Karaçavuş M. (37)	12.52	3316.46	15.07	264.81	220.06	64.05	707.88	4.69
Bulanık (Akdoğan M.) (35)	Ahlat (38)	19.71	10409.39	21.66	528.02	480.67	33.68	2877.27	3.62
Murat M. (36)	Ahır Mountain (39)	21.19	5812.85	24.31	274.37	239.08	188.91	1477.77	3.93
Murat M. (36)	Bulkaz Mountain (40)	32.55	12507.16	38.31	384.29	326.45	107.28	2293.18	5.45
Karaçavuş M. (37)	Eastern Anatolia block (51)	5.74	1048	7	182.74	149.71	131.76	311.34	3.37

Ahlat (38)	Eastern Anatolia block (51)	10.97	4847.72	22.66	442.11	213.97	61.44	2129.5	2.28
Ahır Mountain (39)	Bulkaz Mountain (40)	23.76	8225.59	25.8	346.24	318.85	49.98	1825.09	4.51
Ahır Mountain (39)	Çivril (Akdağ) (44)	28.12	11755.69	44.53	418.13	264.02	50.43	2133.91	5.51
Ahır Mountain (39)	Sultan Mountains (47)	60.96	25776	63	422.85	409.14	89.08	9655.55	2.67
Ahır Mountain (39)	Eğirdir (49)	66.46	27764.37	87.5	417.74	317.32	94.34	16130	1.72
Bulkaz Mountain (40)	Çivril (Akdağ) (44)	15.72	2778.26	17.9	176.73	155.22	120.1	345.59	8.04
Bingöl Mountains (41)	Karaoğlan Mountain (43)	36.95	6578.59	41.11	178.04	160.02	164.67	1041.74	6.32
Bingöl Mountains (41)	Şakşak Mountain (45)	45.93	9450.86	57.11	205.75	165.48	122.29	1800.69	5.25
Bingöl Mountains (41)	Eastern Anatolia block (51)	1	330	2	330	165	331.72	119.08	2.77
Hasan M. (42)	Karaoğlan Mountain (43)	1	197.5	1	197.5	197.5	103.3	197.5	1
Hasan M. (42)	Yeşilyurt (48)	53.02	11638.85	60.77	219.51	191.53	83.47	2342.69	4.97
Hasan M. (42)	Eastern Anatolia block (51)	42.8	12912.34	64.33	301.72	200.74	91.32	2464.49	5.24
Karaoğlan Mountain (43)	Şakşak Mountain (45)	3.85	956	6	248.18	159.33	146.43	257.34	3.71
Çivril (Akdağ) (44)	Eğirdir (49)	43.55	23718.08	57.01	544.65	416.02	112.31	9258.08	2.56
Şakşak Mountain (45)	Nemrut Mountain (46)	12.37	2455.06	15.31	198.55	160.33	163.72	429.87	5.71
Nemrut Mountain (46)	Yeşilyurt (48)	20.04	4601	21	229.56	219.1	131.32	1445.43	3.18
Sultan Mountains (47)	Eğirdir (49)	40.44	10113.55	46.56	250.09	217.23	69.25	5663.03	1.79
Sultan Mountains (47)	Loras Mountain (54)	40.55	17396.86	52.21	429.04	333.19	58.08	2545.93	6.83
Sultan Mountains (47)	Kızıldağ (55)	21.03	7118.38	26.97	338.42	263.94	110.17	1819.77	3.91
Yeşilyurt (48)	Sarımsak Mountain (52)	149.77	44530.69	164.24	297.34	271.14	155.16	12071.7	3.69
Eğirdir (49)	Kızıldağ (55)	9.19	1913.93	11.24	208.38	170.25	147.15	422.66	4.53
Eğirdir (49)	Bozburun Mountain (56)	23.59	6540.74	26.04	277.31	251.17	65.69	2036.81	3.21
Eğirdir (49)	Beydağları (60)	144.41	68326.9	158.84	473.16	430.16	31.47	34787.6	1.96
Yazlıca Mountain (50)	Eastern Anatolia block (51)	9.11	1966.5	11	215.89	178.77	60	1009.72	1.95
Eastern Anatolia block (51)	Hakkari Mountains (57)	20.08	6475.32	29.49	322.44	219.61	60	457.75	14.15
Sarımsak Mountain (52)	Aladağlar (53)	77.92	32805.54	88.6	421.04	370.28	96.7	5580.19	5.88
Sarımsak Mountain (52)	Zorkun Upland (58)	68.26	24210.17	82.28	354.7	294.23	111.54	10874.5	2.23
Aladağlar (53)	Zorkun Upland (58)	112.01	58106	175.05	518.74	331.93	72.99	17948.6	3.24
Aladağlar (53)	Geyik Mountains	217.31	74095.86	259.66	340.97	285.35	163.86	21414.4	3.46
Loras Mountain (54)	Geyik Mountains	30.05	14372.7	33.56	478.28	428.32	60.76	1790.66	8.03
Kızıldağ (55)	Bozburun Mountain (56)	14.25	4245.66	15.9	297.96	267.04	53.88	953.81	4.45
Kızıldağ (55)	Geyik Mountains (61)	12.54	2552.64	15.49	203.53	164.85	142.01	644.43	3.96
Bozburun Mountain (56)	Beydağları (60)	97.03	60374.45	123.11	622.24	490.4	34.43	41397.7	1.46
Bozburun Mountain (56)	Geyik Mountains (61)	17.42	5896	18	338.54	327.56	74.29	1401.84	4.21
Zorkun Upland (58)	Amanos Mountains (59)	3.59	889.32	4.83	247.79	184.2	60	192.16	4.63

The centrality of each core area and linkage was determined by aggregating the cumulative flow of the iterative 1-amp current. The mean core habitat patch centrality score was 238 (SD = 223, ranged = 60 – 1,168) (Table 3.1). Patch centrality score, which indicates the most essential patches to maintaining landscape-wide connectivity, was especially higher in the Black Sea and Eastern Anatolia regions (Fig. 3.3). Eastern Anatolia block, Western Black Sea block, and Samsun, respectively, had the highest current centrality scores (Fig. 3.3, Table 3.1). On the other hand, I obtained standardized measures to consider the contribution of small habitat patches to connectivity, and the centrality values dramatically changed. The mean area-corrected centrality score for core habitat patches was 0.86 (SD = 0.71, range = 0.01 – 3.37) (Table 3.1). Taşova, Uludağ, and Karaoğlan Mountain had the highest area-corrected centrality score (Fig. 3.3, Table 3.1). When I considered the area-corrected centrality, the importance of small patches connecting the Mediterranean to the Black Sea and Marmara in the west of the country and the stepping stones patches connecting to the Eastern Anatolia habitat block increased (Fig. 3.3).

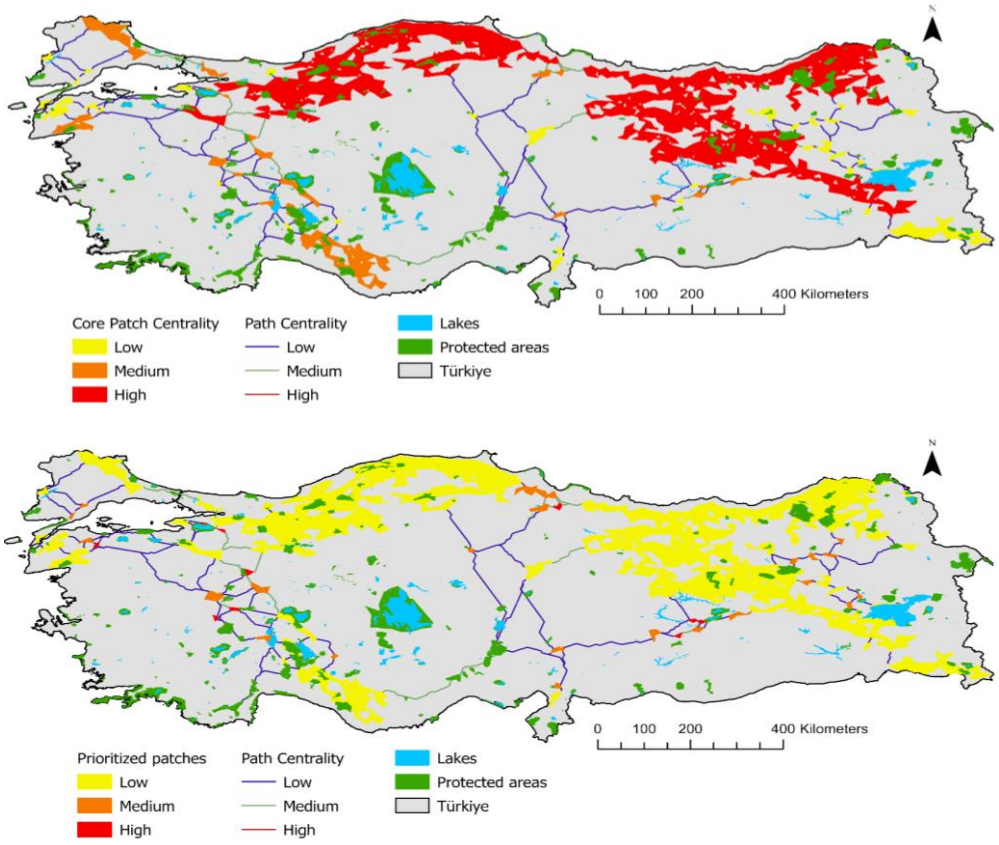

Figure 3.3: The centrality scores (top) and area-corrected centrality scores (bottom) of core patches and paths across the country.

The mean corridor centrality score was 120 (SD = 107, range = 25 – 843) in the linkage network of brown bears for the present day (Table 3.3). While path centrality varied across the country (Fig. 3.3), the linkages between Samsun – Western Black Sea block, Taşova – Eastern Anatolia block, and Bingöl Mountains – Eastern Anatolia block, respectively, had top highest current flow centrality (Table 3.3). To evaluate the quality of paths among the core habitat patches, there are different quality metrics commonly used, such as Absolute Resistance (CwD:LCP), Absolute Distance (CwD:EucD), Effective resistance ($\hat{R}$), and the ratio of cost-weighted distance to effective resistance (CwD:$\hat{R}$). Therefore, I separately considered distinct metrics to determine the highest quality corridors. Absolute distance measures the ratio of the cost-weighted distance of the LCP to Euclidean distance between the patches; the higher values indicate the movement difficulty from one patch to another (Dutta et al., 2016). The mean absolute distance value was 345 (SD = 134, range = 144 – 715) for the present day (Fig. 3.4, Table 3.2). The linkage that exhibited the highest absolute distance values was between Boğazkale to Akdağmadeni and Aladağlar in Central Anatolia since inner Anatolia has more resistance to the movement of brown bears (Fig. 3.4, Table 3.2). In contrast, the lowest absolute distance value was between Samanlı Mountains – İznik, and between the scattered core patches (e.g. Varto, Hınıs) throughout the Akdoğan Mountains (Fig. 3.4, Table 3.2). Absolute resistance gives the resistance per length unit cost along the least-cost path corridors among patches, and higher values indicate increased difficulty for movement (Dutta et al., 2016). The mean absolute resistance value for linkages of core patches was 283 (SD = 116, range = 104 – 656) (Fig. 3.4, Table 3.2). The lowest absolute resistance was determined in the linkages between core patches throughout the Akdoğan Mountains (e.g. Varto – Hınıs – Karaçoban), and Samanlı Mountains – Kartepe (Fig. 3.4, Table 3.2). Effective resistance measures the connectivity degree between connected patches, and the degree is influenced by proximity to other core areas, the number of connections, and the resistance matrix (Keeley et al., 2021). Lower effective resistance values indicate low resistance to movement. The mean value of effective resistance was 7,560 (SD = 13,277, range = 76 – 82,759) (Fig. 3.4, Table 3.2). Except for a few paths in Central and Western Anatolia, most of the paths exhibited low to mid-effective resistance values (Fig. 3.4, Table 3.2).

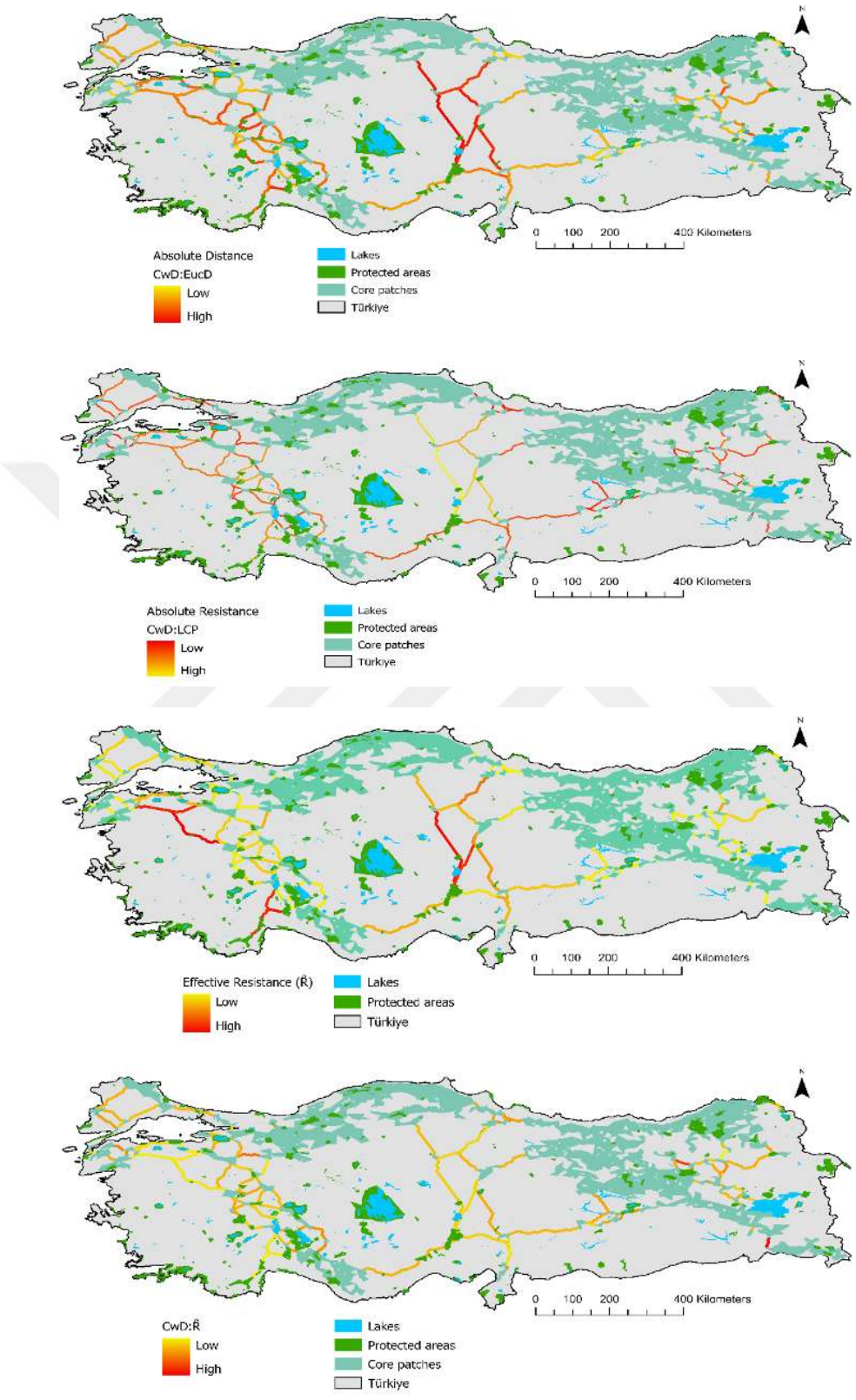

Figure 3.4: Different quality metrics for the paths among the core patches.

3.3.2. Barriers Hindering Movement and Key Restoration Areas

Barrier Mapper identifies barriers throughout a corridor network that can significantly impact the quality and placement of the corresponding corridors. To provide a brief summary of the findings across the radii and multiple patch pairs, I calculated the sum of improvement scores indicating the barriers that isolate multiple pairs of patches (Yang et al., 2022). The improvement score states how much connectivity could improve via habitat restoration. Higher improvement scores represent worse barriers to the movement among the patches. Barrier mapping showed that there are major barriers to the dispersal of brown bears, especially in the central Anatolia (Fig. 3.5). According to my results, connecting core habitats in inner Anatolia, such as Boğazkale, Akdağmadeni, and Aladağlar to each other and Western Black Sea block is difficult (Fig. 3.5). Moreover, the intersection of Murat Mountain, Türkmenbaba Mountain, and Odunpazarı represents the biggest connectivity barrier in the Western Türkiye (Fig. 3.5).

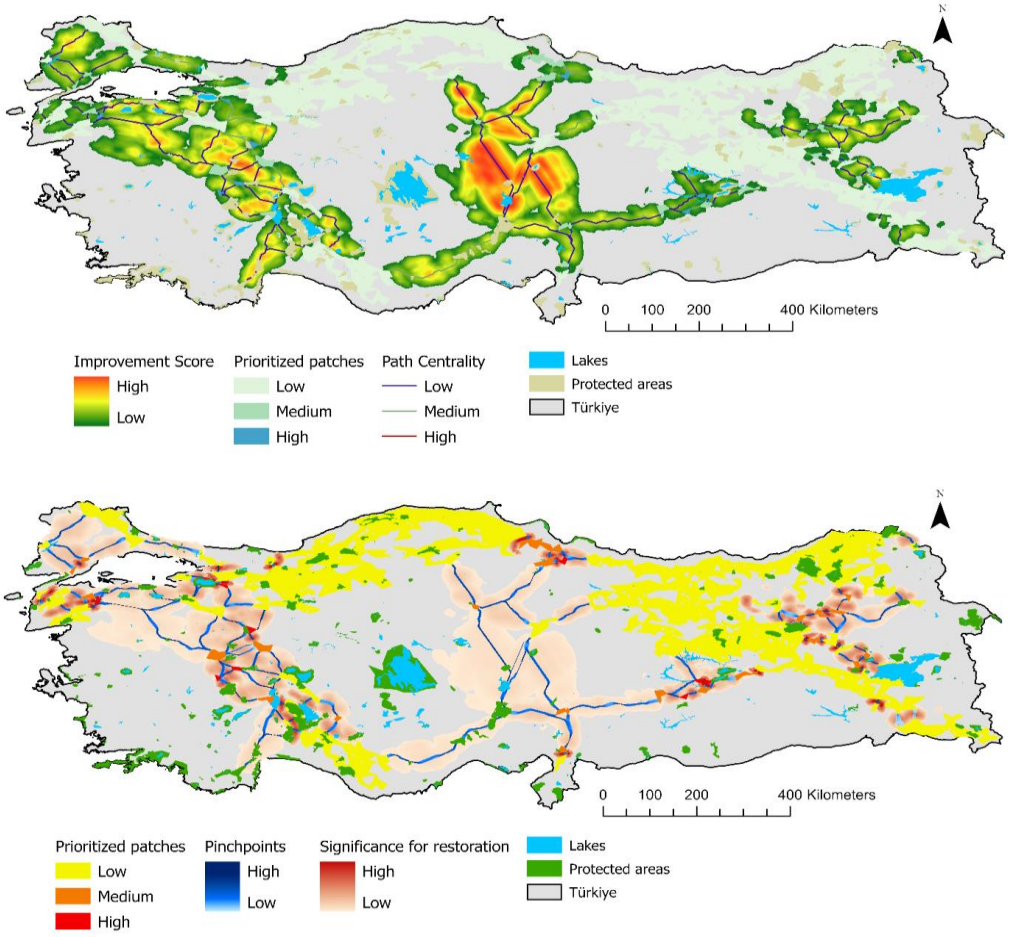

Figure 3.5: The barriers among the core patches and the restoration areas to strength connectivity across Türkiye.

I calculated adjacent paired bottlenecked corridors via the Pinchpoint mapper. Pinchpoint mapper identifies the areas along the most cost-effective routes. The movement-restricted areas represent the pinchpoints, and the restriction derives from unfavorable habitat conditions for brown bears. Therefore, higher pinch-point values indicate the priority areas for conservation. In addition, the areas with higher significance for restoration obtained from the Barrier Mapper tool and Pinchpoint values represent the priority areas for restoration. The model found that many such critical areas across the country facilitate the ecological connection of brown bear habitats. For instance, in western Türkiye, the intersection of Mount Ida, Biga Mountains and Karlık Mountain core patches were of great importance in order for the brown bear populations not to remain isolated in this area and to increase their population viability (Fig. 3.5). Similarly, the area among Kocaeli Hills, Kartepe, and Uludağ is critical to connect these fragmented patches in the Marmara region to the Western Black Sea block (Fig. 3.5). The connection of Akçakoca Mountains to Western Black Sea block is also important (Fig. 3.5). The most significant connection for restoration is in the Central Black Sea; this area is the most important brown bear habitat connection in Türkiye connects the Western Black Sea habitat block to the Eastern Anatolia block, the two most important blocks in the country. The core patches called Samsun, Akdağ (Ladik), and Taşova between the Küre Mountains and the Canik Mountains, and the conservation of natural areas around them is an emergency priority to enhance connectivity (Fig. 3.5). Another significant restoration area is around the Türkmenbaba Mountain and between Kızıldağ – Eğirdir. Other areas that have high significance for restoration are the regions between Bozburun Mountain – Geyik Mountains, and Zorkun Mountain – Amanos Mountains in the Mediterranean. In the East of the country, the connection of rugged patches to each other and the Eastern Anatolian main habitat block has significant restoration value, including the Bingöl Mountains, Akdoğan Mountains, Karaçavuş Mountain, Yazlıca Mountain, Şakşak Mountain, Hasan Mountain, Tortum, Pasinler, and Palandöken Mountain.

3.3.3. Climate Change Effects on the Ecological Network of Brown Bears

Climate change will affect the habitat connectivity network of brown bears in Türkiye. Climate change caused fragmentation in each future scenario by increasing the number of core patches (Fig. 3.6). For present day, brown bears had 61 core patches, which increased to 76-82 and 65-79 depending on the scenario for 2050 and 2070, respectively (Table 3.3). In addition,

the area of total core patches dramatically declined as climate change effects increased. The loss ratio of total core patches compared with present day changes from 43% to 51%, and from 43% to 68%, depending on the scenarios, for 2050 and 2070, respectively (Table 3.3). Furthermore, the area of the largest component greatly decreased in any scenario in the near future, also decreasing component integrity. Due to the increasing number patches because of fragmentation, the path number will increase in the future (Table 3.4). Moreover, despite the increasing number of core patches in the near future, the mean LCP length increased in each future scenario (Table 3.4). Lastly, compared with the present day, the path centrality score will increase as climate change effects increase (Fig. 3.6, Table 3.4). All these results showed that climate change-driven shifts will cause the disruption of the ecological network of brown bears across Türkiye in the near future.

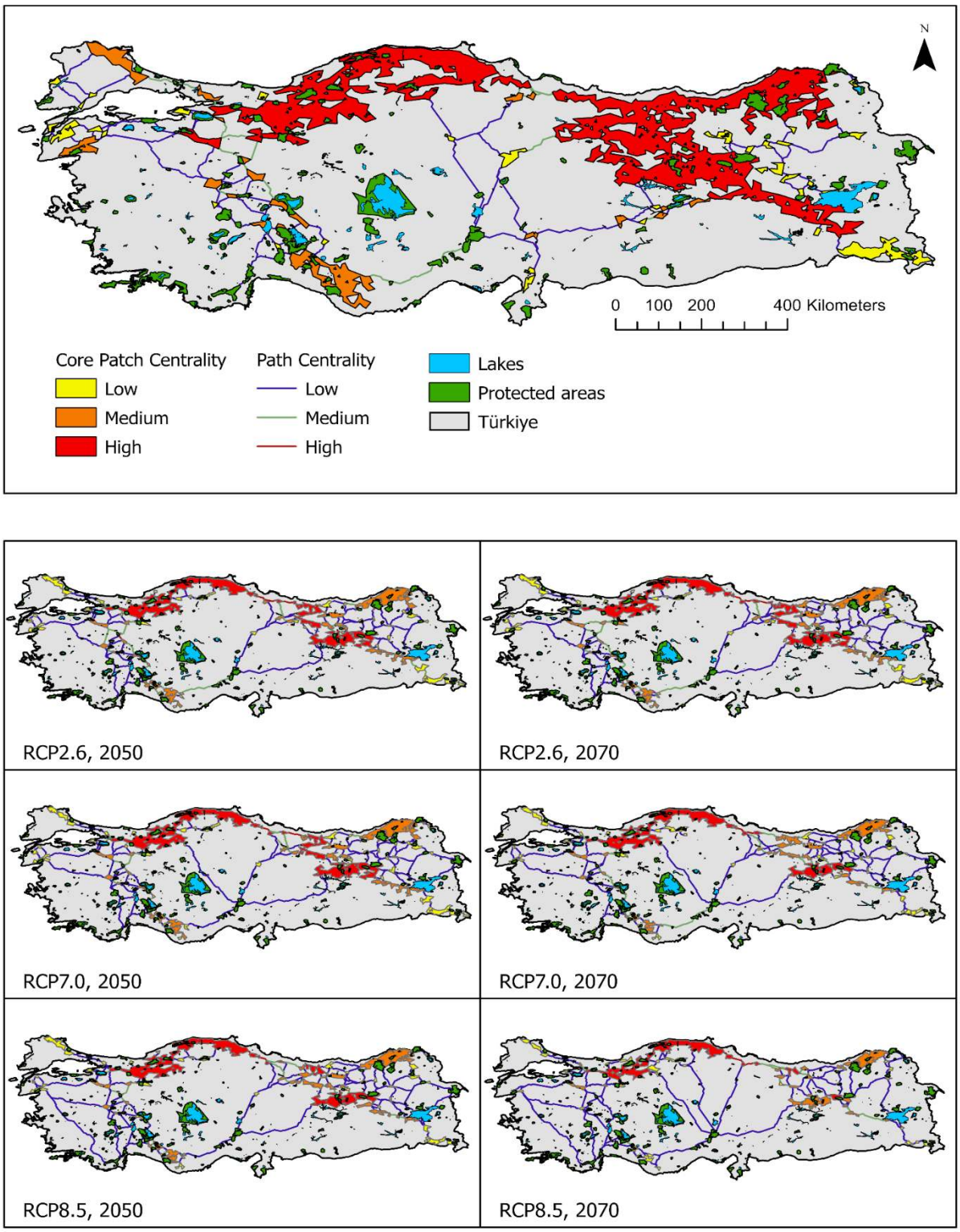

Figure 3.6: Climate change effects on the centrality of core patches and paths.

Table 3.3: Properties of core habitats under different climate change scenarios.

Scenario	No. of core patches	Total core Patches (km^2)	Decreasing ratio in total core patches (km^2)	Area of largest component (km^2)	Mean area (km^2)	Patch centrality scores	Area-corrected centrality
Present-day	61	134,885	NA	64,220	2,211 ± 9,407	238 ± 223	0.86 ± 0.71
RCP2.6, 2050	76	76,779	-43.08	22,578	1,010 ± 3,036	401 ± 338	1.57 ± 1.68
RCP7.0, 2050	79	77,462	-42.57	22,580	981 ± 2,978	431 ± 355	1.70 ± 2.10
RCP8.5, 2050	82	66,541	-50.67	21,507	811 ± 2,675	481 ± 356	2.25 ± 2.36
RCP2.6, 2070	79	77,143	-42.81	22,859	976 ± 2,963	452 ± 383	1.82 ± 2.09
RCP7.0, 2070	76	63,674	-52.79	22,144	838 ± 2,797	422 ± 320	1.89 ± 1.95
RCP8.5, 2070	65	42,979	-68.14	8,930	661 ± 1,663	342 ± 255	1.47 ± 1.11

Table 3.4: Properties of linkages under different climate change scenarios.

Scenario	No. of paths	LCP length (km)	Path centrality score	Euclidean distance (km)	Cost-weighted distance (km)	Absolute distance (CWD/EuC)	Absolute resistance (CWD/LCP)	Effective resistance ($\hat{R}$)	CWD/$\hat{R}$
Present-day	106	53 ± 56	120 ± 107	45 ± 48	19,161 ± 26,729	345 ± 134	283 ± 117	7,560 ± 13,277	3.89 ± 2.06
RCP2.6, 2050	131	49 ± 61	211 ± 200	41 ± 49	17,289 ± 27,483	316 ± 129	258 ± 115	7,032 ± 12,290	3.58 ± 1.98
RCP7.0, 2050	141	53 ± 66	220 ± 218	44 ± 55	18,809 ± 31,142	322 ± 131	264 ± 114	7,526 ± 13,611	3.58 ± 1.70
RCP8.5, 2050	152	55 ± 68	238 ± 222	46 ± 59	20,061 ± 32,815	328 ± 137	270 ± 116	8,215 ± 15,531	3.73 ± 1.77
RCP2.6, 2070	134	50 ± 59	244 ± 262	42 ± 50	18,107 ± 28,294	319 ± 135	260 ± 123	7,274 ± 13,135	3.67 ± 1.82
RCP7.0, 2070	136	57 ± 65	215 ± 208	49 ± 56	20,883 ± 32,663	331 ± 136	273 ± 116	8,601 ± 14,500	3.66 ± 2.04
RCP8.5, 2070	113	78 ± 96	179 ± 173	67 ± 85	30,596 ± 52,392	324 ± 138	270 ± 120	12,687 ± 23,298	3.83 ± 2.27

3.4. Discussion

I present a landscape-level habitat structural connectivity map and the potential areas for maintaining the movement of brown bears across Türkiye. Various resistance states can be considered for landscapes, such as movement difficulty, increased mortality, and behavioral avoidance. Large human-dominated areas such as dams, highways, and settlements lead to high resistance as they cause increased mortality (Rahimi & Dong, 2023; see Chapter 4). I used the habitat suitability maps I previously obtained (Chapter 2) to generate resistance surfaces, also known as friction layers, as the input for connectivity modeling. This approach provides a more objective map compared to the approaches containing expert opinion (Brown, 2014). Moreover, continuous resistance surfaces are better when modeling landscape structure (Stoddard, 2010), and it is common practice to parameterize habitat suitability models to generate resistance maps (Mohammadi et al., 2021; Rezaei et al., 2022; Mallory & Boyce, 2018). Additionally, the use of habitat suitability models is the best option to assess structural connectivity when telemetry or genetic data are not available (Mateo-Sánchez et al., 2015a; Mateo-Sánchez et al., 2015b; Mohammadi et al., 2021). I eliminated the suitable patches that were not enough for a male bear average home range size (83 km^2, Ambarlı et al., 2016) to consider more integrated core habitats. Therefore, the results here regarding connectivity offer a robust evaluation. However, home range may vary seasonally and regionally (Pop et al., 2018), and differs between sexes because of female philopatry in the dispersal of brown bears (Proctor et al., 2004). On the other hand, whether habitat suitability reflects the movement of the target species across the landscape depends on the predictors that produce the suitability map and their scale (Dar et al., 2021). Furthermore, SDMs may incorrectly predict potential species distributions when the data for both sexes are pooled, leading to overestimates, particularly for females (Gantchoff et al., 2019).

My findings show that brown bears in Türkiye are structured into three main habitat blocks, including the Western Black Sea, Eastern Anatolia, and the Mediterranean, the last of which is significantly more vulnerable to climate change (Chapter 2; Ozturk et al., 2015; Newbold et al., 2020). In addition to these, I observed that there are three other important separate patches for bears in the Amanos Mountains, around Mount Ida, and the Hakkari Mountains (Fig. 3.2). Many stepping stones that are scattered between these core patches can provide connectivity. Considering the area-corrected centrality, Uludağ, Kartepe and Ahır

Mountain in the West; Karaoğlan Mountain, Nemrut Mountain and Hasan Mountain in the East; and Taşova in the central Black Sea region are critical stepping stones for connectivity (Fig. 3.3). However, the potential contributions of these locations in terms of mitigation should be examined with detailed field surveys, and their existing connectivity should be evaluated by considering restoration measures (Tobgay & Mahavik, 2020). Although some small patches are not currently known to host brown bear populations, they are suitable habitats that should be protected as they contribute significantly to landscape connectivity. The importance of these small patches should not be underestimated, as the dispersal of individuals across the landscape depends on the availability of local resources. On the other hand, although the centrality of the Hakkari Mountains was relatively low (Fig. 3.3), this mountain range is the extension of the Zagros Mountains, and it is known that this region as a belt continuing towards Iran constitutes a suitable habitat for brown bears (Mohammadi et al., 2021; Ashrafzadeh et al., 2022; Rahimi & Dong, 2023). Therefore, transboundary landscape connectivity should be examined here, and transboundary measures should be implemented to support uninterrupted movement. Unfortunately, southwest Asian brown bears have now lost much of their historical range, and brown bears in the Zagros Mountains across Iran are experiencing local extinction (Karami et al., 2015). Thus, transboundary conservation management is important for the persistence of the local population there by facilitating genetic dispersal and bears' continued movement in response to climate change impacts.

In Türkiye, I detected 106 linkages among 61 core patches (Table 3.2). Across Anatolia, brown bears mostly prefer forested areas (Chapter 2). While forested areas represent more conductive areas, they included reproduction and establishment, and resistance increased in non-forested areas (Fig. 3.1). However, bears can also be common in cropland and near human settlements that act as moderately permeable barriers (Cozzi et al., 2016; Gantchoff & Belant, 2017; Morales-Gonzallez et al., 2020) since bears can be highly adaptable to landscape transformation (Bombieri et al., 2021; Cozzi et al., 2016). This situation increases the risk of human-bear conflict (see Chapter 4) and poses a threat to population viability (Penteriani et al., 2018). However, because of this foraging behavior of bears, lower quality corridors may have importance for connectivity (Greenspan et al., 2021). For instance, although the Circuitscape algorithm is based on a random walk between the cells, representing the broadest possible connection (McRae et al., 2008), brown bears rely on their perceptual environment knowledge for habitat usage (Donatelli et al., 2022; Lamb et al., 2020). The feeding spots, such as open

garbage dumps or near the orchards where they can easily find food, can mediate bears' dispersal routes (Cozzi et al., 2016). Spatial structure and configuration of habitats ultimately affect individual movement (Parsons et al., 2022; Kemahlı et al., 2023). Hence, it is necessary to evaluate the landscape-specific dispersal ability with fine-scale studies. Although the main roads represent mostly a barrier for movement, bears may prefer some roads along their feeding and breeding areas depending on various factors such as traffic density (Find'o et al., 2019). Only 34 of 106 linkages among the core patches were not bisected by main roads. In addition to roads providing human access to pristine areas, roads bisect the core habitats, and they are one of the main reasons for bear casualties across the country, especially in the Black Sea and Eastern Anatolia regions (Chapter 4). Providing wildlife overpasses in locations where brown bears' cross the main roads most frequently would reduce bear-vehicle collesions (Proctor et al., 2015), also saving human lives. This study suggests some important locations in this context. For instance, the linkages between the Akçakoca Mountain – Western Black Sea block, İznik – Uludağ, Eceabat – Biga Mountains, Akdoğan Mountains – Eastern Anatolia block, Palandöken – Akdoğan Mountains, and Kop Mountain – Eastern Anatolia block were bisected by highways. It should be noted that many bears use highways as boundaries of their habitat (Cushman et al., 2013; Mateo-Sánchez et al., 2014; Proctor et al., 2015; González-Bernardo et al., 2023) and such roads may lead to sex-bias filtering (García-Sánchez et al., 2021). Therefore, in these mentioned linkages, bear crossing areas can be determined by monitoring, and effective precautions such as overpasses, underpasses, wildlife fences, and non-structural methods (e.g. warning signs and speed limits) can be taken to facilitate movement (Sawaya et al., 2014; Rytwinski et al., 2016).

The status of protected areas at the global scale is far from maintaining the world's biodiversity (Yang et al., 2020; Elsen et al., 2020; Mingarro et al., 2023) and unfortunately, Türkiye is no different (Şekercioğlu et al., 2011a,b; Atmiş, 2018). While the globally agreed target for countries is to conserve 17% of land and inland water areas in protected areas, all of Türkiye terrestrial protected areas cover only 7.7% of the country's land area (NCNP, 2022), and only 5.5% of this area is enough to meet the ecological requirements of brown bears (Chapter 2). In Chapter 2, I show that if the established protected areas are not reconsidered and redesigned, a conservation gap will occur for potential future bear habitats because of climate change driving range shifts. It has been shown in other studies that protected area status is very important for dispersal ability of large carnivores (Elliot et al., 2014; Haddad et al., 2003).

Although only 6.7% of core habitats detected in this study have protected area status, 41 of 106 LCPs between the core habitats pass on the protected areas. Furthermore, six significant areas for restoration to enhance the connectivity were determined around the protected areas (e.g., the regions between Eğirdir & Kızıldağ Mountain, Bozburun Mountain – Geyik Mountain, Hasan Mountain –Karaoğlan Mountain, Şakşak Mountain – Karaoğlan Mountain, Pasinler – Palandöken Mountain, Karaçavuş Mountain – Eastern Anatolian block) (Fig. 3.5). Increasing the effectiveness of protected areas by including the mentioned stepping stones and enforcing regulations more strictly within and around the protected areas will contribute to long-term population establishment and successful bear recolonization.

The impact of climate change on wildlife is increasing daily. Although the habitats of specialist species are particularly seriously threatened (Ma et al., 2018), the current landscape transformation also has devastating consequences for generalist and wide-ranging species such as brown bears (Su et al., 2018; Dai et al., 2019a; Ashrafzadeh et al., 2022). In this chapter, ecological niche modeling and connectivity modeling were integrated to understand the effects of climate change-driven shifts on the ecological networks of brown bears. Considering potential habitat suitability in the near future, I previously showed that bears' suitable habitats will shift northward and towards higher altitudes (Chapter 2). These results show that the size of bears' core habitats will decrease in the future and will be more fragmented. As habitat fragmentation increases, the landscape resistance to bear movement will also increase in the near future. Fragmentation affects the number of pinchpoints and creates new barriers along the dispersal routes. Three LCPs are longer than 200 km, twelve are between 100 and 200 km, sixty-two are between 50 and 100 km, and thirty-five are shorter than 50 km (Table 3.2). Female bears can have dispersal distances of up to 90 km and male bears up to 467 km (Støen et al., 2006). However, it is important to note that this dispersal distance is strongly dependent on habitat continuity, quality, connectivity, and resource availability. With climate change effects, LCP length among the patches is increasing, and the colonization of new patches is becoming a challenge (Fig. 3.6). These lead to a decrease in gene flow and demographic exchange among fragmented habitats over time, resulting in more isolated populations (Benazzo et al., 2017). Demographic exchange, which is important for the success of species' recolonization and expansion, is particularly critical for brown bears because of females' philopatric patterns (Støen et al., 2006; Zedrosser et al., 2007). Isolated populations will accelerate the local extinction of species that will have high ecological requirements due to climate change. For

example, a study performed on Himalayan brown bears predicted that climate change will cause an increase in the number of isolated patches (Dar et al., 2023), as I predict here for Türkiye.

As a limitation, it should be noted that circuit theory does not incorporate scale dependency of dispersal capability (Mohammadi et al., 2021). Dispersal ability significantly affects a species' recolonization success (Dar et al., 2022; Landguth et al., 2012). While this study only provides insight into structural connectivity, more reliable data such as satellite tracking (Recio et al., 2021; Whittington et al., 2022) and landscape genetics (Ashrafzadeh et al., 2018; Draheim et al., 2018) are needed for connectivity prioritization. With such data, the most suitable restoration points can be effectively determined. When determining restoration points, restoration of alternative paths, as well as the optimal path, may be beneficial and should be considered. Considering that connectivity designs should include large areas (Theobald et al., 2012), the contributions of these evaluations of structural connectivity are important for conservation management. However, I should point out that conservation strategies based on resistance surfaces produced through empirical modeling at a finer scale and verified by expert opinion are an urgent need, especially for highly human-dominated areas such as the shrinking natural areas of the Mediterranean and Marmara regions. Distributions of species may be limited by factors such as intraspecies competition and resource availability, which are not included in this model (Duquette et al., 2017; Penteriani et al., 2019; Lucas et al., 2023). Understanding movement between habitat patches and developing effective management for population persistence are urgent priorities to mitigate the effects of climate change and landscape transformation.

