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Modeling of Potential Distribution of *Castanea sativa* Mill. in Bolu Regional Directorate of Forestry Depending on Climate and Topographic Variables*

Castanea Sativa Mill.'in Bolu Orman Bölge Müdürlüğü Sınırları İçindeki Olası Yayılış Alanlarının İklim ve Topoğrafik Değişkenlere Bağlı Modellenmesi

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Abstract

In this study, we assessed the potential impacts of climate change on *Castanea sativa* habitats using the MaxEnt model under SSP2-4.5 and SSP5-8.5 scenarios for 2050, 2070, and 2090 in the Bolu Regional Directorate of Forestry, northwestern Turkey. Bioclimatic and topographic variables were selected through ecological and correlation analyses. The model performed well, with AUC values of 0.961 (training) and 0.959 (test). Bio17 (precipitation in the driest quarter), Bio15 (precipitation seasonality), and Bio4 (temperature seasonality) were the most influential variables. Under SSP5-8.5, unsuitable areas slightly increase while high suitability areas decrease from 310.92 ha to 266.47 ha by 2090. SSP2-4.5 projects a greater reduction in high suitability (to 133.26 ha) and an increase in medium suitability areas, suggesting habitat transitions. *C. sativa* is currently found predominantly at elevations below 1000 meters, with 20.2% of suitable habitats located between 0–100 meters; in the future, the species is expected to shift to relatively lower elevations. These findings highlight the importance of adaptive forestry and conservation strategies to reduce habitat loss and fragmentation.

Keywords: Climate change, habitat suitability, SSP5-8.5, SSP2-4.5, Türkiye, Worldclim

Özet

Bu çalışmada, *Castanea sativa* (Anadolu Kestanesi) habitatlarının iklim değişikliğinden nasıl etkilenebileceği, MaxEnt tür dağılım modeli kullanılarak SSP2-4.5 ve SSP5-8.5 iklim senaryoları altında 2050, 2070 ve 2090 yılları için Bolu Orman Bölge Müdürlüğü sınırlarında değerlendirilmiştir. Biyoklimatik ve topoğrafik değişkenler, ekolojik uygunluk ve korelasyon analizleri ile seçilmiştir. Model yüksek doğruluk göstermiştir (AUC: eğitim verisi için 0.961, test verisi için 0.959). En etkili değişkenler sırasıyla Bio17 (en kurak çeyrekte yağış), Bio15 (yağışın mevsimselliği) ve Bio4 (sıcaklık mevsimselliği) olmuştur. SSP5-8.5 senaryosunda uygun olmayan alanlar hafifçe artarken, yüksek uygunluk gösteren alanlar 310.92 hektardan 266.47 hektara düşmektedir. SSP2-4.5 senaryosu ise yüksek uygunluk alanlarında daha belirgin bir azalma (133.26 ha'ya) ve orta düzeyde uygun alanlarda artış öngörmektedir; bu da geçiş habitatlarının artabileceğini göstermektedir. *C. sativa* günümüzde çoğunlukla 1000 metrenin altındaki yükseltilerde görülmekte olup, uygun alanların %20.2'si 0–100 metre arasındadır; gelecekte bu türün nispeten daha düşük rakımlara kayması beklenmektedir. Bu sonuçlar, habitat kaybı ve parçalanmayı azaltmak için uyarlanabilir ormancılık ve koruma stratejilerinin önemini vurgulamaktadır.

Anahtar Kelimeler: İklim değişikliği, habitat uygunluğu, SSP5-8.5, SSP2-4.5, Türkiye, Worldclim

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1. Introduction

In recent years, species distribution models (SDMs) have become important tools for predicting the potential geographic distribution of plant and animal species (Franklin, 2009). Climate system have a strong influence on the distribution of plant taxa and habitats (Bertrand et al., 2011). Throughout 4.5 billion years of Earth's history, climate systems have undergone continuous change. Global climate change has accelerated in recent years, with an average increase of 0.85°C over the last century. If the climate system continues to change in this way, a temperature increase of at least 0.3-1.7°C and at most 2.6-4.8°C is projected by 2100 (IPCC, 2014). Many species with limited habitats are affected and face the threat of habitat loss and extinction (Thuiller et al., 2005; Lawler et al., 2009; Cobben et al., 2015; Ashraf et al., 2016; Yi et al., 2016; Zhang et al., 2018). In this sense, such studies are important to observe future distribution areas and populations of plants and to take conservation measures in advance if necessary (Gaston and Blackburn, 1996).

Different models were used to determine species distributions. The most widely used habitat suitability models include ENFA (ecological niche factor analysis), GARP (genetic algorithm for rule-set prediction) and MaxEnt (Maximum Entropy) (Zhang et al. 2022; Li et al., 2023). Maxent is a modelling technique based on the principle of maximum entropy that uses existing species distribution data to determine the probability distributions associated with environmental variables (Elith and Leathwick, 2009). This model is preferred in many studies, particularly because of its ability to work with limited datasets. Many studies have been conducted in Turkey and worldwide to determine the potential distribution of species using species distribution models (Beaumont et al., 2008; Williams et al., 2009; Beale and Lennon, 2012; Wisz et al., 2013; Akyol and Örücü, 2019; Koç et al., 2022; Gabor et al., 2022; Uzun and Örücü, 2023; Dutucu, 2023; Cedano Giraldo and Küçüker, 2023).