3.5. Conclusion

In this chapter, I presented my findings on the structural connectivity of brown bear habitats across Türkiye. Developing conservation strategies to prevent degradation and identifying priority habitats is much cheaper and more effective than habitat restoration (Fedorca et al., 2019). Therefore, the results of this study provide support for urgent and essential decisions regarding conservation management in Türkiye. According to my findings, the two main habitat blocks across Türkiye; Eastern Anatolia and the Western Black Sea, remain relatively intact and have not yet been degraded. Although this is positive for the connectivity of brown bear populations, which can have a high potential for expansion due to

their opportunistic omnivores with long dispersal distances (Zarzo-Arias et al., 2019; García-Rodríguez et al., 2021), the situation is critical in the Mediterranean. This spatially explicit modeling framework also demonstrates the effects of climate change on the structural connectivity of brown bear populations. Model results show that climate change will disrupt the ecological network of bears across the country in the future and reduce the connectivity of habitat patches. Functional connectivity studies that consider factors such as population density, biotic interactions, and dispersal limitation are needed to understand the effects of climate change and landscape transformation on Anatolian brown bears. Monitoring efforts using camera traps and GPS collaring will allow more precise corridors to be defined.

Chapter 4

4. Human – Brown Bear Conflicts Across Türkiye

4.1. Introduction

Human dominance causes loss of quality and degradation in brown bear habitats. Brown bears rely on their perceptual environmental knowledge for habitat usage (Donatelli et al., 2022; Lamb et al., 2020) and develop plastic strategies (Cozzi et al., 2016; Deacy et al., 2017; Pereira et al., 2021; Ogurtsov et al., 2024). By comparing the potential risks people present with the benefits of the food they provide, they can forage in human-modified areas with high risk (Parsons et al., 2022). Therefore, they exhibit synantrophic behavior (Peirce & van Daele, 2006; Cozzi et al., 2016). Conflict causes at the global scale include increasing anthropogenic activities such as logging, overgrazing (Fernández et al., 2012; Fortin et al., 2016), fragmentation of bear habitats (Khosravi et al., 2023; Kudrenko et al., 2022), seasonal decreasing local resources (Zarzo-Arias et al., 2021; Schrag et al., 2008), attraction to areas around human settlements (Cozzi et al., 2016; Lamb et al., 2017), human-associated food conditioning (Naves et al., 2018; Cozzi et al., 2016), decreased tolerance to bears (Obbard et al., 2014), increasing bear populations (Can & Togan, 2004).

Human-bear conflict is a common phenomenon across Türkiye that originates from different reasons, most importantly habitat fragmentation and patchiness (Ambarlı et al., 2016) and an increase in human footprint in prime forest habitats, especially along the Black Sea (Ambarlı et al., 2018). As brown bears are forced to live in increasingly human-dominated landscapes, bear-related incidents near human settlements are on the rise, posing a significant threat to human-brown bear coexistence. This situation not only makes brown bears more vulnerable to natural and anthropogenic environmental change but also fosters negative attitudes toward their conservation (Kurth et al., 2024). Unfortunately, our knowledge of the spatial distribution and factors driving these conflicts in Türkiye remains limited. Obtaining spatial information on human-brown bear conflicts (HBCs) can help us detect ecological traps or sink habitats by determining the factors responsible for these conflicts (Broekhuis et al., 2017) and to develop conservation and management strategies to reduce HBCs (Khosravi et al.,

2023; Can et al., 2014). Therefore, this chapter aims to quantify the spatial and temporal trends of HBCs across Türkiye and increase our understanding of the social and ecological dynamics underlying these conflicts. Understanding these dynamics is crucial not only for brown bear conservation but also for fostering harmonious coexistence between humans and bears in Türkiye's unique ecosystems.

4.2. Materials and Methods

4.2.1. Data Collection

To determine the dynamics of HBCs in Türkiye, I collected and reviewed news stories on brown bear-human encounters between 2017-2023. To this end, I conducted Google searches using the following keywords: “bear + sighting”, “bear + attack”, “bear + attack + human/barn/beehive/orchards/crops/fence/yard/damages”, “bear + mortality” + “bear + road accidents” in Turkish. All positive hits (i.e. conflict events) were geo-referenced based on the location information. In cases where location information was absent, I tried to reach out to eyewitnesses or sought confirmation from the local village chief (muhtar), who serves as the representative of the state in Turkish villages. When direct eyewitnesses were unavailable, I assigned a georeferenced point randomly within a five kilometer radius of the potential event location (Kimmig et al., 2020). I classified conflicts into seven categories in relation to the nature and cause of the conflict: i) Attack on livestock (Livestock), ii) Attack on beehives (Beekeeping), iii) Damage to crops, iv) Encounters/attacks during human activity in forests (i.e. gathering resource/food, trekking, camping, logging, picnic), v) Road accidents involving brown bears and vi) Illegal/Inadvertent poaching. I classified the conflicts not falling into these classes as “vii) Other”. I used Chi-square goodness-of-fit tests to determine significant differences between conflict types and whether the overall distribution of conflicts deviated from a uniform distribution. I also used the Chi-square test for significant differences between conflict events across years, seasons, and the three major biogeographic regions in Türkiye; Euro-Siberian, Irano Anatolian, and Mediterranean (Davis, 1971; Noroozi et al., 2019).

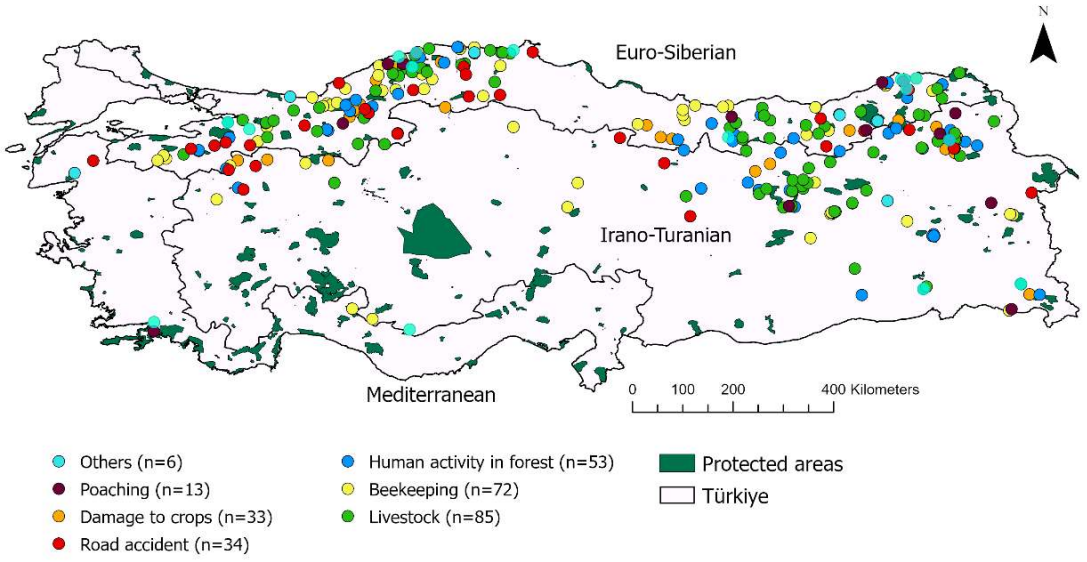

Figure 4.1: Distribution and the number of recorded conflict events and types across Türkiye between 2017-2023.

4.2.2. Environmental Variables

I used a combination of anthropogenic variables and key bioclimatic predictors, including Distance to Forest, Distance to Farmland, Distance to Water, Distance to Road, Distance to Villages, Distance to Protected areas, Population Density, Human Footprint Index, Slope, Net Primary Productivity, Maximum Temperature, Minimum Temperature, Mean Temperature, Precipitation, and Frequency of Wet Days (Table 4.1). Based on the literature, I selected these 15 environmental predictors with a high potential to influence HBCs. For instance, roads, villages, and farmlands can be hotspots in terms of HBCs since they exhibit high-risk, low-gain landscape features for bears and represent ecological traps in most cases (Bombieri et al., 2021; Parsons et al., 2022). Water sources such as springs and rivers are important locations for both wildlife as well as human activity such as livestock, camping etc (Parsons et al., 2022). Brown bears rely on forested habitats for foraging, sheltering, and denning (Recio et al., 2021; Ziółkowska et al., 2016); so forests were included in the model. Population Density and Human Footprint Index are important to understand the potential role of human dominancy in terms of HBCs in rural areas (Dai et al., 2019b) Protected areas that have low human footprint play a crucial role in conserving biodiversity and providing refuge for species threatened by habitat loss (Tammeleht et al., 2020; Dai et al., 2020). The model included the slope variable since a high slope represents low human access as a general pattern (Goldstein et al., 2010). Bioclimatic variables, including minimum, maximum, mean

temperatures, precipitation, frequency of wet days, and net primary production features, drive the abundance, richness, and accessibility of natural resources of brown bears as well as human land usage (Penteriani et al., 2019; Zarzo-Arias et al., 2021; Pérez-Girón et al., 2024). I included the rasters I used in Chapter 2, named Distance to Forest, Distance to Farmland, Distance to Road, Distance to Villages, Distance to Water, Slope, and Human Footprint Index. I generated the proximity layer named Distance to Protected Areas by using the layers containing previously selected protected areas attributes (see Chapter 2) with the Euclidean Distance Tool in ArcGIS. In this chapter, I downloaded Population density data from WorldPop in contrast to Chapter 2. I downloaded the Minimum Temperature, the Maximum Temperature, the Mean Temperature, the Frequency of Wet Days, the Precipitation data from CRU TS Version 4.04 (Climatic Research Unit, University of East Anglia) data source (Harris et al., 2020). Considering the dramatic increase in extreme weather events every year since the 2000s (Walsh et al., 2020), I chose the CRU database because it covers the relevant time range (2010-present) for these predictors, unlike Worldclim (1970-2000) database. I downloaded yearly Net Primary Productivity (NPP) data between 2016-2022 from the Terra/Modis database. Then, I took the average of these years as a final NPP raster file. Before the modeling, I resampled the rasters with the Nearest or Bilinear interpolation approach depending on the rasters' cell size and cropped and masked them based on the study area.

I checked multicollinearity among the variables using *usdm* (Naimi, 2023) and *corrplot* (Wei & Simko, 2021) packages (Fig. 4.2, Fig. 4.3) and excluded them if they displayed high correlation ($|r| > 0.7$) and high variance inflation (e.g., VIF > 5) (Fig. 4.2, Table 4.1) (Dormann et al., 2013; Elith et al., 2006). Ultimately, 13 variables were retained except the Mean Temperature and the Minimum Temperature predictors.

Table 4.1: Environmental variables used for risk modeling of human – brown bear conflict across Türkiye. The bold variables were selected to run final model.

Source	Variable	Unit	Link
Corine Land Use Land Cover 2018	**Distance to Forest**	km	https://land.copernicus.eu/pan-european/corine-land-cover/clc2018
	Distance to Farmland	km	
HydroRIVERS – HydroSHEDS	**Distance to Water**	km	https://www.hydrosheds.org/products/hydrorivers
Open Street Map	**Distance to road**	km	https://www.openstreetmap.org/
Nature Conservation and Natural Parks	**Distance to Protected areas**	km	https://www.arcgis.com/apps/View/index.html?appid=5f3978146c4643438ab446620e275269
SEDAC	**Human Footprint Index**	HFI	https://sedac.ciesin.columbia.edu/data/set/wildareas-v3-2009-human-footprint
WorldPop	**Population Density**	No. of persons/km^2	https://hub.worldpop.org/project/categories?id=18
-	**Distance to Villages**	km	-
Climatic Research Unit (CRU TS Version 4.04)	**Maximum Temperature**	ºC	https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.04/
	Minimum Temperature	ºC	
	Mean Temperature	ºC	
	Precipitation	mm day^{-1}	
	Frequency of Wet Days	Day	
Worldclim SRTM Data	**Slope**	º	https://www.worldclim.org/data/worldclim21.html
TERRA/MODIS	**Net Primary Productivity**	g C m^{-2} yr^{-1}	https://neo.gsfc.nasa.gov/view.php?datasetId=MOD17A3H_Y_NPP

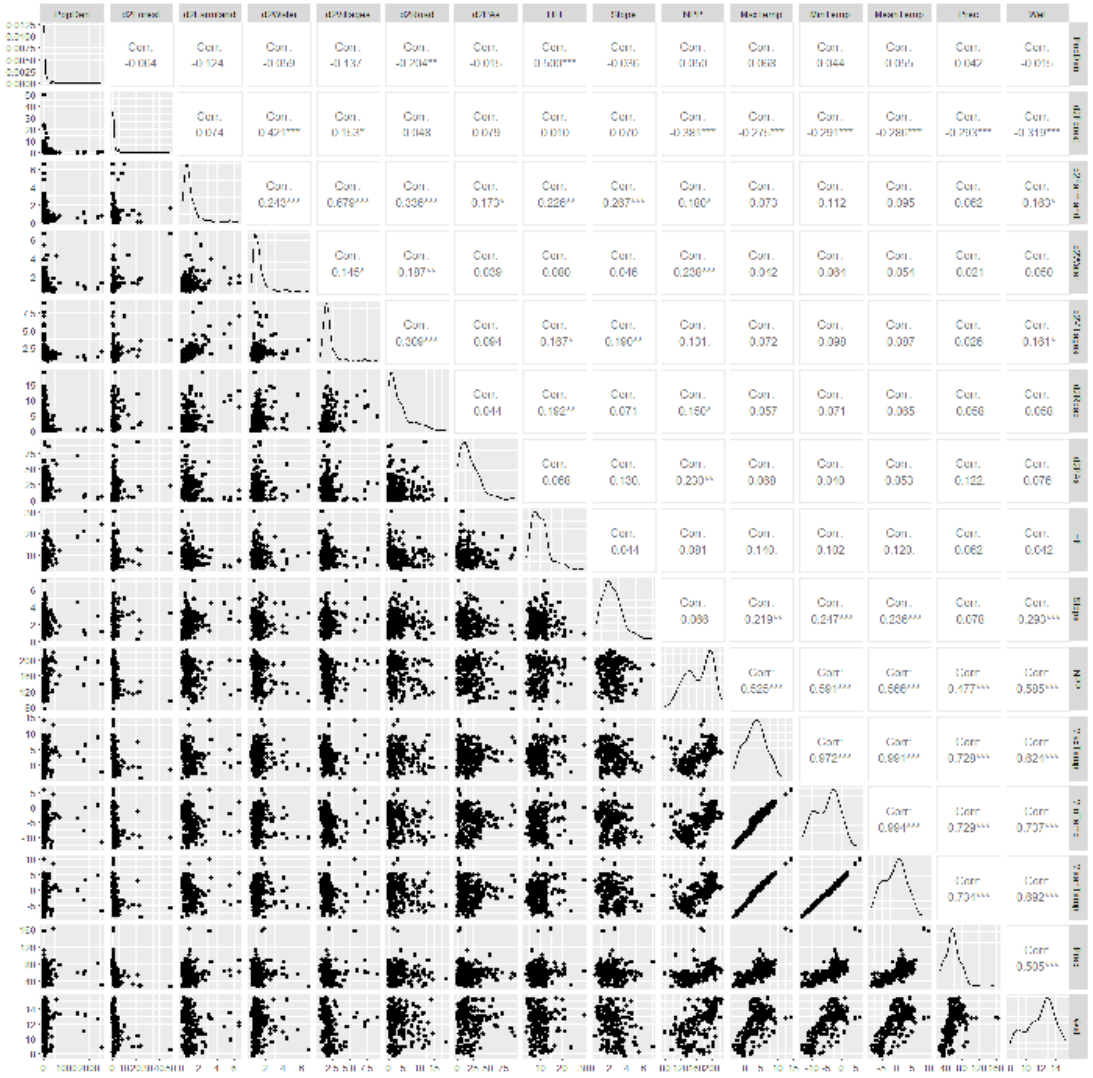

Figure 4.2: Correlation matrix of environmental predictors for human – brown bear conflict risk modeling.

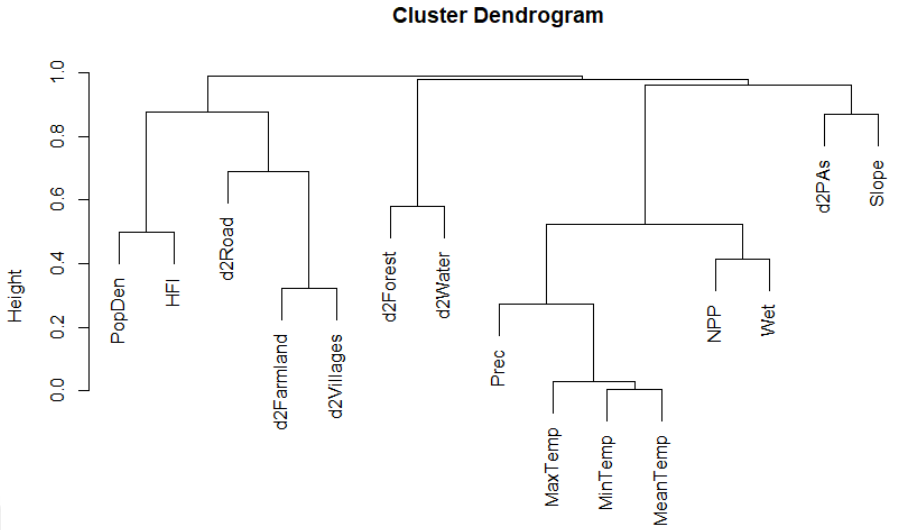

Figure 4.3: Cluster dendrogram of environmental predictors for human – brown bear conflict risk modeling.

4.2.3. Human – Brown Bear Conflict Risk Modeling

Human-brown bear conflict risk modeling was based on 296 geo-referenced conflict records (Fig. 4.1). I used the *spThin* package in R (*version* 4.3.2) (Aiello-Lammens et al., 2015) to filter the spatial clustering of points at the 10 km scale across the study area. 201 conflict events were used as the final dataset for conflict risk modeling.

I used species distribution modeling to determine the distribution of human-brown bear conflict risk probabilities across Türkiye using the *biomod2* package in the R. Specifically, I employed eleven different algorithms as follows: 1) Generalized Linear Model, 2) Generalized Additive Model, 3) Maximum Entropy, 4) Random Forest, 5) Artificial Neural Network, 6) Multivariate Adaptive Regression Spline, 7) Generalized Boosted Model, 8) Classification Tree Analyses, 9) Flexible Discriminant Analysis, 10) Surface Response Envelope, and 11) eXtreme Gradient Boosting Training (Chen et al., 2015).

Modeling was performed by generating 1,000 random pseudo-absence points and splitting the collected data into training (80%) and testing (20%) datasets (Pant et al., 2021). To avoid sampling bias, pseudo-absence points were generated three times for each model and cross-validated per model using bootstrapping (Carvalho et al., 2021). I evaluated and compared the performance and accuracy of each model considering AUC and TSS. To determine risk probabilities across Türkiye and to reduce the uncertainty among algorithms, I

constructed a final ensemble conflict risk model by weight averaging the eleven different algorithms as implemented in the *biomod2* (Thuiller et al., 2014). I averaged predictions across three replicated runs for each model and selected model runs with a TSS > 0.5 for generating the ensemble model. The probability map obtained from the ensemble model was rescaled by using the linear method in Rescale by Function Tool in ArcGIS. Then, the scale was classified with equal five intervals as follows: no-risk areas (< 0.2), low-risk areas (0.2 – 0.4), moderate-risk areas (0.4 – 0.6), high-risk areas (0.6 – 0.8), and extreme risk areas (> 0.8).

To better understand the conflict risk probabilities and human activity around protected areas, I created two separate buffered layers around each selected protected area: a layer spanning an area of i) a 5 km radius and ii) a 10 km radius from the border of each PA attributes. I then determined conflict risk probabilities, settlement density, and the HFI index within these layers. Finally, I presented the contribution of each variable to the ensemble model and used the response curves to visualize the relationship of each variable to the predicted risk assessment.

4.3. Results

4.3.1. Spatio-Temporal Pattern of Human – Brown Bear Conflicts

I collected 296 conflict events across Türkiye from 2017 to 2023 (Fig. 4.1). The annual number of HBCs averaged 42.3 ± 16.8, ranging from 26 to 70 across the seven-year period (Table 4.2). Statistical analysis using the Chi-square test confirmed significant variability in HBC frequency among years (x^2=46.868, *df*=6, *p-value*=2.00e-08) (Table 4.2). This trend was further evident for specific conflict types, including crop damage (x^2=20.667, *df*=6, *p-value*=0.002) and human activity in forest (x^2=44.075, *df*=6, *p-value*=7.14e-08) (Table 4.2). Notably, the highest number of conflict events were recorded in 2023 and 2021, respectively (Fig. 4.4; Table 4.2).

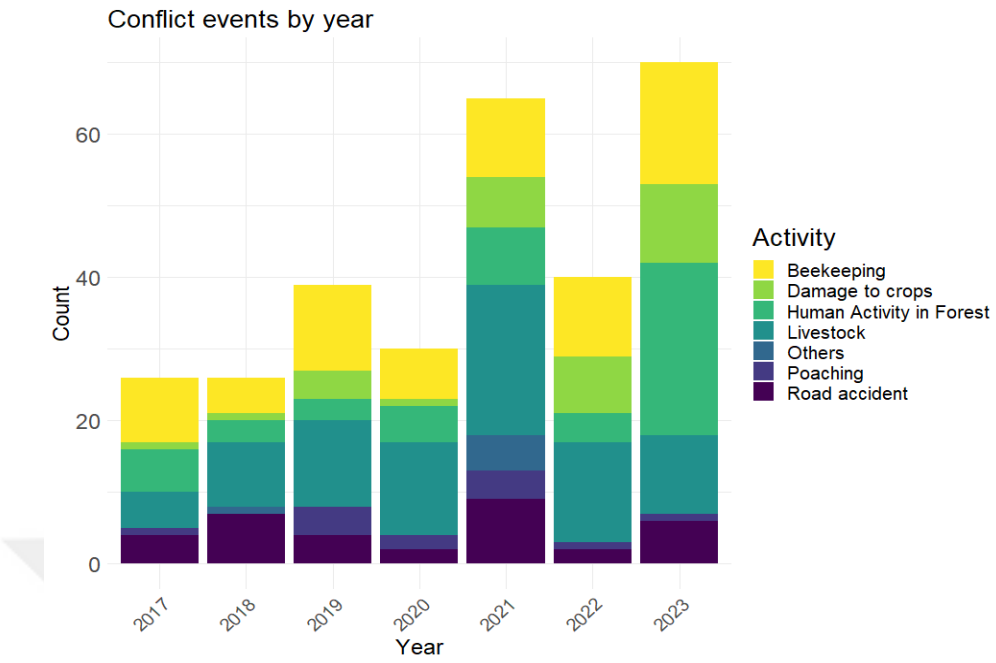

Figure 4.4: Number of conflict events across years.

Table 4.2: The frequency of conflict events by years and their statistical comparison.

Conflcit Type	2017	2018	2019	2022	2021	2022	2023	X^2	df	p-value
Livestock	5	9	12	13	21	14	11	11.929	6	0.06356
Beekeeping	9	5	12	7	11	11	17	8.6944	6	0.1915
Damage to Crops	1	1	4	1	7	8	11	20.667	6	**0.002105**
Human activity in forest	6	3	3	5	8	4	24	44.075	6	**7.14E-08**
Road accident	4	7	4	2	9	2	6	8.4118	6	0.2095
Poaching	1	0	4	2	4	1	1	5.2	6	0.5184
Others	0	1	0	0	5	0	0	11.231	6	0.0815
Total	26	26	39	30	65	40	70	46.858	6	**2.00E-08**

Seasonal analysis revealed Autumn, Summer, Spring, and Winter as the seasons with the most frequent encounters, respectively (Fig. 4.5). A statistically significant difference in HBC frequency was observed among seasons (x^2=82.568, *df*=3, *p-value*=2.20e-16) (Table 4.3). Interestingly, the individual conflict types except beekeeping, others, and poaching exhibited significant seasonal variations (Table 4.3).

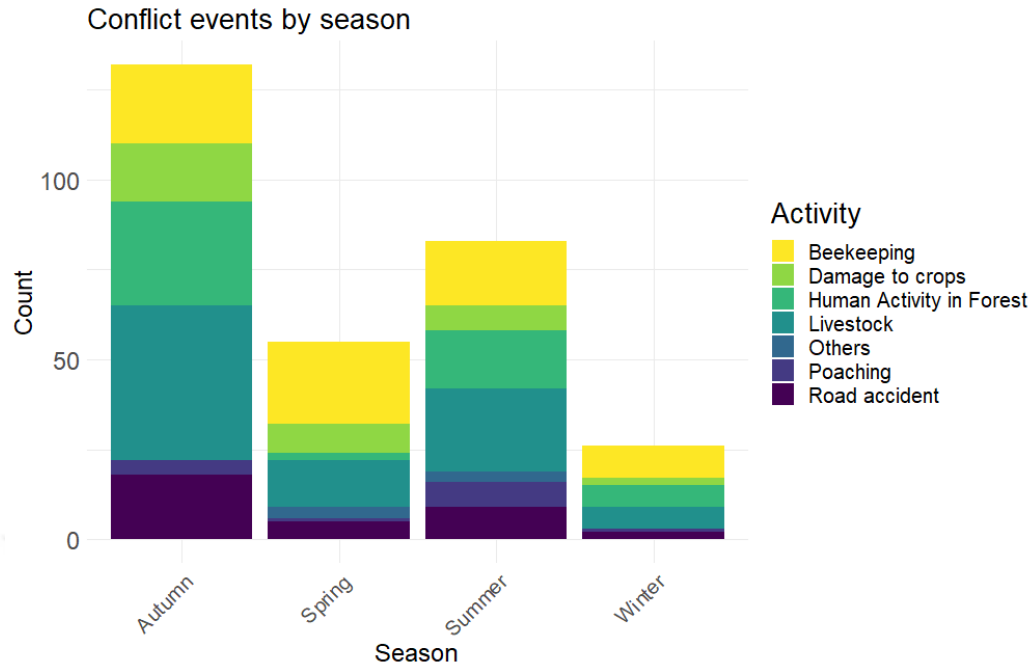

Figure 4.5: Number of conflict events across seasons.

Table 4.3: The frequency of conflict events by seasons and their statistical comparison.

Conflcit Type	Winter	Spring	Summer	Autumn	X^2	df	p-value
Livestock	6	13	23	43	36.553	3	**5.72E-08**
Beekeeping	9	23	18	22	6.7778	3	0.07933
Damage to Crops	2	8	7	16	12.212	3	**0.006691**
Human activity in forest	6	2	16	29	32.811	3	**3.53E-07**
Road accident	2	5	9	18	17.059	3	**0.000687**
Poaching	1	1	7	4	7.6154	3	0.05467
Others	0	3	3	0	3.6	3	0.308
Total	26	55	83	132	82.568	3	**2.20E-16**

Seasonal trends revealed an increase in HBCs during Summer and Autumn, coinciding with the bears' hyperphagia period. In Türkiye, hibernation typically occurs by late December, depending on altitude, with emergence from dens in mid-spring for cub-rearing or mating. While being primarily herbivorous and avoiding humans during this period, brown bears feed with berries and hard mast (e.g., beech, oak, common hazel) in late summer and autumn, respectively (Ciucci et al., 2014). Accordingly, the dataset was categorized into seasons: Denning (January 1 – April 15), Mating (April 16 – June 30), and Hyperphagia (July 1 – December 31). As expected, most HBCs occurred during the hyperphagia season followed by

the mating, and denning seasons, respectively (Fig. 4.6). Statistical analysis confirmed a significant difference in HBC frequency across bear seasons (x^2=203.22, *df*=2, *p-value*=2.20e-16) (Table 4.4). Furthermore, individual conflict types also exhibited significant differences between them. Despite a general pattern of brown bears avoiding humans during mating and denning, the Human Activity in Forest conflict type doubled in frequency during hyperphagia (Table 4.4). Additionally, an increased incidence of brown bear involvement in road accidents was observed during this period (Fig. 4.6).

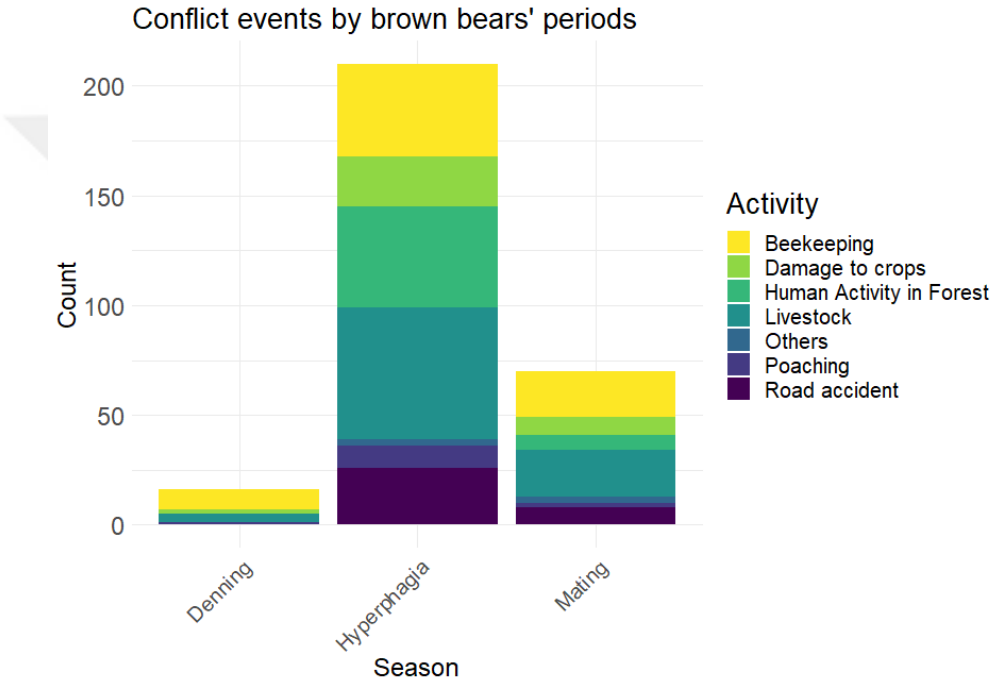

Figure 4.6: Number of conflict events across brown bear seasons.

Table 4.4: The frequency of conflict events by bears seasons and their statistical comparison.

Conflcit Type	Denning	Hyperphagia	Mating	X^2	df	p-value
Livestock	4	60	21	58.188	2	**2.32E-13**
Beekeeping	9	42	21	23.25	2	**8.94E-06**
Damage to Crops	2	23	8	21.273	2	**2.40E-05**
Human activity in forest	0	46	7	65.821	2	**5.09E-15**
Road accident	0	26	8	28.767	2	**5.70E-07**
Poaching	1	10	2	11.231	2	**3.64E-03**
Others	0	3	3	2	2	**3.68E-01**
Total	16	210	70	203.22	2	**2.20E-16**

A statistically significant variation (x^2=121.82, *df*=6, *p-value*=2.2e-16) was observed in the frequency of different conflict types across the country. Livestock attacks (n=85) constituted the most frequent events, followed by beekeeping-related conflicts (n=72), human activity in the forest (n=53), road accidents (n=34), and crop damage (n=33) (Fig. 4.1). Although the total number of conflicts exhibited substantial variation across biogeographic regions (Fig. 4.7), no significant correlation was found with area size (r = 0.005; *p-value* = 0.997). Despite having the smallest area, the Caucasus and Western Black Sea habitats within the Euro-Siberian region (146,694 km^2) exhibited the highest number of conflicts (n=191), translating to a rate of 0.13 events per 100 km^2. This rate was significantly higher compared to the Irano-Turanian region (n=101, 480,937 km^2, 0.02 conflict events per 100 km^2) (Fig. 4.7; Table 4.5). Conversely, the Mediterranean region recorded the least number of conflicts (n=4, 153,073 km^2, 0.003 conflict events per 100 km^2) (Table 4.5). The dominant conflict types differed between regions. While beehive and livestock attacks were most prevalent within the Euro-Siberian region, livestock attacks and human activity in forests were more common in the Irano-Turanian region. Additionally, road accidents exhibited a higher frequency in the Euro-Siberian region compared to other ones (Table 4.5).

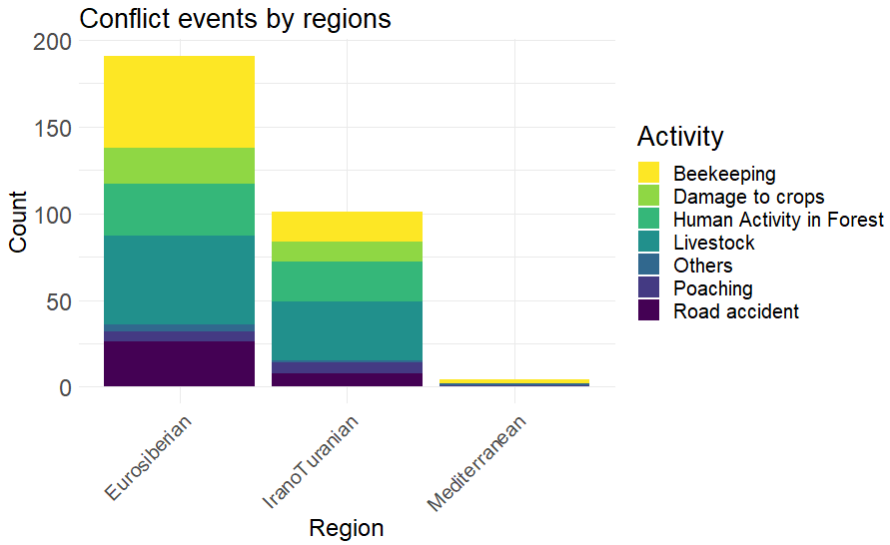

Figure 4.7: Number of conflict events across biogeographic regions.

Table 4.5: The frequency of conflict events by regions and their statistical comparison.

Conflict Type	Number	Euro-Siberian	Irano-Turanian	Mediterranean	X^2	df	p-value
Livestock	85	51	34	0	45.977	2	**1.04E-10**
Beekeeping	72	53	17	2	57.25	2	**3.70E-13**
Damage to Crops	33	21	12	0	18.5	2	**9.61E-05**
Human activity in forest	53	30	23	0	26.393	2	**1.86E-06**
Road accident	34	26	8	0	28.757	2	**5.70E-07**
Poaching	13	6	6	1	3.8462	2	0.1462
Others	6	4	1	1	3.00	2	0.2231
Total	296	191	101	4	177.29	2	**2.20E-16**

Financial losses were incurred in 135 conflict cases for diverse reasons, but the major ones were livestock predation (n=34, 25.2%) and apiary destruction (n=71, 52.6%). Notably, 67% of incidents involving financial loss occurred during the hyperphagia period. Of the 296 recorded HBCs, 103 (34.8%) involved human attacks, resulting in 95 injuries and 14 fatalities (Fig. 4.8a). The majority of conflict events leading to human attacks stemmed from livestock herding (n=47, 45.6%), followed by agricultural activities (n=15, 14.6%), trekking (n=12, 11.7%), gathering mushrooms (n=9, 8.7%), berry picking (n=6, 5.8%), vehicle collisions (n=3), logging (n=2), poaching (n=2), apiary maintenance (n=1), and other miscellaneous activities (n=6). Attacks within farmlands were relatively frequent (14.6%). The recorded gender distribution of humans that were attacked showed 96 male and 6 female victims, with their age demographics presented in (Fig. 4.9b). Conversely, 64 conflict events (21.6%) resulted in brown bear casualties, encompassing 23 injuries and 42 fatalities. Road accidents (n=30) and poaching (n=12) were the primary reasons that led to brown bear casualties.

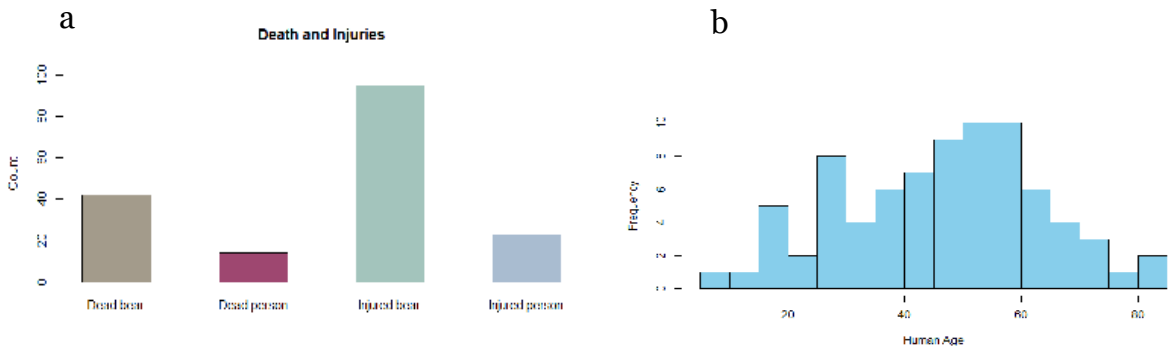

Figure 4.8: a) Number of dead or injured people or bears across encounters. b) The histogram of the age of people across encounters.

4.3.2. Conflict Modeling and The Factors Affecting Human – Brown Bear Conflicts

An evaluation of eleven different algorithms revealed that SRE and CTA exhibited the lowest AUC and TSS values (Fig. 4.9). Conversely, GBM, xGBoost, and RF algorithms achieved the highest AUC values, while GBM, GLM, and GAM algorithms achieved the highest TSS values (Fig. 4.9). The ensemble model, which aggregated predictions from all eleven algorithms, yielded a weighted average AUC of 0.93 and a weighted average TSS of 0.73, demonstrating its overall strong discriminatory power (Fig. 4.9).

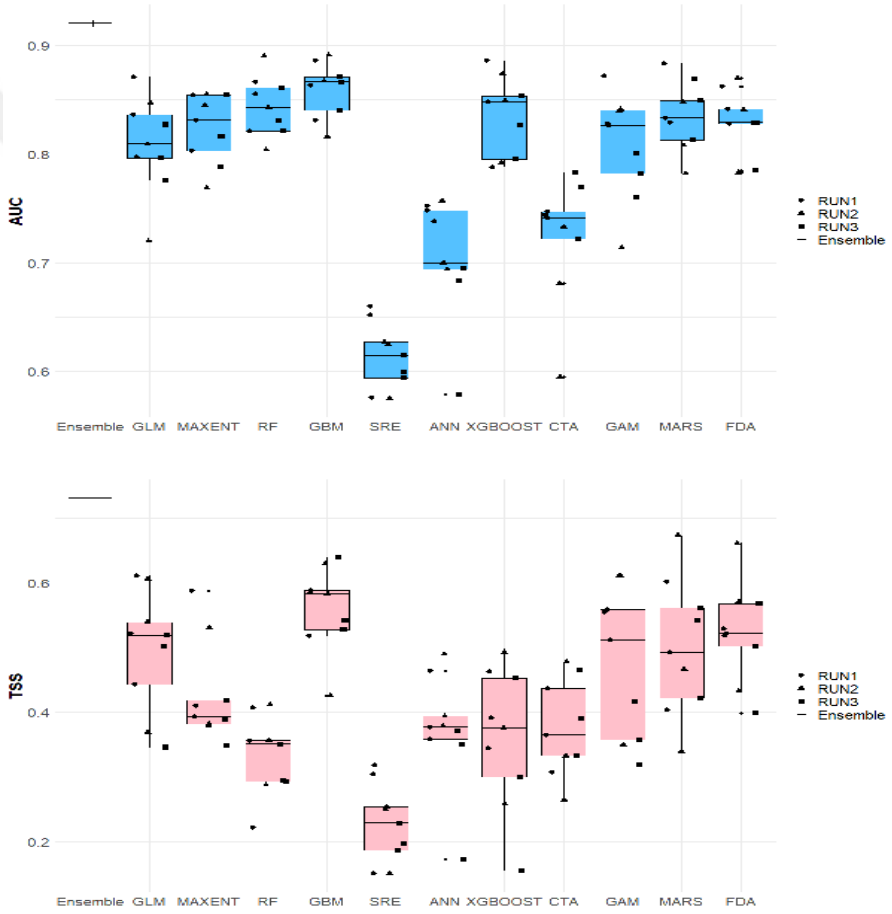

Figure 4.9: Receiver operating characteristic (ROC) area under the curve (AUC) (top) and True skill statistics (TSS) (bottom) values as the predictive performance of different modeling techniques were used in human–brown conflict risk modeling.

The ensemble model identified four key predictors contributing to conflict risk: Maximum Temperature (31%), Net Primary Productivity (16%), Population density (14%), and Distance to Forest (12%) (Fig. 4.10). Response curves for these predictors are presented in (Fig. 4.11).

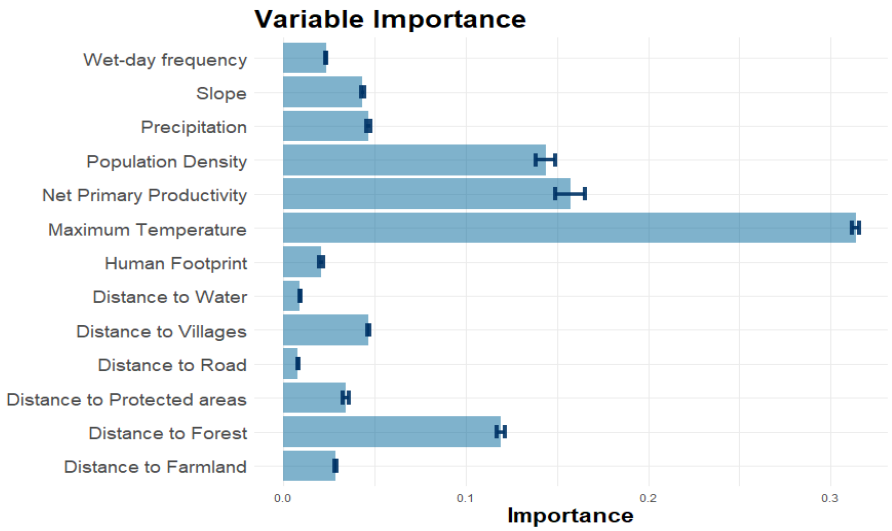

Figure 4.10: Percent contribution of environmental predictors to the final ensemble model for predicting human-brown bear conflicts across Türkiye.

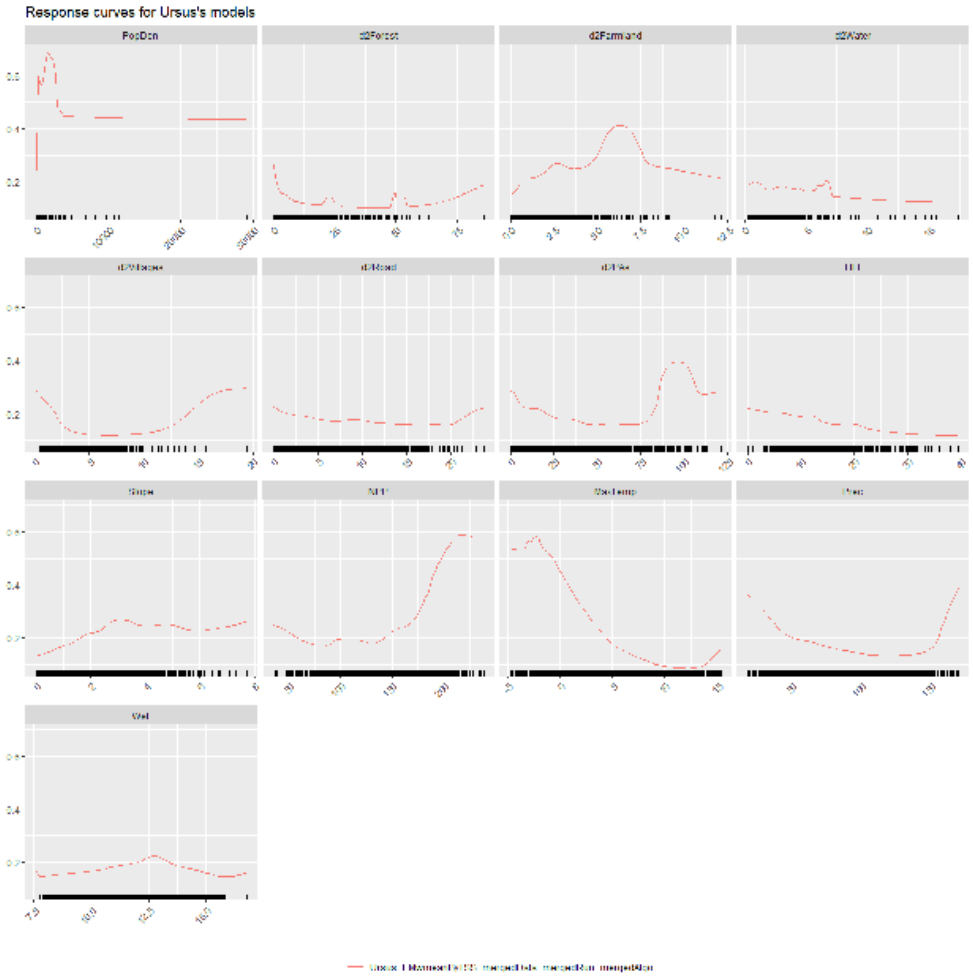

Figure 4.11: Response curves of the environmental predictors in the ensemble model for predicting human-brown bear conflicts across Türkiye.

Analysis of the ensemble conflict risk model revealed that an area of 146,604 km^2 (18.71% of the country) is under potential human-brown bear conflict risk. High-risk areas were primarily concentrated along the Black Sea coast and in Eastern Türkiye (Fig. 4.12). The binary map indicated that 6.73% of conflict areas are located within protected areas (Fig. 4.12). Furthermore, analysis of buffer zones with radii of 5 km and 10 km around PAs' centers revealed that 21.7% and 38.4% of all conflict areas lie within a 5 km and 10 km radius of these protected zones, respectively (Fig. 4.15). Additionally, the buffer zone analysis identified high human activity (HFI > 10) and many human settlements (>6,000 settlements) surrounding PAs (Table 4.6).

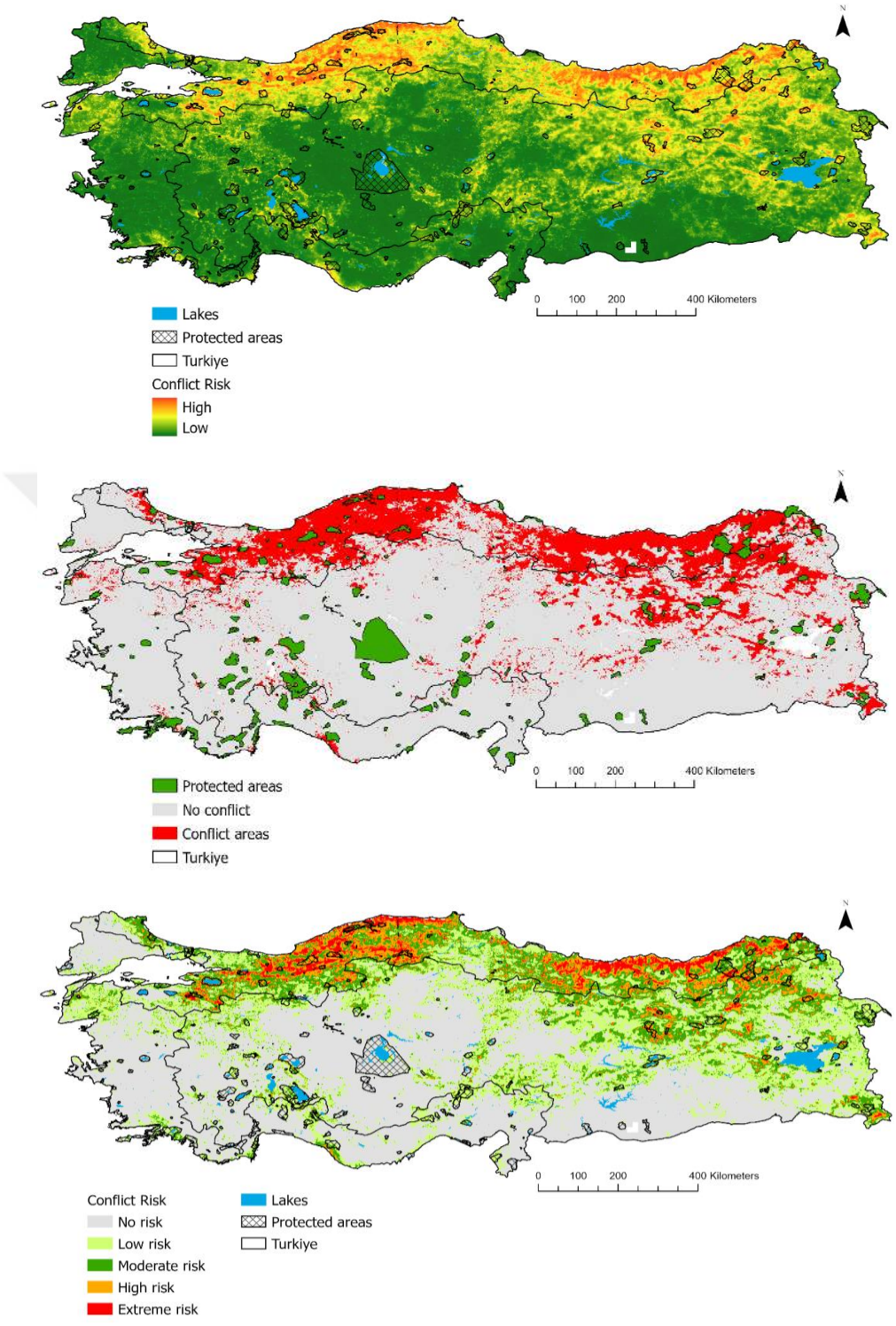

Figure 4.12: Ensemble model for risk probability of human – brown bear conflict across Türkiye (top). Binary map of conflict risk across Türkiye based on ensemble model (mid). The scaled conflict risk probability across the country (bottom).

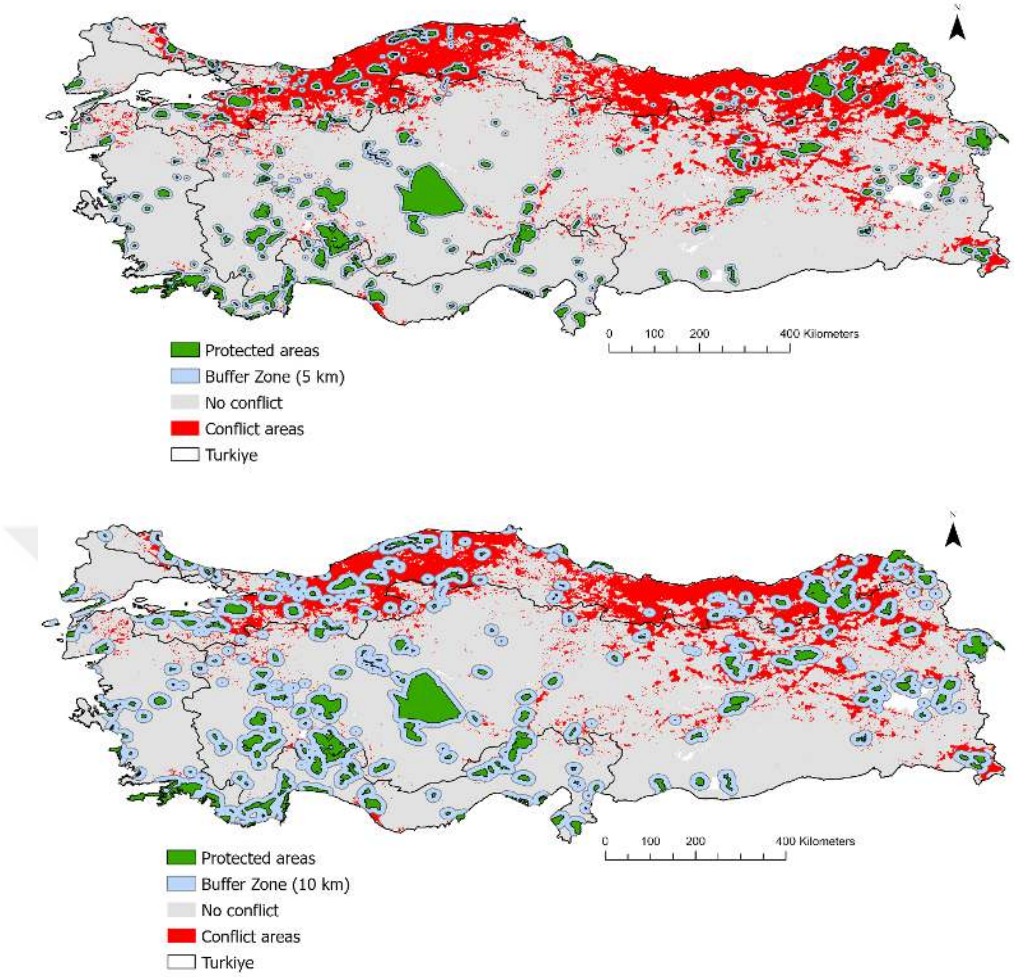

Figure 4.13: Binary map of conflict risk across Türkiye based on ensemble model for 5 km (top) and 10 km (bottom) buffer zones around selected protected areas.

Table 4.6: The anthropogenic impacts around the protected areas, and 5 km and 10 km buffer zones around their border.

Variable	Protected areas – No Buffer Zone	Protected areas – 5 km Buffer zone	Protected areas – 10 km Buffer zone	Whole country
Human Footprint Index (HFI)	9.81 ± 5.80	10.94 ± 6.37	11.11 ± 6.41	11.19 ± 6.01
Number of human settlements	1200	6609	13400	51689

4.4. Discussion

Data provided by social media and traditional media sources can provide resources for various research questions in conservation biology, such as the understanding of spatio-temporal dynamics of HBCs (Eid & Handal, 2017; Nayeri et al., 2022). In this study, I improved

a model of the spatial pattern of HBCs in Türkiye. This is the first comprehensive study to document and assess nationwide cases of human-brown bear conflicts based on the previously published version of this dataset (Sıkdokur et al., 2024). Brown bear is one of Türkiye's most abundant and widely distributed large mammals, and HBCs are a common occurrence across the country (Can & Togan, 2004). Several factors have been proposed to explain the frequent occurrence of HBCs in Türkiye, including habitat fragmentation and patchiness, increased development and construction in forest habitats, and higher bear density, especially along the Black Sea region of Türkiye (Ambarlı et al., 2018).

The ensemble model identified high-conflict risk areas and the majority of HBCs concentrated along the Black Sea coast and partly Eastern Anatolia, highlighting these regions as a hotspot for such interactions. Several factors that contribute to conflicts in these areas are listed below. First, the Black Sea region harbors the highest forest cover in Türkiye, providing suitable habitat for large bear populations. Second, human activities significantly contribute to conflict risk. Historically characterized by rural lifestyles and human settlements within forested areas (Koç et al., 2015), the region also sees the most beekeeping activity in Türkiye (Koday & Karadağ, 2020). Unsafely placed apiaries within/around forests are readily accessible to bears, as evidenced by the fact that 74% of beehive attacks occur in this region. This issue urgently requires mitigation strategies. Third, anthropogenic impact is rapidly growing in the region. Ongoing non-forestry activities (e.g. tourism, mining, energy facilities) in forested areas lead to fragmentation of habitats and increased human access. Additionally, seasonal pastoralist migrations to high altitudes within the Euro-Siberian and Irano-Turanian regions coincide with the bears' hyperphagia period, leading to increased livestock attacks. For instance, similar observations were reported in China's Sanjiangyuan region, where nomadic herding contributed to higher bear damage (Dai et al., 2020; Dai et al., 2021b). Lastly, in areas with high conflict frequency, public negative perceptions of bears are escalating (personal observation).

While population estimates indicate that Anatolia harbors more bears than many other parts of Europe and Asia, with over 3,000 individuals estimated across the Euro-Siberian and Irano-Turanian regions (Ambarlı et al., 2016), a direct link between population growth and increased conflict risk currently lacks robust scientific evidence because systematic population monitoring of brown bears across the country has not yet been carried. In addition, this study

did not include public attitude surveys (Ambarlı & Bilgin, 2008; Chynoweth et al., 2016) or news content analyses in terms of attitudes and perceptions (Frank et al., 2015; Hughes et al., 2020; Nanni et al., 2020). Conducting such research and implementing appropriate measures remain crucial.

Human – wildlife conflicts are an expected outcome whenever people and animals share the same space (Bombieri et al., 2023; Nayeri et al., 2022). The mean annual rate of bear attacks on people in Türkiye was calculated to be 14.7 attacks per year, surpassing continent-wide rates in North America (11.4 attacks/year) and Europe (10 attacks/year, excluding Romania) (Bombieri et al., 2019). Apart from human casualties, bear casualties were also high, with 21.62% of all encounters ending with harm to bears. Most bear casualties were the result of road accidents (n=30). The frequency of human-brown bear encounters may show different patterns depending on sex and age. Factors that direct these patterns are bear density, high ecological benefit for bears in risky areas (Parsons et al., 2022; Donatelli et al., 2022), life stage of individuals (Elliot et al., 2014), natural food availability (Bautista et al., 2023), and habitat quality (Ordiz et al., 2013). Hence, HBCs frequency displays landscape-specific characteristics. Additionally, although brown bears generally show nocturnal or crepuscular activity (Kaczensky et al., 2006), anthropogenic factors affect their patterns. For instance, they may exhibit more diurnal activity in areas that have a lower human footprint (Donatelli et al., 2022). On the other hand, females with cubs and subadult individuals may use high-risk areas more frequently than do adult males (MacHutchon et al., 1998; Gibeau et al., 2002). Male bears, with a polygamous mating system and sexual dimorphism, generally have a tendency to take more risks than females (Andersson, 1994). Therefore, especially subadult males may spend more time in high-risk areas compared to solitary females or adult males (Lamb et al., 2020) since adult males dominate high-quality habitats to maximize their fitness (Andersson et al., 1994). Brown bears have a despotic social organization (Elfström et al., 2014). Infanticide is a widespread behavior in bears and male dominant bears often exhibit the killing behavior of cubs of other males. For this reason, especially in small areas where the bear population is dense, females with cubs can take risks and forage in human-modified landscapes compared to other bear groups (Steyaert et al., 2013). Yet there is no clear pattern of bear behavior varying with age and sex at the global scale. Unfortunately, since I obtained my data from media coverage, I could not develop a detailed analysis of the sex and age status of bears in the context of HBCs. However, it should be noted that a database that would be developed on brown bear

deaths at the national scale would not only reveal ecological traps but will also enable sex and age-specific comparisons and the detection of areas that serve as potential filters.

Environmental variables to improve conflict risk modeling were selected by considering the literature. For instance, the maximum, minimum, and mean temperature values drive the spatio-temporal dynamics of HBCs because they direct the bears' biology and foraging behavior. Temperature-related changes can affect the seasonal food resources of brown bears (Penteriani et al., 2019; Zarzo-Arias et al., 2021; Roberts et al., 2014; Garcia-Mozo et al., 2012; Afif-Khouri et al., 2011; Nestby et al., 2011; Caprio & Quame, 2011; Bautista et al., 2023). Furthermore, brown bears can change their food preferences depending on temperature fluctuations (Zarzo-Arias et al., 2021; Kozakai et al., 2011; Deacy et al., 2017). Ultimately, the main temperature variables affect HBC frequency by forcing the bears to visit human-dominated areas (Lewis et al., 2015). Besides, temperature can modulate factors influencing the length of hyperphagia or cub-rearing season and entry/exit times of denning (González-Bernardo et al., 2020b), affecting the likelihood of encountering humans (Ordiz et al., 2017). Similarly, the predictors of Precipitation and Frequency of Wet Days affect both bear foraging strategy and human activities (Su et al., 2018; Pigeon et al., 2016). It is evident that they affect conflict events, including trekking, logging, road accidents, and human activity in forests (Dağtekin et al., 2024; Parsons et al., 2022). Additionally, these variables drive the bears' food sources abundance and richness in natural areas (Garcia-Mozo et al., 2012; Afif-Khouri et al., 2011). Lastly, Net Primary Productivity, which refers to the variation in the amount of energy available in the landscape from vegetation, is crucial because it indicates the productivity of brown bear habitats (Galetti et al., 2009; Rettler, 2018; Bowersock et al., 2024). Changes in NPP can lead to insufficient productivity in forest and grassland ecosystems, prompting the bears to turn to anthropogenic sources (Bowersock et al., 2024).

When examining the importance of variables to the model, I observed that the Maximum Temperature (31%), and NPP (16%) variables contribute the most to the model. The results indicate that high temperatures increase the risk of HBCs throughout Türkiye (Fig. 4.11). This may imply that HBCs will continue with an increasing trend in the future, considering Türkiye's future vulnerability to climate change (Ozturk et al., 2015; Demircan et al., 2017). NPP exhibited a positive relationship with increased conflict probability. This is an indication that human modification can modulate NPP in natural areas, as well as increase human-wildlife

conflict.

Anthropogenic variables also contribute significantly (in total ~41%) and direct conflict risk modeling across the country, but all variables are in close interaction with each other. Among them, Population Density (14%) and Distance to Forest (12%) were the variables that contributed the most to the model, respectively. These findings agree with the literature (Hipólito et al., 2020; Pop et al., 2023). Considering the rapid increase in logging and other interventions in Türkiye's forests in recent years, it can be said that the number of HBCs will increase in the future unless necessary precautions are taken. For the last two decades, Türkiye's forests have been faced with very serious deforestation (Hansen et al., 2013), and in parallel with this, the logging industry has also exhibited large growth (TIM, 2023). This unsustainable increase in logging and the resulting deforestation and forest degredation are affecting the quality of existing forest habitats and increasing the fragmented areas (TOD, 2022). Wrong forestry policies, improper industrial afforestation practices, and non-forestry use permits can significantly increase the conflict risk in forests and their periphery. Logging activities in forests have the potential to seriously affect the habitat usage of large carnivores (Colton et al., 2021). In addition to feeding and sheltering habitats for brown bears, forests also serve as buffers that protect brown bears from overheating (Nellemann et al., 2007; Rogers et al., 2021). Summer and winter temperatures, which can reach extreme levels due to climate change since the early 2000s (Walsh et al., 2020), are also changing the usage patterns of brown bears in patches containing young and aged forests (Stewart et al., 2013). Road and human presence also direct their habitat usage (Roever et al., 2010). Such human interventions in forest habitats may have consequences that will increase the likelihood of conflict by changing the habitat usage and circadian rhythms of brown bears (Donatelli et al., 2022).

Proximity to villages emerged as a significant variable contributing to the conflict risk model. Villages attract bears due to the presence of orchards, crops, and garbage dumps in their vicinity. Orchards and accessible crops readily attract bears, potentially converting agricultural fields into ecological traps. When space and food availability are restricted in natural habitats, wide-ranging mammals like bears may shift towards human-dominated landscapes offering predictable and easily obtainable food sources with lower foraging costs (Bautista et al., 2023; Kemahlı et al., 2023). Indeed, bear-human interactions in local populations exhibit intriguing patterns shaped by factors such as nutrient availability and human activity. The Sarıkamış

population in Eastern Anatolia presents a unique case area. The district garbage dump bordering fragmented Scotch pine (*Pinus slyvestris*) forests provides a readily accessible food source for bears, serving as a major feeding area. Few natural resources and increasing human presence in the region further encourage bears towards this feeding strategy. Analyses of GPS collar data reveal individual variations in behavior (Cozzi et al., 2016). While some bears exhibit sedentary behavior, spending most of their time near the garbage dump, others maintain migratory patterns within their natural habitats, covering larger distances (Cozzi et al., 2016; Kemahlı et al., 2023). Thus, inter-individual variability influences movement patterns. Similar hotspots as feeding areas for bears, such as the picnic area in the Nemrut Crater Lake of Bitlis, attract bears with human garbage. Unfortunately, many similar locations exist across the country. Unlike Türkiye, central European countries strictly prohibit supplementary feeding near settlements to prevent food conditioning (Huber et al., 2008). Conversely, numerous garbage piles exist near rural settlements in Türkiye, coupled with improper waste disposal/storage instruments, habituating bears to human-derived food (Lewis et al., 2015). This problem demands urgent attention from authorities such as rural municipalities. While supplementary feeding might act as a stopgap solution in cases of insufficient natural resources, as seen in Sarıkamış, unfortunately, bears in these locations have become dependent on human-derived food. For example, during the hyperphagia period, over thirty-five bears can be observed simultaneously feeding at the Sarıkamış garbage dump (Chynoweth et al., 2016). Such artificial feeding can modulate bear body size and energy budgets (Robbins et al., 2004). Fluctuations in energy budgets due to diet-induced thermogenesis during hibernation may potentially cause additional stress (Erlenbach et al., 2014).

Crop and orchard damage by brown bears is a common phenomenon in Türkiye, although media coverage on this issue is relatively limited. This underrepresentation likely introduces bias into my dataset, as only sensational cases like bear attacks on humans tend to gain media attention. While this chapter relies on media data, it is important to note that the actual number of HBCs in Türkiye likely exceeds what is reported in the media. While acknowledging the limitations of solely relying on media data, this study highlights its relevance in identifying human-caused mortality and conflict hotspots for large carnivores, particularly in scenarios where comprehensive research funding is scarce and official authorities refrain from publishing confidential data (Nayeri et al., 2022).

Most human-induced conflicts stem from direct human activities in forested areas, including logging, poaching, and recreational activities. Accidental road kills also contribute significantly to bear mortality. Human Footprint Index (HFI) serves as an indicator of cumulative human pressure on the environment. Interestingly, the ensemble model revealed that conflict risk was highest in areas with low to moderate human footprint based on HFI (Venter et al., 2016), whereas areas with very high human pressure exhibited lower risk, likely because these areas do not meet brown bears' ecological requirements (Fig. 4.11). Overall, the average HFI within and around protected areas in Türkiye is remarkably high (9.81 ± 5.80) (Table 4.6). Furthermore, the high level of human activity within and around PAs potentially explains the relatively high rate of bear attacks on humans. Echoing these findings, Lamb et al. reported that humans are the primary cause of brown bear mortality in areas exceeding an HFI of twelve. They further suggest that maintaining population stability requires an additional increase of 1-2% in immigrant brown bears for each unit increase in HFI (Lamb et al., 2020). The established PAs offer limited protection for natural bear habitats, with only a small cover of forested areas in the Black Sea and Eastern Anatolia regions being protected. Additionally, some of these protected forests are subject to legal logging and mining threats (Atmiş et al., 2018; Atmiş et al., 2024). Compounding these challenges, the immediate vicinity of PAs in Türkiye is densely populated, with 26% of all human settlements located within a 10 km radius of the selected PAs (Table 4.6). Based on the model results, areas around PAs appear to be hotspots for HBCs due to their vulnerability to human pressure. Therefore, stricter regulations and restrictions on human activities within and around PAs are essential to mitigate human-wildlife conflicts.

Although there were 34 road accident cases, distance to roads had a surprisingly relatively low contribution to the conflict risk model. Brown bears utilize roads for various purposes such as migration (Cozzi et al., 2016), dispersal (Boulanger & Stenhouse, 2014), and daily activities (Kite et al., 2016). Additionally, there are many attractive feeding spots for bears around roads, such as maize fields and orchards (Robertson et al., 2013). This complex interplay positions roads as critical components and potential ecological traps leading to higher conflict events (Lamb et al., 2017). This is particularly the case in the Black Sea region of Türkiye, where road construction through forested areas is rapidly expanding (e.g., Yeşil Yol Project) (WWF, 2015; URL1). Despite the complexity of bear-road interactions, the impact of roads can vary depending on the landscape (Find'o et al., 2019), sex of bears (Graham et al., 2010), traffic

volume (Chen & Koprowski, 2019; Jacobson et al., 2016), and daytime (Støen et al., 2020). Roads can also skew bear demographics by introducing gender (Steyaert et al., 2013; Graham et al., 2010; Lewis et al., 2011) and age-related (Boulanger & Stenhouse, 2014) biases, potentially leading to demographic imbalances. Furthermore, road barriers (Kusak et al., 2009) that have high traffic volume (Waller & Servheen, 2005; Graves et al., 2006) can negatively impact gene flow and decrease genetic diversity (Fedorca et al., 2019; Thatte et al., 2020). Bears often favor denning in areas with higher slopes and distance from human influence and roads (González-Bernardo et al., 2020a). They can affect cub survival in low-quality habitats with dense populations, as bears may be forced to abandon or avoid denning near roads (Elfström & Swenson, 2009). The results revealed that most vehicle collisions occurred in the Black Sea region (n=26 in Euro-Siberian, n=8 in Irano-Turanian), where roads increasingly bisect forests. Examining seasonal patterns, 76.4% of road accidents occurred during the hyperphagia period, likely due to increased foraging activity along roads. Although these findings approximate road accident estimates, more data is needed to generate a high-resolution risk map. Collaboration between traffic police, gendarme, the General Directorate of Highways, and the General Directorate of Nature Conservation and National Parks is crucial to map precise locations of wild animal road kills and create a more robust risk map. Subsequently, this detailed risk map can inform mitigation and interventions such as decreased speed limits in hotspots, speed control cameras, warning signs, and the construction of wildlife overpasses/underpasses (Kusak et al., 2009).

4.5. Conclusion

The results of this chapter indicate that the frequency of HBCs has been increasing across Türkiye, resulting in human and bear casualties, financial losses, and a negative public attitude toward conservation efforts. Conflict frequencies showed different patterns by years, seasons, bear seasons, and regions. Core habitats and migration routes of brown bears increasingly intersect with human settlements in Türkiye. This chapter underscores that the high incidence of HBCs in Türkiye predominantly arises from limited protected area coverage, insufficient natural habitats and resources available to brown bears, and the escalating encroachment of human activities in and around vital wildlife habitats. Addressing these critical factors will be pivotal in preserving sustainable bear populations in Türkiye and achieving a harmonious coexistence between humans and brown bears.

Chapter 5

5. Population Genetics of Brown Bears in Southwest Asia

5.1. Introduction

The ability of an individual to move from one region to another depends on the dispersal ability of the species (Støen et al., 2006). It is affected by many biotic and abiotic variables such as landscape configuration, climate conditions, competition, population density, and resource availability (Cushman et al., 2006; Ma et al., 2018; Thatte et al., 2020; Calderón et al., 2024). Although this dispersal ability can vary depending on the species' movement capacity under these conditions, it can be effective or non-effective (Burgess et al., 2016). Effective dispersal results in gene flow, whereas the disperser fails to pass its genes to the next generation in another region in the case of non-effective dispersal (Cayuela et al., 2018). In this context, landscape genetics uses analytical approaches developed to investigate microevolutionary processes driven by habitat fragmentation (Balkenhol et al., 2015). For instance, the barriers caused by anthropogenic or natural factors may have a serious effect on the gene flow between populations (McRae, 2006; Mateo-Sánchez et al., 2015a; Carvalho et al., 2018). Ultimately, small and isolated populations carry a high risk of extinction, as they are more sensitive to environmental and demographic changes.

Gene flow increases population genetic diversity and homogenizes genetic variation (Matosiuk et al., 2019; Kopatz et al., 2021). Genetic diversity decreases over time in fragmented habitats, while demographic isolation induces population genetic structuring (Slatkin, 1987). This situation causes reproductive isolation and speciation over time (Feder et al., 2012). Loss of genetic variation in isolated and small populations and increased frequency of rare deleterious alleles because of inbreeding reduces the ability of the species to respond to novel environmental challenges (Robinson et al., 2019). Therefore, avoidance of inbreeding and spatial heterogeneity are important influences on species distribution (Hamilton & May, 1977). Gene flow positively affects the species adaptation in most cases. While some diet-generalist and high-plasticity species, such as brown bears, can adapt to landscape-derived factors relatively more easily (Cozzi et al., 2016), the destruction of connectivity can be much more

devastating for this species (Benazzo et al., 2017).

Population differentiation mainly depends on the balance between the strength of selection and gene flow. Their contribution to the shaping of genetic diversity depends on factors such as population size and connectivity (Murphy et al., 2018). Genetic differentiation can be the result of drift becoming stronger in a fragmented landscape. In this case, an increase in gene flow positively affects population health (Prunier et al., 2017). On the other hand, long-term habitat change can enable species to adapt to new conditions through natural selection if they contain a slow rate of degradation and the ecological needs of species (Franks & Hoffmann, 2012). It leads to local adaptation. Changing environments can cause niche differentiation. If the local conditions are similar, they can cause niche overlap among the populations. However, as the conditions change, distinct environments cause increased niche divergence (Ashrafzadeh et al., 2018; Moreira & Smith, 2023). In this case, the isolation patterns can explain observed genetic diversity.

Changing climate and human interventions on the landscape continue to cause habitat fragmentation. Ultimately, the habitats are fragmented and the movement of individuals is restricted. In case of long-term isolation, loss of genetic diversity due to genetic drift increases further, resulting in inbreeding depression (Lacy, 1987). Large carnivores are particularly vulnerable to factors that can modulate such population dynamics. They require large undisturbed areas. Furthermore, factors such as hunting, human-wildlife conflict, and vehicle collisions also negatively affect population dynamics by increasing mortality rates (Boulanger & Stenhouse, 2014; Gosselin et al., 2015; Khosravi et al., 2023). These influences may be age-mediated, sex-mediated, life-history specific, or landscape specific (Shirane et al., 2019; de Jong et al., 2023, Peck et al., 2017) These dynamics direct microevolutionary processes and can reduce the adaptability of populations, push them to develop different behavioral strategies, and affect the fitness of individuals and the reproductive success of populations. One of the main ways to cope with such dynamics is to maintain habitat connectivity and to facilitate the demographic exchange of populations (Kopatz et al., 2021). Brown bears have been historically distributed throughout Southwest Asia. In addition to Türkiye, they are found in mixed and evergreen forests along the Zagros and Albroz Mountains in Iran (Mohammadi et al., 2021). However, all these core habitats are seriously shrinking due to the human footprint (Chapter 2, Ambarlı et al., 2016; Ashrafzadeh et al., 2018; Mohammadi et al., 2021; Ashrafzadeh et al.,

2022). Besides, Southwest Asia is one of the most vulnerable regions to climate change in the future (Newbold et al., 2020; Ozturk et al., 2015). Three key factors have been identified as driving the evolution of brown bears: northward expansions, dispersal primarily driven by males, and limited interaction between local populations (Endo et al., 2021). So far, there are few studies on the genetic diversity of brown bears in Southwest Asia, including Anatolia and Iran (Çilingir et al., 2016; Ashrafzadeh et al., 2016; Ambarlı et al., 2018; Ashrafzadeh et al., 2018; Kemahlı et al., 2023). In this chapter, I analyzed the population structure of brown bears across Türkiye and Iran and examined their genetic diversity as well as the potential importance of isolation patterns on population structuring.

5.2. Materials and Methods

5.2.1. Sample Collection, DNA Extraction, Sequencing and Mapping

First, we collected 566 scat samples and four tissue samples opportunistically from dead individuals during our field work across Anatolia. We stored the scat samples in a refrigerator during fieldwork and then stored them in laboratory freezer. We preserved the muscle samples in the alcohol. Second, Prof. İrfan Kandemir from Ankara University shared with us six tissue samples obtained opportunistically and with the necessary permissions. Third, I used eleven sequences obtained from tissue samples of Iranian brown bear. Finally, I used sixteen sequences obtained from the blood samples belonging to the brown bears living in Sarıkamış, Kars region of Türkiye. The information about the process of the collection and sequencing of these blood samples can be found in Kemahlı et al., (2023) .

Total genomic DNA from the scat samples and tissue samples were extracted using the QIAmp DNA Stool (or Tissue) Mini Kit following the manufacturer's protocol. Brown bear DNA was confirmed by assessing each sample's Cq values after qPCR amplification with the G10P primer pair (Paetkau & Strobeck, 1998). DNA concentration of each sample was quantified with the Qubit 2.0 Fluorometer and Qubit dsDNA BR Assay Kit. The degradation status was checked on 1.5% agarose gel. Then, the adequate samples were normalized to a concentration of 20 ng/µl. Ninety-three scat and five tissue samples were chosen based on their spatial distribution across Türkiye. The plate was sent to Floragenex Inc. (Oregon, USA) for the Restriction Site Associated DNA Sequencing (RAD-Seq). In RAD-seq, which represents a reduced representation of the genome, the target genome is fragmented via restriction enzyme and sequenced with the next-generation sequencing (NGS) platform. Here, 150 bp paired-end

sequence reads were generated using the *Sbf1* restriction enzyme. The RAD protocol was described in Ali et al., (2016). Sequencing was performed on the Illumina NovaSeq 6000 platform, and the resulting reads were sorted into individually matched forward and reverse fastq files using unique 8 bp barcodes.

I conducted alignment and filtering process according to the pipeline outlined in Sağlam et al., (2021). I used the Burrows-Wheeler Alignment (BWA) tool and used the *Ursus arctos* reference genome (UrsArc2.0, GCA_023065955.2) for all subsequent analyses. I aligned demultiplexed sequences for all individuals to the reference genome BWA-minimal exact match (MEM) algorithm implemented in BWA software. I outputted alignment maps as Sequence Alignment/Map (SAM) files, converted them to Binary Alignment/map (BAM) files using Samtools, sorted proper pairs, and removed duplicates by using Picard, and indexed them with Samtools v1.14 (Li et al., 2009). All analyses were carried out in the Koç University Advanced Computing Center High-Performance Computing Cluster. Some of the sequences from the scat samples were resequenced due to low read counts. The sorted bam files derived from different fastq files belonging to the same individuals were first merged using Samtools, and the same steps were performed as explained above. Lastly, each sample's raw aligned reads, properly paired reads and duplicates removed aligned reads number was presented in (Table 5.1).

5.2.2. Genotyping, Population Structure, and Diversity

I conducted the population genetic analyses using the probabilistic framework implemented in ANGSD, where genotype uncertainty is incorporated (Korneliussen et al., 2014). I carried out a framework using the Samtools genotype likelihood model (-*GL* 1), considering minimum base quality of 20 (-*minQ* 20) and mapping quality of 10 (-*minMapQ* 10), and generated a beagle likelihood file (-*doGlf* 2) for admixture analysis. I designated polymorphic sites with a high probability of being variable (-*SNP_pval* 1e-6), inferred major and minor alleles from the genotype likelihoods (-*doMajorMinor* 1), estimated allele frequencies (-*doMaf* 1), required sites to be present half percent of individuals (-*minInd*), dropped reads with high depth across samples (-*setMinDepth* 220), discarded the reads without unique mapping (-*uniqueOnly* 1), bad reads (-*removed_bads* 1), unmapped reads (-*only_proper_pairs* 1).

I examined the population structure using Principal Component Analysis (PCA), which fits orthogonal principal components (PC) that summarize overall variability between individuals. All filters described above were performed by assuming the reference variant as ancestral. The covariance matrix was generated using by PCAngsd (Meisner & Albrechtsen, 2018) to infer eigenvalues. Eigenvector decomposition and plots were performed in R. Moreover, to infer ancestral proportions of individuals, I performed admixture analysis using NGSadmix (Skotte et al., 2013) based on the beagle file output including genotype likelihoods by assuming K values ranging from 1 to 10 and by repeating 30 times per K with different random seeds to avoid convergence to local optima. The optimal value of K was selected by calculating ΔK with the Evanno method (Evanno et al., 2005) in CLUMPAK (Kopelman et al., 2015). The final admixture plots were visualized in R.