Turkey is located in the Mediterranean climate zone and is one of the regions affected by climate change. Similar to all plant species in this climate zone, the tree species *C. sativa* shows changes in habitat area due to climate change. Studies have also highlighted that the range of *C. sativa*'s will decrease. Metreveli et al. investigated the potential distribution and suitable habitats of *C. sativa*. In this study, the distribution of *C. sativa* was modelled using the Chelsa and WorldClim climate datasets, and potential habitat changes were assessed under climate change scenarios. The results showed that the distribution of *C. sativa* is significantly affected by climate change (Metreveli et al., 2023). In another important study, Beridze et al. identified conservation priorities for *C. sativa* populations in the South

Caucasus using genetic and ecological metrics. The study predicted that *C. sativa* could experience a 70% decline in distribution under climate change (Beridze et al., 2023). Dutucu used MaxEnt-based species distribution modelling to determine the potential range of Anatolian chestnut (*Castanea sativa*) today and in 2100. According to climate projections, suitable habitat areas will decrease by 33.9% in the SSP2-4.5 scenario and by 79.7% in the SSP5-8.5 scenario, with highly suitable areas shrinking, particularly in the Black Sea and Marmara regions (Dutucu, 2023). *C. sativa* is an important tree species for ecosystems in Turkey and worldwide. The species has a wide range of economic and ecological benefits. Turkey plays an important role in the production of *C. Sativa,* and the conservation and sustainable management of this species are crucial for both the local economy and biodiversity.

The use of species distribution models is essential for the conservation of ecosystems and sustainable management of biodiversity. Models such as Maxent provide an effective tool for understanding the environmental factors that influence species distribution and for predicting future scenarios of change. In this context, studies conducted worldwide and in Turkey have provided essential information for species conservation and habitat management. The modelling capabilities provided by Maxent play a vital role in maintaining ecosystem health and preserving biodiversity.

In recent years, various studies have modelled the potential distribution of *Castanea sativa* under climate change scenarios using species distribution models, particularly MaxEnt. These studies commonly rely on bioclimatic variables derived from sources such as WorldClim and employ future projections based on SSP scenarios. While there is a degree of methodological convergence in the general modeling framework, important differences exist in terms of study area, baseline climate data, variable selection, and ecological scope. Unlike previous research, which often applies standard baseline datasets and primarily focuses on horizontal (spatial) distribution patterns, the present study uses a distinct set of current climate data tailored to the ecological conditions of the Bolu Regional Directorate of Forestry. Moreover, this study uniquely incorporates a detailed assessment of the vertical (elevational) distribution of *C. sativa*, providing a more comprehensive understanding of habitat shifts under changing climate conditions. Additionally, the use of 1014 occurrence points ensures high model reliability and robustness. These aspects collectively form the core of the study's originality, offering region-specific insights and practical implications for the sustainable management and conservation of *C. sativa* in northwestern Turkey.

2. Material and Method

2.1. Study Area

The Bolu Regional Directorate of Forestry (BRDF), which covers the provinces of Duzce and Bolu in northwestern Turkey, was selected for this study. The working area, 30°29'00" - 32°38'00" east longitude and 40°03'00" - 41°10'00" north latitude, has a topography that rises to 2400 m above sea level (Figure 1). With a total area of 983901.2 hectares, approximately 60% of the BRDF is forested. Karadere, Seben and Aladağ forests stand out among the important forest areas in the region and are rich ecosystems with both high biodiversity and high quality timber production. In addition, the Aladağ Forests, which were among the first FSC-certified forests in Turkey, are also located in this study area.

The Abant Mountains form an important part of the study area, and are located in the Euro-Siberian phytogeographic zone. The region serves as an ecological boundary between the Euxine floristic region connected to the Black Sea coast and the Irano-Turanian floristic region extending to Central Anatolia (Sargıncı and Beyazyüz, 2022; Aydın and Sivri, 2023). The study area is located in a continental climate zone, and according to 30-year climate data, the average daily sunshine duration is 5.2 hours, the average annual precipitation is 691 mm, the average annual number of rainy days is 136, and the average annual temperature is 10.5 °C (Öztürk et al., 2017).

In terms of vegetation cover, broadleaf species are widespread at low altitudes and coniferous species are widespread at high altitudes (Öztürk et al., 2017). As part of the study, the distribution areas of *Castanea sativa* were identified based on stand type maps obtained from forest management plans. Spatial analyses were conducted using ArcGIS software, through which all stands containing *C. sativa*, either as pure or mixed formations, were selected via attribute-based querying. Subsequently, presence points were systematically assigned to these identified stands to be used in the modeling process (Figure 1).

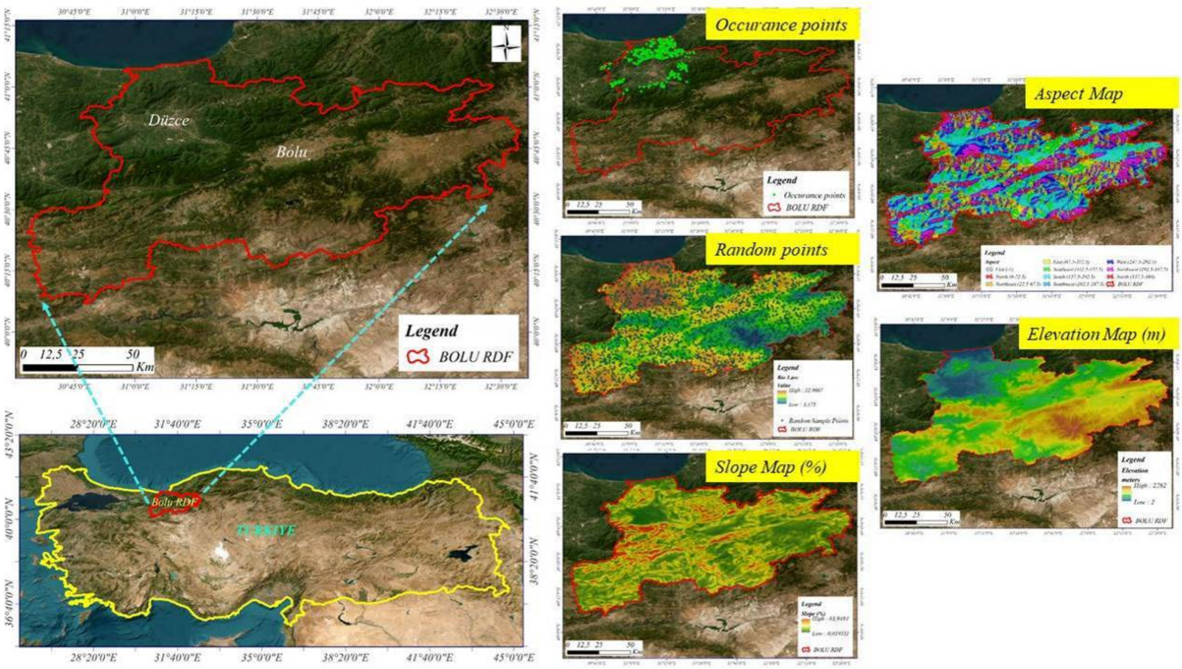

Figure 1. Geographical location of the study area and some descriptive maps.