To evaluate genetic diversity among the populations, I calculated several measures of genetic variation including Watterson's theta (θw) (Watterson, 1975), pairwise nucleotide variation (π) (Tajima, 1989a), and neutrality test Tajima's D (Tajima, 1989a) by using a method implemented in ANGSD. I first calculated the site frequency spectrum (SFS), summarizing the distribution of different allele frequencies along the genome, based on computed genotype likelihoods by using realSFS with the arguments as follow: *-GL* 1 *-doSaf* 1 *-minMapQ* 20 *-minQ* 20 *-uniqueOnly* 1 *-remove_bads* 1 *-only_proper_pairs* 1 *-baq* 2. Before computing SFS, I generated a consensus sequence of polar bear genomes (Cahill et al., 2013) in ANGSD (*-minQ* 20 *-minMapQ* 20) by using *-doFasta* 1 in order to consider the ancestral state of each nucleotide position. I utilized folded SFS to calculate genome-wide diversity metrics by using thetaStat in ANGSD. Lastly, I estimated allele frequency differentiation between populations using the F_{ST} metrics after calculating unfolded SFS for each population and 2D-SFS across four populations.

To infer the effects of the isolation patterns, including isolation by distance (IBD) and isolation by environment (IBE), I calculated pairwise linear genetic distance among the individuals using genotype likelihoods with ngsDist (Vieira et al., 2016). I generated a pairwise geographic distance matrix with distGeo function from the *geosphere* package in R (Hijmans et al., 2017). In addition, I downloaded 19 bioclimatic variables from the Worldclim database (Fick & Hijmans, 2017). I extracted the values of variables for each point with *raster* package (Hijmans, 2015). I generated an environmental dissimilarity matrix based on bioclimatic variables. I performed a Mantel test via the *vegan* package (Dixon, 2003), and determined

regression coefficients and their significance based on Pearson's correlation coefficient method with 9,999 random permutations in order to understand the isolation patterns' effects on genetic differentiation. I additionally employed the partial Mantel test to evaluate how one factor influences genetic distance while controlling for another factor.

5.3. Results

5.3.1. RAD Sequencing and Filtering

After the quality checks from the extracted samples, 93 scat samples were sent for sequencing, and 69 of them were resequenced. Half of the tissue samples from Türkiye were found qualified and sent for sequencing. In addition, 10 Iranian Brown bear sequences were used. The reading results of the sequences are shown in Table 5.1.

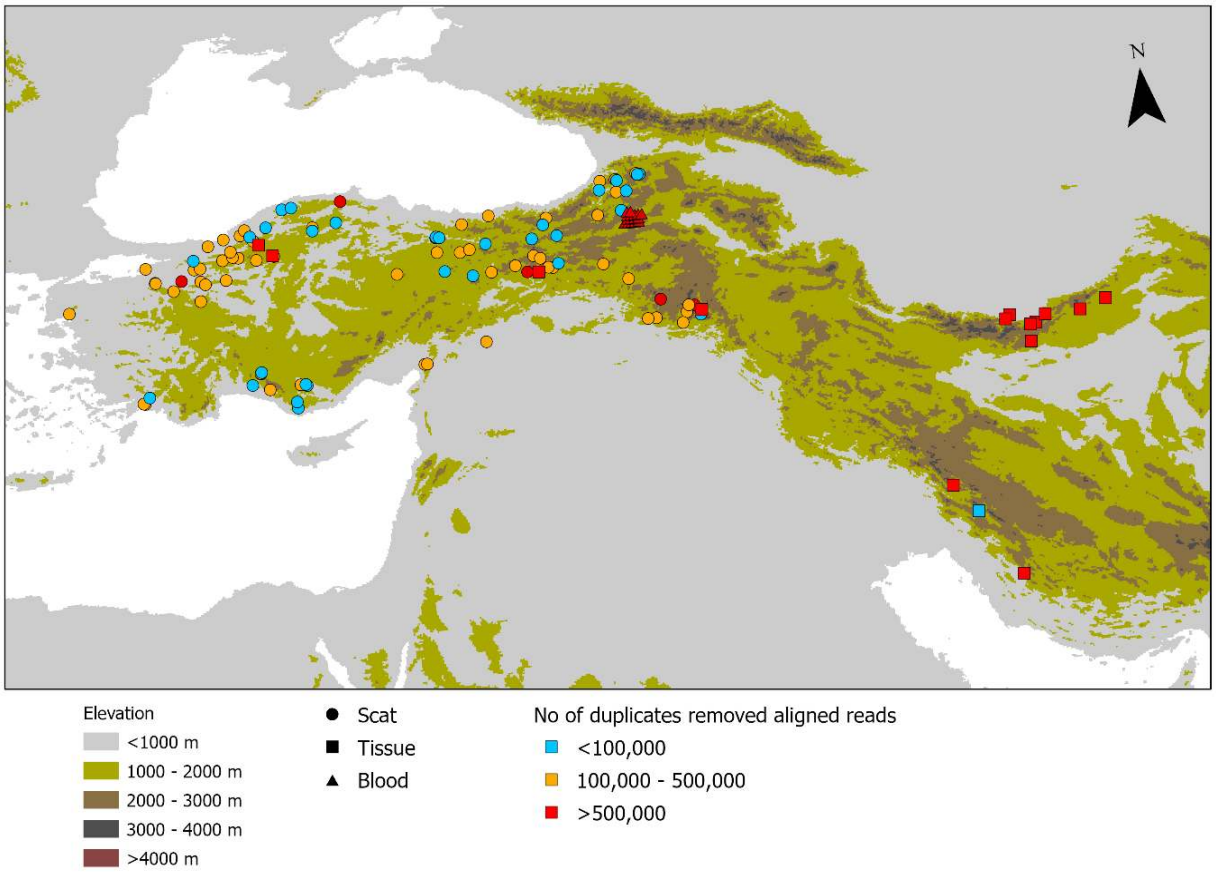

Figure 5.1: Sampling locations by type and by numbers of duplicates removed aligned reads across Middle East including Anatolia and Iran.

Table 5.1: Sample information including ID, sample type, city, assigned population name, and reads number.

Sample ID	Sample Material	City	Pop	No of raw aligned reads	No of proper paired reads	No of duplicates removed aligned reads
BTR006_M	Blood	Sarikamis (Kars)	Sarikamis	12650404	12565947	5206573
BTR002_F	Blood	Sarikamis (Kars)	Sarikamis	6440080	6332358	4922402
BTR029_M	Blood	Sarikamis (Kars)	Sarikamis	10365366	10296408	4335066
BTR003_M	Blood	Sarikamis (Kars)	Sarikamis	5522199	5430880	4264910
BTR005_M	Blood	Sarikamis (Kars)	Sarikamis	9337713	9274505	3901341
BTR019_M	Blood	Sarikamis (Kars)	Sarikamis	4908036	4827195	3814521
BTR032_F	Blood	Sarikamis (Kars)	Sarikamis	4377447	4305069	3422681
BTR054_M	Blood	Sarikamis (Kars)	Sarikamis	4286334	4214608	3342886
BTR060_M	Blood	Sarikamis (Kars)	Sarikamis	3631023	3570815	2845993
IBB5	Tissue	Shahroud	Iran	14324985	13916126	2781722
BTR061_M	Blood	Sarikamis (Kars)	Sarikamis	3467212	3408711	2712815
BTR030_F	Blood	Sarikamis (Kars)	Sarikamis	3222526	3168546	2524924
BTR055_M	Blood	Sarikamis (Kars)	Sarikamis	2883325	2835183	2273247
BTR058_N	Blood	Sarikamis (Kars)	Sarikamis	2566439	2523553	2032007
BTR059_M	Blood	Sarikamis (Kars)	Sarikamis	2499400	2457580	1976084
BTR040_F	Blood	Sarikamis (Kars)	Sarikamis	2421653	2380305	1911285
BTR056_M	Blood	Sarikamis (Kars)	Sarikamis	2333279	2294979	1847829
BTR227	Tissue	Ankara	West	5941809	5750615	1846793
BTR226	Tissue	Bolu	West	5248009	5074423	1636547
IBB221	Tissue	Shahrekora	Iran	6998437	6801870	1370468
IBB223	Tissue	Amol	Iran	6409918	6211070	1295466
IBB225	Tissue	Amol	Iran	5907516	5738142	1169752
BTR221	Tissue	Hakkari	East	3015479	2909167	946517
IBB9	Tissue	Semnan	Iran	2813558	2732886	841642
IBB12	Tissue	Semnan	Iran	4085436	3986711	748241
BTR422	Tissue	Tunceli	East	2293970	2218796	726508
IBB4	Tissue	Shiraz	Iran	2550106	2482254	717036
IBB6	Tissue	Semnan	Iran	3636902	3540676	702198
IBB10	Tissue	Damghan	Iran	3472383	3382513	662425
BTR601	Scat	Bursa	West	3899989	3687434	656022
BTR577	Scat	Van	East	4189332	4124392	599460
BTR550	Scat	Hakkari	East	4516555	3780878	589966
BTR057	Scat	Bilecik	West	3709116	3677319	554767
BTR409	Scat	Tunceli	East	3304883	3214958	539974
IBB15	Tissue	Shahroud	Iran	2941901	2869746	528114
BTR295	Scat	Sinop	West	3652679	3632402	518586
BTR216	Scat	Duzce	West	2580958	2551532	434912
BTR205	Scat	Bolu	West	2462198	2361554	399468
BTR186	Scat	Kütahya	West	2243615	2225587	398295
BTR337	Scat	Erzincan	East	2582117	2561335	389721
BTR436	Scat	Sivas	East	2320787	2305742	382398
BTR439	Scat	Sivas	East	2611001	2599853	377561
BTR045	Scat	Bolu	West	1554537	1425940	347404
BTR358	Scat	Artvin	East	1797953	1780082	343092
BTR431	Scat	Sivas	East	2171032	2158508	341144
BTR053	Scat	Bilecik	West	2299011	2288833	337839
BTR066	Scat	Eskisehir	West	2164272	2150834	327668
BTR113	Scat	Antalya	Med	1950055	1809619	321327
BTR406	Scat	Trabzon	East	2747235	2727572	296284
BTR369	Scat	Artvin	East	1818511	1707616	289280
BTR012	Scat	Eskisehir	West	2468351	2451643	284657
BTR442	Scat	Yozgat	East	1508413	1483170	277708
BTR094	Scat	Mugla	Med	1377829	1226604	272566
BTR161	Scat	Antalya	Med	1361889	1081893	264435
BTR499	Scat	Bitlis	East	1651623	1636064	257540
BTR131	Scat	Bolu	West	1176268	1157763	247591
BTR095	Scat	Mugla	Med	1132908	1086347	240651
BTR324	Scat	Giresun	East	2345867	2291380	234730
BTR619	Tissue	Sarikamis (Kars)	Sarikamis	1316013	1310345	223133
BTR513	Scat	Sirnak	East	1495735	1482468	216250
BTR485	Scat	Mus	East	1478045	1469556	214160
BTR134	Scat	Bolu	West	991118	862734	212208

BTR256	Scat	Zonguldak	West	984113	960208	208616
BTR410	Scat	Tunceli	East	1266051	1252905	198955
BTR097	Scat	Antalya	Med	896331	778454	192742
BTR522	Scat	Hakkari	East	699494	651802	189614
BTR051	Scat	Sakarya	West	1338007	1327107	188571
BTR322	Scat	Ordu	East	923332	915006	185706
BTR612	Scat	Kahramanmaras	Med	508833	493642	182506
BTR191	Scat	Eskisehir	West	661836	555348	173768
BTR217	Scat	Sakarya	West	707289	652703	171265
BTR510	Scat	Sirnak	East	973215	959286	164610
BTR542	Scat	Hakkari	East	1429235	1383236	162172
BTR390	Scat	Bursa	West	857327	849450	159224
BTR375	Scat	Ardahan	East	565619	470702	156906
BTR554	Scat	Hakkari	East	620135	600048	148016
BTR091	Scat	Balikesir	West	694055	660912	142086
BTR459	Scat	Tunceli	East	854023	784610	141318
BTR200	Scat	Ankara	West	718638	644691	138911
BTR592	Scat	Erzincan	East	854314	848318	136920
BTR212	Scat	Duzce	West	737065	586361	135839
BTR250	Scat	Zonguldak	West	718224	713911	132927
BTR593	Scat	Erzincan	East	996303	991166	127150
BTR350	Scat	Erzurum	East	895495	889964	125306
BTR604	Scat	Bursa	West	895311	870641	124211
BTR331	Scat	Tunceli	East	683846	681228	120176
BTR305	Scat	Tokat	East	534210	463036	119166
BTR607	Scat	Osmaniye	Med	564157	559532	118888
BTR092	Scat	Balikesir	West	488846	441912	111836
BTR170	Scat	Karaman	Med	483049	440468	110660
BTR451	Scat	Bingol	East	1780072	1773137	106257
BTR198	Scat	Eskisehir	West	547478	544378	105860
BTR273	Scat	Ankara	West	450531	390970	105130
BTR301	Scat	Tokat	East	631446	607552	103698
BTR609	Scat	Osmaniye	Med	474973	470476	102270
BTR278	Scat	Kastamonu	West	514017	401592	101520
BTR574	Scat	Hakkari	East	1008991	1002766	91590
BTR353	Scat	Artvin	East	802409	797459	88829
BTR143	Scat	Mersin	Med	345722	340254	77134
BTR075	Scat	Erzurum	East	169952	145150	75826
BTR447	Scat	Sivas	East	1079722	1073264	74658
BTR380	Scat	Ardahan	East	768620	763595	70429
BTR344	Scat	Bayburt	East	299797	294850	67794
BTR388	Scat	Mugla	Med	429599	427368	64410
BTR378	Scat	Ardahan	East	368889	360447	58369
BTR220	Scat	Mersin	Med	388014	341982	58064
BTR281	Scat	Corum	West	819043	812734	58022
BTR304	Scat	Tokat	East	284878	282056	57074
BTR365	Scat	Artvin	East	662217	658562	56634
BTR271	Scat	Cankiri	West	203583	161597	55387
BTR232	Scat	Karabuk	West	963891	959971	53755
BTR140	Scat	Sakarya	West	563015	558448	47238
BTR445	Scat	Sivas	East	417250	414736	45678
BTR126	Scat	Antalya	Med	271463	269999	41951
BTR240	Scat	Bartin	West	143510	141121	36815
BTR141	Scat	Mersin	Med	82676	61986	36206
BTR425	Scat	Sivas	East	70240	66895	34405
BTR463	Scat	Bingol	East	253983	83736	11250
IBB11	Tissue	Lordegann	Iran	33249	31970	6280
BTR309	Scat	Tokat	East	77107	19626	2668
BTR238	Scat	Bartin	West	22487	4520	2574
BTR245	Scat	Kastamonu	West	2072	166	134
BTR148	Scat	Mersin	Med	6353	0	0
BTR178	Scat	Konya	Med	10423	0	0
BTR259	Scat	Zonguldak	West	2927	0	0
BTR341	Scat	Bayburt	East	3485	0	0
BTR345	Scat	Bayburt	East	6396	0	0
BTR372	Scat	Ardahan	East	6650	0	0

Since many scat samples have low coverage, they cannot be successful in explaining the overall variation in the sample set as a common issue. Therefore, I first picked up the individuals with more than 100,000 duplicates removed aligned reads. I generated this 100k-sample set with the sequences from 90 Türkiye samples (20 bloods, 65 scats, 5 tissues) and 10 Iranian brown bear samples (Fig. 5.1). I performed SNP calling by using filtering criteria as follow: *-GL* 1 *-doMajorMinor* 1 *-minMapQ* 20 *-minQ* 20 *-only_proper_pairs* 1 *-remove_bads* 1 *-doCounts* 1 *-doGlf* 2 *-doMaf* 1 *-uniqueOnly* 1 *-minMaf* 0.05 *-SNP_pval* 1e-6 *-minInd* 50 *-setMinDepth* 220. Ultimately, I was only able to obtain 15 SNPs, which was insufficient for further analyses.

I decided to revise this sample set and created a new one containing the individuals with 500,000 duplicates removed aligned reads. This 500k-sample set (n=36) included 26 samples (16 blood, 4 tissue, 6 scat samples) from Türkiye and 10 tissue samples from Iran. As a result of SNP calling applied with the same filtering criteria (*-minInd* 18), I detected 96,379 SNPs.

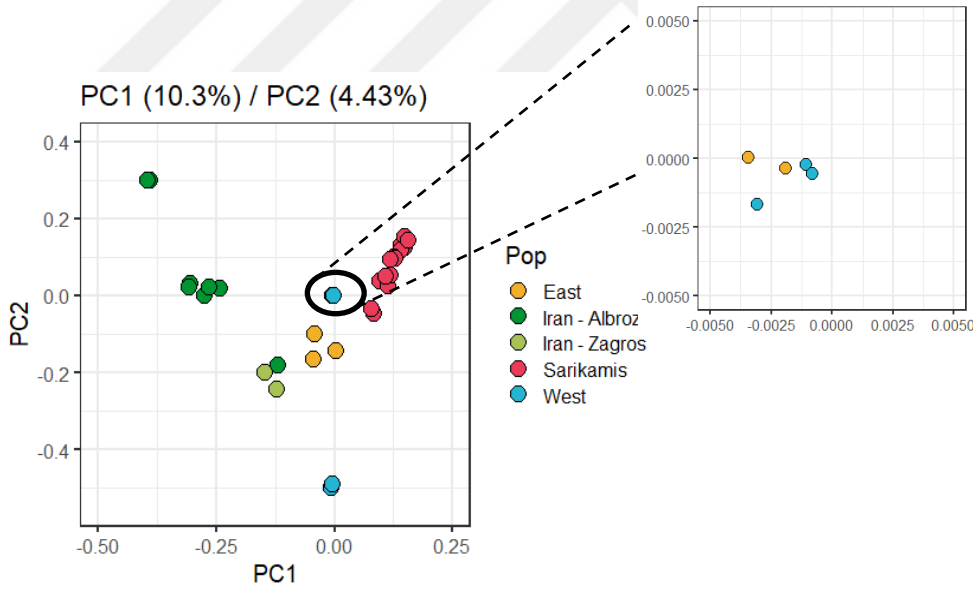

Figure 5.2: The PCA plot for the Brown bear samples (n=36) across Türkiye and Iran.

5.3.2. Genomic Population Structure

The ordination plot from PCAngsd, based on a set of 96,379 SNPs, indicated that the Sarıkamış population clustered together (Fig. 5.2). While PC1 explained 10.3% of the total variation, the ratio was 4.43% for PC2. The first component clearly separated the Sarıkamış

samples from the other individuals. Iran populations clustered closer to the eastern population compared to the Sarıkamış population along PC1 and mostly separated from western individuals along PC2. Remarkably, Zagros individuals (IBB221, IBB4) in the Iranian population were separated from other Albroz individuals, except for IBB10, and were included in PC2.

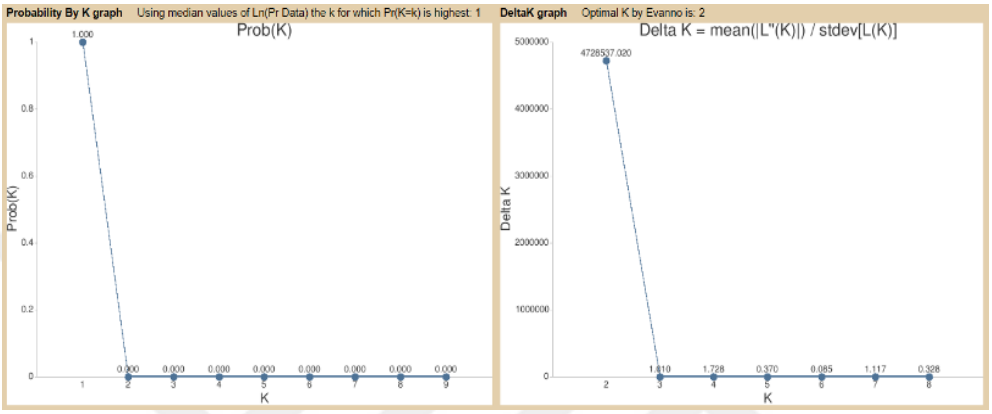

Figure 5.3: Delta K value and probability for each K by Evanno's method.

Admixture analyses showed a significant population structure. It suggested that the pattern of ancestry was best represented by K=2 as the most likely based on Evanno's method (Fig. 5.3), and at K=2 the Sarıkamış population was distinct from the others (Fig. 5.4). Remarkably, while the Sarıkamış population exhibited lower amounts of mixed ancestry compared with remaining Anatolia populations, East population, and Western Anatolia populations displayed higher amounts of mixed ancestry at each K. In addition, Iranian bears were separated from each other as of K=3, and Zagros and Albroz populations formed their own distinct cluster (Fig. 5.4). Similarly, western Anatolian bears form their own distinct cluster at K=4, and this different pattern lasts in the case of K=5, except for BTR295 (Sinop). It should be noted that unequal number of individuals from different populations can lead to misleading conclusions about admixture. Therefore, I created a subset including 5 individuals from each population (total=20, 5 for East, West, and Sarıkamış populations, 3 Albroz + 2 Zagros individuals for Iran), and checked the results after generating the beagle file. The NGSadmix gave the same pattern in terms of the most likely grouping (K=2).

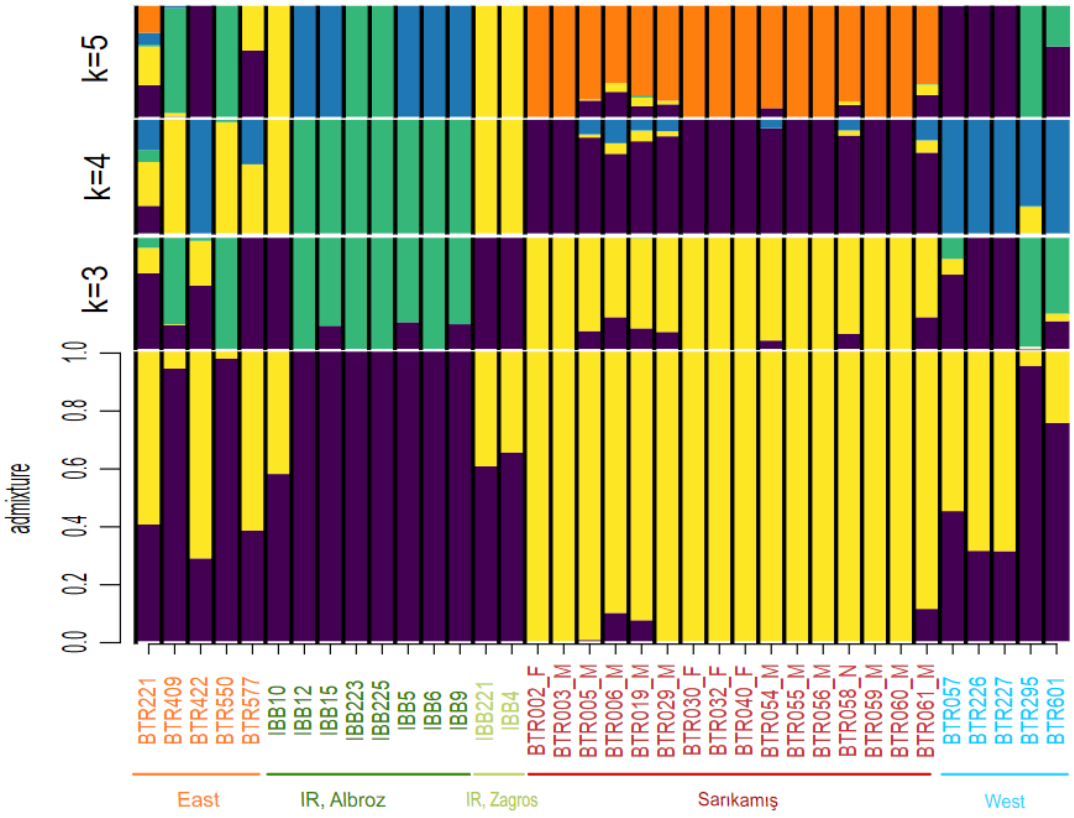

Figure 5.4: Admixture plot for West, East, Sarıkamış, and Iran populations from K=2 to K=5.

5.3.3. Genetic Diversity, Differentiation, and Isolation Patterns

Genetic diversity was assessed in four populations (East, West, Iran, Sarıkamış) encompassing 36 individuals using various indices (Table 5.2). Watterson's theta (θw), reflecting the total number of heterozygous sites, ranged from $16x10^{-4}$ to $21x10^{-4}$, with the highest values observed in West and Iran populations. Conversely, Sarıkamış and East populations shared the lowest θw. Pairwise nucleotide differences (π) varied between $19x10^{-4}$ and $22x10^{-4}$ (Table 5.2) All populations displayed similar and relatively high mean π values (Fig 5.5). All populations exhibited a positive mean Tajima's D, indicating a higher prevalence of high frequency variants than expected under the neutral model of evolution. However, the values differed significantly across populations, ranging from 0.12 to 0.76. West and Iran populations exhibited the lowest mean Tajima's D, while East and Sarıkamış populations showed the highest values (Fig 5.5).

Table 5.2: Various diversity indices including Watteron's theta (θw), pairwise nucleotide (π), and Tajima's D for each population.

Population	n	Watterson's Theta, θw	Pairwise nucleotide differences, π	Tajima's D
East (Anatolia)	5	16 x 10^{-4}	19 x 10^{-4}	0.755
Iran	10	20 x 10^{-4}	21 x 10^{-4}	0.121
Sarıkamış	16	16 x 10^{-4}	20 x 10^{-4}	0.598
West (Anatolia)	5	21 x 10^{-4}	22 x 10^{-4}	0.230

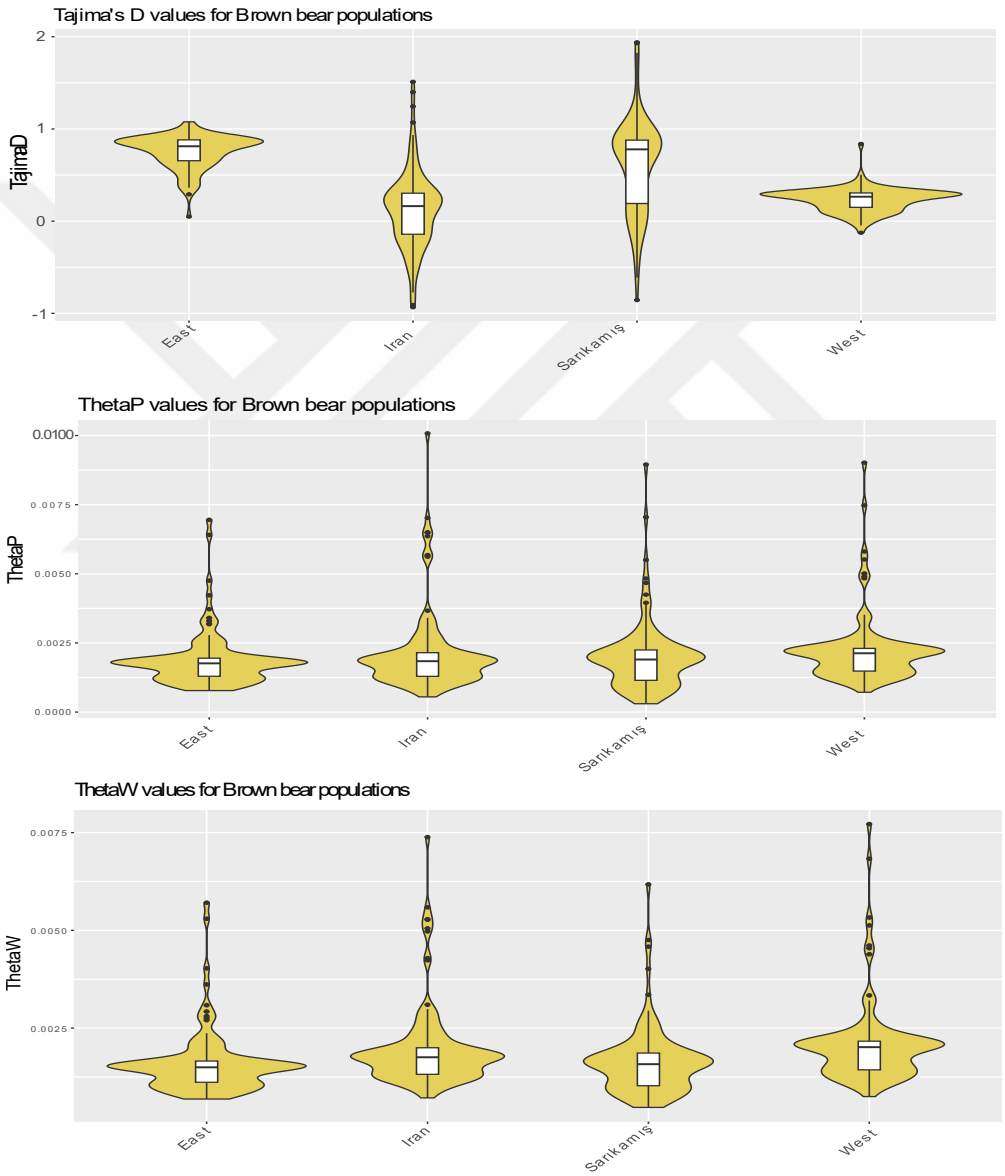

Figure 5.5: Violin plots for Tajima's D, pairwise nucleotide differences (π), and Watterson's theta (θw) indices of the populations.

Pairwise F_{ST} values ranged from 0.08 to 0.17 (Fig. 5.6). While the highest pairwise F_{ST} was observed between West and Iran populations, the lowest pairwise F_{ST} value was seen between Sarıkamış and East populations. Pairwise F_{ST} value was 0.14 between West and East/Sarıkamış and 0.17 between West and Iran populations. However, the F_{ST} value comparing the Sarıkamış population and others was 0.08 for the East and 0.12 for Iran populations. Lastly, the pairwise F_{ST} value between the populations of Iran and East was 0.1 and relatively lower (Fig. 5.6).

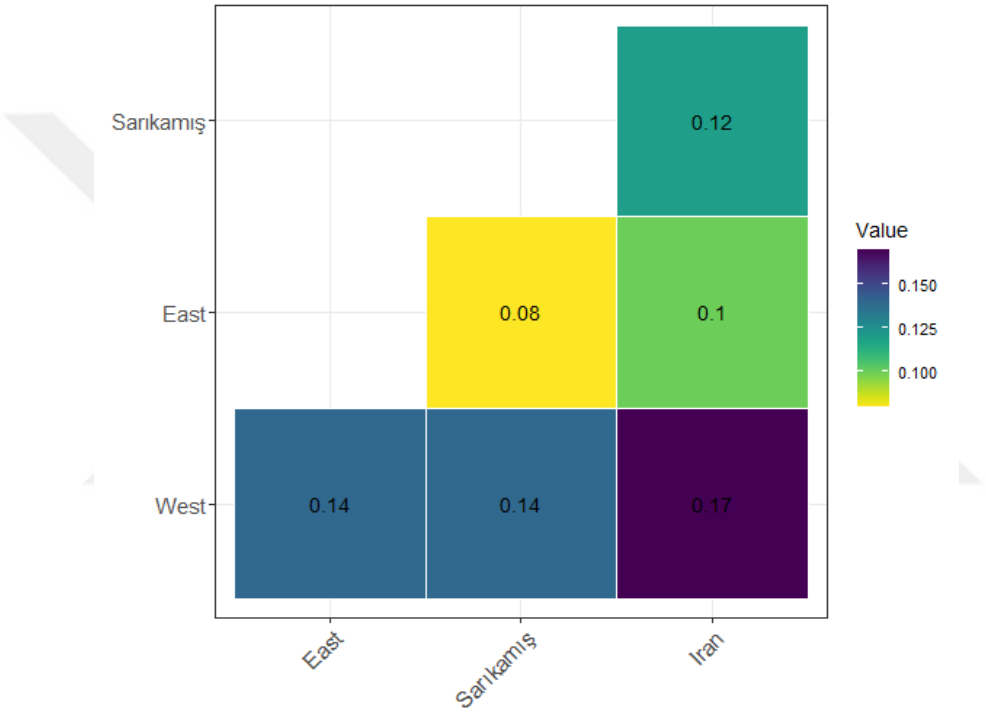

Figure 5.6: Pairwise F_{ST} between brown bear populations.

Mantel test of pairwise genetic distance based on ngsDist and pairwise geographic distance revealed a significant relationship (Mantel test, $R=0.41$, $p<0.001$), suggesting a pattern of isolation by distance. However, this relationship remained non-significant after controlling for environmental conditions (partial Mantel test, $R=0.18$, $p=0.06$). On the other hand, genetic distance was strongly related to environmental distance (Mantel test, $R=0.50$, $p<0.001$), suggesting a pattern of isolation by environment, and this relationship remained highly significant after controlling for geographic distance (partial Mantel test, $R=0.35$, $p<0.005$).

5.4. Discussion

With advances in sequencing technology, the analysis of genetic markers has provided

important insights to elucidate diversity and demographic formation in populations (Hohenlohe et al., 2021). Brown bear continue to be an important model species for population genetics and evolutionary studies (Valdiosera et al., 2007) and is, therefore, referred to as a paradigm species (Hewitt 2004). Non-invasive methods that do not harm organisms, such as collecting fecal samples, offer important opportunities in terms of genetic monitoring (Taberlet et al., 1997). In this chapter, brown bear DNA sequences, mostly obtained from fecal samples, as well as blood and tissue samples, were analyzed with the goal of discovering population structure and genetic variation across the study area. SNP markers were obtained from RAD-Seq of brown bear genomes. However, it should be noted that the sequence information obtained from most scat samples did not provide sufficient data for further analysis. Of the 93 scat samples, 69 of which were resequenced, only 6 of them contained over 500,000 duplicates removed aligned reads. Various factors may have caused this. Although it has many advantages as a non-invasive approach (De Barba et al., 2010), it offers much lower readings compared to the tissue and blood samples, making this source of limited use. One reason for this can be the decrease in DNA quality because of environmental exposure of the collected scats to external factors. For example, in a study conducted with brown bear scats, it was reported that genotyping success showed significant seasonal variation and was lower in the summer months, some of the possible reasons being increased UV exposure and humidity (Kopatz et al., 2020). Another reason can be the high allelic drop-out, which is a common problem encountered when working with scat samples (McKelvey & Schwartz, 2004). Besides, many organisms in the scat can break down brown bear DNA, leading to degradation. As a result, population structure and genetic diversity analyses were conducted with a subsample of 36 brown bear sequences, 16 of which were obtained from blood, 14 from tissue, and 6 from scat material. The individuals in this sample set were assigned to four different populations: Iran (Zagros (2), Albroz (8)); West (Sinop, Ankara, Bolu, Bilecik, Bursa); East (Tunceli (2), Van, Hakkari(2)); and Sarıkamış (16). It should be noted as an important deficiency that no individual from the Mediterranean region (e.g. Ida Mountains, Beydağları, Geyik Mountains, Amanos Mountains etc.) could be included in this study.

Brown bears have a wide distribution across Anatolia (Chapter 2). While the recent studies showed that the haplotypes of brown bears in Anatolia were divided into three different maternal lineages, namely Clade 1, Clade 3 and Clade 7 (Çilingir et al., 2016; Çeltik, 2023), Calvignac et al. (2009) reported that Iranian brown bears exhibited quite different haplotypes,

they placed between western and eastern lineages (Ashrafzadeh et al., 2016). Lastly, Çeltik (2023) showed that the bears in Iran are genetically close to bears in Türkiye based on evolutionary lineages. Moreover, the latest study conducted on the Sarıkamış population reported that although the genetic diversity in this population is higher compared to the other bear populations in the world, the Sarıkamış population exhibits a highly isolated character (Kemahlı et al., 2023). The results represented here are also in agreement with the previous study, confirming the unique isolated character of the Sarıkamış population (Kemahlı et al., 2023). According to the admixture analysis, the Sarıkamış population exhibited low levels of admixture, unlike other regions of Türkiye (Fig. 5.4). Only three individuals in the Sarıkamış region showed mixed ancestry at K=2. On the other hand, it was observed that the Iran population shared a common ancestry with the East and West populations, while the Sarıkamış population showed a distinct pattern, especially when compared to the Iranian population as of K = 3 (Fig 5.4). Kemahlı et al. (2023) reported that Sarıkamış brown bears remain genetically different even from the Georgian population, with which they have a relatively strong contact potential. According to the PCA results, Zagros and Albroz samples were separated from each other, which confirms the results of the previous study showing a clear distinction between Albroz and Zagros bears (Ashrafzadeh et al., 2018).

It is known that changing environmental conditions and anthropogenic factors can break the connections between individual subpopulations (Sawaya et al., 2014; Proctor et al., 2015; Lara-Diaz et al., 2021). This may explain the isolated character of the Sarıkamış population. However, to make further inferences for the Sarıkamış population, sequences of individuals throughout the study area, especially from regions close to the Caucasus, are needed. On the other hand, the West population differs from the Sarıkamış and East populations based on PCA (Fig. 5.2). Detecting gene flow between populations is essential to ensure population persistence and to make wildlife corridors effective (Ma et al., 2018; Calderón et al., 2024). Therefore, examining gene flow between the populations in the region is urgently needed to assist in brown bear conservation. It should be noted that there is significant sex bias in the dispersal of brown bears (Støen et al., 2006; Zedrosser et al., 2007), but this depends on local conditions. While females can disperse over long distances mainly in undisturbed habitats (Swenson et al., 1998; Jerine & Adamic; 2008), gene flow is generally maintained by males (Peck et al., 2017). Although the high admixture seen in the East and West populations is thought to be a result of gene flow between populations, analytical methods to test this have not

been applied across this chapter. An example of how effective wildlife corridors are important in reducing the substantial effects of habitat degradation is the Cantabrian brown bear population. Recently, it was reported that this brown bear population, which was divided into two different nuclei approximately 100 years ago, avoided being isolated because of the maintenance of gene flow provided by conservation measures (Gonzalez et al., 2016). The southernmost population of brown bears in the world is in the Mediterranean part of Türkiye, and bear habitats in this region are highly vulnerable (Chapter 2). The impact of climate change and landscape transformation on the genetic diversity of brown bears throughout the Mediterranean may be greater than expected. The connection of this region with the Euro-Siberian and Irano-Turanian regions has been decreasing dramatically (see Chapter 3), especially in the last decades. The absence of data from the Mediterranean region in the sample set prevents us from gaining insights into the effect of a decrease in landscape continuity on genetic diversity. Considering that the human footprint across the Mediterranean region is predicted to cause natural habitat loss much faster than in other regions (Chapter 2), understanding the genomic vulnerability (or genetic offset) (Fitzpatrick & Keller, 2015) of the region's population is a critical future priority.

The analysis of intraspecific polymorphism through Tajima's D revealed a consistent pattern across all brown bear populations. Positive Tajima's D values suggest a past population bottleneck followed by expansion (Tajima, 1989b), indicating a departure from neutrality after the last glacial period. This implies that these populations did not maintain constant sizes and experienced genetic exchange through migration. It is also known that brown bears have lost most of their historical habitat throughout the Middle East (Calvignac et al., 2009; de Jong et al., 2023). As a matter of fact, recent increases in the effective population size for the Sarıkamış population were reported by Kemahlı et al. (2023). Iran and West populations exhibited significantly lower Tajima's D values compared to the East and Sarıkamış populations. Although these results indicate that brown bear populations across Southwest Asia may have experienced significant demographic fluctuations (i.e. contraction, expansion, recolonization), historical analysis of change in demographic formation is a gap in the literature. Therefore, elucidating the demographic processes that drive the genetic formation of brown bear populations throughout Southwest Asia is an important suggestion for the future. It is noteworthy that genetic diversity is quite high across the Türkiye and Iran populations. While θw and π values were higher in the West and Iran populations than in the East and Sarıkamış

populations, the situation was the opposite in terms of Tajima's D value. This indicates that genetic diversity is relatively lower in the Sarıkamış and East populations, but the frequency of rare variants is higher (Tajima, 1989a). However, Kemahlı et al. (2023) have previously reported that the Sarıkamış population has higher diversity than other bear populations in the world based on genome-wide variation. Ambarlı et al. (2018) found a similar result in the bears of the Kaçkar Mountains located northwest of Sarıkamış. All these findings indicate that Southwest Asia represents an important genetic reserve. θw and π estimators also provide us with important insights into the trajectory of genetic diversity. Accordingly, while $\theta w > \pi$ is considerably larger than the value in the East and Sarıkamış populations, the same pattern is observed in the Iranian and West populations, but this difference has decreased much more and approached stable genetic diversity (Table 5.2). While $\theta w > \pi$ is a signal of loss, $\theta w < \pi$ indicates an increase of genetic diversity, and equality indicates that genetic diversity remains stable (Peek et al., 2021). This decreasing genetic diversity in the Sarıkamış and East populations may lead to the accumulation of detrimental alleles over time. Therefore, ensuring habitat connectivity of these populations across the country, as well as their continuity to the Caucasus and Iran, is an important conservation priority (Chapter 3).

F_{ST} values can reflect processes of divergence and migration. According to pairwise F_{ST} results, the highest differentiation is between the West and Iran populations, while it is lower between the Sarıkamış and East populations and the East and Iran populations (Fig. 5.6). Therefore, F_{ST} results indicate that connectivity continues between geographically adjacent populations, but also indicate that geographical distance and environmental dissimilarity may play a role in genetic differentiation. Therefore, I also tested whether geographical distance or environmental heterogeneity influenced it. In Isolation by distance (IBD), genetic differentiation is a function of the genetic distance between individuals or populations, based on the assumption that the greater geographic distance, the greater the differentiation (Wright, 1943). IBD does not consider environmental heterogeneity or landscape resistance. On the other hand, Isolation by Environment (IBE) assumes that the environmental conditions to which organisms are exposed may also play a role in genetic differentiation through divergent selection (Wang & Bradburd, 2014). Both IBD and IBE can modulate genetic variation by affecting the gene flow between populations. According to my findings, while genetic variation by IBD between populations was significant, it was non-significant when environmental heterogeneity was considered. However, IBE has a significant role in the differentiation of

populations, and this pattern was confirmed even when geographic distance was considered as a constraint. Additionally, environmental heterogeneity made more contributions to shaping population differentiation than geographic distance for brown bear populations. This indicates that the environmental conditions to which populations are exposed may increase their local adaptation. To evaluate such a prediction more comprehensively, there is a need to apply genotype-environment association (GEA) analyses such as (partial) Redundancy analysis, BayEnv, and Latent Factor Mixed Model (Forester et al., 2018). GEA methods help to determine the frequencies of alleles whose frequencies have unusually strong correlations with environmental variables. The alleles that display local adaptation have higher frequency since they increase fitness, otherwise, the allele causing decreasing in fitness will have a lower frequency (Lewontin & Krakauer, 1973). It should be noted that IBE may increase genomic vulnerability by inhibiting the exchange of beneficial alleles. Although brown bear exhibits a slow life history, habitat degradation and isolation of brown bear populations can cause genetic differentiation in just a few generations (Straka et al., 2012; Benazzo et al., 2017; Kemahlı et al., 2023). Moreover, various human-induced landscape features may affect the behavior and movement patterns of brown bears (Cozzi et al., 2016; Colton et al., 2021; González-Bernardo et al., 2023) and this induction may lead to some adaptive variations. Kemahlı et al. (2023) reported that distinct genotypes that may play a role in adaptation in such different behavioral groups may be outliers in the Sarıkamış population.

The reduction of the connectivity of populations by through human impact is critical, and it seriously reduces the probability of genetic exchange among them. For instance, it has been reported that the loss of connection between European bear populations since Neolithic times due to human-induced habitat loss has caused a 40-fold population decrease in the Apennine bears (Benazzo et al., 2017). Today, the effects that lead to the loss of genetic variation continue with increasing mortality rates in correlation with the expansion of road networks and human settlements, deforestation, poaching, and human-brown bear conflict (Boulanger & Steenouse, 2014; Gosselin et al., 2015; Lamb et al., 2020). Various landscape features, such as roads, act as filter on individuals, reducing demographic exchange and inducing spatial genetic structure (Lecis et al., 2022). Populations may not be able to develop microevolutionary responses in such a limited time to adapt to increased human-caused mortality, and they may quickly disappear at the local scale, given decreasing reproductive rates. Therefore, it is critical to implement measures to support human-bear coexistence. In this

chapter, the genetic structure and genetic diversity of brown bear populations were examined by analyzing the genetic data obtained from individuals across Türkiye and Iran. These results provide important and preliminary insights into the population structure across the region. Analysing larger samples in the future is critical in understanding the genetic structure, demographic history, gene flow, selection, interaction with the environment, and responses to climate change of brown bear populations. This type of conservation genetics research will help ensure the long-term persistence of brown bear populations by improving conservation management strategies. Genetic monitoring to be carried out for this purpose are essential for detecting populations that exhibit inbreeding and vulnerability to extinction. With these data, populations that have high conservation priority can be identified and action plans for the conservation of brown bears can be implemented.

Chapter 6

6. Conservation Implications for Brown Bears Across Türkiye

In Chapter 2, I assessed the potential distribution of brown bears across the country and investigated their potential future distribution under various climate change scenarios. My analyses project a serious range contraction is for brown bears in the future, and it is important to evaluate the existing protected areas of Türkiye by reconsidering potential brown bears' distribution in the future in order to prevent conservation gaps. In Chapter 3, I modelled the structural connectivity of brown bears' habitats across the country and discussed potential priority patches and linkages. Moreover, climate change expected to disrupt the ecological network of brown bears in Türkiye in the future. In Chapter 4, I analyzed the spatiotemporal dynamics of human–brown bear conflicts across the country and generated a conflict risk map. I found that HBCs were caused by limited protected area coverage and insufficient natural habitats and resource availability. Finally, in Chapter 5, I conducted a preliminary assessment of population structure and genetic diversity of brown bears across Middle East. Considering all these findings, in this chapter I discuss the conservation implications for brown bears across Türkiye.

Brown bears are included in conservation plans as an umbrella species because their high ecological requirements cover the needs of many other species. These predators, at the top of the trophic chain, have a wide range of diet. They perform many ecosystem services and are indicator species for habitat quality. As a result, they are also considered as flagship species for conservation efforts.

Forests are the most important land cover for sheltering, feeding, and breeding of brown bears (Ziółkowska et al., 2016; Stewart et al., 2013) and almost half of the potential suitable habitats of brown bears across Türkiye are located in the forest ecosystems (Chapter 2). Türkiye's wildlife and pristine areas are experiencing a growing crisis in recent years (Şekercioğlu et al., 2011a,b) and consequently the major threat to brown bear core habitats throughout Türkiye is deforestation. The primary cause of deforestation is the allocation of forest areas to non-forestry uses. As of the end of 2020, a total of 748,000 ha of forest area has

been allocated to mining, energy, and tourism usage (GDF, 2022). Among these uses, mining is one of the most worrying ones. While a mere 1,186 mining licenses were granted between 1923-2002, a staggering 386,000 concessions have been issued in the last 15 years alone (URL2), with permits even covering over 110,000 hectares of forest land in the past decade (GDF, 2022). Of the current total of over 15,000 active licenses nationwide (MAPEG, 2020), hundreds include areas crucial for brown bears such as pastures, forests, and even protected areas (TEMA, 2022). Another major threat to bear habitats is the degradation of natural areas caused by the construction of power plants, power transmission lines, and large dams (WWF, 2010; Şekercioğlu et al., 2011a,b). The allocation of forest areas to the energy sector across the country exceeded 30,000 ha in 2020 alone (Atmiş et al., 2024). In particular, the construction of large dams inundates large natural areas (Wu et al., 2019; Li et al., 2021), while power plants (i.e. hydroelectrical power plants, wind power plants, coal power plants etc.) cause the road network to expand and the human footprint to increase (Venter et al., 2016). They lead to the degradation of remote ecosystems and reduce sustainability. Ultimately, this disrupts local connectivity for many species, as well as the displacement of individuals (McCaffery et al., 2018). Considering the bears' core habitats, many road projects (i.e. the Anatolia Highway, Yeşil Yol Project) have been found to both restrict movement within patches and disrupt the linkages among them (Chapter 3, 4). While the connectivity modeling for brown bears across the country has been performed for the first time, it is important to improve conservation management by selecting areas that overlap with the results of such connectivity analyses for other species. Moreover, maintaining functional corridors may be more effective than creating new PAs in some cases (Cushman et al., 2006). Therefore, in addition to maintaining the quality and extent of core patches, efforts to support coexistence and the development of linkage networks are important priorities. In this context, mitigation of road impacts is one of the primary interventions. For this purpose, recording vehicle collisions including wildlife, in cooperation with various official authorities will enable the improvement of much more effective protection. Warning signs, animal detection systems, wildlife-friendly road designs, lighting in areas with high vegetation cover, fencing, overpasses, and underpasses for wildlife (i.e., green bridges, tunnels, culverts, viaducts), and reducing traffic volumes on roads bisecting core habitats are some of the mitigation strategies (Kusak et al., 2009; Rytwinski et al., 2016; Huijser et al., 2016; Psaralexi et al., 2022).

Finally, another main threat to wildlife is wildfires, which have turned into mega-fires

in recent years (Aydin-Kandemir & Demir, 2023; El Garroussi et al., 2024). They constitute one of the major risks, especially in the Mediterranean region but also in the rest of the country (Daşdemir et al., 2021). Compared to the past, the frequency of wildfires is increasing in correlation with the rise in human footprint, which is the cause of many wildfires, and the amount of burned area has also gone up significantly (GDF, 2022). For instance, while the mean forest area burnt per fire was 3.30 hectares between 2009 and 2020, this amount increased to 49.95 hectares in 2021 (TOD, 2022). The amount of are lost to wildfires each year is a quarter of the forest area allocated to non-forestry usage, which show the impact of this threat (TOD, 2022).

Ultimately, there is an urgent need to implement strict conservation precautions to prevent deforestation across the country. Hunting of brown bears is illegal in Türkiye. In fact, harvesting is not one of the major causes of mortality for brown bears (Chapter 4). Since the major causes of bear mortality across the country are linked to ecological traps due to landscape transformation, the situation can only be reduced by much more comprehensive actions, not by regulatory policies (Lamb et al., 2017).

Increasing the connectivity of species' populations may be one of the most important approaches to alleviate their extinction rates (Rodrigues et al., 2022). There are some efforts in Türkiye. For example, in Sarıkamış, Kars, there is a project to create Türkiye's first wildlife corridor is one of them (KuzeyDoga, 2012). The correct aims to connect the fragmented bear habitats in Sarıkamış to the main habitat block in the Eastern Black Sea. Indeed, Chapter 3 and 5 emphasize the importance of these endeavors. It can be important to develop similar restoration efforts, especially for core patches in the Mediterranean region (Soyumert et al., 2020; Hepcan et al., 2009; Gülci & Akay, 2015). Ensuring the continuity of the natural areas between Muğla forests and Amanos along the Taurus Mountains, and the habitats in Mount Ida and Marmara with the Western Black Sea forests are among the important bear conservation strategies in the long term (see Chapter 3, Ambarlı et al., 2016). Consequently, restoration efforts to improve the adaptability of brown bears should be prioritized as an important conservation approach.

Administrative borders do not make sense for wildlife. Consequently, the distributions of populations can include a wide range and involve multiple jurisdictions, especially for species that can travel long distances, such as brown bears (Reljic et al., 2018; Almasieh et al.,

2019; Greenspan et al., 2021; Recio et al., 2021). For instance, eight out of ten brown bear populations in Europe are located within the borders of different countries (Chapron et al., 2014). Frontier regions might represent areas where there is less scientific research, mainly for security reasons. Therefore, cooperative management efforts, including systematic monitoring, are especially needed in such locations (Almasieh et al., 2019). For example, Türkiye's border regions with Iran and the Caucasus regions are important areas for carnivores, such as lynx, brown bear, and another flagship species, leopard (Karataş et al., 2021). While there is ecosystem and habitat continuum in these regions (Dagtekin et al., 2020), barriers placed by humans may prevent animal movement (Pokorny et al., 2017).

Protected areas (PAs) are the cornerstones of biodiversity conservation (Gray et al., 2016). By reducing habitat loss, PAs represent a refugia for threatened species and ensure the persistence of essential ecosystem services. Although the number of PAs has increased globally in recent years (Juffe-Bignoli et al., 2014), only 16.1% of the planet's land mass and 8.2% of the seas are protected (UNEP-WCMC, 2023). Despite its rich biodiversity, Türkiye faces conservation challenges, as only 13.7% of its total area is protected, with a mere 7.8% of terrestrial (NCNP, 2022), and the percentage of PAs across the country could not have reached the desired CBD target (http://www.cbd.int/sp/targets). Unfortunately, the governance of PAs in Türkiye is extremely complex legally and administratively (Birben, 2020; Yıldız & Aydın, 2023). For instance, some areas have more than one protection status (Atmiş, 2018; WWF, 2021). These complexities bring some governance and cooperation issues for PA management (Atmiş, 2018), as well as harmony issues with IUCN criteria (Atmiş, 2018; Yıldız & Aydın, 2023). Different types of PAs have different conservation. For example, there is a significant difference in the restrictions between nature reserve areas and nature parks in terms of human activity. Less legal protection and a lack of conservation enforcement, such as rangers in natural areas, make them more susceptible to anthropogenic impacts (Khosravi et al., 2022; Appleton et al., 2022). This conservation bias can have serious effects on wildlife. While 8% of the Earth's forests are designated as PAs (Schmitt et al., 2009), this ratio is lower in Türkiye's forests (Birben, 2020). Due to climate change, species may undergo dramatic range shifts (Chapter 2, Chen et al., 2011; VanDerWal et al., 2013), and the management of PAs must, therefore, be dynamic. Otherwise, the conservation value of PAs may decrease significantly (Lemes et al., 2014). Thus, PAs should increase the connectivity between habitats and facilitate recolonization in response to climate change. Although the majority of large carnivores are

globally in decline (Ripple et al., 2014), many populations throughout Europe are recovering (Chapron et al., 2014), and the main factors for the recovery are pan-European agreements, strict laws, and socioeconomic regulations (Trouwborst, 2010; Jongman et al., 2011). There is an urgent need for such strict actions to prevent wildlife from facing local extinction across Türkiye.

There may be some biases in the design of PAs due to various reasons. For instance, these biases may be the result of different conservation goals arising from more political and anthropocentric considerations. Avoiding such biases is critical for optimal conservation, as is minimizing the human impact on PAs (Stewart et al., 2007). As seen in the case of brown bears, most high-quality and low-risk habitats are located in topographically remote areas (Chapter 2). Therefore, transforming such areas into effective PAs will significantly contribute to reducing human impact on bear habitats. However, especially in recent years, the area covered by PA attributes that prioritize conservation sensibility (e.g., nature reserve areas, protection forests, wildlife enhancement areas) has decreased dramatically throughout the country, while the area covered by those that prioritize the utilization function (e.g. national parks, nature parks, nature monuments) are increasing both in number and size (Atmiş, 2018). In many cases, it may be politically difficult to design new PAs (Mohammadi et al., 2021), so a suggested strategy instead is to strengthen the connectivity of good-quality core habitats and enhance the conservation function of established PAs (Cushman et al., 2006). When evaluating the effectiveness of PAs, another important factor is to consider the spatial configuration of PAs to strengthen the connectivity of species that require large undisturbed areas, such as brown bears. Thus, strategies to interconnect PAs in areas that exhibit connectivity for multiple species should be prioritized (de Sousa Miranda et al., 2021). Moreover, climatic suitability should also be considered in PA design. Otherwise, the irreversible loss of these reserves, which serve as buffers against climate change, may limit future conservation efforts (Burrows et al, 2014).

Although the human-bear conflict frequency is lower in the PAs across the country, it is obvious that the conflict risk is highly concentrated around the PAs (Chapter 4). PAs, unfortunately, cover only a small portion of sutaible habitat around them in most cases. Increasing human activity around the PAs poses the risk of turning them into paper parks and ecological traps (Maiorano et al., 2019), and this is a significant threat for brown bears in the long term. PAs do not necessarily alleviate the fragmentation of the landscape around them as

PAs continue to play a role in attracting human activities (Lawrence et al., 2021; Kubacka et al., 2022). If the prioritization in the planning of PAs in Türkiye continues to be the societal utilization function, around of these locations will continue to be hotspots for HBCs. To be effective, PAs require strict governance, including law enforcement (Critchlow et al., 2017). For instance, the presence of rangers is one of the most important deterrents to ongoing illegal human activity in primary habitats and ensures the stability of conservation efforts (Appleton et al., 2022; Moore et al., 2018). Moreover, the presence of rangers is an important source of data for collecting conflict/mortality records, occurrence points, biological samples, and incidental observations from the field (Critchlow et al., 2017; Moore et al., 2018; Kuiper et al., 2020). Therefore, the systematic assortment of these efforts will be valuable for generating reliable scientific evaluations. For example, as part of long-term population monitoring programs, it is recommended to document bear deaths and use this information and sample collections to create long-term genetic databases (Parsons et al., 2022). The success of PAs is measured by how well they prevent the loss of natural areas (Pressey et al., 2015) Thereby, efforts such as studies involving camera traps or other monitoring methodologies will provide important insights to assess the protection effectiveness of both established PAs and new potential areas for vulnerable wildlife species (Soyumert et al., 2020; Dagtekin et al., 2023; Kemahlı et al., 2023).

Resolving HBCs requires recording and analyzing cases, the evaluation of financial costs and preventive measures. Wildlife-related damage compensation is one of the coexistence-enhancing approaches implemented in various countries (Ravenelle & Nyhus, 2017). Although there are some court decisions in cases of damage arising from HBCs in Türkiye, there is no systematic compensation program carried out by official authorities. However, such compensation can be available in cases covered by insurance (e.g., TARSIM, https://tarsim.gov.tr/en). Damage compensation plans might be a helpful instrument in reducing conflict by enabling local people to adopt a more tolerant attitude (Hipólito et al., 2020). Damage compensation is paid posteriori in most countries (Bautista et al., 2019). However, when damage verification processes are unreliable and slow, such instruments may lead to abuse (Dickman et al., 2011; Bautista et al., 2019). In most European countries, more budgets are devoted to prevention than compensation against bear damages, which is more sustainable for the health of humans and bear populations. Therefore, for such a community development plan to mitigate conflict events in Türkiye; i) strict monitoring must be implemented to prevent

abuse, ii) preventive precautions be a prerequisite for compensation, iii) there should be transparency in budget management, and iv) regional socio-cultural aspects should be taken into consideration (Bautista et al., 2019; Redpath et al., 2017).

Beekeeping is one of the most important agricultural activities in Türkiye (GDARP, 2022). Although highly productive beekeeping is carried out across the country, there is an aggregation in the number of hives, especially along the Black Sea region (Koday & Karadağ, 2020). This creates one of the important conflict types in regions with dense bear populations because access to hives provides a high-energy award with low effort for bears. For instance, Naves et al., (2018) have shown that damage to beehives is positively related to apiary size and surrounding vegetation. To minimize attacks on beehives, deterrent precautions must be taken. Various precautions, such as practical elevated bear-proof beehive platforms, mesh fences, and electrified fences, are highly effective in preventing bear damage and should be promoted (Can et al., 2014; Di Vittorio et al., 2016). A similar situation is also valid for raising livestock. The use of well-trained, appropriate sheepdogs (such as the giant breed Anatolian sheep dog created for protection from bears and wolves) accompanying the shepherds and the construction of more sheltered barns are important preventive practices that will reduce livestock predation by wildlife (Kusak & Şekercioğlu, 2021; Dai et al., 2019b). On the other hand, individual avoidance behaviors of people living in settlements overlapping with brown bear habitat against possible encounters also make a difference (URL3; URL4). Therefore, it is important to educate people about ensuring their own safety in ways that do not threaten wildlife.

Another major problem for wildlife across the country is improper waste disposal and storage. Garbage dumps and unsanitary disposal areas on the periphery of natural landscapes transform them and cause significant environmental problems. Moreover, pristine areas and places around them, such as camping and recreation spots, cause food conditioning in brown bears and make them accustomed to humans (Braunstein et al., 2020; Chynoweth et al., 2016). Garbage is accessible throughout the year and displays clustered distribution, making it attractive to bears (van Bommel et al., 2020). Such places represent notable ecological traps and pose many dangers. For example, these points increase interspecific competition and injuries, disease spread, and exposure to environmental contaminants (Plaza & Lambertucci, 2017). They can also inhibit ecosystem services provided by species (e.g. seed dispersal) (Tavşanoğlu et al., 2021). Thus, using appropriate garbage storage instruments (e.g., bear-

resistant trash cans) at such points and increasing the public's environmental awareness in the context of waste management will reduce human–wildlife conflict by making the vicinity of human settlements less energetically beneficial for foraging (Lewis et al., 2015).

Although brown bears are defined as an umbrella species, it should be noted that conservation practices focusing only on them will undoubtedly be inadequate. More dynamic conservation plans are needed for more effective area protection (Mukherjee et al., 2021; Díaz-Fernández et al., 2023). This requires more dynamic conservation plans that aim to holistically reduce the human influence on nature. Furthermore, strategies to conserve biodiversity include protecting the network of important habitats for many species, and this integration both positively improves responses to climate change and increases management efficiency (Asaad et al., 2017). In addition, protecting biodiversity depends on the awareness and efforts of local communities. Therefore, supporting and educating local communities and including them in conservation efforts are among the priorities that need to be reconciled (Pascual et al., 2021).

Increasing temperatures in the future are predicted to limit the denning time of bears (González-Bernardo et al., 2020). This situation, combined with decreasing natural resources, may lead to the modulation of the species' energy budget (Pigeon et al., 2016). For instance, bears give birth to and feed their cubs during the denning period. It is expected that cub survival will decrease because of shorter denning times (Pigeon et al., 2016). Considering the decrease in resources and the fact that bears are opportunistic species, it is inevitable that human-wildlife conflict will increase (Penteriani et al., 2019). For all these reasons, monitoring the dens of bear populations, especially in vulnerable habitats, should be noted as a future suggestion to help improve conservation strategies. Unfortunately, our planet is getting warmer and civilization is moving away from optimistic future emission targets day by day. This is predicted to lead to dramatic habitat loss over large areas for many species, like brown bears (Chapter 2). Serious restrictive and deterrent precautions are required to deal with climate change. To deal with such a global problem, in situ conservation efforts may not be sufficient to conserve the species (Greenwood et al., 2016). Mitigating climate change to increase the success of in situ conservation requires a struggle and cooperation on a global scale. Therefore, it is important to include adaptation to climate change in conservation strategies.

The disappearance of species at the top of the trophic chain, such as brown bears, from their habitats will inhibit the extent to which many ecosystem functions are performed. Bears

not only serve to disperse seeds in their habitat (García-Rodríguez et al., 2021), but they also have many other roles. For example, brown bears generate deep gashes in trees to remove their parasites and search for food (González-Bernardo et al., 2021). Zyśk-Gorczyńska et al. (2014) showed that tree wounds perpetrated by bears attract saproxylic insects and insectivorous birds with bears acting as niche constructors and ecological engineers. Hilderbrand et al. (1999) showed that brown bears can become an important vector of salmon-derived nitrogen in riparian ecosystems. Bears also exhibit scavenging (Elgmork & Tjørve, 1995). Bears can compete with other sympatric omnivores and put pressure on their populations (Diserens et al., 2020). Bears can modulate the density of ungulate populations, especially for agricultural pests like wild boars (Niedziałkowska et al., 2019). Brown bears, a charismatic species, are also a flagship for conservation practices and, therefore, contribute to the destination image of PAs. Tattoni et al. (2024) showed that the advertising equivalent of this contribution exceeded the amount of payments spent to manage the brown bear in the Apennines. Hence, brown bears can be important conservation targets in terms of ecotourism. Consequently, ensuring the continuing presence of brown bears in their habitats will stabilize ecological processes and increase the resilience of ecosystems against both climate change and landscape transformation (Diserens et al., 2020).

With growing landscape transformation and changing climate conditions altering brown bears' distributions and patterns of space use, bears are rendered more vulnerable to global change. It is essential to understand how bears respond to human-induced variability to establish conservation plans that will promote coexistence. Proactive management is a wide-ranging framework that includes the upkeeping of suitable habitats, landscape connectivity, population persistence, conflict mitigation practices, and climate adaptation strategies. Using this framework, it is imperative to build a body of knowledge for different facets of bear ecology in Türkiye and apply this knowledge for effective on-the-ground conservation of brown bears and their habitats across the country.

BIBLIOGRAPHY

- Adler, F. R., Green, A. M., & Şekercioğlu, Ç. H. (2020). Citizen science in ecology: a place for humans in nature. Annals of the New York Academy of Sciences, 1469(1), 52-64.
- Adriaensen, F., Chardon, J. P., De Blust, G., Swinnen, E., Villalba, S., Gulinck, H., & Matthysen, E. (2003). The application of least-cost modelling as a functional landscape model. Landscape and Urban Planning, 64(4), 233-247.
- Afif-Khouri, E., Alvarez-Alvarez, P., Fernandez-Lopez, M.J., Oliveira-Prendes, J.A. & Camara-Obregon, A. (2011). Influence of climate, edaphic factors and tree nutrition on site index of chestnut coppice stands in north-west Spain. Forestry 84, 385–396
- Aiello-Lammens, M. E., Boria, R. A., Radosavljevic, A., Vilela, B., & Anderson, R. P. (2015). spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. Ecography, 38(5), 541-545.
- Akman, Y., & Ketenoğlu, O. (1986). The climate and vegetation of Turkey. Proceedings of the Royal Society of Edinburgh, Section B: Biological Sciences, 89, 123-134.
- Ali, H., Din, J.U., Bosso, L., Hameed, S., Kabir, M., Younas, M., Nawaz, M.A., 2021. Expanding or shrinking? Range shifts in wild ungulates under climate change in Pamir-Karakoram mountains, Pakistan. PLoS One 16(1): e0260031.
- Ali, O. A., O'Rourke, S. M., Amish, S. J., Meek, M. H., Luikart, G., Jeffres, C., & Miller, M. R. (2016). RAD capture (Rapture): flexible and efficient sequence-based genotyping. Genetics, 202(2), 389-400
- Allouche, O., Tsoar, A., & Kadmon, R. (2006). Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). Journal of Applied Ecology, 43(6), 1223-1232.
- Almasieh, K., Rouhi, H., & Kaboodvandpour, S. (2019). Habitat suitability and connectivity for the brown bear (Ursus arctos) along the Iran-Iraq border. European Journal of Wildlife Research, 65, 1-12.
- Ambarlı, H., & Bilgin, C. C. (2008). Human–brown bear conflicts in Artvin, northeastern Turkey: Encounters, damage, and attitudes. Ursus, 19(2), 146-153.
- Ambarlı, H., 2016. Litter size and basic diet of brown bears (Ursus arctos, Carnivora) in northeastern Turkey. Mammalia 80(4): 369-375.
- Ambarlı, H., Ertürk, A., & Soyumert, A. (2016). Current status, distribution, and conservation of brown bear (Ursidae) and wild canids (gray wolf, golden jackal, and red fox; Canidae) in Turkey. Turkish Journal of Zoology, 40(6), 944-956.
- Ambarlı, H., Mengüllüoğlu, D., Fickel, J., Förster, D.W., 2018. Population genetics of the main population of brown bears in southwest Asia. PeerJ 6: e5660.
- Andersson M (1994) Sexual Selection. Princeton University Press, Princeton, New Jersey, USA.
- Appleton, M. R., Courtiol, A., Emerton, L., Slade, J. L., Tilker, A., Warr, L. C., Malvido M. A., Barborak, J. R., de Bruin, L., Chapple, R., Daltry, J. C., Hadley, N. P., Jordan, C. A., Rousset F., Singh, R., Sterling, E. J., Wessling, E. G., Long, B. (2022). Protected area personnel and ranger numbers are insufficient to deliver global expectations. Nature Sustainability, 5(12), 1100-1110.
- Araújo, M. B., & New, M. (2007). Ensemble forecasting of species distributions. Trends in Ecology & Evolution, 22(1), 42-47.

- Asaad, I., Lundquist, C. J., Erdmann, M. V., & Costello, M. J. (2017). Ecological criteria to identify areas for biodiversity conservation. Biological Conservation, 213, 309-316.
- Ashrafzadeh, M. R., Kaboli, M., & Naghavi, M. R. (2016). Mitochondrial DNA analysis of Iranian brown bears (Ursus arctos) reveals new phylogeographic lineage. Mammalian Biology, 81(1), 1-9.
- Ashrafzadeh, M. R., Khosravi, R., Ahmadi, M., & Kaboli, M. (2018). Landscape heterogeneity and ecological niche isolation shape the distribution of spatial genetic variation in Iranian brown bears, Ursus arctos (Carnivora: Ursidae). Mammalian Biology, 93, 64-75.
- Ashrafzadeh, M. R., Naghipour, A. A., Haidarian, M., & Khorozyan, I. (2019). Modeling the response of an endangered flagship predator to climate change in Iran. Mammal Research, 64, 39-51.
- Ashrafzadeh, M. R., Khosravi, R., Mohammadi, A., Naghipour, A. A., Khoshnamvand, H., Haidarian, M., & Penteriani, V. (2022). Modeling climate change impacts on the distribution of an endangered brown bear population in its critical habitat in Iran. Science of the Total Environment, 837, 155753.
- Atmiş, E. (2018). A critical review of the (potentially) negative impacts of current protected area policies on the nature conservation of forests in Turkey. Land Use Policy, 70, 675-684.
- Atmiş, E., Yıldız, D., & Erdönmez, C. (2024). A different dimension in deforestation and forest degradation: Non-forestry uses of forests in Turkey. Land Use Policy, 139, 107086.
- Austin, M. P., & Van Niel, K. P. (2011). Improving species distribution models for climate change studies: variable selection and scale. Journal of Biogeography, 38(1), 1-8.
- Ayan, S., Bugday, E., Varol, T., Özel, H. B., & Thurm, E. A. (2022). Effect of climate change on potential distribution of oriental beech (Fagus orientalis Lipsky.) in the twenty-first century in Turkey. Theoretical and Applied Climatology, 148(1), 165-177.
- Aydin-Kandemir, F., & Demir, N. (2023). 2021 Turkey mega forest Fires: Biodiversity measurements of the IUCN Red List wildlife mammals in Sentinel-2 based burned areas. Advances in Space Research, 71(7), 3060-3075.
- Baggio, J. A., Salau, K., Janssen, M. A., Schoon, M. L., & Bodin, Ö. (2011). Landscape connectivity and predator–prey population dynamics. Landscape Ecology, 26, 33-45.
- Balkenhol, N., Cushman, S., Storfer, A., & Waits, L. (2015). Landscape genetics: concepts, methods, applications. John Wiley & Sons.
- Barbet-Massin, M., Jiguet, F., Albert, C.H., & Thuiller, W. (2012). Selecting pseudo-absences for species distribution models: How, where and how many? Methods in Ecology and Evolution, 3(2), 327-338.
- Bautista, C., Revilla, E., Naves, J., Albrecht, J., Fernández, N., Olszańska, A., Adamec, M., Berezowska-Cnota, T., Ciucci, P., Groff, C., Härkönen, S., Huber, D., Jerina, K., Jonozovič, M., Karamanlidis, A. A., Palazón, S., Quenette, P-Y., Rigg, R., Seijas, J, Swenson, J. E., Talvi, T. & Selva, N. (2019). Large carnivore damage in Europe: Analysis of compensation and prevention programs. Biological Conservation, 235, 308-316.
- Bautista, C., Oeser, J., Kuemmerle, T., & Selva, N. (2023). Resource pulses and human–wildlife conflicts: linking satellite indicators and ground data on forest productivity to predict brown bear damages. Remote Sensing in Ecology and Conservation, 9(1), 90-

103.
- Bedia, J., Herrera, S., & Gutiérrez, J. M. (2013). Dangers of using global bioclimatic datasets for ecological niche modeling. Limitations for future climate projections. Global and Planetary Change, 107, 1-12.
- Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W., & Courchamp, F. (2012). Impacts of climate change on the future of biodiversity. Ecology Letters, 15(4), 365-377.
- Benazzo, A., Trucchi, E., Cahill, J. A., Maisano Delser, P., Mona, S., Fumagalli, M., Bunnefeld, L., Cornetti, L., Ghirotto, S., Girardi, M., Ometto, L., Panziera, A., Rota-Stabelli, O., Zanetti, E., Karamanlidis, A., Groff, C., Paule, L., Gentile L., Vilà, C., Vicario, S., Boitani, L., Orlando, L., Fuselli, S., Vernesi, C., Shapiro, B., Ciucci, P., & Bertorelle, G. (2017). Survival and divergence in a small group: The extraordinary genomic history of the endangered Apennine brown bear stragglers. Proceedings of the National Academy of Sciences, 114(45), E9589-E9597.
- Bilici, E., & Akay, A.E. (2021). Forestry and forest operations in Turkey: Challenges and developments. Revista Pădurilor, 136(1), 1-64.
- Birben, Üstüner. The effectiveness of protected areas in biodiversity conservation: The case of Turkey. Cerne 25 (2020): 424-438.
- Boavida, J., Assis, J., Silva, I., & Serrão, E. A. (2016). Overlooked habitat of a vulnerable gorgonian revealed in the Mediterranean and Eastern Atlantic by ecological niche modelling. Scientific Reports, 6(1), 36460.
- Bombieri, G., Naves, J., Penteriani, V., Selva, N., Fernández-Gil, A., López-Bao, J. V., Ambarli, H., Bautista, C., Bespalova, T., Bobrov, V., Bolshakov, V., Bondarchuk, S., Camarra, J. J., Chiriac, S., Ciucci, P., Dutsov, A., Dykyy, J., Fedriani, M., García-Rodríguez, A., Garrote, P. J., Gashev, S., Groff, C., Gutleb, B., Haring, M., Härkönen, S., Huber, D., Kaboli, M., Kalinkin, Y., Karamanlidis, A. A., Karpin, V., Kastrikin, V., Khlyap, L., Khoetsky, P., Kojola I., Kozlow, Y., Korolev, A., Korytin, N., Kozsheechkin, V., Krofel, M., Kurhinen, J., Kuznetsova, I., Larin, E., Levykh, A., Mamontov, V., Männil, P., Melovski, D., Mertzanis, Y., Meydus, A., Mohammadi, A., Norberg, H., Palazón, S., Pătrașcu, L. M., Pavlova, K., Pedrini, P., Quenette, P. Y., Revilla, E., Rigg, R., Rozhkov, Y., Russo, L. F., Rykov, A., Saburova, L., Sahlén, V., Saveljev, A. P., Seryodkin, I. V., Shelekhov, A., Shishikin, A., Shkvyria, M., Sidorovich, V., Sopin, V., Støen, O., Stofik, J., Swenson, J. E., Triski, D., Vasin, A., Wabakken, P., Yarushina, L., Zwijacz-Kozica, T., & Delgado, M. M. (2019). Brown bear attacks on humans: a worldwide perspective. Scientific Reports, 9(1), 1-10.
- Bombieri, G., Penteriani, V., Delgado, M. D. M., Groff, C., Pedrotti, L., & Jerina, K. (2021). Towards understanding bold behaviour of large carnivores: The case of brown bears in human-modified landscapes. Animal Conservation, 24(5), 783-797.
- Bombieri G, Penteriani V, Almasieh K, Ambarlı H, Ashrafzadeh MR, Das CS, Dharaiya N, Hoogesteijn R, Hoogesteijn A, Ikanda D, Jędrzejewski W, Kaboli M, Kirilyuk A, Jangid AK, Sharma RK, Kushnir H, Lamichhane BR, Mohammadi A, Monroy-Vilchis O, Mukeka JM, Nikolaev I, Ohrens O, Packer C, Pedrini P, Ratnayeke S, Seryodkin I, Sharp T, Palei HS, Smith T, Subedi A, Tortato F, Yamazaki K, Delgado MDM. A worldwide perspective on large carnivore attacks on humans. PLoS Biology. 2023.
- Boulanger, J., & Stenhouse, G. B. (2014). The impact of roads on the demography of grizzly bears in Alberta. PloS One, 9(12), e115535.
- Bowersock, N. R., Litt, A. R., Sawaya, M. A., Gunther, K. A., & van Manen, F. T. (2024). Spatial variation in density of American black bears in northern Yellowstone

National Park. The Journal of Wildlife Management, 88(1), e22497.
- Braunstein, J. L., Clark, J. D., Williamson, R. H., & Stiver, W. H. (2020). Black bear movement and food conditioning in an exurban landscape. The Journal of Wildlife Management, 84(6), 1038-1050.
- Breiman, L. (2001). Random forests Mach Learn 45 (1): 5–32.
- Broekhuis, F., Cushman, S. A., & Elliot, N. B. (2017). Identification of human–carnivore conflict hotspots to prioritize mitigation efforts. Ecology and Evolution, 7(24), 10630-10639.
- Broennimann, O., Cola, V. Di, Petitpierre, B., Breiner, F., Scherrer, D., D'Amen, M., Randin, C., Engler, R., Hordijk, W., Mod, H., Pottier, J., Febbraro, M. Di, Pellissier, L., Pio, D., Mateo, R.G., Dubuis, A., Maiorano, L., Psomas, A., Ndiribe, C., Salamin, N., Zimmermann, N., Guisan, A. (2018). Ecospat: spatial ecology miscellaneous methods. Package "ecospat". (R Packag. Version 3.0).
- Brown, J. L. (2014). SDM toolbox: a python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. Methods in Ecology and Evolution, 5(7), 694-700.
- Burgess, S. C., Baskett, M. L., Grosberg, R. K., Morgan, S. G., & Strathmann, R. R. (2016). When is dispersal for dispersal? Unifying marine and terrestrial perspectives. Biological Reviews, 91, 867–882.
- Burrows, M. T., Schoeman, D. S., Richardson, A. J., Molinos, J. G., Hoffmann, A., Buckley, L. B., Moore, P. J., Brown, C. J., Bruno, J. F., Duarte, C. M., Halpern, B. S., Hoegh-Guldberg, O., Kappel, C. V., Kiessling, W., O'Connor, M. I., Pandolfi, J. M., Parmesan, C., Sydeman, W. J., Ferrier, S., Williams, K. J. & Poloczanska, E. S. (2014). Geographical limits to species-range shifts are suggested by climate velocity. Nature, 507(7493), 492-495.
- Busby, J. R. (1991). BIOCLIM-a bioclimate analysis and prediction system.
- Cahill, J. A., Green, R. E., Fulton, T. L., Stiller, M., Jay, F., Ovsyanikov, N., Salamzade, R., St. John, J., Stirling, I., & Slatkin, M. (2013). Genomic evidence for island population conversion resolves conflicting theories of polar bear evolution. PLoS Genetics, 9(3), e1003345.
- Calderón, A. P., Landaverde-Gonzalez, P., Wultsch, C., Foster, R., Harmsen, B., Figueroa, O., Garcia-Anleu, R., Castañeda, F., Amato, G., Grimm, V., Kramer-Schadt, S. & Zeller, K. A. (2024). Modelling jaguar gene flow in fragmented landscapes offers insights into functional population connectivity. Landscape Ecology, 39(2), 12.
- Calvignac, S., Hughes, S., & Hänni, C. (2009). Genetic diversity of endangered brown bear (Ursus arctos) populations at the crossroads of Europe, Asia and Africa. Diversity and Distributions, 15(5), 742-750.
- Can, Ö.E., & Togan, I. (2004). Status and management of brown bears in Turkey. Ursus, 15(2), 48-54.
- Can, Ö. E., D'Cruze, N., Garshelis, D. L., Beecham, J., & Macdonald, D. W. (2014). Resolving human-bear conflict: a global survey of countries, experts, and key factors. Conservation Letters, 7(6), 501-513.
- Canturk, U., & Kulaç, Ş. (2021). The effects of climate change scenarios on Tilia ssp. in Turkey. Environmental Monitoring and Assessment, 193(12), 771.
- Caprio, J. M., & Quamme, H. A. (2006). Influence of weather on apricot, peach and sweet cherry production in the Okanagan Valley of British Columbia. Canadian Journal of Plant Science, 86(1), 259-267.