2.2. Environmental Data

The WorldClim 2.1 database (WorldClim, 2020) was used to determine the potential range of the species. This dataset, published in 2020, contains monthly minimum, maximum, and average temperatures, precipitation, wind speed, water vapor pressure, solar radiation and total precipitation data from 1970 to 2000. It also includes 19 different bioclimatic variables that are commonly used to understand the ecological requirements of species (Fick and Hijmans, 2017).

Climate data with a spatial resolution of 30 arc-seconds (approximately 1 km²) were used to determine the current distribution range of the species. In addition, topographic variables elevation, slope, and aspect were derived from a digital elevation model (DEM) generated using 10-meter interval contour lines through TIN (Triangulated Irregular Network) interpolation in ArcGIS. The resulting DEM was then used to calculate slope and aspect maps. All topographic layers were resampled to match the spatial resolution of the bioclimatic data obtained from WorldClim (30 arc-seconds) to ensure consistency in the analysis. All spatial processing and analyses were carried out using ArcGIS software (Table 1).

In the modelling process, the MaxEnt model was used to assess the contribution of environmental variables to the species' distribution. The model was run with 500 replicates to ensure robustness and reliability of the results, in line with recommendations in the literature (Pearson et al., 2007). The jackknife test was employed to evaluate the sensitivity of the model to each variable. This test revealed the relative importance of each environmental predictor and identified the key factors shaping the ecological niche of the species.

Table 1. Worlclim data used in the study environmental variables.

Variable	Parameters	Unit
Bio1	Annual mean temperature	°C
Bio2	Mean diurnal range [mean of monthly (max temp–min temp)]	°C
Bio3	Isothermality (bio2/bio7) (* 100)	°C
Bio4	Temperature seasonality (standard deviation *100)	°C
Bio5	Max temperature of warmest month	°C
Bio6	Min temperature of coldest month	°C
Bio7	Temperature annual range (bio5–bio6)	°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 (coefficient of variation: mean/sd*100)	%
Bio16	Precipitation of wettest quarter	mm
Bio17	Precipitation of driest quarter	mm
Bio18	Precipitation of warmest quarter	mm
Bio19	Precipitation of coldest quarter	mm
Elevation	Elevation	m
Aspect	Aspect	Degrees
Slope	Slope	%

In this study, the Institute Pierre Simon Laplace Climate Modelling (IPSL CM6A-LR) climate model was used to estimate the potential future range of species. The IPSL CM6A-LR is the latest version of the IPSL climate model and provides robust projections of climate change scenarios. Future scenarios were determined using the Coupled Model Intercomparison Project Phase 6 (CMIP6) scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) in its 6th Assessment Report (IPCC, 2020). These scenarios cover climate projections for the 21st century and have been developed to model possible future trends in greenhouse-gas emissions.

In CMIP6, the Representative Concentration Pathways (RCPs) used in previous climate projections have been updated and renamed shared socio-economic pathways (SSPs). The new SSP scenarios provide a multi-dimensional approach that includes not only greenhouse gas concentrations but also economic, social, and political variables (O'Neill et al., 2016; CarbonBrief, 2018). The RCP and SSP scenarios worked together to help model future global emission trends and their environmental impact.

2.3. General SSP scenarios and scenarios used in the study

SSP1-2.6 (Sustainability Scenario): A low-emissions future is envisaged, prioritizing environmental sustainability and social equity. SSP2-4.5 (Middle Path Scenario): Global development progresses unevenly while climate policies are partially implemented. SSP4-6.0 (Rising inequality scenario): Economic and social inequalities are evident and climate policies are limited. SSP5-8.5 (fossil fuel-dominated scenario): A high-emissions future characterized by rapid economic growth and increased use of fossil fuels (O'Neill et al., 2016; CarbonBrief, 2018).

In this study, SSP2-4.5 (medium emissions scenario) and SSP5-8.5 (high emissions scenario) were used. The modelling evaluated projections for the periods 2050 (2041-2060), 2070 (2061-2080) and 2090 (2081-2100). The current and future ranges of *C. sativa* were determined separately using the MaxEnt model, according to the selected climate scenarios. In addition, to analyze the vertical distribution of the species, elevation data in the study area were evaluated by classifying them at 100 m intervals.

In order to minimize multicollinearity among the environmental variables and enhance the predictive power of the model, a correlation analysis was first conducted on the 19 bioclimatic variables using SPSS 23.0. Pairwise Pearson correlation coefficients were calculated, and in line with common practice, when the correlation between two variables exceeded 0.80 ($|r| > 0.80$), one of them was excluded to avoid redundancy. The variable selection process was based not only on statistical correlation but also on the ecological relevance and interpretability of the variables. All environmental variables were resampled and calibrated to the same spatial resolution (30 arc-seconds, ~1 km^2) to ensure compatibility before the analysis.

Although principal component analysis (PCA) was conducted to visualize the overall correlation structure and identify clusters of related variables, it was not used for direct variable reduction in this study. Instead, variable elimination was based on pairwise correlation analysis and expert judgment, in line with previous studies emphasizing ecological rationale in predictor selection.