- Carvalho, F., Lourenço, A., Carvalho, R., Alves, P. C., Mira, A., & Beja, P. (2018). The effects of a motorway on movement behaviour and gene flow in a forest carnivore: Joint evidence from road mortality, radio tracking and genetics. Landscape and Urban Planning, 178, 217-227.
- Carvalho, J. S., Graham, B., Bocksberger, G., Maisels, F., Williamson, E. A., Wich, S., Sop, T., Amarasekaran, B., Barca, B., Barrie, A., Bergl, R. A., Boesch, C., Boesch, H., Brncic, T. M., Buys, B., Chancellor, R., Danquah, E., Doumbé, O. A., Le-Duc, S. Y., Galat-Luong, A., Ganas, J., Gatti, S., Ghiurghi, A., Goedmakers, A., Granier, N., Hakizimana, D., Haurez, B., Head, J., Herbinger, I., Hillers, A., Jones, S., Junker, J., Maputla, N., Manasseh, E-N., McCarthy, M. S., Molokwu-Odozi, M., Morgan, B. J., Nakashima, Y., N'Goran, P. K., Nixon, S., Nkembi, L., Normand, E., Nzooh, L. D. Z., Olson, S. H., Payne, L., Petre, C-A., Piel, A. K., Pintea, L., Plumptre, A. J., Rundus, A., Serckx, A., Stewart, F. A., Sunderland-Groves, J., Tagg, N., Todd, A., Vosper, A., Wenceslau, J. F. C., Wessling, E. G., Willie, J., & Kühl, H. S. (2021). Predicting range shifts of African apes under global change scenarios. Diversity and Distributions, 27(9), 1663-1679.
- Cayuela, H., Rougemont, Q., Prunier, J. G., Moore, J. S., Clobert, J., Besnard, A., & Bernatchez, L. (2018). Demographic and genetic approaches to study dispersal in wild animal populations: A methodological review. Molecular Ecology, 27(20), 3976-4010.
- CBD, 2022 Convention on Biological Diversity, Aichi Biodiversity Target.
- Çeltik, E. Phylogenetic Analysis of Brown Bear (Ursus arctos) Populations Across Türkiye. Master Thesis, 2023, Graduate School of Science and Engineering, Koç University.
- Chapron, G., Kaczensky, P., Linnell, J. D., Von Arx, M., Huber, D., Andrén, H., López-Bao, J. V., Adamec, M, Álvares, F., Anders, O., Balčiauskas, L., Balys, V., Bedö, P., Bego, F., Blanco, J. C., Breitenmoser, U., Brøseth, H, Bufka, L., Bunikyte, R., Ciucci, P., Dutsov, A., Engleder, T., Fuxjäger, C., Groff, C., Holmala, K., Hoxha, B., Iliopoulos, Y., Ionescu, O., Jeremić, J., Jerine, K., Kluth, G., Knauer, F., Kojola, I., Krofel, M., Kubala, J., Kunovac, S., Kusak, J., Kutal, M., Liberg, O., Majić, A., Männil, P., Manz, R., Marboutin, E., Marucco, F., Melovski, D., Mersini, K., Mertzanis, Y., Mysłajek, R. W., Nowak, S., Odden, J., Ozolins, J., Palomero, G., Paunović, M., Persson, J., Potočnik, H., Quenette, P-Y., Rauer, G., Reinhardt, I., Rigg, R., Ryser, A., Salvatori, V., Skrbinšek, T., Stojanov, A., Swenson, J. E., Szemethy, L., Trajçe, A., Tsingarska-Sedefcheva, E., Váňa, M., Veeroja, R., Wabakken, P., Wölfl, M., Wölfl, S., Zimmermann, F., Zlatanova, D., Boitani, L. (2014). Recovery of large carnivores in Europe's modern human-dominated landscapes. Science, 346(6216), 1517-1519.
- Chen, I. C., Hill, J. K., Ohlemüller, R., Roy, D. B., & Thomas, C. D. (2011). Rapid range shifts of species associated with high levels of climate warming. Science, 333(6045), 1024-1026.
- Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., Cho, H., Chen, K., Mitchell, R., Cano, I. & Zhou, T. (2015). Xgboost: extreme gradient boosting. R package version 0.4-2, 1(4), 1-4.
- Chen, H. L., & Koprowski, J. L. (2019). Can we use body size and road characteristics to anticipate barrier effects of roads in mammals? A meta-analysis. Hystrix, 30(1), 1.
- Chynoweth, M., Coban, E., Altin, Ç., & Şekercioğlu, Ç. (2016). Human-wildlife conflict as a barrier to large carnivore management and conservation in Turkey. Turkish Journal of Zoology, 40(6), 972-983.
- Çilingir, F. G., Akın Pekşen, Ç., Ambarlı, H., Beerli, P., & Bilgin, C. C. (2016).

Exceptional maternal lineage diversity in brown bears (Ursus arctos) from Turkey. Zoological Journal of the Linnean Society, 176(2), 463-477.
- Ciucci, P., Tosoni, E., Di Domenico, G., Quattrociocchi, F., & Boitani, L. (2014). Seasonal and annual variation in the food habits of Apennine brown bears, central Italy. Journal of Mammalogy, 95(3), 572-586.
- Colton, C. P., Coops, N. C., & Burton, A. C. (2021). Grizzly bear (Ursus arctos) responses to forest harvesting: A review of underlying mechanisms and management recommendations. Forest Ecology and Management, 497, 119471.
- Compton, B. W., McGarigal, K., Cushman, S. A., & Gamble, L. R. (2007). A resistant-kernel model of connectivity for amphibians that breed in vernal pools. Conservation Biology, 21(3), 788-799.
- Cozzi, G., Chynoweth, M., Kusak, J., Coban, E., Çoban, A., Ozgul, A., & Şekercioğlu, Ç. H. (2016). Anthropogenic food resources foster the coexistence of distinct life history strategies: year-round sedentary and migratory brown bears. Journal of Zoology, 300(2), 142-150.
- Çolak, A. H., & Rotherham, I. D. (2006). A review of the forest vegetation of Turkey: its status past and present and its future conservation. In Biology and Environment: Proceedings of the Royal Irish Academy (Vol. 106, No. 3, pp. 343-354). Royal Irish Academy.
- Cristescu, B., Stenhouse, G. B., & Boyce, M. S. (2016). Large omnivore movements in response to surface mining and mine reclamation. Scientific Reports, 6(1), 19177.
- Critchlow, R., Plumptre, A.J., Alidria, B., Nsubuga, M., Driciru, M., Rwetsiba, A., Wanyama, F. & Beale, C. M. (2017). Improving law-enforcement effectiveness and efficiency in protected areas using ranger-collected monitoring data. Conservation Letters, 10(5), 572-580.
- Crooks, K. R., Burdett, C. L., Theobald, D. M., Rondinini, C., & Boitani, L. (2011). Global patterns of fragmentation and connectivity of mammalian carnivore habitat. Philosophical Transactions of the Royal Society B: Biological Sciences, 366(1578), 2642-2651.
- Crooks, K. R., Burdett, C. L., Theobald, D. M., King, S. R., Di Marco, M., Rondinini, C., & Boitani, L. (2017). Quantification of habitat fragmentation reveals extinction risk in terrestrial mammals. Proceedings of the national Academy of Sciences, 114(29), 7635-7640.
- Cunningham, S. C., & Ballard, W. B. (2004). Effects of wildfire on black bear demographics in central Arizona. Wildlife Society Bulletin, 32(3), 928-937.
- Cushman, S. A., McKelvey, K. S., Hayden, J., & Schwartz, M. K. (2006). Gene flow in complex landscapes: testing multiple hypotheses with causal modeling. The American Naturalist, 168(4), 486-499.
- Cushman, S. A., McKelvey, K. S., & Schwartz, M. K. (2009). Use of empirically derived source-destination models to map regional conservation corridors. Conservation Biology, 23(2), 368-376.
- Cushman, S. A., & Landguth, E. L. (2012). Multi-taxa population connectivity in the Northern Rocky Mountains. Ecological Modelling, 231, 101-112.
- Cushman, S. A., Lewis, J. S., & Landguth, E. L. (2013). Evaluating the intersection of a regional wildlife connectivity network with highways. Movement Ecology, 1, 1-11.
- Cushman, Samuel A., Nicholas B. Elliot, Dominik Bauer, Kristina Kesch, Laila Bahaa-El-Din, Helen Bothwell, Michael Flyman, Godfrey Mtare, David W. Macdonald, and

Andrew J. Loveridge. (2018). Prioritizing core areas, corridors and conflict hotspots for lion conservation in southern Africa. PloS One, 13(7), e0196213.
- Dagtekin, D., Şahan, E.A., Denk, T., Köse, N., & Dalfes, H.N. (2020). Past, present and future distributions of Oriental beech (Fagus orientalis) under climate change projections. PLoS One, 15(7), e0242280.
- Dagtekin, D., Ertürk, A., Sommer, S., Ozgul, A., Soyumert, A. (2023). Seasonal habitat-use patterns of large mammals in a human-dominated landscape, Journal of Mammalogy, 105(1), 122-133.
- Dai, Y., Hacker, C.E., Zhang, Y., Li, W., Zhang, Y., Liu, H., Zhang, J., Ji, Y., Xue, Y. & Li, D. (2019a). Identifying climate refugia and its potential impact on Tibetan brown bear (Ursus arctos pruinosus) in Sanjiangyuan National Park, China. Ecology and Evolution, 9(23), 13278-13293.
- Dai, Y., Hacker, C.E., Zhang, Y., Li, W., Li, J., Zhang, Y., Bona, G., Liu, H., Li, Y., Xue, Y. & Li, D. (2019b). Identifying the risk regions of house break-ins caused by Tibetan brown bears (Ursus arctos pruinosus) in the Sanjiangyuan region, China. Ecology and Evolution, 9(24), 13979-13990.
- Dai, Y., Hacker, C. E., Zhang, Y., Li, Y., Li, J., Xue, Y., & Li, D. (2020). Conflicts of human with the Tibetan brown bear (Ursus arctos pruinosus) in the Sanjiangyuan region, China. Global Ecology and Conservation, 22, e01039.
- Dai, Y., Peng, G., Wen, C., Zahoor, B., Ma, X., Hacker, C. E., & Xue, Y. (2021a). Climate and land use changes shift the distribution and dispersal of two umbrella species in the Hindu Kush Himalayan region. Science of the Total Environment, 777, 146207.
- Dai, Y., Hacker, C.E., Cao, Y., Cao, H., Xue, Y., Ma, X., Liu, H., Zahoor, B., Zhang, Y. & Li, D. (2021b). Implementing a comprehensive approach to study the causes of human-bear (Ursus arctos pruinosus) conflicts in the Sanjiangyuan region, China. Science of the Total Environment, 772, 145012.
- Dalfes HN, Karaca M, Şen ÖL, Güven Ç (Ed.) (2007) Climate change scenarios for Turkey. Climate change & Turkey impacts, sectoral analyses, socio economic dimensions. Ankara: United Nations Development
- Dar, S.A., Singh, S.K., Wan, H.Y., Kumar, V., Cushman, S.A., & Sathyakumar, S. (2021). Projected climate change threatens Himalayan brown bear habitat more than human land use. Animal Conservation, 24(6), 749-760.
- Dar, S. A., Singh, S. K., Wan, H. Y., Cushman, S. A., Bashir, T., & Sathyakumar, S. (2022). Future land use and climate change escalate connectivity loss for Himalayan brown bears. Animal Conservation, 26(2), 199-215
- Daşdemir, İ., Aydın, F., & c, M. (2021). Factors affecting the behavior of large forest fires in Turkey. Environmental Management, 67, 162-175.
- Davis PH. Distribution patterns in Anatolia with particular reference to endemism. Plant Life of South-West Asia. 1971.
- Deacy, W.W.; Armstrong, J.B.; Leacock, W.B.; Robbins, C.T.; Gustine, D.D.; Ward, E.J.; Erlenbach, J.A.; Stanford, J.A. (2017). Phenological synchronization disrupts trophic interactions between Kodiak brown bears and salmon. Proceedings of the National Academy of Sciences 114, no. 39: 10432-10437.
- De'ath G. Boosted trees for ecological modeling and prediction. Ecology. 2007.
- De Barba, M., Waits, L. P., Genovesi, P., Randi, E., Chirichella, R., & Cetto, E. (2010). Comparing opportunistic and systematic sampling methods for non-invasive genetic monitoring of a small translocated brown bear population. Journal of Applied Ecology,

47(1), 172-181.
- de Jong, M.J., Niamir, A., Wolf, M., Kitchener, A.C., Lecomte, N., Seryodkin, I.V., Fain, S.R., Hagen, S.B., Saarma, U. & Janke, A. (2023). Range-wide whole-genome resequencing of the brown bear reveals drivers of intraspecies divergence. Communications Biology, 6(1), 153.
- Demircan, M., Gürken, H., Eskioğlu, O., Arabacı, H., & Coşkun, M. (2017). Climate change projections for Turkey: three models and two scenarios. Turkish Journal of Water Science and Management, 1(1), 22-43.
- de Oliveira, G., Rangel, T. F., Lima-Ribeiro, M. S., Terribile, L. C., & Diniz-Filho, J. A. F. (2014). Evaluating, partitioning, and mapping the spatial autocorrelation component in ecological niche modeling: a new approach based on environmentally equidistant records. Ecography, 37(7), 637-647.
- de Sousa Miranda, L., Awade, M., Jaffé, R., Costa, W.F., Trevelin, L.C., Borges, R.C., de Brito, R.M., Tambosi, L.R. & Giannini, T. C. (2021). Combining connectivity and species distribution modeling to define conservation and restoration priorities for multiple species: a case study in the Eastern Amazon. Biological Conservation, 257, 109148.
- Di Minin, E., Slotow, R., Hunter, L.T., Montesino Pouzols, F., Toivonen, T., Verburg, P.H., Leader-Williams, N., Petracca, L. & Moilanen, A. (2016). Global priorities for national carnivore conservation under land use change. Scientific Reports, 6(1), 1-9.
- Di Vittorio M, Costrini P, Rocco M, Bragalanti N, Borsetta M. Assessing the efficacy of electric fences to prevent Bear Damage in Italy. Carnivore Damage Prevention News. 2016; 12: 31–37.
- Díaz-Fernández, M., Naves, J., & Revilla, E. (2023). Conservation implications of range dynamics in endangered populations: An example with brown bears. Conservation Science and Practice, 5(3), e12894.
- Dickman, A. J., Macdonald, E. A., & Macdonald, D. W. (2011). A review of financial instruments to pay for predator conservation and encourage human–carnivore coexistence. Proceedings of the National Academy of Sciences, 108(34), 13937-13944.
- Dickson, B.G., Albano, C.M., Anantharaman, R., Beier, P., Fargione, J., Graves, T.A., Gray, M.E., Hall, K.R., Lawler, J.J., Leonard, P.B., Littlefield C. E., McClure, M. L., Novembre, J., Schloss, C., A., Schumaker, N. H, Shah, V. B., & Theobald, D. M. (2019). Circuit-theory applications to connectivity science and conservation. Conservation Biology, 33(2), 239-249.
- Diserens, T. A., Churski, M., Bubnicki, J. W., Stępniak, K., Pekach, A., Selva, N., & Kuijper, D. P. J. (2020). A, dispersing bear in Białowieża Forest raises important ecological and conservation management questions for the central European lowlands. Global Ecology and Conservation, 23, e01190.
- Dixon, P. (2003). VEGAN, a package of R functions for community ecology. Journal of Vegetation Science, 14(6), 927-930.
- Donatelli, A., Mastrantonio, G., & Ciucci, P. (2022). Circadian activity of small brown bear populations living in human-dominated landscapes. Scientific Reports, 12(1), 15804.
- Dormann CF, Elith J, Bacher S, Buchmann C, Carl G, Carré G, García Marquéz, J. R., Gruber, B., Lafourcade, B., Leitão, P. J., Münkemüller, T., McClean, C., Osborne, P. E., Reineking, B., Schröder, B., Skidmore, A. K., Zurell, D., & Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their

performance. Ecography 36, no. 1 (2013): 27-46.
- Draheim, H. M., Moore, J. A., Fortin, M. J., & Scribner, K. T. (2018). Beyond the snapshot: Landscape genetic analysis of time series data reveal responses of American black bears to landscape change. Evolutionary Applications, 11(8), 1219-1230.
- Duquette, J.F., Belant, J.L., Wilton, C.M., Fowler, N., Waller, B.W., Beyer Jr, D.E., Svoboda, N.J., Simek, S.L. & Beringer, J. (2017). Black bear (Ursus americanus) functional resource selection relative to intraspecific competition and human risk. Canadian Journal of Zoology, 95(3), 203-212.
- Dutta, T., Sharma, S., McRae, B. H., Roy, P. S., & DeFries, R. (2016). Connecting the dots: mapping habitat connectivity for tigers in central India. Regional Environmental Change, 16, 53-67.
- Eid, E., & Handal, R. (2018). Illegal hunting in Jordan: using social media to assess impacts on wildlife. Oryx, 52(4), 730-735.
- El Garroussi, S., Di Giuseppe, F., Barnard, C., & Wetterhall, F. (2024). Europe faces up to tenfold increase in extreme fires in a warming climate. npj Climate and Atmospheric Science, 7(1), 30.
- Elfström, M., Swenson, J.E., 2009. Effects of sex and age on den site use by Scandinavian brown bears. Ursus 20, 85e93.
- Elfström, M., Zedrosser, A., Jerina, K., Støen, O. G., Kindberg, J., Budic, L., Jonozovič, M., & Swenson, J. E. (2014). Does despotic behavior or food search explain the occurrence of problem brown bears in Europe? The Journal of Wildlife Management, 78(5), 881-893.
- Elgmork, K., & Tjørve, E. (1995). Brown bear Ursus arctos scavenging patterns. Wildlife Biology, 1(4), 239-242.
- Elliot, N. B., Cushman, S. A., Macdonald, D. W., & Loveridge, A. J. (2014). The devil is in the dispersers: predictions of landscape connectivity change with demography. Journal of Applied Ecology, 51(5), 1169-1178.
- Elith J, H. Graham C, P. Anderson R, Dudík M, Ferrier S, Guisan A, Hijmans, R. J., Huettmann, F., Leathwick, J. R., Lehmann, A., Li, J., Lohmann, L. G., Loiselle, B. A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton J. M. M., Peterson, A. T., Phillips, S. J., Richardson, K., Scachetti-Pereira, R., Schapire, R. E., Soberón, J., Williams, S., Wisz, M. S., Zimmermann, N. E. (2006). Novel methods improve prediction of species' distributions from occurrence data. Ecography 29, no. 2: 129-151.
- Elsen, P. R., Monahan, W. B., Dougherty, E. R., & Merenlender, A. M. (2020). Keeping pace with climate change in global terrestrial protected areas. Science Advances, 6(25), eaay0814.
- Elsen, P. R., Monahan, W. B., & Merenlender, A. M. (2020). Topography and human pressure in mountain ranges alter expected species responses to climate change. Nature Communications, 11(1), 1974.
- Elton, C. S. (1927). Animal ecology. University of Chicago Press (2001).
- Endo, Y., Osada, N., Mano, T., & Masuda, R. (2021). Demographic history of the brown bear (Ursus arctos) on Hokkaido Island, Japan, based on whole-genomic sequence analysis. Genome Biology and Evolution, 13(9), evab195.
- Epps, C. W., & Keyghobadi, N. (2015). Landscape genetics in a changing world: disentangling historical and contemporary influences and inferring change. Molecular Ecology, 24(24), 6021-6040.
- Ergüner, Y., Kumar, J., Hoffman, F. M., Dalfes, H. N., & Hargrove, W. W. (2019).

Mapping ecoregions under climate change: a case study from the biological 'crossroads' of three continents, Turkey. Landscape Ecology, 34, 35-50.
- Erlenbach, J. A., Rode, K. D., Raubenheimer, D., & Robbins, C. T. (2014). Macronutrient optimization and energy maximization determine diets of brown bears. Journal of Mammalogy, 95(1), 160-168.
- Estrada, E., & Bodin, Ö. (2008). Using network centrality measures to manage landscape connectivity. Ecological Applications, 18(7), 1810-1825.
- Evanno, G., Regnaut, S., & Goudet, J. (2005). Detecting the number of clusters of individuals using the software STRUCTURE: a simulation study. Molecular Ecology, 14(8), 2611-2620.
- Evans, A. L., Singh, N. J., Friebe, A., Arnemo, J. M., Laske, T. G., Fröbert, O., Swenson, J. E., & Blanc, S. (2016). Drivers of hibernation in the brown bear. Frontiers in Zoology, 13, 7.
- Feder, J. L., Egan, S. P., & Nosil, P. (2012). The genomics of speciation-with-gene-flow. Trends in Genetics, 28(7), 342-350.
- Fedorca, A., Russo, I.R.M., Ionescu, O., Ionescu, G., Popa, M., Fedorca, M., Curtu, A.L., Sofletea, N., Tabor, G.M. & Bruford, M. W. (2019). Inferring fine-scale spatial structure of the brown bear (Ursus arctos) population in the Carpathians prior to infrastructure development. Scientific Reports, 9(1), 9494.
- Feng, X., Park, D. S., Walker, C., Peterson, A. T., Merow, C., & Papeş, M. (2019). A checklist for maximizing reproducibility of ecological niche models. Nature Ecology & Evolution, 3(10), 1382-1395.
- Fernández, N., Selva, N., Yuste, C., Okarma, H., & Jakubiec, Z. (2012). Brown bears at the edge: Modeling habitat constrains at the periphery of the Carpathian population. Biological Conservation, 153, 134-142.
- Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology, 37(12), 4302-4315.
- Find'o, S., Skuban, M., Kajba, M., Chalmers, J., & Kalaš, M. (2019). Identifying attributes associated with brown bear (Ursus arctos) road-crossing and roadkill sites. Canadian Journal of Zoology, 97(2), 156-164.
- Fitzpatrick, M. C., & Keller, S. R. (2015). Ecological genomics meets community-level modelling of biodiversity: Mapping the genomic landscape of current and future environmental adaptation. Ecology Letters, 18(1), 1-16.
- Fletcher, R. J., Burrell, N. S., Reichert, B. E., Vasudev, D., & Austin, J. D. (2016). Divergent perspectives on landscape connectivity reveal consistent effects from genes to communities. Current Landscape Ecology Reports, 1, 67-79.
- Forester, B. R., Lasky, J. R., Wagner, H. H., & Urban, D. L. (2018). Comparing methods for detecting multilocus adaptation with multivariate genotype–environment associations. Molecular Ecology, 27(9), 2215-2233.
- Fortin, J. K., Rode, K. D., Hilderbrand, G. V., Wilder, J., Farley, S., Jorgensen, C., & Marcot, B. G. (2016). Impacts of human recreation on brown bears (Ursus arctos): A review and new management tool. PLoS One, 11(1), e0141983.
- Frank, J., Johansson, M., & Flykt, A. (2015). Public attitude towards the implementation of management actions aimed at reducing human fear of brown bears and wolves. Wildlife Biology, 21(3), 122-130.
- Franks, S. J., & Hoffmann, A. A. (2012). Genetics of climate change adaptation. Annual Review of Genetics, 46(1), 185-208.

- Franklin, J. (2010). Mapping species distributions: spatial inference and prediction. Cambridge University Press.
- Galetti M, Giacomini HC, Bueno RS, Bernardo CS, Marques RM, Bovendorp RS, Steffler CE, Rubim P, Gobbo SK, Donatti CI, Begotti RA, Meirelles F, Nobre RDA, Chiarello AG, Peres CA (2009). Priority areas for the conservation of Atlantic forest large mammals. Biological Conservation 142:1229–1241.
- Gantchoff, M. G., & Belant, J. L. (2017). Regional connectivity for recolonizing American black bears (Ursus americanus) in southcentral USA. Biological conservation, 214, 66-75.
- Gantchoff, M., Conlee, L., & Belant, J. (2019). Conservation implications of sex-specific landscape suitability for a large generalist carnivore. Diversity and Distributions, 25(9), 1488-1496
- Garcia-Mozo, H., Dominguez-Vilchez, E. & Galan, C. (2012). A model to account for variations in holm-oak (Quercus ilex subsp. ballota) acorn production in southern Spain. Annals of Agricultural and Environmental Medicine 19, no. 3.
- García-Rodríguez, A., Albrecht, J., Szczutkowska, S., Valido, A., Farwig, N., & Selva, N. (2021). The role of the brown bear Ursus arctos as a legitimate megafaunal seed disperser. Scientific Reports, 11(1), 1282.
- García-Sánchez, M.P., González-Ávila, S., Solana-Gutiérrez, J., Popa, M., Jurj, R., Ionescu, G., Ionescu, O., Fedorca, M. & Fedorca, A. (2021). Sex-specific connectivity modelling for brown bear conservation in the Carpathian Mountains. Landscape Ecology, 1-19.
- Garshelis, D. L. (2022). Understanding species–habitat associations: A case study with the world's bears. Land, 11(2), 180.
- GDARP, 2022. Ministry of Agriculture and Forestry, General Directorate of Agricultural Research and Policies, Türkiye Beekeeping Statistics.
- GDF, 2022. Ministry of Agriculture and Forestry, General Directorate of Forestry, Forestry Statistics 2022. Accessed 08.03.2024. https://www.ogm.gov.tr/tr/e-kutuphane-sitesi/Istatistikler/Forestry%20Statistics/Forestry%20Statistics%202022.zip
- Gibeau ML, Clevenger AP, Herrero S, Wierzchowski J (2002) Grizzly bear response to human development and activities in the Bow River Watershed, Alberta, Canada. Biological Conservation 103: 227–236.
- Gillingham, P. K., Huntley, B., Kunin, W. E., & Thomas, C. D. (2012). The effect of spatial resolution on projected responses to climate warming. Diversity and Distributions, 18(10), 990-1000.
- Giorgetta, M. A., et al. (2020). MPI-ESM1.2-LR: An ensemble of climate simulations for the Coupled Model Intercomparison Project Phase 6. Geoscientific Model Development, 13(12), 6159-6191.
- Goldstein, M.I., Poe, A.J., Suring, L.H., Nielson, R.M., McDonald, T.L., 2010. Brown Bear Den Habitat and Winter Recreation in South-Central Alaska. The Journal of Wildlife Management.
- Gonzalez, E. G., Blanco, J. C., Ballesteros, F., Alcaraz, L., Palomero, G., & Doadrio, I. (2016). Genetic and demographic recovery of an isolated population of brown bear Ursus arctos L., 1758. PeerJ, 4, e1928.
- González-Bernardo, E., Russo, L. F., Valderrábano, E., Fernández, Á., & Penteriani, V. (2020a). Denning in brown bears. Ecology and Evolution, 10(13), 6844-6862.
- González-Bernardo, E., Bombieri, G., del Mar Delgado, M., & Penteriani, V. (2020b).

The role of spring temperatures in the den exit of female brown bears with cubs in southwestern Europe. Ursus, 2020(31e13), 1-11.

- González-Bernardo, E., Bagnasco, C., Bombieri, G., Zarzo-Arias, A., Ruiz-Villar, H., Morales-González, A., Lamamy, C., Ordiz, A., Cañedo, D., Díaz, J., Chamberlain, D., E. & Penteriani, V. (2021). Rubbing behavior of European brown bears: factors affecting rub tree selectivity and density. Journal of Mammalogy, 102(2), 468-480.
- González-Bernardo, E., Delgado, M.D.M., Matos, D.G.G., Zarzo-Arias, A., Morales-González, A., Ruiz-Villar, H., Skuban, M., Maiorano, L., Ciucci, P., Balbontín, J. & Penteriani, V. (2023). The influence of road networks on brown bear spatial distribution and habitat suitability in a human-modified landscape. Journal of Zoology, 319(1), 76-90.
- Gosselin, J., Zedrosser, A., Swenson, J. E., & Pelletier, F. (2015). The relative importance of direct and indirect effects of hunting mortality on the population dynamics of brown bears. Proceedings of the Royal Society B: Biological Sciences, 282(1798), 20141840.
- Graham, K., Boulanger, J., Duval, J., & Stenhouse, G. (2010). Spatial and temporal use of roads by grizzly bears in west-central Alberta. Ursus, 21(1), 43-56.
- Graves, T. A., Farley, S., & Servheen, C. (2006). Frequency and distribution of highway crossings by Kenai Peninsula brown bears. Wildlife Society Bulletin, 34(3), 800-808.
- Gray, C.L., Hill, S.L., Newbold, T., Hudson, L.N., Börger, L., Contu, S., Hoskins, A.J., Ferrier, S., Purvis, A. & Scharlemann, J. P. (2016). Local biodiversity is higher inside than outside terrestrial protected areas worldwide. Nature Communications, 7(1), 12306.
- Greenspan, E., Montgomery, C., Stokes, D., Wantai, S., & Moo, S. S. B. (2021). Large felid habitat connectivity in the transboundary Dawna-Tanintharyi landscape of Myanmar and Thailand. Landscape Ecology, 36(11), 3187-3205.
- Greenwood, O., Mossman, H. L., Suggitt, A. J., Curtis, R. J., & Maclean, I. M. (2016). Using in situ management to conserve biodiversity under climate change. Journal of Applied Ecology, 53(3), 885-894.
- Grinnell, J. (1917). The niche-relationships of the California Thrasher. The Auk, 34(4), 427-433.
- Gülci, S., & Akay, A. E. (2015). Assessment of ecological passages along road networks within the Mediterranean forest using GIS-based multi criteria evaluation approach. Environmental monitoring and assessment, 187, 1-13.
- Gür, H. (2022). The future impact of climate and land-use changes on Anatolian ground squirrels under different scenarios. Ecological Informatics, 70, 101693.
- Haddad, N. M., Bowne, D. R., Cunningham, A., Danielson, B. J., Levey, D. J., Sargent, S., & Spira, T. (2003). Corridor use by diverse taxa. Ecology, 84(3), 609-615.
- Haddad, N.M., Brudvig, L.A., Clobert, J., Davies, K.F., Gonzalez, A., Holt, R.D., Lovejoy, T.E., Sexton, J.O., Austin, M.P., Collins, C.D., Cook, W. M., Damschen, E. I., Ewers, R. M., Foster, B. L., Jenkins, C. N., King, A. J., Laurance, W. F., Levey, D. J., Margules, C. R., Melbourne, B. A., Nicholls A. O., Orrock, J. L., Song, D-X & Townshend, J. R. (2015). Habitat fragmentation and its lasting impact on Earth's ecosystems. Science Advances, 1(2), e1500052.
- Hamilton, W. D., & May, R. M. (1977). Dispersal in stable habitats. Nature, 269(5629), 578-581.
- Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina,

A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O. &Townshend, J. R. (2013). High-resolution global maps of 21st-century forest cover change. Science, 342(6160), 850-853.

- Hao, T., Elith, J., Guillera-Arroita, G., & Lahoz-Monfort, J. J. (2019). A review of evidence about use and performance of species distribution modelling ensembles like BIOMOD. Diversity and Distributions, 25(5), 839-852.
- Harris, J., Chapple, D. G., McLean, C. A., & Melville, J. (2023). Genetic footprints of fire: Understanding the genetic implications of fire regimes for fauna and effective conservation strategies. Biological Conservation, 284, 110169.
- Harris, I., Osborn, T. J., Jones, P., & Lister, D. (2020). Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Scientific Data, 7(1), 109.
- Hastie T, Tibshirani R, Buja A. Flexible discriminant analysis by optimal scoring. Journal of the American statistical association 89, no. 428 (1994): 1255-1270
- Hastie, T. J. (2017). Generalized additive models. In Statistical models in S (pp. 249-307). Routledge.
- Hepcan, Ş., Hepcan, Ç. C., Bouwma, I. M., Jongman, R. H., & Özkan, M. B. (2009). Ecological networks as a new approach for nature conservation in Turkey: a case study of Izmir Province. Landscape and Urban Planning, 90(3-4), 143-154.
- Hewitt, G. M. (2004). Genetic consequences of climatic oscillations in the Quaternary. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 359(1442), 183-195.
- Hijmans, R.J., Van Etten, J., Cheng, J., Mattiuzzi, M., Sumner, M., Greenberg, J.A., Lamigueiro, O.P., Bevan, A., Racine, E.B., Shortridge, A. & Hijmans, M. R. J. (2015). Package 'raster'. R package, 734, 473.
- Hijmans, R. J., Williams, E., Vennes, C., & Hijmans, M. R. J. (2017). Package 'geosphere'. Spherical trigonometry, 1(7), 1-45.
- Hilderbrand, G. V., Hanley, T. A., Robbins, C. T., & Schwartz, C. C. (1999). Role of brown bears (Ursus arctos) in the flow of marine nitrogen into a terrestrial ecosystem. Oecologia, 121, 546-550.
- Hipólito, D., Reljić, S., Rosalino, L. M., Wilson, S. M., Fonseca, C., & Huber, Đ. (2020). Brown bear damage: Patterns and hotspots in Croatia. Oryx, 54(4), 511-519.
- Hohenlohe, P. A., Funk, W. C., & Rajora, O. P. (2021). Population genomics for wildlife conservation and management. Molecular Ecology, 30(1), 62-82.
- Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (Vol. 398). John Wiley & Sons.
- Huber, D., Kusak, J., Majić-Skrbinšek, A., Majnarić, D., & Sindičić, M. (2008). A multidimensional approach to managing the European brown bear in Croatia. Ursus, 19(1), 22-32.
- Hughes, C., Foote, L., Yarmey, N. T., Hwang, C., Thorlakson, J., & Nielsen, S. (2020). From human invaders to problem bears: A media content analysis of grizzly bear conservation. Conservation Science and Practice, 2(4), e176.
- Huijser, M. P., Fairbank, E. R., Camel-Means, W., Graham, J., Watson, V., Basting, P., & Becker, D. (2016). Effectiveness of short sections of wildlife fencing and crossing structures along highways in reducing wildlife–vehicle collisions and providing safe crossing opportunities for large mammals. Biological Conservation, 197, 61-68.
- Hutchinson, G. E. (1957, January). Concluding remarks. In Cold Spring Harbor symposia on quantitative biology (Vol. 22, pp. 415-427). Cold Spring Harbor

Laboratory Press.
- Inman, R., Franklin, J., Esque, T., & Nussear, K. (2021). Comparing sample bias correction methods for species distribution modeling using virtual species. Ecosphere, 12(3), e03422.
- IPCC (Intergovernmental Panel on Climate Change), 2014. Climate Change 2014: the Physical Science Basis. Cambridge University Press, Cambridge
- IPCC (Intergovernmental Panel on Climate Change), 2023. AR6 Synthesis Report: Climate Change 2023.
- Jacobson, S. L., Bliss-Ketchum, L. L., de Rivera, C. E., & Smith, W. P. (2016). A behavior-based framework for assessing barrier effects to wildlife from vehicle traffic volume. Ecosphere, 7(4), e01345.
- Jerina K, Adamic M (2008) Fifty years of brown bear population expansion: effects of sex-biased dispersal on rate of expansion and population structure. Journal of Mammalogy,89, 1491–1501.
- Jongman, R. H., Bouwma, I. M., Griffioen, A., Jones-Walters, L., & Van Doorn, A. M. (2011). The pan European ecological network: PEEN. Landscape Ecology, 26, 311-326.
- Jufe-Bignoli, D., Burgess, N.D., Bingham, H., Belle, E.M.S., de Lima, M.G., Deguignet, M., Bertzky, B., Milam, A.N., Martinez-Lopez, J., Lewis, E., Eassom, A., Wicander, S., Geldmann, J., van Soesbergen, A., Arnell, A.P., O'Connor, B., Park, S., Shi, Y.N., Danks, F.S., MacSharry, B., Kingston, N. (2014). Protected Planet Report 2014. UNEP-WCMC: Cambridge, UK.
- Kaczensky, P., Huber, D., Knauer, F., Roth, H., Wagner, A., Kusak, J., 2006. Activity patterns of brown bears (Ursus arctos) in Slovenia and Croatia. Journal of Zoology, 269(4).
- Karamanlidis, A.A., Straka, M., Drosopoulou, E., de Gabriel Hernando, M., Kocijan, I., Paule, L., & Scouras, Z. (2012). Genetic diversity, structure, and size of an endangered brown bear population threatened by highway construction in the Pindos Mountains, Greece. European Journal of Wildlife Research, 58(4), 559-570.
- Karami M, Ghadirian T, Faizolahi K (2015) The atlas of the mammals of Iran. In: Department of the Environment of Iran. Iran, Tehran.
- Karataş, A., Bulut, Ş., & Akbaba, B. (2021). Camera trap records confirm the survival of the Leopard (Panthera pardus L., 1758) in eastern Turkey (Mammalia: Felidae). Zoology in the Middle East, 67(3), 198-205.
- Keeley, A. T., Beier, P., & Gagnon, J. W. (2016). Estimating landscape resistance from habitat suitability: effects of data source and nonlinearities. Landscape Ecology, 31, 2151-2162.
- Keeley, A. T., Beier, P., & Jenness, J. S. (2021). Connectivity metrics for conservation planning and monitoring. Biological Conservation, 255, 109008.
- Kemahlı Aytekin, M.Ç., Kusak, J., Chynoweth, M., Çoban, E., Çoban, A., Naderi, M., Kavaklı, İ.H., Şekercioğlu, Ç.H. & Sağlam, İ. K. (2023). Genetic changes influence behavioral shifts of brown bears in response to human-dominated landscapes in Eastern Türkiye.
- Kelly, A.E., & Goulden, M.L. (2008). Rapid shifts in plant distribution with recent climate change. Proceedings of the National Academy of Sciences, 105(33), 11803-11807.
- Khosravi, R., Hemami, M.R., Malakoutikhah, S., Ashrafzadeh, M.R., & Cushman, S.A. (2021). Prey availability modulates predicted range contraction of two large felids in

response to changing climate. Biological Conservation, 257, 109018.
- Khosravi, R., Pourghasemi, H.R., Adavoudi, R., Julaie, L., & Wan, H.Y. (2022). A spatially explicit analytical framework to assess wildfire risks on brown bear habitat and corridors in conservation areas. Fire Ecology, 18(1), 3.
- Khosravi, R., Wan, H. Y., Sadeghi, M. R., & Cushman, S. A. (2023). Identifying human–brown bear conflict hotspots for prioritizing critical habitat and corridor conservation in southwestern Iran. Animal Conservation, 26(1), 31-45.
- Kimmig, S. E., Beninde, J., Brandt, M., Schleimer, A., Kramer-Schadt, S., Hofer, H., Börner, K., Schulze, C., Wittstatt, U., Heddergott, M, Halczok, T., Staubach, C. & Frantz, A. C. (2020). Beyond the landscape: Resistance modelling infers physical and behavioural gene flow barriers to a mobile carnivore across a metropolitan area. Molecular Ecology, 29(3), 466-484.
- Kite, R., Nelson, T., Stenhouse, G., Darimont, C., 2016. A movement-driven approach to quantifying grizzly bear (Ursus arctos) near-road movement patterns in west-central Alberta, Canada. Biological Conservation, 195.
- Koç A, Schacht WH, Erkovan HI. The history and current direction of rangeland management in Turkey. Rangelands. 2015.
- Koday, Z., & Karadağ, H. (2020). Türkiye'deki Arıcılık Faaliyetleri ve Bal Üretiminin Bölgesel Dağılımı (2007-2018). Atatürk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 24(1), 495-510. (in Turkish)
- Kopatz, A., Kleven, O., & Flagstad, Ø. (2020). Seasonal variation of success in DNA-extraction from brown bear fecal samples.
- Kopatz, A., Kleven, O., Kojola, I., Aspi, J., Norman, A.J., Spong, G., Gyllenstrand, N., Dalén, L., Fløystad, I., Hagen, S.B., Kindberg, J., & Flagstad, Ø. (2021). Restoration of transborder connectivity for Fennoscandian brown bears (Ursus arctos). Biological Conservation, 257, 108936.
- Kopelman, N. M., Mayzel, J., Jakobsson, M., Rosenberg, N. A., & Mayrose, I. (2015). Clumpak: a program for identifying clustering modes and packaging population structure inferences across K. Molecular Ecology Resources, 15(5), 1179-1191.
- Korneliussen, T. S., Albrechtsen, A., & Nielsen, R. (2014). ANGSD: analysis of next generation sequencing data. BMC Bioinformatics, 15(1), 1-13.
- Kozakai, C., Yamazaki, K., Nemoto, Y., Nakajima, A., Koike, S., Abe, S., Masaki, T. & Kaji, K. (2011). Effect of mast production on home range use of Japanese black bears. The Journal of Wildlife Management, 75(4).
- Kubacka, M., Żywica, P., Subirós, J. V., Bródka, S., & Macias, A. (2022). How do the surrounding areas of national parks work in the context of landscape fragmentation? A case study of 159 protected areas selected in 11 EU countries. Land Use Policy, 113, 105910.
- Kudrenko, S., Ordiz, A., Stytsenko, F., Barysheva, S. L., Bartalev, S., Baskin, L., & Swenson, J. E. (2022). Brown bear-caused human injuries and fatalities in Russia are linked to human encroachment. Animal Conservation, 25(3), 427-437.
- Kuiper, T., Kavhu, B., Ngwenya, N. A., Mandisodza-Chikerema, R., & Milner-Gulland, E. J. (2020). Rangers and modellers collaborate to build and evaluate spatial models of African elephant poaching. Biological Conservation, 243, 108486.
- Kurth, K. A., Malpeli, K. C., Clark, J. D., Johnson, H. E., & van Manen, F. T. (2024). A systematic review of the effects of climate variability and change on black and brown bear ecology and interactions with humans. Biological Conservation, 291, 110500.

- Kusak, J., Huber, D., Gomerčić, T., Schwaderer, G., & Gužvica, G. (2009). The permeability of highway in Gorski kotar (Croatia) for large mammals. European Journal of Wildlife Research, 55, 7-21.
- Kusak, J., & Şekercioğlu, Ç. (2021). Large Carnivores and Livestock in Northeast Turkey: A Pragmatic Coexistence. Carnivore Damage Prevention News, 21.
- KuzeyDoga, 2012. Türkiye'nin İlk Yaban Hayatı Koridoru Projesi. Accessed 08.03.2024. https://kuzeydoga.net/alan-koruma/yaban-hayati-koridoru/
- Lacy, R. C. (1987). Loss of genetic diversity from managed populations: interacting effects of drift, mutation, immigration, selection, and population subdivision. Conservation Biology, 1(2), 143-158.
- Lamamy, C., Bombieri, G., Zarzo-Arias, A., González-Bernardo, E., & Penteriani, V. (2019). Can landscape characteristics help explain the different trends of Cantabrian brown bear subpopulations?. Mammal Research, 64, 559-567.
- Lamb, C. T., Mowat, G., McLellan, B. N., Nielsen, S. E., & Boutin, S. (2017). Forbidden fruit: human settlement and abundant fruit create an ecological trap for an apex omnivore. Journal of Animal Ecology, 86(1), 55-65.
- Lamb, C.T., Ford, A.T., McLellan, B.N., Proctor, M.F., Mowat, G., Ciarniello, L., Nielsen, S.E. & Boutin, S. (2020). The ecology of human–carnivore coexistence. Proceedings of the National Academy of Sciences, 117(30), 17876-17883.
- Landguth, E. L., Hand, B. K., Glassy, J., Cushman, S. A., & Sawaya, M. A. (2012). UNICOR: a species connectivity and corridor network simulator. Ecography, 35(1), 9-14.
- Lara-Díaz, N. E., Coronel-Arellano, H., Delfín-Alfonso, C. A., Espinosa-Flores, M. E., Peña-Mondragón, J. L., & López-González, C. A. (2021). Connecting mountains and desert valleys for black bears in northern Mexico. Landscape Ecology, 36, 2811–2830.
- Lawrence, A., Friedrich, F., & Beierkuhnlein, C. (2021). Landscape fragmentation of the Natura 2000 network and its surrounding areas. PLoS One, 16(10), e0258615.
- Leathwick JR, Rowe D, Richardson J, Elith J, Hastie T. (2005). Using multivariate adaptive regression splines to predict the distributions of New Zealand's freshwater diadromous fish. Freshwater Biology, 50(12).
- Lecis, R., Dondina, O., Orioli, V., Biosa, D., Canu, A., Fabbri, G., Iacolina, L., Cossu, A., Bani, L., Apollonio, M. & Scandura, M. (2022). Main roads and land cover shaped the genetic structure of a Mediterranean island wild boar population. Ecology and Evolution, 12(4), e8804.
- Lehner, B., & Grill, G. (2013). Global river hydrography and network routing: Baseline data and new approaches to study the world's large river systems. Hydrological Processes, 27(24), 3608-3624.
- Lek, S., & Guégan, J. F. (1999). Artificial neural networks as a tool in ecological modelling, an introduction. Ecological Modelling, 120(2-3), 65-73.
- Lemes, P., Melo, A. S., & Loyola, R. D. (2014). Climate change threatens protected areas of the Atlantic Forest. Biodiversity and Conservation, 23, 357-368.
- Lewis, J. S., Rachlow, J. L., Horne, J. S., Garton, E. O., Wakkinen, W. L., Hayden, J., & Zager, P. (2011). Identifying habitat characteristics to predict highway crossing areas for black bears within a human-modified landscape. Landscape and Urban Planning, 101(2), 99-107.
- Lewis, D.L., Baruch-Mordo, S., Wilson, K.R., Breck, S.W., Mao, J.S. & Broderick, J. (2015). Foraging ecology of black bears in urban environments: Guidance for human-

bear conflict mitigation. Ecosphere 6,1–18.
- Lewontin, R. C., and J. Krakauer. 1973. Distribution of gene frequency as a test of theory of selective neutrality of polymorphisms. Genetics 74:175–195.
- Li, H., & Durbin, R. (2009). Fast and accurate short read alignment with burrows-Wheeler transform. Bioinformatics, 25(14), 1754–1760.
- Liang, G., Liu, J., Niu, H., & Ding, S. (2022). Influence of land use changes on landscape connectivity for North China leopard (Panthera pardus japonensis). Ecology and Evolution, 12(10), e9429.
- Linnell, J. D., Swenson, J. E., & Andersen, R. (2000). Conservation of biodiversity in Scandinavian boreal forests: large carnivores as flagships, umbrellas, indicators, or keystones?. Biodiversity and Conservation, 9, 857-868.
- Littlefield, C. E., Krosby, M., Michalak, J. L., & Lawler, J. J. (2019). Connectivity for species on the move: supporting climate-driven range shifts. Frontiers in Ecology and the Environment, 17(5), 270-278.
- Lucas, P.M., Thuiller, W., Talluto, M.V., Polaina, E., Albrecht, J., Selva, N., De Barba, M., Maiorano, L., Penteriani, V., Guéguen, M., et al. (2023). Including biotic interactions in species distribution models improves the understanding of species niche: a case study with the brown bear in Europe. bioRxiv, 2023-03.
- Ma, T., Hu, Y., Russo, I.R.M., Nie, Y., Yang, T., Xiong, L., Ma, S., Meng, T., Han, H., Zhang, X., Bruford, M. W. & Wei, F. (2018). Walking in a heterogeneous landscape: Dispersal, gene flow and conservation implications for the giant panda in the Qinling Mountains. Evolutionary Applications, 11(10), 1859-1872.
- MacHutchon G, Himmer S, Davis H, Gallagher M (1998) Temporal and spatial activity patterns among coastal bear populations. Ursus 10: 539–546.
- Maiorano, L., Chiaverini, L., Falco, M., & Ciucci, P. (2019). Combining multi-state species distribution models, mortality estimates, and landscape connectivity to model potential species distribution for endangered species in human dominated landscapes. Biological Conservation, 237, 19-27.
- Mallory, C. D., & Boyce, M. S. (2019). Prioritization of landscape connectivity for the conservation of Peary caribou. Ecology and Evolution, 9(4), 2189-2205.
- Mantyka-Pringle, C. S., Visconti, P., Di Marco, M., Martin, T. G., Rondinini, C., & Rhodes, J. R. (2015). Climate change modifies risk of global biodiversity loss due to land-cover change. Biological Conservation, 187, 103-111.
- MAPEG, 2020. General Directorate of Mining and Petroleum Affairs. 2020 Performance Program.
- Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R. K., & Thuiller, W. (2009). Evaluation of consensus methods in predictive species distribution modelling. Diversity and Distributions, 15(1), 59-69.
- Martin, J., Basille, M., Van Moorter, B., Kindberg, J., Allaine, D., & Swenson, J. E. (2010). Coping with human disturbance: spatial and temporal tactics of the brown bear (Ursus arctos). Canadian Journal of Zoology, 88(9), 875-883.
- Martinez Cano, I., Taboada, F. G., Naves, J., Fernández-Gil, A., & Wiegand, T. (2016). Decline and recovery of a large carnivore: environmental change and long-term trends in an endangered brown bear population. Proceedings of the Royal Society B: Biological Sciences, 283(1843), 20161832.
- Mateo-Sánchez, M. C., Cushman, S. A., & Saura, S. (2014). Connecting endangered brown bear subpopulations in the Cantabrian Range (north-western Spain). Animal

Conservation, 17(5), 430-440.
- Mateo-Sánchez, M. C., Balkenhol, N., Cushman, S., Pérez, T., Domínguez, A., & Saura, S. (2015a). A comparative framework to infer landscape effects on population genetic structure: are habitat suitability models effective in explaining gene flow?. Landscape Ecology, 30, 1405-1420.
- Mateo-Sánchez, M. C., Balkenhol, N., Cushman, S., Pérez, T., Domínguez, A., & Saura, S. (2015b). Estimating effective landscape distances and movement corridors: comparison of habitat and genetic data. Ecosphere, 6(4), 1-16.
- Matosiuk, M., Śmietana, W., Czajkowska, M., Paule, L., Štofik, J., Krajmerová, D., Bashta, A.T., Jakimiuk, S. & Ratkiewicz, M. (2019). Genetic differentiation and asymmetric gene flow among Carpathian brown bear (Ursus arctos) populations—Implications for conservation of transboundary populations. Ecology and Evolution, 9(3), 1501-1511.
- McCaffery, R., McLaughlin, J., Sager-Fradkin, K., & Jenkins, K. J. (2018). Terrestrial fauna are agents and endpoints in ecosystem restoration following dam removal. Ecological Restoration, 36(2), 97-107.
- McCullagh P. & Nelder JA. Generalized linear models. Chapman and Hall. 1989.
- McKelvey, K. S., & Schwartz, M. K. (2004). Genetic errors associated with population estimation using non-invasive molecular tagging: problems and new solutions. The Journal of Wildlife Management, 68(3), 439-448.
- McKenney, D.W., Pedlar, J.H., Lawrence, K., Campbell, K., & Hutchinson, M.F. (2007). Potential impacts of climate change on the distribution of North American trees. Bioscience, 57(11), 900-910.
- McLellan, M. L., & McLellan, B. N. (2015). Effect of season and high ambient temperature on activity levels and patterns of grizzly bears (Ursus arctos). PLoS One, 10, e0117734.
- McLellan, B.N., Proctor, M.F., Huber, D., & Michel, S. (2017). Ursus arctos (amended version of 2017 assessment). The IUCN Red List of Threatened Species 2017: e.T41688A121229971.
- McRae, B. H. (2006). Isolation by resistance. Evolution, 60(8), 1551-1561.
- McRae, B.H., Dickson, B.G., Keitt, T.H., Shah, V.B. (2008). Using circuit theory to model connectivity in ecology, evolution, and conservation. Ecology, 89(10): 2712-2724
- McRae, B. H., and D. M. Kavanagh. 2011. Linkage mapper connectivity analysis software. The Nature Conservancy, Seattle. Available from https://circuitscape.org/ (accessed January 2024).
- McRae, B., Shah, V., and Mohapatra, T. (2014). Circuitscape: A GIS tool for connectivity conservation. Remotely Wild, 30: 20-22.
- Meisner, J., & Albrechtsen, A. (2018). Inferring population structure and admixture proportions in low-depth NGS data. Genetics, 210(2), 719-731.
- MGM, 2022. Turkish State, Meteorological Service. Accessed 12.03.2024. https://www.mgm.gov.tr/veridegerlendirme/il-ve-ilceler-istatistik.aspx?k=parametrelerinTurkiyeAnalizi
- Mingarro, M., & Lobo, J. M. (2023). European National Parks protect their surroundings but not everywhere: A study using land use/land cover dynamics derived from CORINE Land Cover data. Land Use Policy, 124, 106434.
- Mohammadi, A., Almasieh, K., Nayeri, D., Ataei, F., Khani, A., López-Bao, J.V.,

Penteriani, V. & Cushman, S. A. (2021). Identifying priority core habitats and corridors for effective conservation of brown bears in Iran. Scientific Reports, 11(1), 1-13.
- Moore, J. F., Mulindahabi, F., Masozera, M. K., Nichols, J. D., Hines, J. E., Turikunkiko, E., & Oli, M. K. (2018). Are ranger patrols effective in reducing poaching-related threats within protected areas?. Journal of Applied Ecology, 55(1), 99-107.
- Morales-González, A., Ruiz-Villar, H., Ordiz, A., & Penteriani, V. (2020). Large carnivores living alongside humans: Brown bears in human-modified landscapes. Global Ecology and Conservation, 22, e00937.
- Moreira, L. R., & Smith, B. T. (2023). Convergent genomic signatures of local adaptation across a continental-scale environmental gradient. Science Advances, 9(20), eadd0560.
- Mukherjee, T., Sharma, L.K., Kumar, V., Sharief, A., Dutta, R., Kumar, M., Joshi, B.D., Thakur, M., Venkatraman, C. & Chandra, K. (2021). Adaptive spatial planning of protected area network for conserving the Himalayan brown bear. Science of the Total Environment, 754, 142416.
- Murphy, S. M., Laufenberg, J. S., Clark, J. D., Davidson, M., Belant, J. L., & Garshelis, D. L. (2018). Genetic diversity, effective population size, and structure among black bear populations in the Lower Mississippi Alluvial Valley, USA. Conservation Genetics, 19(5), 1055-1067.
- Müller, A., Dahm, M., Bøcher, P. K., Root-Bernstein, M., & Svenning, J. C. (2017). Large herbivores in novel ecosystems-Habitat selection by red deer (Cervus elaphus) in a former brown-coal mining area. PLoS One, 12(5), e0177431.
- Naimi, B., Capinha, C., Ribeiro, J., Rahbek, C., Strubbe, D., Reino, L., Araújo, M.B. (2022). Potential for invasion of traded birds under climate and land-cover change. Global Change Biology, 28(21), 6505-6518.
- Naimi, B., Hamm, N. A., Groen, T. A., Skidmore, A. K., & Toxopeus, A. G. (2014). Where is positional uncertainty a problem for species distribution modelling?. Ecography, 37(2), 191-203.
- Naimi, B., 2023. Package “usdm” Title Uncertainty Analysis for Species Distribution Models. CRAN.
- Nanni, V., Caprio, E., Bombieri, G., Schiaparelli, S., Chiorri, C., Mammola, S., Pedrini, P. & Penteriani, V. (2020). Social media and large carnivores: Sharing biased news on attacks on humans. Frontiers in Ecology and Evolution, 71.
- Naves, J., Ordiz, A., Fernández-Gil, A., Penteriani, V., Delgado, M.D.M., López-Bao, J.V., Revilla, E. & Delibes, M. (2018). Patterns of brown bear damages on apiaries and management recommendations in the Cantabrian Mountains, Spain. PloS one, 13(11), e0206733.
- Nayeri, D., Mohammadi, A., Hysen, L., Hipólito, D., Huber, D., & Wan, H. Y. (2022). Identifying human-caused mortality hotspots to inform human-wildlife conflict mitigation. Global Ecology and Conservation, 38, e02241.
- NCNP, 2022. Ministry of Agriculture and Forestry, General Directorate of and Nature Conservation and National Parks. Protected Area Statistics. Accessed 08.03.2024. https://www.tarimorman.gov.tr/DKMP/Belgeler/Tabiat%20Koruma%20Durum%20Raporu/TKDR_EN_2022.pdf
- Nellemann, C., Støen, O.G., Kindberg, J., Swenson, J.E., Vistnes, I., Ericsson, G., Katajisto, J., Kaltenborn, B.P., Martin, J. & Ordiz, A. (2007). Terrain use by an expanding brown bear population in relation to age, recreational resorts and human

settlements. Biological Conservation, 138(1-2), 157-165.
- Nestby, R., Percival, D., Martinussen, I., Opstad, N., & Rohloff, J. (2011). The European blueberry (Vaccinium myrtillus L.) and the potential for cultivation. European Journal of Plant Science and Biotechnology, 5, 5-16.
- Newbold, T., Oppenheimer, P., Etard, A., & Williams, J. J. (2020). Tropical and Mediterranean biodiversity is disproportionately sensitive to land-use and climate change. Nature Ecology & Evolution, 4(12), 1630-1638.
- Niedziałkowska, M., Hayward, M. W., Borowik, T., Jędrzejewski, W., & Jędrzejewska, B. (2019). A meta-analysis of ungulate predation and prey selection by the brown bear Ursus arctos in Eurasia. Mammal Research, 64, 1-9.
- Noroozi, J., Zare, G., Sherafati, M., Mahmoodi, M., Moser, D., Asgarpour, Z., & Schneeweiss, G. M. (2019). Patterns of endemism in Turkey, the meeting point of three global biodiversity hotspots, based on three diverse families of vascular plants. Frontiers in Ecology and Evolution, 7, 159.Northrup, J. M., Pitt, J., Muhly, T. B., Stenhouse, G. B., Musiani, M., & Boyce, M. S. (2012). Vehicle traffic shapes grizzly bear behaviour on a multiple-use landscape. Journal of Applied Ecology, 49(5), 1159-1167.
- Obbard, Martyn E., Eric J. Howe, Linda L. Wall, Brad Allison, Ron Black, Peter Davis, Linda Dix-Gibson, Michael Gatt, and Michael N. Hall. (2014). Relationships among food availability, harvest, and human–bear conflict at landscape scales in Ontario, Canada. Ursus, 25(2), 98-110.
- Ogurtsov, S. S., Khapugin, A. A., Zheltukhin, A. S., Fedoseeva, E. B., Antropov, A. V., del Mar Delgado, M., & Penteriani, V. (2024). Brown bear food habits in natural and human-modified landscapes in West-European Russia. Ursus, 2023(34e11), 1-19.
- Olsoy, P. J., Zeller, K. A., Hicke, J. A., Quigley, H. B., Rabinowitz, A. R., & Thornton, D. H. (2016). Quantifying the effects of deforestation and fragmentation on a range-wide conservation plan for jaguars. Biological Conservation, 203, 8-16.
- Ordiz, A., Støen, O. G., Sæbø, S., Sahlén, V., Pedersen, B. E., Kindberg, J., & Swenson, J. E. (2013). Lasting behavioural responses of brown bears to experimental encounters with humans. Journal of Applied Ecology, 50(2), 306-314.
- Ordiz, A., Kindberg, J., Sæbø, S., Swenson, J.E., & Støen, O.G. (2014). Brown bear circadian behavior reveals human environmental encroachment. Biological Conservation, 171, 253-261.
- Ordiz, A., Støen, O. G., Delibes, M., & Swenson, J. E. (2017). Staying cool or staying safe in a human-dominated landscape: which is more relevant for brown bears?. Oecologia, 185, 191-194.
- Ozturk, T., Ceber, Z. P., Türkeş, M., & Kurnaz, M. L. (2015). Projections of climate change in the Mediterranean Basin by using downscaled global climate model outputs. International Journal of Climatology, 35(14), 4276-4292.
- Paetkau, D., & Strobeck, C. (1998). Ecological genetic studies of bears using microsatellite analysis. Ursus, 299-306.
- Palmer, M. A., Bernhardt, E. S., Schlesinger, W. H., Eshleman, K. N., Foufoula-Georgiou, E., Hendryx, M. S., Lemly, A. D., Likens, G, E., Loucks, O. L., Power, M. E., White, P. S. & Wilcock, P. R. (2010). Mountaintop mining consequences. Science, 327(5962), 148-149.
- Pant, G., Maraseni, T., Apan, A., & Allen, B.L. (2021). Predicted declines in suitable habitat for greater one-horned rhinoceros (Rhinoceros unicornis) under future climate and land use change scenarios. Ecology and Evolution, 11(13), 8421-8436.

- Papeş, M., & Gaubert, P. (2007). Modelling ecological niches from low numbers of occurrences: assessment of the conservation status of poorly known viverrids (Mammalia, Carnivora) across two continents. Diversity and Distributions, 13(6), 890-902.
- Parsons, B., Wilson, A. E., Graham, K., & Stenhouse, G. B. (2022). Grizzly bear (Ursus arctos) movements and habitat use predict human-caused mortality across temporal scales. Canadian Journal of Zoology, 101(2), 81-94.
- Pascual, U., Adams, W. M., Díaz, S., Lele, S., Mace, G. M., & Turnhout, E. (2021). Biodiversity and the challenge of pluralism. Nature Sustainability, 4(7), 567-572.
- Pecl, G.T., Araújo, M.B., Bell, J.D., Blanchard, J., Bonebrake, T.C., Chen, I.C., Clark, T. D., Colwell, R.K., Danielsen F., Evengård, D., Falconi, L., Ferrier, S., Frusher, S., Garcia, R.A., Griffis, R.B., Hobday, A.J., Janion-Scheepers, C., Jarzyna, M.A., Jennings, S., Lenoir, J., Linnetved, H.I., Martin, V.Y., McCormack, P.C., McDonald, J., Mitchell, N.J., Mustonen, T., Pandolfi, J.M., Pettorelli, N., Popova, E., Robinson, S.A, Scheffers B.R., Shaw, J.D., Sorte, C.J.B., Strugnell, J.M., Sunday, J.M., Tuanmu, M.-N., Vergés, A., Villanueva, C., Wernberg, T., Wapstra, E., Williams, S.E. (2017). Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. Science, 355(6324), eaai9214.
- Peck, C. P., Van Manen, F. T., Costello, C. M., Haroldson, M. A., Landenburger, L. A., Roberts, L. L., Bjornlie, D. D. & Mace, R. D. (2017). Potential paths for male-mediated gene flow to and from an isolated grizzly bear population. Ecosphere, 8(10), e01969.
- Peek RA, O'Rourke SM, Miller MR (2021) Flow modification associated with reduced genetic health of a river-breeding frog, Rana boylii. Ecosphere 12(5):e03496.
- Peirce KN, Van Daele LJ (2006). Use of a garbage dump by brown bears in Dillingham, Alaska. Ursus 17: 165–177.
- Penteriani, V., Delgado, M. D. M., Krofel, M., Jerina, K., Ordiz, A., Dalerum, F., Zarzo-Arias A., & Bombieri, G. (2018). Evolutionary and ecological traps for brown bears Ursus arctos in human-modified landscapes. Mammal Review, 48(3), 180-193.
- Penteriani, V., Zarzo-Arias, A., Novo-Fernández, A., Bombieri, G., & López-Sánchez, C. A. (2019). Responses of an endangered brown bear population to climate change based on predictable food resource and shelter alterations. Global Change Biology, 25(3), 1133-1151.
- Penteriani, V., & Melletti, M. (Eds.). (2020). Bears of the world: Ecology, conservation and management. Cambridge University Press.
- Pereira, J., Viličić, L., Rosalino, L. M., Reljić, S., Habazin, M., & Huber, Đ. (2021). Brown bear feeding habits in a poor mast year where supplemental feeding occurs. Ursus, 2021(32e1), 1-13.
- Pérez-Girón, J. C., Álvarez-Álvarez, P., Ballesteros, F., & López-Bao, J. V. (2024). Potential impacts of climate change on wild cherry distribution and associated consequences on brown bears. Biological Conservation, 289, 110390.
- Pérez-Girón, J. C., Díaz-Varela, E. R., Álvarez-Álvarez, P., Palacios, O. H., Ballesteros, F., & López-Bao, J. V. (2022). Linking landscape structure and vegetation productivity with nut consumption by the Cantabrian brown bear during hyperphagia. Science of the Total Environment, 813, 152610.
- Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E., & Blair, M. E. (2017). Opening the black box: An open-source release of Maxent. Ecography, 40(7), 887-893.
- Piédallu, B.; Quenette, P.-Y.; Bombillon, N.; Gastineau, A.; Miquel, C.; Gimenez, O.

Determinants and patterns of habitat use by the brown bear Ursus arctos in the French Pyrenees revealed by occupancy modelling. Oryx 2019, 53, 334–343.
- Pigeon, K. E., Stenhouse, G., & Côté, S. D. (2016). Drivers of hibernation: linking food and weather to denning behaviour of grizzly bears. Behavioral Ecology and Sociobiology, 70, 1745-1754.
- Plaza, P. I., & Lambertucci, S. A. (2017). How are garbage dumps impacting vertebrate demography, health, and conservation?. Global Ecology and Conservation, 12, 9-20.
- Pokorny, B., Flajšman, K., Centore, L., Krope, F. S., & Šprem, N. (2017). Border fence: a new ecological obstacle for wildlife in Southeast Europe. European Journal of Wildlife Research, 63, 1-6.
- Pop, M. I., Iosif, R., Miu, I. V., Rozylowicz, L., & Popescu, V. D. (2018). Combining resource selection functions and home-range data to identify habitat conservation priorities for brown bears. Animal Conservation, 21(4), 352-362.
- Pop, M. I., Dyck, M. A., Chiriac, S., Lajos, B., Szabó, S., Iojă, C. I., & Popescu, V. D. (2023). Predictors of brown bear predation events on livestock in the Romanian Carpathians. Conservation Science and Practice, 5(3), e12884.
- Powers, R. P., & Jetz, W. (2019). Global habitat loss and extinction risk of terrestrial vertebrates under future land-use-change scenarios. Nature Climate Change, 9(4), 323-329.
- Pressey, R. L., Visconti, P., & Ferraro, P. J. (2015). Making parks make a difference: poor alignment of policy, planning and management with protected-area impact, and ways forward. Philosophical Transactions of the Royal Society B: Biological Sciences, 370(1681), 20140280.
- Proctor, M. F., McLellan, B. N., Strobeck, C., & Barclay, R. M. (2004). Gender-specific dispersal distances of grizzly bears estimated by genetic analysis. Canadian Journal of Zoology, 82(7), 1108-1118.
- Proctor, M. F., Nielsen, S. E., Kasworm, W. F., Servheen, C., Radandt, T. G., Machutchon, A. G., & Boyce, M. S. (2015). Grizzly bear connectivity mapping in the Canada–United States trans-border region. The Journal of Wildlife Management, 79(4), 544-558.
- Prunier, J. G., Dubut, V., Chikhi, L., & Blanchet, S. (2017). Contribution of spatial heterogeneity in effective population sizes to the variance in pairwise measures of genetic differentiation. Methods in Ecology and Evolution, 12(10), 3218–3221.
- Psaralexi, M., Lazarina, M., Mertzanis, Y., Michaelidou, D. E., & Sgardelis, S. (2022). Exploring 15 years of brown bear (Ursus arctos)-vehicle collisions in northwestern Greece. Nature Conservation, 47, 105-119.
- Rahimi, E., & Dong, P. (2023). Identifying barriers and pinch-points of large mammal corridors in Iran. Journal of Environmental Studies and Sciences, 1-13.
- Ravenelle, J., & Nyhus, P. J. (2017). Global patterns and trends in human–wildlife conflict compensation. Conservation Biology, 31(6), 1247-1256.
- Recio, M. R., Knauer, F., Molinari-Jobin, A., Huber, Đ., Filacorda, S., & Jerina, K. (2021). Context-dependent behaviour and connectivity of recolonizing brown bear populations identify transboundary conservation challenges in Central Europe. Animal Conservation, 24(1), 73-83.
- Redpath, S. M., Linnell, J. D., Festa-Bianchet, M., Boitani, L., Bunnefeld, N., Dickman, A., Gutiérrez, R. J., Irvine, R. J., Johansson M., Majić A., McMahon, B. J., Pooley, S., Sandström, C., Sjölander-Lindqvist, A., Skogen, K., Swenson J. E., Trouwborst, A.,

Young, J. & Milner-Gulland, E. J. (2017). Don't forget to look down–collaborative approaches to predator conservation. Biological Reviews, 92(4), 2157-2163.
- Reljic, S., Jerina, K., Nilsen, E.B., Huber, D., Kusak, J., Jonozovic, M., & Linnell, J.D.C. (2018). Challenges for transboundary management of a European brown bear population. Global Ecology and Conservation, 16, e00488.
- Rettler, S.J., 2018. Reduced natural foods alter bottom-up pressures on American black bears (Doctoral dissertation, University of Minnesota).
- Rezaei, S., Mohammadi, A., Malakoutikhah, S., & Khosravi, R. (2022). Combining multiscale niche modeling, landscape connectivity, and gap analysis to prioritize habitats for conservation of striped hyaena (Hyaena hyaena). Plos One, 17(2), e0260807.
- Riley, S. J., DeGloria, S. D., & Elliot, R. (1999). Index that quantifies topographic heterogeneity. Intermountain Journal of Sciences, 5(1-4), 23-27.
- Ripple, W. J., Estes, J. A., Beschta, R. L., Wilmers, C. C., Ritchie, E. G., Hebblewhite, M., Berger, J., Elmhagen, B., Letnic, M., Nelson, M. P., Schmitz, O., J., Smith, D. W., Wallach, A. D. & Wirsing, A. J. (2014). Status and ecological effects of the world's largest carnivores. Science, 343(6167), 1241484.
- Robbins CT, Schwartz CC, Felicetti LA (2004) Nutritional ecology of ursids: a review of newer methods and management implications. Ursus 15: 161–171.
- Roberts, D. R., Nielsen, S. E., & Stenhouse, G. B. (2014). Idiosyncratic responses of grizzly bear habitat to climate change based on projected food resource changes. Ecological Applications, 24, 1144–1154.
- Robertson, B. A., Rehage, J. S., & Sih, A. (2013). Ecological novelty and the emergence of evolutionary traps. Trends in Ecology & Evolution, 28(9), 552-560.
- Robinson, J. A., Räikkönen, J., Vucetich, L. M., Vucetich, J. A., Peterson, R. O., Lohmueller, K. E., & Wayne, R. K. (2019). Genomic signatures of extensive inbreeding in Isle Royale wolves, a population on the threshold of extinction. Science Advances, 5(5), eaau0757.
- Rodrigues, R. G., Srivathsa, A., & Vasudev, D. (2022). Dog in the matrix: envisioning countrywide connectivity conservation for an endangered carnivore. Journal of Applied Ecology, 59(1), 223-237.
- Roever, C. L., Boyce, M. S., & Stenhouse, G. B. (2010). Grizzly bear movements relative to roads: Application of step selection functions. Ecography, 33, 1113–1122.
- Rogelj J (2013) Long-term climate change: projections, commitments and irreversibility. In: Climate change 2013: the physical science basis. IPCC working group I contribution to AR5—the physical science basis. IPCC working group I contribution to AR5, Cambridge University Press, Cambridge UK and New York, USA, pp 1029–1136
- Rogers, S. A., Robbins, C. T., Mathewson, P. D., Carnahan, A. M., van Manen, F. T., Haroldson, M. A., Porter, W., P., Rogers, T. R., Soule, T. & Long, R. A. (2021). Thermal constraints on energy balance, behaviour and spatial distribution of grizzly bears. Functional Ecology, 35(2), 398-410.
- Rytwinski, T., Soanes, K., Jaeger, J. A., Fahrig, L., Findlay, C. S., Houlahan, J., van der Ree, R., & van der Grift, E. A. (2016). How effective is road mitigation at reducing road-kill? A meta-analysis. PLoS One, 11(11), e0166941.
- Sağlam, İ. K., Hobbs, J., Baxter, R., Lewis, L. S., Benjamin, A., & Finger, A. J. (2021). Genome-wide analysis reveals regional patterns of drift, structure, and gene flow in

longfin smelt (Spirinchus thaleichthys) in the northeastern Pacific. Canadian Journal of Fisheries and Aquatic Sciences, 78(12), 1793-1804.

- Santos, M. J., Smith, A. B., Dekker, S. C., Eppinga, M. B., Leitão, P. J., Moreno-Mateos, D., Morueta-Holme, N. & Ruggeri, M. (2021). The role of land use and land cover change in climate change vulnerability assessments of biodiversity: a systematic review. Landscape Ecology, 36(12), 3367-3382.
- Sawaya, M. A., Kalinowski, S. T., & Clevenger, A. P. (2014). Genetic connectivity for two bear species at wildlife crossing structures in Banff National Park. Proceedings of the Royal Society B: Biological Sciences, 281(1780), 20131705.
- Sawaya, M. A., Ramsey, A. B., & Ramsey, P. W. (2017). American black bear thermoregulation at natural and artificial water sources. Ursus, 27, 129–135.
- Scharf, A.K., & Fernández, N. (2018). Up-scaling local-habitat models for large-scale conservation: Assessing suitable areas for the brown bear comeback in Europe. Diversity and Distributions, 24(12), 1505-1517.
- Schmitt, C. B., Burgess, N. D., Coad, L., Belokurov, A., Besançon, C., Boisrobert, L.,
- Campbell, A., Fish, L., Gliddon, D., Humphries, K., Kapos, V., Loucks, C., Lysenko, I., Miles, L., Mills, C., Minnemeyer, S., Pistorius, T., Ravilious, C., Steininger, M. & Winkel, G. (2009). Global analysis of the protection status of the world's forests. Biological Conservation, 142(10), 2122-2130.
- Schrag, A.M., Bunn, A.G., & Graumlich, L.J. (2008). Influence of bioclimatic variables on tree-line conifer distribution in the Greater Yellowstone Ecosystem: Implications for species of conservation concern. Journal of Biogeography, 35(11), 1894-1904.
- Şekercioğlu, Ç.H., Anderson, S., Akçay, E., Bilgin, R., Can, Ö.E., Semiz, G., Tavşanoğlu, Ç., Yokeş, M.B., Soyumert, A., Ipekdal, K., Sağlam, I.K., Yücel, M., Nüzhet Dalfes, H. (2011). Turkey's globally important biodiversity in crisis. Biological Conservation 144, no. 12 (2011a): 2752-2769.
- Şekercioğlu, Ç. H., Anderson, S., Akçay, E., & Bilgin, R. (2011). Turkey's rich natural heritage under assault. Science, 334(6063), 1637-1639.
- Servheen, C. (1990). The Status and Conservation of the Bears of the World. Eighth Int. Conf. Bear Res. Manag. - Monogr. Ser. No. 2.
- Shirane, Y., Shimozuru, M., Yamanaka, M., Tsuruga, H., Nakanishi, M., Ishinazaka, T., Nose, T., Kasai, S., Shirayanagi, M., Masuda, Y., Fujimoto, Y., Mano, T., Sashika, M. & Tsubota, T. (2019). Sex-biased dispersal and inbreeding avoidance in Hokkaido brown bears. Journal of Mammalogy, 100(4), 1317-1326.
- Shokri, S., Jafari, A., Rabei, K., Hadipour, E., Alinejad, H., Zeppenfeld, T., Soufi, M., Qashqaei, A., Ahmadpour, M., Zehzad, B., Kiabi, B. H., Pavey, C. R., Balkenhol, N., Waltert, M. & Soofi, M. (2021). Conserving populations at the edge of their geographic range: The endangered Caspian red deer (Cervus elaphus maral) across protected areas of Iran. Biodiversity and Conservation, 30, 85-105.
- Sıkdokur, E., Naderi, M., Çeltik, E., Aytekin, M. Ç. K., Kusak, J., Sağlam, İ. K., & Şekercioğlu, Ç. H. (2024). Human-brown bear conflicts in Türkiye are driven by increased human presence around protected areas. Ecological Informatics, 102643.
- Sillero, N., Arenas-Castro, S., Enriquez-Urzelai, U., Vale, C. G., Sousa-Guedes, D., Martínez-Freiría, F., Real, R. & Barbosa, A. M. (2021). Want to model a species niche? A step-by-step guideline on correlative ecological niche modelling. Ecological Modelling, 456, 109671.
- Sillero, N., & Barbosa, A. M. (2021). Common mistakes in ecological niche models.

International Journal of Geographical Information Science, 35(2), 213-226.
- Siqueira-Gay, J., Sonter, L. J., & Sánchez, L. E. (2020). Exploring potential impacts of mining on forest loss and fragmentation within a biodiverse region of Brazil's northeastern Amazon. Resources Policy, 67, 101662.
- Skotte, L., Korneliussen, T. S., & Albrechtsen, A. (2013). Estimating individual admixture proportions from next generation sequencing data. Genetics, 195(3), 693-702.
- Skuban, M., Finďo, S., Kajba, M., Koreň, M., Chamers, J., & Antal, V. (2017). Effects of roads on brown bear movements and mortality in Slovakia. European Journal of Wildlife Research, 63(5), 1-9.
- Slatkin, M. (1987). Gene flow and the geographic structure of natural populations. Science, 236(4803), 787-792.
- Smith, J. G., Jennings, M. K., Boydston, E. E., Crooks, K. R., Ernest, H. B., Riley, S. P., Serieys, L. E. K., Sleater-Squires, S. & Lewison, R. L. (2020). Carnivore population structure across an urbanization gradient: a regional genetic analysis of bobcats in southern California. Landscape Ecology, 35, 659-674.
- Soberon, J., & Peterson, A. T. (2005). Interpretation of models of fundamental ecological niches and species' distributional areas.
- Soyumert, A., Ertürk, A., & Tavşanoğlu, Ç. (2020). Fire-created habitats support large mammal community in a Mediterranean landscape. Mammal Research, 65, 323-330.
- Stanton, J. C., Pearson, R. G., Horning, N., Ersts, P., & Reşit Akçakaya, H. (2012). Combining static and dynamic variables in species distribution models under climate change. Methods in Ecology and Evolution, 3(2), 349-357.
- Stewart, R. R., Ball, I. R., & Possingham, H. P. (2007). The effect of incremental reserve design and changing reservation goals on the long-term efficiency of reserve systems. Conservation Biology, 21(2), 346-354.
- Stewart, B. P., Nelson, T. A., Laberee, K., Nielsen, S. E., Wulder, M. A., & Stenhouse, G. (2013). Quantifying grizzly bear selection of natural and anthropogenic edges. The Journal of Wildlife Management, 77(5), 957-964.
- Steyaert, S. M., Kindberg, J., Swenson, J. E., & Zedrosser, A. (2013). Male reproductive strategy explains spatiotemporal segregation in brown bears. Journal of Animal Ecology, 82(4), 836-845.
- Stoddard ST (2010). Continuous versus binary representations of landscape heterogeneity in spatially-explicit models of mobile populations. Ecological Modelling, 221(19), 2409-2414.
- Støen, O. G., Zedrosser, A., Sæbø, S., & Swenson, J. E. (2006). Inversely density-dependent natal dispersal in brown bears Ursus arctos. Oecologia, 148, 356-364.
- Støen, O. G., Ordiz, A., Elfström, M., Hertel, M., Sahlén, V., Kindberg, J., & Swenson, J. E. (2020). Effects of human disturbance on brown bear behavior. Bears of the world: Ecology, conservation and management, 250-259.
- Straka, M., Paule, L., Ionescu, O., Štofík, J., & Adamec, M. (2012). Microsatellite diversity and structure of Carpathian brown bears (Ursus arctos): Consequences of human caused fragmentation. Conservation Genetics, 13, 153–164.
- Su, J., Aryal, A., Hegab, I. M., Shrestha, U. B., Coogan, S. C., Sathyakumar, S., Dalannast, M., Dou, Z., Suo, Y., Dabu, X., Fu, H. & Ji, W. (2018). Decreasing brown bear (Ursus arctos) habitat due to climate change in Central Asia and the Asian Highlands. Ecology and Evolution, 8(23), 11887-11899.