For the MaxEnt model, 75% of the data were selected for model training, and 25% for model testing (Phillips and Dudik, 2008). The receiver operating characteristic (ROC) curve and area under the ROC curve (AUC) values were used to evaluate the performance of the model (Wang et al., 2007; Phillips et al., 2017). The AUC value determined whether the model was better than a random estimate. An AUC > 0.5 means that the model is better than a random guess (Phillips and Elith, 2010). The closer the AUC is to 1, the better the accuracy and complementarity of the model.

The MaxEnt model results were converted into distribution maps using ArcGIS 10.8TM software. In the model, the distribution of a species is represented by a value between 0-1, and as these values approach 1, the probability of the species occurring in these areas increases. In the current and potential future distribution maps, suitability categories were classified based on the preferred areas in the studies. Habitat suitability values were classified as 0-0.25 (not suitable), 0.25-0.5 (low), 0.5-0.75 (medium) and 0.75-1 (high) (Yan et al., 2021; Neldner, 2014; Aouinti et al., 2022). This classification was used to calculate estimated distribution areas in hectares (ha) (Çoban et al., 2020). The selection of variables during the modelling process increased the predictive power of the model, resulting in more reliable and ecologically meaningful results

3. Results and Discussion

3.1. Correlation Analysis and Selected Variables

When selecting the WorldClim variables to be used in the MaxEnt model, the problem of multicollinearity was minimized by selecting only one of the highly correlated variables ($r>0.8$). In particular, only one of the variables with correlation values above 0.8 was used. In addition, ecologically and biologically significant variables that were relevant to the subject of the study and that directly influenced the distribution of the species were selected. To improve the performance of the model, a balanced representation of both temperature and precipitation related variables was considered. The correlation coefficients between variables are shown on a color scale, with red shading indicating a strong positive correlation (close to $r = 1.0$) and blue shading indicating a strong negative correlation (close to $r = -1.0$) (Figure 2). In line with this analysis, only one of the highly correlated pairs of variables was preferred when selecting variables to be included in the model.

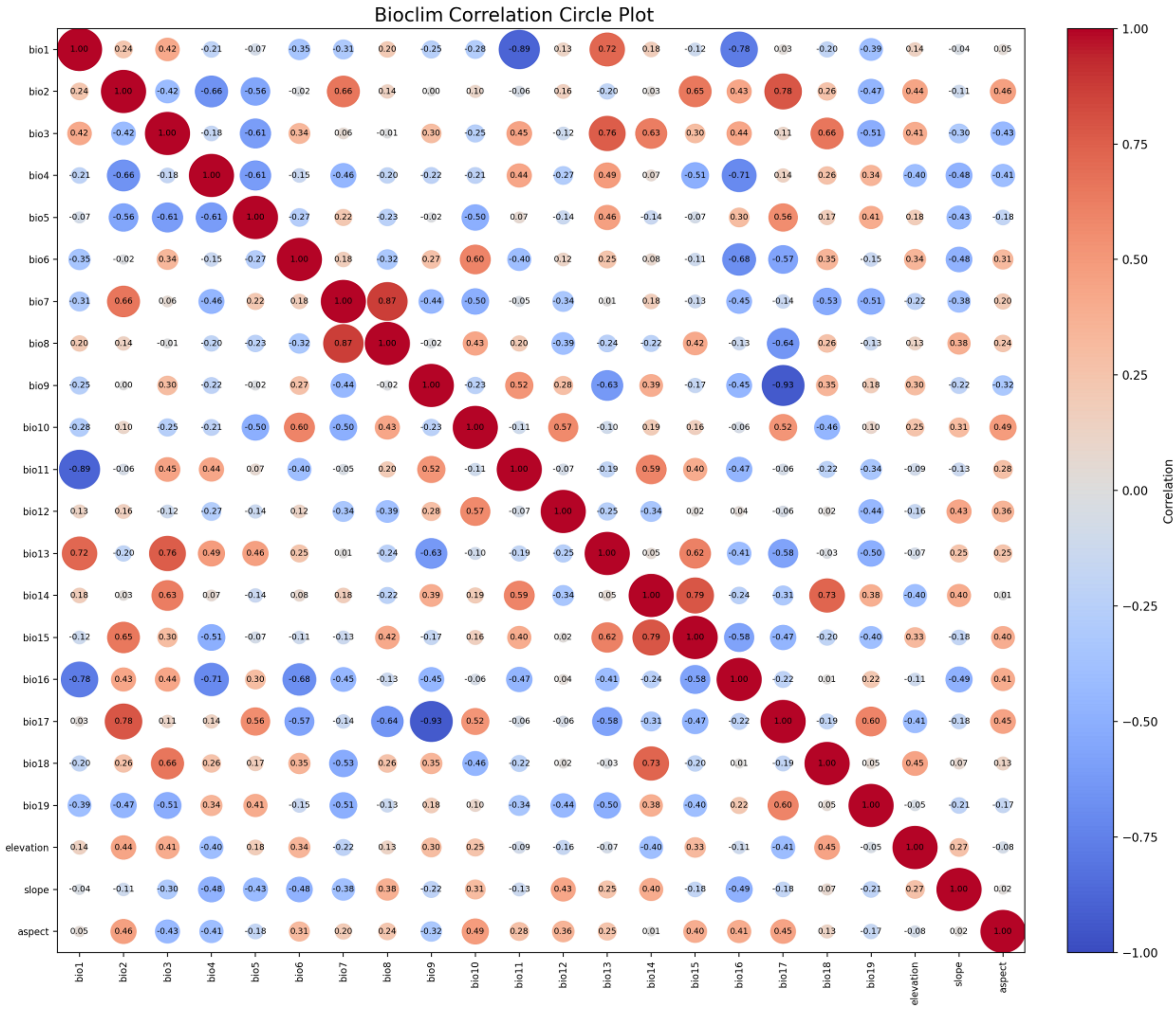

Figure 2. Correlation analysis results of Bioclim variables used in the MaxEnt model.