- Suel, H. (2019). Brown bear (Ursus arctos) habitat suitability modelling and mapping. Applied Ecology & Environmental Research, 17(2).
- Suksavate, W., Duengkae, P., & Chaiyes, A. (2019). Quantifying landscape connectivity for wild Asian elephant populations among fragmented habitats in Thailand. Global Ecology and Conservation, 19, e00685.
- Swenson JE, Sandegren F, Soderberg A (1998) Geographic expansion of an increasing brown bear population: evidencefor presaturation dispersal. Journal of Animal Ecology,67, 819–826.
- Syfert, M. M., Smith, M. J., & Coomes, D. A. (2013). The effects of sampling bias and model complexity on the predictive performance of MaxEnt species distribution models. PloS One, 8(2), e55158.
- Taberlet, P., Camarra, J. J., Griffin, S., Uhres, E., Hanotte, O., Waits, L. P., Dubois-Paganon, C., Burke, T. & Bouvet, J. (1997). Noninvasive genetic tracking of the endangered Pyrenean brown bear population. Molecular Ecology, 6(9), 869-876.
- Tajima, F. (1989a). Statistical method for testing the neutral mutation hypothesis by DNA polymorphism. Genetics, 123, 585–595.
- Tammeleht, E., Kull, A., & Pärna, K. (2020). Assessing the importance of protected areas in human-dominated lowland for brown bear (Ursus arctos) winter denning. Mammal Research, 65, 105-115.
- Tattoni, C., Galaverni, M., Pollutri, A., Preatoni, D. G., Martinoli, A., & Araña, J. E. (2024). Not only seeds: a cultural ecosystem service provided by the Apennine brown bear. Human Dimensions of Wildlife, 29(1), 14-29.
- Tavşanoğlu, Ç., Kazancı, D. D., Soyumert, A., Ertürk, A., & Değirmenci, C. Ü. (2021). Seed dispersal by the brown bear in a mixed temperate forest: fruit type matters. Mammal Research, 66(1), 137-147.
- Tavsanoglu, Ç., & Pausas, J. G. (2022). Turkish postfire action overlooks biodiversity. Science, 375(6579), 391-391.
- TEMA, 2022. TEMA Foundation. Türkiye Maden Ruhsatlarının Tehdidi Altında: 24 İlde 20 Bine Yakın Maden Ruhsatı. Accessed 08.03.2024. https://www.tema.org.tr/basin-odasi/basin-bultenleri/turkiye-maden-ruhsatlarinin-tehdidi-altinda
- Temam, R. (2024). Navier–Stokes equations: theory and numerical analysis (Vol. 343). American Mathematical Society.
- Thatte, P., Chandramouli, A., Tyagi, A., Patel, K., Baro, P., Chhattani, H., & Ramakrishnan, U. (2020). Human footprint differentially impacts genetic connectivity of four wide-ranging mammals in a fragmented landscape. Diversity and Distributions, 26(3), 299-314.
- Theobald, D. M., Reed, S. E., Fields, K., & Soule, M. (2012). Connecting natural landscapes using a landscape permeability model to prioritize conservation activities in the United States. Conservation Letters, 5(2), 123-133.
- Thuiller, W., Lafourcade, B., Engler, R., & Araújo, M.B. (2009). BIOMOD - A platform for ensemble forecasting of species distributions. Ecography, 32(3), 369-373.
- Thuiller W. Editorial commentary on "BIOMOD - optimizing predictions of species distributions and projecting potential future shifts under global change." Global Change Biology. 2014.
- Thuiller, W., Guéguen, M., Renaud, J., Karger, D.N., & Zimmermann, N.E. (2019). Uncertainty in ensembles of global biodiversity scenarios. Nature Communications,

10(1), 3440.
- Tiago, P., Pereira, H. M., & Capinha, C. (2017). Using citizen science data to estimate climatic niches and species distributions. Basic and Applied Ecology, 20, 75-85.
- TIM, 2023. Turkey Export Strategy Project Sectoral Break down, Project Report, Turkey Export Council (Türkiye İhracatcılar Birliği, TIM). 2023. Available: https://www.tim.org.tr/en/
- Tobgay, S., & Mahavik, N. (2020). Potential habitat distribution of Himalayan red panda and their connectivity in Sakteng Wildlife Sanctuary, Bhutan. Ecology and Evolution, 10(23), 12929-12939.
- Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. Economic Geography, 46(sup1), 234-240.
- TOD (2022). Türkiye Ormancılığı 2022: Türkiye'de Ormansızlaşma ve Orman Bozulması. Editör: Erdoğan Atmiş. Türkiye Ormancılar Derneği Yayını. 200 S. Ankara.
- Trainor, A. M., Walters, J. R., Morris, W. F., Sexton, J., & Moody, A. (2013). Empirical estimation of dispersal resistance surfaces: a case study with red-cockaded woodpeckers. Landscape Ecology, 28, 755-767.
- Trouwborst, A. (2010). Managing the carnivore comeback: international and EU species protection law and the return of lynx, wolf and bear to Western Europe. Journal of Environmental Law, 22(3), 347-372.
- Trujillo, S. M., McKenney, E. A., Hilderbrand, G. V., Mangipane, L. S., Rogers, M. C., Joly, K., Gustine, D. D., Erlenbach, J. A., Mangipane, B. A. & Lafferty, D. J. (2022). Intrinsic and extrinsic factors influence on an omnivore's gut microbiome. PloS One, 17(4), e0266698.
- Tucker, M.A., Böhning-Gaese, K., Fagan, W.F., Fryxell, J.M., Van Moorter, B., Alberts, S.C., et al. (2018). Moving in the Anthropocene: Global reductions in terrestrial mammalian movements. Science, 360(6393), 1196-1201.
- UNEP-WCMC, IUCN, & NGS. (2020). Protected Planet. https://www.protectedplanet.net/en [Accessed 20.05.2024].
- Urban, M.C. (2015). Accelerating extinction risk from climate change. Science, 348(6234), 571-573.
- URL1. 140journos, 2015. Yeşil Yol Projesi ve İklim Üzerine Olası Etkileri, 22 July 2015. https://140journos.com/ye%C5%9Fil-yol-projesi-ve-i%CC%87klim-%C3%BCzerine-etkisi-3c9b01f66fed (Accessed in 21.02.2024).
- URL2. GazeteDuvar, Son 15 yılda 386 bin maden ruhsatı verildi. Accessed 16.03.2024. https://www.gazeteduvar.com.tr/son-15-yilda-386-bin-maden-ruhsati-verildi-haber-1669831
- URL3. Know Your Bear Facts Brochure. Alaska Department of Fish and Game. Accessed 08.03.2024. https://www.adfg.alaska.gov/static/species/livingwithwildlife/bears/pdfs/know_your_bear_facts_brochure.pdf
- URL4. How you can stay safe in bear country. BC Parks, British Columbia Ministry of Environment and Climate Change Strategy. Accessed 08.03.2024. https://nrs.objectstore.gov.bc.ca/kuwyyf/bearbooklet_a3f02405ad.pdf
- Valdiosera CE, Garcia N, Anderung C, Dalén L, Crégut-Bonnoure E, Kahlke R-D, Stiller, M., Brandström, M., Thomas, M. G., Arsuaga, J. L.,Götherström, A., Barnes, I. (2007) Staying out in the cold: glacial refugia and mitochondrial DNA phylogeography in ancient European brown bears. Molecular Ecology 16: 5140–5148.

- van Bommel, J. K., Badry, M., Ford, A. T., Golumbia, T., & Burton, A. C. (2020). Predicting human-carnivore conflict at the urban-wildland interface. Global Ecology and Conservation, 24, e01322.
- VanDerWal, J., Murphy, H. T., Kutt, A. S., Perkins, G. C., Bateman, B. L., Perry, J. J., & Reside, A. E. (2013). Focus on poleward shifts in species' distribution underestimates the fingerprint of climate change. Nature climate change, 3(3), 239-243.
- van Proosdij, A. S., Sosef, M. S., Wieringa, J. J., & Raes, N. (2016). Minimum required number of specimen records to develop accurate species distribution models. Ecography, 39(6), 542-552.
- Varela, S., Anderson, R. P., García-Valdés, R., & Fernández-González, F. (2014). Environmental filters reduce the effects of sampling bias and improve predictions of ecological niche models. Ecography, 37(11), 1084-1091.
- Varol, T., Çetin, M., Özel, H.B., Sevik, H., & Zeren Çetin, I. (2022). The Effects of Climate Change Scenarios on Carpinus betulus and Carpinus orientalis in Europe. Water, Air, and Soil Pollution, 223(8), 5249-5265.
- Vayssières, M. P., Plant, R. E., & Allen-Diaz, B. H. (2000). Classification trees: An alternative non-parametric approach for predicting species distributions. Journal of vegetation science, 11(5), 679-694.
- Venter, O., Sanderson, E.W., Magrach, A., Allan, J.R., Beher, J., Jones, K.R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., Watson, J. E. M. (2016). Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. Nature Communications, 7(12558).
- Vieira, F. G., Lassalle, F., Korneliussen, T. S., & Fumagalli, M. (2016). Improving the estimation of genetic distances from next-generation sequencing data. Biological Journal of the Linnean Society, 117, 139–149.
- Vlková, K., Zýka, V., Papp, C. R., & Romportl, D. (2024). An ecological network for large carnivores as a key tool for protecting landscape connectivity in the Carpathians. Journal of Maps, 20(1), 2290858.
- Voldoire, A., et al. (2020). CNRM-CM6-1: A new climate model for the CMIP6 ensemble. Geoscientific Model Development, 13(12), 6121-6157.
- Waller, J. S., & Servheen, C. (2005). Effects of transportation infrastructure on grizzly bears in northwestern Montana. The Journal of Wildlife Management, 69(3), 985-1000.
- Walsh, J. E., Ballinger, T. J., Euskirchen, E. S., Hanna, E., Mård, J., Overland, J. E., Tangen, H. & Vihma, T. (2020). Extreme weather and climate events in northern areas: A review. Earth-Science Reviews, 209, 103324.
- Wang, G., Cushman, S. A., Wan, H. Y., Liu, M., & Jombach, S. (2022). Comparison of Least-cost Path and UNICOR Cumulative Resistant Kernel Analyses in Mapping Ecological Connectivity Networks in Luohe Region, China. Journal of Digital Landscape Architecture, 176-190.
- Wang, I. J., & Bradburd, G. S. (2014). Isolation by environment. Molecular Ecology, 23(23), 5649-5662.
- Watanabe, M., et al. (2020). MIROC6: A new global climate model for the next generation of climate change research. Journal of Advances in Modeling Earth Systems, 12(7), e2020MS002590.
- Watterson, G. (1975). On the number of segregating sites in genetical models without recombination. Theoretical Population Biology, 7, 256–276.
- Wei, T., & Simko, V. (2021). R package 'corrplot': Visualization of a Correlation Matrix

(Version 0.92) [Manual]. Retrieved from https://github.com/taiyun/corrplot
- Wenger, S. J., & Olden, J. D. (2012). Assessing transferability of ecological models: An underappreciated aspect of statistical validation. Methods in Ecology and Evolution, 3(2), 260– 267.
- Whittington, J., Hebblewhite, M., Baron, R. W., Ford, A. T., & Paczkowski, J. (2022). Towns and trails drive carnivore movement behaviour, resource selection, and connectivity. Movement ecology, 10(1), 17.
- Wisz, M. S., & Guisan, A. (2009). Do pseudo-absence selection strategies influence species distribution models and their predictions? An information-theoretic approach based on simulated data. BMC Ecology, 9(1), 1-13.
- Wright, S. (1943). Isolation by distance. Genetics, 28(2), 114.
- Wu, H., Chen, J., Xu, J., Zeng, G., Sang, L., Liu, Q., Yin, Z., Dai, J., Yin, D., Liang, J. & Ye, S. (2019). Effects of dam construction on biodiversity: A review. Journal of Cleaner Production, 221, 480-489.
- WWF Türkiye, 2010. Korunan Alanlarda HES Baskıları Artıyor.. http://www.wwf.org.tr/?1160 (Accessed 08.03.2024).
- WWF Türkiye, 2015. Yeşil Yol Karadeniz'i Yoldan Çıkaracak, 6 July 2015. https://www.wwf.org.tr/?4320/yesilyolkaradeniziyoldancikaracak (Accessed 21.02.2024).
- WWF, 2021. Korumazsak Kaybederiz: Sürdürülebilir Bir Türkiye Için Korunan Alanlar Hedef: 2030'a Kadar %30. https://www.wwf.org.tr/?10900/Korumazsak- kaybederiz (Accessed 09.01.2024).
- Yang, R., Cao, Y., Hou, S., Peng, Q., Wang, X., Wang, F., Tseng, T-H., Yu, L., Carver, S., Convery, I., Zhao, Z., Shen, X., Li, S., Zheng, Y., Liu, H., Gong, P. & Ma, K. (2020). Cost-effective priorities for the expansion of global terrestrial protected areas: Setting post-2020 global and national targets. Science Advances, 6(37), eabc3436.
- Yang, S., Wang, X., & Hu, J. (2022). Mountain frog species losing out to climate change around the Sichuan Basin. Science of the Total Environment, 806, 150605.
- Yıldız, B., & Aydın, C.C. Türkiye'de Korunan Alanların IUCN Politikaları Kapsamında Değerlendirilmesi. Türkiye Arazi Yönetimi Dergisi, 5(1), 20-30.
- Zarzo-Arias, A., Penteriani, V., Delgado, M. D. M., Peón Torre, P., Garcia-Gonzalez, R., Mateo-Sánchez, M. C., Garcia, P. V. & Dalerum, F. (2019). Identifying potential areas of expansion for the endangered brown bear (Ursus arctos) population in the Cantabrian Mountains (NW Spain). PLoS One, 14(1), e0209972.
- Zarzo-Arias, A., Delgado, M. D. M., Palazón, S., Afonso Jordana, I., Bombieri, G., González-Bernardo, E., Ordiz, A., Bettega, C., García-González, R. & Penteriani, V. (2021). Seasonality, local resources and environmental factors influence patterns of brown bear damages: Implications for management. Journal of Zoology, 313(1), 1-17.
- Zedrosser, A., Støen, O. G., Sæbø, S., & Swenson, J. E. (2007). Should I stay or should I go? Natal dispersal in the brown bear. Animal Behaviour, 74(3), 369-376.
- Zeller KA, McGarigal K, Whiteley AR (2012) Estimating landscape resistance to movement: a review. Landscape Ecol 27:777–797
- Ziółkowska, E., Ostapowicz, K., Radeloff, V.C., Kuemmerle, T., Sergiel, A., Zwijacz-Kozica, T., Zięba, F., Śmietana, W., Selva, N., 2016. Assessing differences in connectivity based on habitat versus movement models for brown bears in the Carpathians. Landscape Ecology.
- Zyśk-Gorczyńska, E., Jakubiec, Z., & Wuczyński, A. (2015). Brown bears (Ursus

arctos) as ecological engineers: the prospective role of trees damaged by bears in forest ecosystems. Canadian Journal of Zoology, 93(2), 133-141.

APPENDICES

Appendix A: The checklist for ODMAP (Overview, Data, Model, Assessment, and Prediction) protocol for ecological niche modeling of Eursian brown bears (*Ursus arctos*) across Türkiye

ODMAP Elements		Contents
Overview	*Model Objective*	**Objective**: Ecological Niche Modeling (ENM) of brown bears across Türkiye **Target outputs**: Potential current and future habitat suitability maps
	Taxon	Brown bear, *Ursus arctos*, Ursidae, Carnivora, Mammalia
	Location	Türkiye, Soutwest Asia
	Scale of analysis	**Spatial extent**: 25.65708, 44.83208, 35.82458, 42.10792 (xmin, xmax, ymin, ymax) **Temporal extent**: Occurrence records – from 2020 to 2021 Bioclimatic predictors (WorldClim) – from 1970 to 2000. Forest, Farmland, Water layers – from 2018; Distance to protected areas, Distance to roads, Distance to villages, Human Footprint Index, Population density – from 2020; **Type of extent boundary**: Political (Republic of Türkiye)
Data	*Biodiversity data overview*	**Observation type:** Presence points including footprints, scat samples, hair samples, rubbing tree signs (**n=608**) **Response/Data type**: Presence-only
	Type of predictors	Bioclimatic, Topographic, Anthropogenic
	Conceptual model / hypothesis	Brown bear distribution is driven by climatic, topographic and human-related factors.
	Data collection	**Data source:** Between May 2020 and October 2021, extensive fieldwork was conducted by our research team to gather data on brown bear presence signs across Türkiye **Absence-data:** I used presence-only data for modeling. Pseudo-absence generation was performed using *biomod2*. **Data filtering:** I used *ecospat* package in R to avoid spatial clustering of occurrence records (Boavida et al., 2016; Broennimann et al., 2018).
	Predictor variables	**Variables** 1. **Bioclimatic variables** – BIO1: Annual mean temperature (°C), BIO2: Mean diurnal range (°C), BIO3: Isothermality, BIO4: Temperature seasonality (°C), BIO5: Max. Temperature of Warmest Month (°C), BIO6: Min. Temperature of Coldest Month (°C), BIO7: Temperature Annual Range (°C), BIO8: Mean Temperature of Wettest Quarter (°C), BIO9: Mean Temperature of Driest Quarter (°C), BIO10: Mean Temperature of Warmest Quarter (°C), BIO11: Mean Temperature of Coldest Quarter (°C), BIO12: Annual Precipitation (mm), BIO13: Precipitation of Wettest Month (mm), BIO14: Precipitation of Driest Month (mm), BIO15: Precipitation Seasonality, BIO16: Precipitation of Wettest Quarter (mm), BIO17: Precipitation of Driest Quarter (mm), BIO18: Precipitation of Warmest Quarter (mm), BIO19: Precipitation of Coldest Quarter (mm)

2. **Topographic Variables** – Elevation (m), Slope (°), Aspect (radians), Terrain Ruggedness Index (TRI)
3. **Anthropogenic Variables** – Distance to forest (km), Distance to farmland (km), Distance to road (km), Distance to villages (km), Distance to water (km), Population Density (no. of people/km^2), Human Footprint Index (HFI-value)

Data Sources

1. Corine Land Cover 2018 - https://land.copernicus.eu/en/products/corine-land-cover/clc2018
2. Worldclim - https://www.worldclim.org/
3. SEDAC - https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11
4. SEDAC - https://sedac.ciesin.columbia.edu/data/set/wildareas-v3-2009-human-footprint
5. Open Street Map - http://download.geofabrik.de/europe/turkey.html
6. HydroRIVERS – HydroSHEDS - https://www.hydrosheds.org/products/hydrorivers
7. Elevation - https://www.worldclim.org/data/worldclim21.html

Spatial resolution of raw data:
Population density (30 arc-sec), Human footprint index (~1 km), BIO1-19 (2.5 arc-min), Corine Land Cover database (100 m), Elevation (2.5 arc-min)

Projection: WGS84

Data processing:

- Bioclimatic variables were downloaded from WorldClim database with 2.5 arc-min resolution (approximately 4.6 km at the equator). These layers were masked and cropped according to Turkiye's border.
- The forest layer was generated by using the Corine LULC 2018 vector database. To do this, *Broad-leaved forest, Coniferous forest*, *Mixed forest*, and *Transitional woodland/shrub* attributes were combined and extracted. Then, the proximity layer called Distance to forest was generated using Euclidean Distance Tool in ArcGIS by arranging its cell-size and extent.
- The farmland layer was generated by using the Corine LULC 2018 vector database. To do this, the attributes named *Non-irrigated arable land, Permanently irrigated land, Rice fields, Vineyards, Fruit trees and berry plantations, Olive groves, Pastures, Annual crops associated with permanent crops, Complex cultivation patterns, Land principally occupied by agriculture with significant areas of natural vegetation, Agro-forestry areas* were combined and extracted. Then, the proximity layer called Distance to farmland was generated using the Euclidean Distance Tool in ArcGIS by arranging its cell size and extent.
- 1st to 4th order river attributes were extracted since this vector layer appropriately covers important water sources across the country, from small springs in/around forests and agricultural fields to large rivers. Then, the proximity layer named Distance to water was generated by using the Euclidean Distance Tool in ArcGIS.
- The *motorways*, *primary, secondary,* and *trunk roads* and *their linked roads* attributes were extracted from the Open Street Map. Then, the proximity layer named Distance to roads was generated by using the Euclidean Distance Tool in ArcGIS.
- The Slope, Aspect *and* Terrain ruggedness index rasters were derived from the Shuttle Radar Topography Mission (SRTM) Elevation data. They were derived after projecting to Lambert Azimuthal Equal-Area

		(ETRS 1989 LAEA), and then projected WGS84 again (Sillero and Barbosa, 2021). • All variables were properly resampled, cropped, and masked based on the study area.
	Transfer data for projection	All topographic and anthropogenic variables were kept static. The bioclimatic variables with a resolution of 2.5 arc-minutes from WorldClim 2.1., based on the CMIP6 (Coupled Model Intercomparison Project Phase 6) data, as featured in the sixth assessment report (AR6) of the IPCC (Intergovernmental Panel on Climate Change). Three widely used GCMs; MIROC6 (Watanane et al., 2020), CNRM-CM6-1 (Vodoire et al., 2020), and MPI-ESM1-2-LR (Giorgetta et al., 2020) since they were already used to predict accurate ENMs across Europe in other studies (Canturk & Kulaç, 2021; Gür, 2022; Naimi et al., 2022). For all three GCMs, three different Shared Socio-economic Pathways/Representative Concentration Pathway scenarios including SSP1/RCP2.6 as an optimistic future, SSP3/RCP7.0 as a moderate future and SSP5/RCP8.5 as a pessimistic future were downloaded for both 2050 (average for 2041-2060) and 2070 (average for 2061-2080) to project future habitat suitability.
Model	*Assumptions*	✓ I assumed that species are at equilibrium with the environment. ✓ Occurrence records were collected by avoiding any observational bias during the fieldwork. ✓ The filtering process is performed to avoid spatial clustering of occurrence records. ✓ Predictor variables are incorporated in the model after checking any error. ✓ Multicollinearity among the environmental predictors was checked.
	Algorithms	Ten SDM algorithms available in *biomod2* package were used. • Artificial Neural Network (ANN) • Flexible Discriminant Analysis (FDA) • Generalised Additive Model (GAM) • Generalised Boosting Model (GBM) • Generalised Linear Model (GLM) • Multiple Adaptive Regression Splines (MARS) • Maxent Entropy (Maxent) • Random Forest (RF) • Surface Range Envelope (SRE) • Classification Tree Analysis (CTA) **Model complexity**: I chose these algorithms to yield complex response surfaces while preventing overfitting.
	Model workflow	To mitigate potential spatial autocorrelation effects, I utilized the Mantel test, implemented using the *ecospat* package (Boavida et al., 2016; Broennimann et al., 2018). The spatial correlogram for environmental predictors reveals a positive autocorrelation in occurrence records extending up to 21.83 km. Consequently, only 87 occurrence records were retained as the final dataset for subsequent ecological niche modeling. I selected thirty environmental variables, including bioclimatic, topographic, and anthropogenic predictors that have a high potential to drive their distribution (Su et al., 2018; Dai et al., 2019a; Dai et al., 2021a; Dar et al., 2021; Mukherjee et al., 2021, Mohammadi et al., 2021; Ashrafzadeh et al., 2022). I checked for multicollinearity and excluded the variables with correlation coefficients ($\|r\|$) >0.7 and variance inflation factor (VIF) > 10 by using *usdm* and *corrplot* package in the R environment (Wei & Simko, 2021; Naimi, 2023). Ultimately, I used 16 environmental variables to perform modeling.

		To predict both current and future distributions of brown bears across Türkiye, I employed an ensemble forecasting approach using the *biomod2* package. The modeling process began with the random generation of 1,000 pseudo-absence points. Subsequently, the dataset was split into training (80%) and testing (20%) datasets. I conducted three cross-validation iterations using a bootstrap approach for each model. Pseudo-absence points were regenerated three times to mitigate random bias. To reduce uncertainty and generate a final model, I selected models with TSS scores greater than 0.6, using a weighted average approach (Araújo and New, 2007; Thuiller et al., 2009). I performed future forecasting with the ensemble model by considering three different CO_2 scenarios for two different future time, 2050 and 2070. I produced nineteen ensemble maps encompassing three distinct GCMs and scenarios for two time periods (2050s and 2070s) in addition to the present day. Binary transformation was performed using a threshold that maximizes TSS to create predictive outputs (Thuiller et al., 2019). To analyze changes in the range size between current and future scenarios, the range size function within the *biomod2* package was employed.
	Software, codes, and data	**Modeling platform**: R (*version 4.2.2*) environment with *biomod2* package. **Dataset and Code**: The datasets used and/or the R codes during the current study are available on reasonable request.
	Data partioning	Occurrence records were split out as training (80%) and testing (20%) datasets.
	Variable selection	• I selected all environmental variables that have a high potential to drive brown bear distribution based on the literature. For instance, roads, villages, and farmlands can represent important ecological traps and affect their foraging behavior as well as population persistence (Lamb et al., 2017; Parsons et al., 2022). • Brown bears rely on forested habitats for cover, foraging, and denning (Recio et al., 2021; Ziółkowska et al., 2016); so they were included in the model. Population density and Human footprint index are important to understand the potential role of human dominancy in their distribution (Dai et al., 2019a). Topographic variables called Elevation, Slope, Aspect, and TRI were included in the model since they are highly associated with human land usage as well as bear behavior (Goldstein et al., 2010). Bioclimatic variables also drive the abundance, richness, and accessibility of natural prey and food sources of brown bears (Zarzo-Arias et al., 2020; Pérez-Girón et al., 2022; Pérez-Girón et al., 2024; Penteriani et al., 2019). • I checked multicollinearity using *usdm* and *corrplot* packages among the variables and excluded them if they displayed high correlation (correlation coefficient > 0.7) and variance inflation (VIF >10). Ultimately, 16 variables were retained.
	Model settings	Reproducing ENM results is important and depends on the processing of occurrence data, environmental data and their processing, model calibration, and repeatability of model transfer processes (Feng et al., 2019). Therefore, the default settings of the algorithms were selected to simplify the interpretation and reproducibility of the results.
Assessment	*Model estimates*	• True Skill Statistics was employed to assess the discrimination capacity of the model. ROC was taken into account for the occupy vs. non-occupy comparison. • The variable importance of the ensemble model was calculated.
	Plausibility check	The ensemble model's response curve and the predictors' ecological plausibility were checked.

	Ensemble model	The models with TSS scores greater than 0.6 were selected using a weighted average approach to generate an ensemble model (Araújo and New, 2007).
	Non-independence	None
	Threshold	TSS maximization threshold was considered for binary predictions.
	Performance Statistics	I evaluated model performance based on TSS value from 90 models run.
Prediction	*Prediction output*	I used continuous predictions of occurrence probability for brown bears living in Türkiye.
	Uncertainty quantification	The ensemble approach significantly increases the prediction performance by combining results from different modeling techniques and thus presents the relationships that are aimed to be captured by the model by separating them from the background noise (Hao et al., 2020).

Appendix B: The checklist for ODMAP (Overview, Data, Model, Assessment, and Prediction) protocol for conflict risk modeling of human - brown bear (*Ursus arctos*) encounters across Türkiye

ODMAP Elements		Contents
Overview	*Model Objective*	**Objective**: Human – Brown bear conflict (HBC) risk probability across Türkiye **Target outputs**: Conflict risk map across the country
	Taxon	Brown bear, *Ursus arctos*, Ursidae, Carnivora, Mammalia
	Location	Türkiye, Soutwest Asia
	Scale of analysis	**Spatial extent**: 25.65708, 44.83208, 35.82458, 42.10792 (xmin, xmax, ymin, ymax) **Temporal extent**: • Conflict risk events: 2017 – 2023 • Forest, Farmland, Water layers: 2018 • Minimum temperature, Maximum temperature, Mean temperature, Precipitation, Wet-day frequency: 2011 – 2019 • Distance to protected areas, Distance to roads, Distance to villages, Human Footprint Index, Population density: 2020 • Net Primary productivity: 2016 – 2022 **Type of extent boundary**: Political (Republic of Türkiye)
Data	*Biodiversity data overview*	**Observation type:** Conflict events information obtained from media coverage + Communicating with local people (**n=296**) **Response/Data type**: Presence-only
	Type of predictors	Bioclimatic, Land Cover, Topographic, Anthropogenic
	Conceptual model / hypothesis	Human – Brown bear conflict events are driven by climatic and human-related factors. While bioclimatic factors can drive their natural prey, denning time, and foraging behaviors, anthropogenic and topographic factors can limit their dispersal and foraging activity.
	Data collection	**Data source:** I conducted Google searches using the following keywords: "Bear + sighting", "bear + attack", "bear + attack + human/barn/beehive/orchards/crop/fence/yard/damages", "bear + mortality", "bear + road accidents" in Turkish. All conflict events were geo-referenced based on the location information. **Absence-data:** I used presence-only data for modeling. Pseudo-absence generation was performed using *biomod2*. **Data filtering:** I used *spThin* package in R to avoid spatial clustering of conflict event points (Aiello-Lammens et al., 2015)
	Predictor variables	**Variable** **Bioclimatic variables** – Bioclimatic variables – Minimum temperature (°C), Maximum temperature (°C), Mean temperature (°C), Precipitation (mm/day), Wet-day frequency (day), Net primary productivity (g C m^{-2} yr^{-1}). **Topographic Variables** – Slope (°) **Land Cover Variables –** Distance to forest (km), Distance to farmland (km), Distance to water (km) **Anthropogenic Variables** – Distance to protected areas (km), Distance to roads (km), Distance to villages (km), Population Density (no. of people/km^2), Human Footprint Index (HFI-value) **Data Sources** 1. Corine Land Cover 2018 - https://land.copernicus.eu/en/products/corine-land-cover/clc2018 2. Climatic Research Unit (CRU TS Version 4.04) - https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.04/ 3. WorldPop - https://neo.gsfc.nasa.gov/view.php?datasetId=MOD17A3H_Y_NPP Net Primary Productivity (1 Year – TERRA/MODIS) - https://neo.gsfc.nasa.gov/view.php?datasetId=MOD17A3H_Y_NPP 4. SEDAC - https://sedac.ciesin.columbia.edu/data/set/wildareas-v3-2009-human-footprint 5. Open Street Map - http://download.geofabrik.de/europe/turkey.html 6. HydroRIVERS – HydroSHEDS - https://www.hydrosheds.org/products/hydrorivers 7. Slope - https://www.worldclim.org/data/worldclim21.html 8. Protected areas of Türkiye - arcgis.com/apps/View/index.html?appid=5f3978146c4643438ab446620e275269

		Spatial resolution of raw data: Population density (30 arc-sec), Human footprint index (30 arc-sec), Corine Land Cover database (100 m), Elevation (2.5 arc-min), Net primary productivity (0.25 degrees), Minimum temperature (0.5 degrees), Maximum temperature (0.5 degrees), Mean temperature (0.5 degrees), Precipitation (0.5 degrees), Wet-day frequency (0.5 degrees), **Projection**: WGS84 **Data processing:** • I downloaded the data from the publicly available data sources. • I generated the forest layer by using the Corine LULC 2018 vector database. To do this, I combined and extracted the *Broad-leaved forest, Coniferous forest*, *Mixed forest*, and *Transitional woodland/shrub* attributes. Then, I generated the proximity layer called Distance to forest using Euclidean Distance Tool in ArcGIS by arranging its cell-size and extent. • I generated the farmland layer by using the Corine LULC 2018 vector database. To do this, I combined the attributes named *Non-irrigated arable land, Permanently irrigated land, Rice fields, Vineyards, Fruit trees and berry plantations, Olive groves, Pastures, Annual crops associated with permanent crops, Complex cultivation patterns, Land principally occupied by agriculture with significant areas of natural vegetation, Agro-forestry areas*, and extracted them. Then, I generated the proximity layer called Distance to farmland using the Euclidean Distance Tool in ArcGIS by arranging its cell size and extent. • I extracted 1st to 4th order river attributes from HydroRIVERS database since this vector layer appropriately covers important water sources across the country, from small springs in/around forests and agricultural fields to large rivers. Then, I generated the proximity layer named Distance to water by using the Euclidean Distance Tool in ArcGIS. • I selected the *motorways*, *primary, secondary,* and *trunk roads* and *their linked roads* attributes from the Open Street Map and extracted them. Then, I generated the proximity layer named Distance to roads by using the Euclidean Distance Tool in ArcGIS. • A spatial point data frame was created based on the center of all human settlements throughout Turkiye. Then, I generated the proximity layer named Distance to villages by using the Euclidean Distance Tool in ArcGIS. • I downloaded the Minimum temperature, the Maximum temperature, the Mean temperature, the Wet-day frequency, the Precipitation data from CRU data source. I resampled them with bilinear interpolation and cropped and masked based on the study area. • I downloaded one-year net primary productivity data between 2016-2022 data from the Terra/Modis database. Then, I took the average of these years as a final net primary productivity raster file • I downloaded the vector data called Protected areas of Türkiye. There are various protected area attributes in Türkiye (NCNP, 2020), so, the relevant protected area attributes in terms of brown bear ecology were selected and extracted as follows: *national parks*, *nature conservation areas*, *special environment protection areas*, *wildlife enhancement areas*, *locally important wetlands*, *nationally important wetlands*, *Ramsar areas*, and *preservation forests*. Then, I generated the proximity layer named Distance to protected areas using the Euclidean Distance Tool in ArcGIS. • I derived the Slope raster from the Shuttle Radar Topography Mission (SRTM) elevation data. It was derived after projecting to Lambert Azimuthal Equal-Area (ETRS 1989 LAEA), and then projected WGS84 again (Sillero and Barbosa, 2021). • I downloaded the Human Footprint Index raster from the relevant data source. • I downloaded Population Density raster from the relevant data source. • All variables were properly resampled, cropped, and masked based on the study area.
Model	*Assumptions*	✓ Conflict events data was gathered from media coverage. If direct eyewitnesses could not be contacted or found, a random location was assigned within 5 km of the event as a georeferenced point (Kimmig et al., 2020). ✓ The filtering process was performed to avoid spatial clustering of occurrence records. ✓ Predictor variables were incorporated in the model after checking any error. ✓ Multicollinearity among the environmental predictors was checked.

	Algorithms	Eleven SDM algorithms available in *biomod2* package were used. • Artificial Neural Network (ANN) • Flexible Discriminant Analysis (FDA) • Generalised Additive Model (GAM) • Generalised Boosting Model (GBM) • Generalised Linear Model (GLM) • Multiple Adaptive Regression Splines (MARS) • Maxent Entropy (Maxent) • Random Forest (RF) • Surface Range Envelope (SRE) • Classification Tree Analysis (CTA) • eXtreme Gradient Boosting Training (XGBOOST) **Model complexity**: I chose these algorithms to yield complex response surfaces but prevent overfitting.
	Model workflow	• I used to *spThin* package in R (Aiello-Lammens et al., 2015) to filter the spatial clustering of points based on 10 km across the study area. 201 conflict events were used as the final dataset for modeling. • I checked the multicollinearity and excluded the variables with correlation coefficients |r| > 0.75 and variance inflation factor (VIF) > 5 by using *usdm* and *corrplot* package in the R (Wei & Simko, 2021; Naimi, 2023). Ultimately, 13 variables were retained. • To predict human – brown bear conflict risk across Türkiye, I employed an ensemble approach using the *biomod2* package. • The modeling process began with the random generation of 1,000 pseudo- absence points. • Subsequently, the dataset was split into training (80%) and testing (20%) datasets. • I conducted three cross-validation iterations using a bootstrap approach for each model. • Pseudo-absence points were regenerated three times to mitigate random bias. • To reduce uncertainty and generate a final model, I selected the models with TSS scores greater than 0.5, using a weighted average approach (Araújo and New, 2007; Thuiller et al., 2009).
	Software, codes, and data	**Modeling platform**: R (*version 4.3.2*) environment with *biomod2* package. **Dataset and Code**: The datasets used and/or the R codes employed for this study are available based on a reasonable request.
	Data partioning	Occurrence records were split out as training (80%) and testing (20%) datasets.
	Variable selection	• I selected 15 environmental variables that have high potential to drive HBC based on literature. For instance, roads, villages, and farmlands are hotspot in terms of HBC since they exhibite high risk - low gain landscape feature for bears and represent ecological traps (Bomberi et al., 2021; Parsons et al., 2022; Khosravi et al., 2023). Water sources such as springs and rivers are important locations for both wildlife as well as human activity such as livestock, trekking etc (Parsons et al., 2022). Brown bears rely on forested habitats for sheltering, foraging, and denning (Recio et al., 2021; Ziółkowska et al., 2016); so forest was included in the model. Population density and Human footprint index are important to understand the potential role of human dominancy in terms of HBC in rural areas (Dai et al., 2019b). Protected areas that have low human footprint play a crucial role in conserving biodiversity and providing refuge for species threatened by habitat loss (Tammeleht et al., 2020; Dai et al., 2020). The slope variable was included in the model since a high slope represents low human access as a general pattern (Goldstein et al., 2010). Bioclimatic variables, including minimum, maximum, mean temperatures, precipitation, wet-day frequency, and net primary production features, drive the abundance, richness, and accessibility of natural prey and food sources of brown bears (Zarzo-Arias et al., 2020; Pérez-Girón et al., 2022; Pérez-Girón et al., 2024). • Multicollinearity was chekced using *usdm* and *corrplot* packages among the variables and excluded them if they display high correlation (correlation coefficient > 0.7) and variance inflation (VIF > 5). Ultimately, 13 variables were retained.
	Model settings	Reproducing ENM results is important and depends on the processing of occurrence data, environmental data and their processing, model calibration, and repeatability of model transfer processes (Feng et al., 2019). Therefore, the default settings of the algorithms were selected to simplify the interpretation and reproducibility of the results.
Assessment	*Model estimates*	• True Skill Statistics was employed to assess the discrimination capacity of the model. ROC was taken into account for conflict vs. non-conflict areas comparison. • The variable importance of the ensemble model was calculated.
	Plausibility	The ensemble model's response curve and the predictors' ecological plausibility were checked.

	check	
	Ensemble model	The models with TSS scores greater than 0.5 were selected using a weighted average approach to generate an ensemble model (Araújo and New, 2007).
	Non-independence	None
	Threshold	TSS maximization threshold was considered for binary predictions.
	Performance Statistics	I evaluated model performance based on TSS value from 90 models run.
Prediction	*Prediction output*	I used continuous predictions of risk probability for human – brown bear conflicts across Türkiye.
	Uncertainty quantification	The ensemble approach significantly increases the prediction performance by combining results from different modeling techniques and thus presents the relationships that are aimed to be captured by the model by separating them from background noise (Hao et al., 2020).