As a result of the correlation analysis, the preferred climate variables in this study were determined based on their use and importance in habitat suitability models. The variables used are, Bio1 (Annual Mean Temperature); average temperature throughout the year to show broad ecological tolerance, Bio4 (Temperature Seasonality); to determine temperature variability and adaptive capacity of trees, Bio5 (Max Temperature of Warmest Month); to determine tolerance of tree species to extreme temperatures, Bio6 (Min Temperature of Coldest Month); for its importance in measuring survival potential during cold periods, Bio10 (Mean Temperature of Warmest Quarter); to evaluate the effect of temperature, especially during growth periods, Bio12 (Annual Precipitation); to determine water availability in general, Bio15 (Precipitation Seasonality); to determine water availability in general, Bio15 (Seasonality of Precipitation); because it helps to understand drought resilience by measuring the variability of precipitation over the year, Bio16 (Precipitation of Wettest Quarter); because of the amount of precipitation during the wettest period and its critical role in growth, and finally Bio17 (Precipitation of Driest Quarter); because they are important for understanding water availability during dry periods.

The use of additional environmental variables, such as elevation, slope, and aspect, along with bioclimate data in MaxEnt species distribution modelling is critical to more accurately predict species distribution. These variables play an important role in understanding species' habitat preferences and ecological requirements. Bioclimate data represent climatic factors, whereas topographic variables such as elevation, slope, and aspect reflect the physical environmental conditions that influence species distribution. For example, altitude directly influences variation on vegetation and climatic conditions. The growth conditions of plant species change as temperature decreases at higher altitudes. Therefore, it is necessary to include elevation data to estimate species distribution at high and low elevations. Tam et al. (2024) reported that topographic variables such as slope and aspect are important factors affecting species distribution. They emphasized that slope affects vegetation development by influencing water flow and soil erosion, and that areas with steep slopes generally retain less water, whereas flat areas allow water to accumulate. This, in turn, could affect plant species preferences. Aspects also have an important effect on plant growth by influencing the length of time plants are exposed to sunlight. Sunny aspects increase the ability of plants to photosynthese, whereas shady aspects may have less vegetation cover (Merow et al., 2013). The MaxEnt model predicts potential species distribution using a combination of these environmental variables. By analyzing the environmental factors that influence the current distribution of species, the model determines the impact of these factors on the distribution of species (Chhogyel et al., 2020). Therefore, using variables such as elevation, slope, and aspect in combination with bioclimate data, increases the accuracy of species distribution models and provides more robust data for species conservation and management (Mollah et al., 2021).

3.2. MaxEnt model results

The Receiver Operating Characteristic (ROC) curve was used to evaluate the predictive ability of the MaxEnt model, and the area under the curve (AUC) was calculated. An AUC value of 0.961 was obtained for the training data, and 0.959 for the test data (Figure 4a). These values indicate that the model predicts species distribution with high accuracy, which is well above the level of random guessing (AUC = 0.5). The high performance of the model suggests that it accurately reflects the effects of the environmental variables on the ecological niche of *Castanea sativa*. In addition, to assess the error rates of the model and the size of the predicted area, the omission and predicted area plots were analyzed, which show the error rates of the model for different cumulative thresholds. For example, for a cumulative threshold of 10,000, the model recorded an omission rate of 6.3% for the training data and a predicted area of 10.1% for the test data. These results suggest that the model performed in a balanced manner, avoiding the risk of overfitting (Figure 4b).Overfitting causes the model to become too dependent on the training data alone, resulting in poor performance on new data. However, this analysis shows that the model captures the overall distribution well and has a generalizable predictive power.

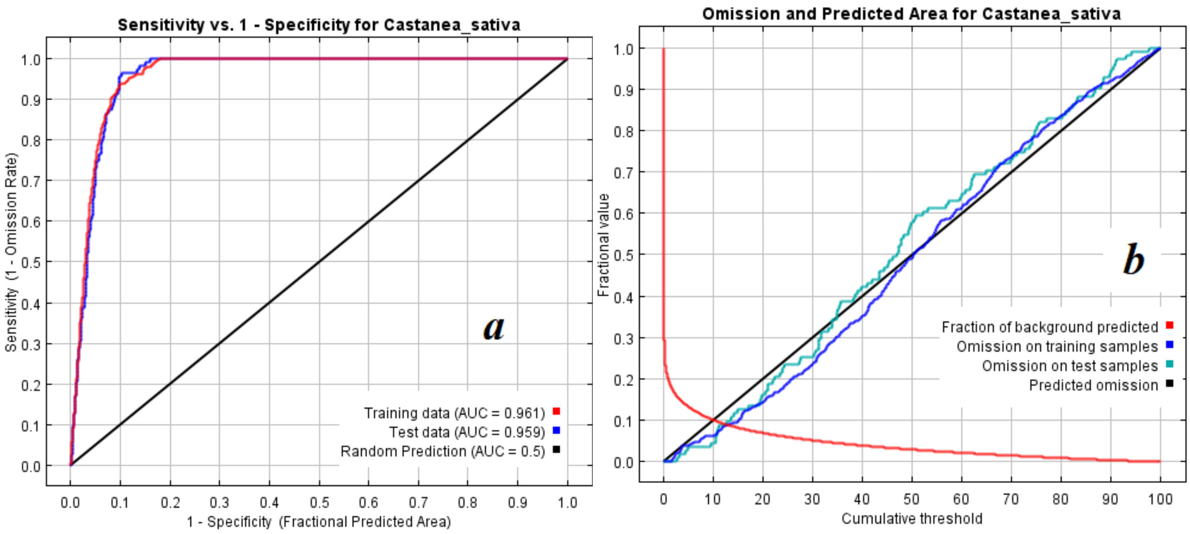

Figure 4. Prediction power and error rates of the MaxEnt model.

According to the MaxEnt model, the most influential environmental variables affecting the potential distribution of *Castanea sativa* were related to precipitation and temperature. As shown in Table 2, the variable with the highest percent contribution to the model was Bio17 (precipitation in the driest quarter) at 42.2%, followed by Bio15 (precipitation seasonality) at 27.6%, and Bio4 (temperature seasonality) at 15.7%. Among these, Bio4 also had the highest permutation importance (53.4%), indicating that it contains substantial unique information critical to model performance. Temperature variables such as Bio5 (maximum temperature of the warmest month, 9.7%) and Bio6 (minimum temperature of the coldest month, 1.5%) also contributed to the model. In contrast, several other variables such as Bio1 (annual mean temperature), Bio10 (mean temperature of warmest quarter), Bio12 (annual precipitation), and Bio16 (precipitation of wettest quarter) showed limited contributions (all below 1%). Furthermore, topographic variables including aspect and slope had minimal influence on the model, both in terms of percent contribution and permutation importance (≤0.2%), suggesting that these variables play a negligible role in shaping the distribution of the species in the study area. While elevation had a slightly higher permutation importance (12.2%), its percent contribution (1.2%) remained low, indicating a relatively limited explanatory power compared to the dominant climatic variables.(Table 2).

Table 2. Contributions of variables to the model.

Variable	Percent contribution	Permutation importance
bio17	42.2	0.7
bio15	27.6	19.6
bio4	15.7	53.4
bio5	9.7	2.1
bio6	1.5	7.1
elevation	1.2	12.2
bio12	0.7	0.1
bio16	0.6	3.5
bio1	0.4	1.2
aspect	0.2	0.2
slope	0	0
bio10	0	0

According to the results of the jackknife test, which is used to evaluate the individual impact of environmental variables on the model and to determine which variables provide the most information and which variables the model is more dependent on, Bio4 alone provides the most information (Figure 5a). This shows that elevation carries important information that the model can learn independently of the other variables. The AUC-based analysis also confirmed that Bio4 and elevation made the greatest contribution to model performance (Figure 5c).

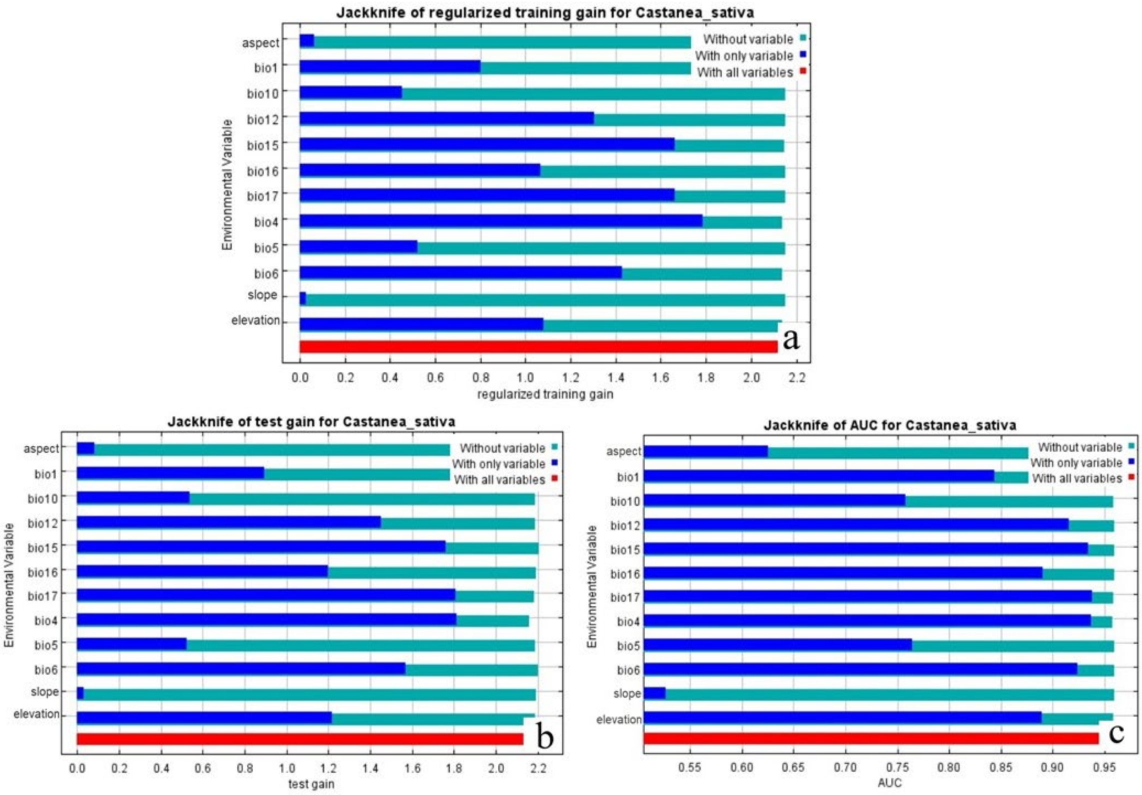

Figure 5. MaxEnt model Jacknife variable importance test results.

When all these results are evaluated together, it is understood that the rainfall regime and temperature variability are the most determining factors for the distribution of *Castanea sativa*. Precipitation variables, such as Bio17 and Bio15, play a critical role in defining suitable habitats for the species, while temperature fluctuations also stand out as important factors affecting habitat suitability. In addition, elevation is an important variable that increases the power of the model and shapes ecological niches.

3.3. Findings on Horizontal Distributions

When the current distribution of the *C. sativa* tree species from the existing data was examined with the MaxEnt, it was observed that 92.2% of the BRDF was not suitable. Of the total area, 4.2% were classified as low suitability, 3.51% as medium suitability, and 0.03% as very suitable (Table 3 and Figure 6).

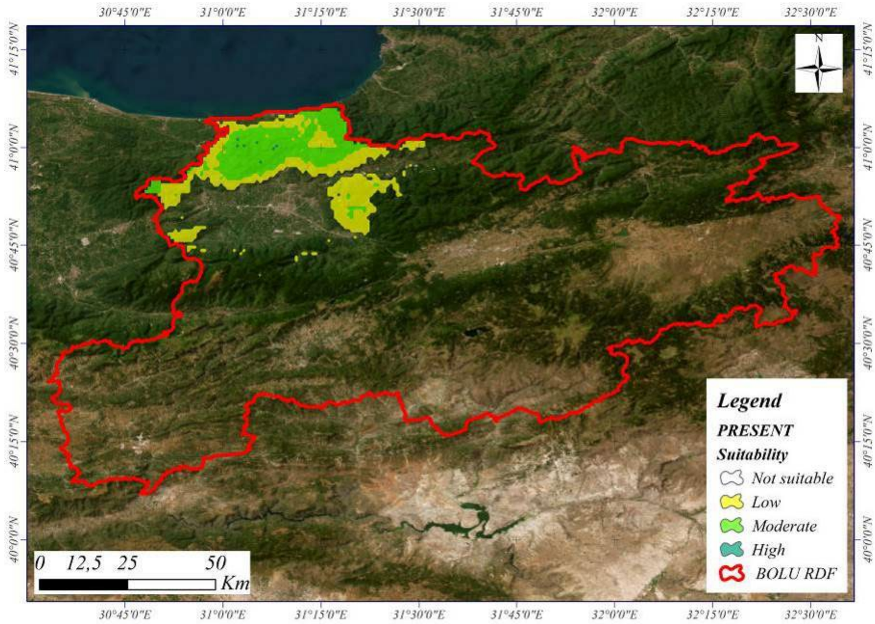

Figure 6. Current distribution areas of C. sativa tree species according to MaxEnt Model.

According to the SSP5-8.5 scenario, the not suitable areas for the tree species *C. sativa* increase by 2518.2 ha to 910104.2 ha in 2050. There was a transition of 3848.7 ha from the not suitable class to the low suitable class. It is expected that 189.74 ha will be transferred from the high to moderate suitability class. In addition, 3147 ha are projected to shift from the moderate to the low suitability class, while 100.8 ha may transition to the high suitability class (Table 3).

Table 3. Areal changes and transitions between the current situation and SSP5-8.5 scenario for 2050.

Suitability		SSP5-8.5_2050 (Area -ha)					
		Not suitable	Low	Moderate	High	Total	%
Present	Not suitable	903737.18	3848.74			907585.92	92.24
	Low	6241.26	31034.55	4144.59		41420.40	4.21
	Moderate	125.72	3147.01	31210.42	100.86	34584.00	3.51
	High			189.74	121.18	310.92	0.03
	Total	910104.16	38030.29	35544.75	222.04	983901.24	100.00
	%	92.50	3.87	3.61	0.02	100.00	

In the 2050-2070 period of the SSP5-8.5 climate scenario, it is estimated that 3966.7 ha of low suitability areas will transition to not suitability areas and 1180 ha to moderately suitable areas. The model predicts that 2703.4 ha of moderate suitability will become low suitability and 88.9 ha high suitability (Table 4). It is also estimated that 2988.1 ha will move from not suitable to low suitable and 24.69 ha to moderate suitability.

Table 4. Expected land status and transitions between 2050 and 2070 in the SSP5-8.5 scenario.

Suitability		SSP5-8.5_2070 (Area-ha)					
		Not suitable	Low	Moderate	High	Total	%
SSP5-8.5_2050	Not suitable	907091.33	2988.14	24.69		910104.16	92.50
	Low	3966.74	32883.28	1180.28		38030.29	3.87
	Moderate		2703.49	32752.33	88.92	35544.75	3.61
	High				222.04	222.04	0.02
	Total	911058.07	38574.91	33957.30	310.96	983901.24	100.00
	%	92.60	3.92	3.45	0.03	100.00	

In the 2070-2090 period of the SSP5-8.5 climate scenario, it is estimated that there will be a transition of 3907,55 ha from low to not Suitable and 7,12 ha from moderate to not Suitable and the amount of not Suitable areas is predicted to increase in each period. An area of 3077,07 ha is expected to move from the moderate to low suitability class and 44,43 ha to the high suitability class. It is estimated that an area of approximately 88.92 ha will move from the high suitability class to the moderate suitability class. (Table 5). In the projection for 2090, it is estimated that there will be a return to the moderate suitability class, especially in the high suitability areas, and according which, *C. sativa* species will shrink in their distribution areas.

Table 5. Land status and transitions expected between 2070 and 2090 in the SSP5-8.5 scenario.

Suitability		SSP5-8.5_2090 (Area-ha)					
		Not suitable	Low	Moderate	High	Total	%
SSP5-8.5_2070	Not suitable	906028,33	5016.58	13.15		911058.07	92.60
	Low	3907.55	30698.97	3968.38	0.00	38574.91	3.92
	Moderate	7.12	3077.07	30828.68	44.43	33957.30	3.45
	High			88.92	222.04	310.96	0.03
	Total	909943.00	38792.63	34899.14	266.47	983901.24	100.00
	%	92.48	3.94	3.55	0.03	100.00	

According to the climate scenario SSP5-8.5, it is assumed that there will be a decrease and narrowing of suitable distribution areas in the horizontal distribution of the tree species *C. sativa*. It can be seen that the areas suitable for the horizontal distribution of the species are generally located in the areas up to 1000 m altitude and within the borders of Düzce province. The distribution of suitability by year is shown in Figure 7 a, b and c.

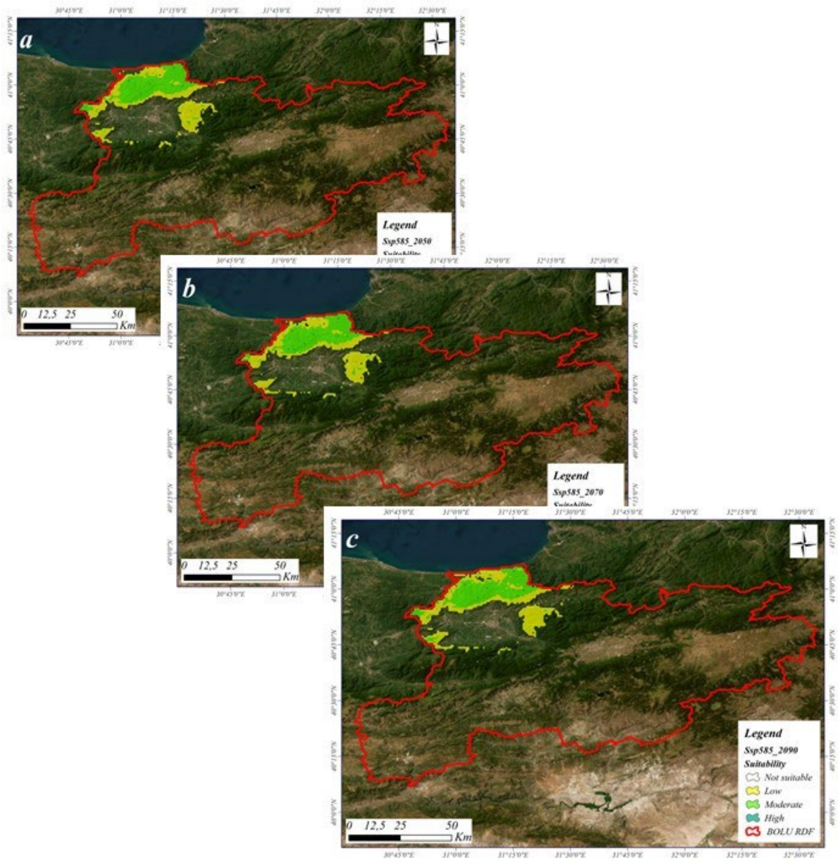

Figure 7. Habitat suitability maps of the tree species C. sativa according to SSP5-8.5 climate scenario and MaxEnt model a) 2050 b) 2070 and c) 2090.

According to the SSP2-4.5 climate scenario, not suitable areas for *C. sativa* will increase by 6681 ha to 914266.9 ha in 2050. In addition, it is estimated that 3806.56 ha of the currently unsuitable areas will move to the low suitability class and 131.9 ha to the medium suitability class. While a net decrease of approximately 8638 ha is expected in the low suitability class, it is predicted that 9754,89 ha will move into not suitable areas and 4694.51 ha will move into the medium suitability class. It is estimated that 864.59 ha of moderate suitability will be transferred to not suitable areas, 2004.87 ha to low suitability and 145.39 ha to high suitability areas. It was estimated that 234.15 ha of high suitability areas would be transformed into areas of moderate suitability (Table 6). With all these transitions and transformations, an increase of 2045.7 ha occurred only in areas of moderate suitability among the areas suitable for the tree species *C. sativa*. A decrease was expected in the areas of other suitability classes (Figure 8 a).

Table 6. Area changes and transitions between the current situation and the SSP2-4.5 scenario for 2050.

Suitability		SSP2-4.5_2050 (Area-ha)					
		Not suitable	Low	Moderate	High	Total	%
Present	Not suitable	903647.46	3806.56	131.90		907585.92	92.24
	Low	9754.89	26970.99	4694.51		41420.40	4.21
	Moderate	864.59	2004.87	31569.14	145.39	34584.00	3.51
	High			234.15	76.77	310.92	0.03
	Total	914266.94	32782.43	36629.70	222.16	983901.24	100.00
	%	92.92	3.33	3.72	0.02	100.00	

According to the SSP2-4.5 climate scenario, 3807.69 hectares of low suitability areas and 3.62 hectares of moderate suitability areas are expected to become unsuitable areas in the period 2050-2070. 7450.94 ha and 3428.52 ha areas converted to low suitability area from not suitable and moderate areas respectively. In the moderate class, it is estimated that 378.4 ha will be converted from the not suitable class, 2180.6 ha from the low suitability class and 133.3 ha from the high suitability class. As a result of all these conversions and transitions that may occur during this period, only the low suitability class is expected to increase, while the other suitability classes are expected to decrease (Figure 8 b).

Table 7. Land status and transitions expected between 2050 and 2070 according to SSP2-4.5 scenario.

Suitability		SSP2-4.5_2070 (Area-ha)					
		Not suitable	Low	Moderate	High	Total	%
SSP2-4.5_2050	Not suitable	906437.59	7450.94	378.41		914266.94	92.92
	Low	3807.69	26794.12	2180.61		32782.43	3.33
	Moderate	3.62	3428.52	33153.16	44.41	36629.70	3.72
	High			133.31	88.86	222.16	0.02
	Total	910248.90	37673.58	35845.49	133.26	983901.24	100.00
	%	92.51	3.83	3.64	0.01	100.00	

In the SSP2-4.5 climate scenario 2070-2090, 3910.19 ha of unsuitable area is projected to change to low suitability and 19.73 ha to medium suitability for C. sativa tree species distribution. It is foreseen that 6475.5 ha of low suitability areas will turn into not suitable areas and 3230.09 ha into moderate suitability areas. From the areas of moderate suitability, 7.9 ha will be converted to not suitable areas, 2825.9 ha to low suitability and 44.4 ha to high suitability. A transition of 44.4 ha from high to medium suitability was expected (Table 8).

As a result, an increase of 2553.5 ha in not suitable areas and 415.9 ha in moderate areas is expected over this period, whereas a decrease of 2969.5 ha is expected in low areas. In the high areas, no change in the total area was expected as a result of the transitions (Figure 8c).

Table 8. Land status and transitions expected between 2070 and 2090 according to SSP2-4.5 scenario.

Suitability		SSP2-4.5_2090 (Area-ha)					
		Not suitable	Low	Moderate	High	Total	%
SSP2-4.5_2070	Not suitable	906318.98	3910.19	19.73		910248.90	92.51
	Low	6475.50	27967.99	3230.09		37673.58	3.83
	Moderate	7.93	2825.93	32967.22	44.41	35845.49	3.64
	High			44.42	88.85	133.26	0.01
	Total	912802.41	34704.11	36261.46	133.26	983901.24	100.00
	%	92.77	3.53	3.69	0.01	100.00	

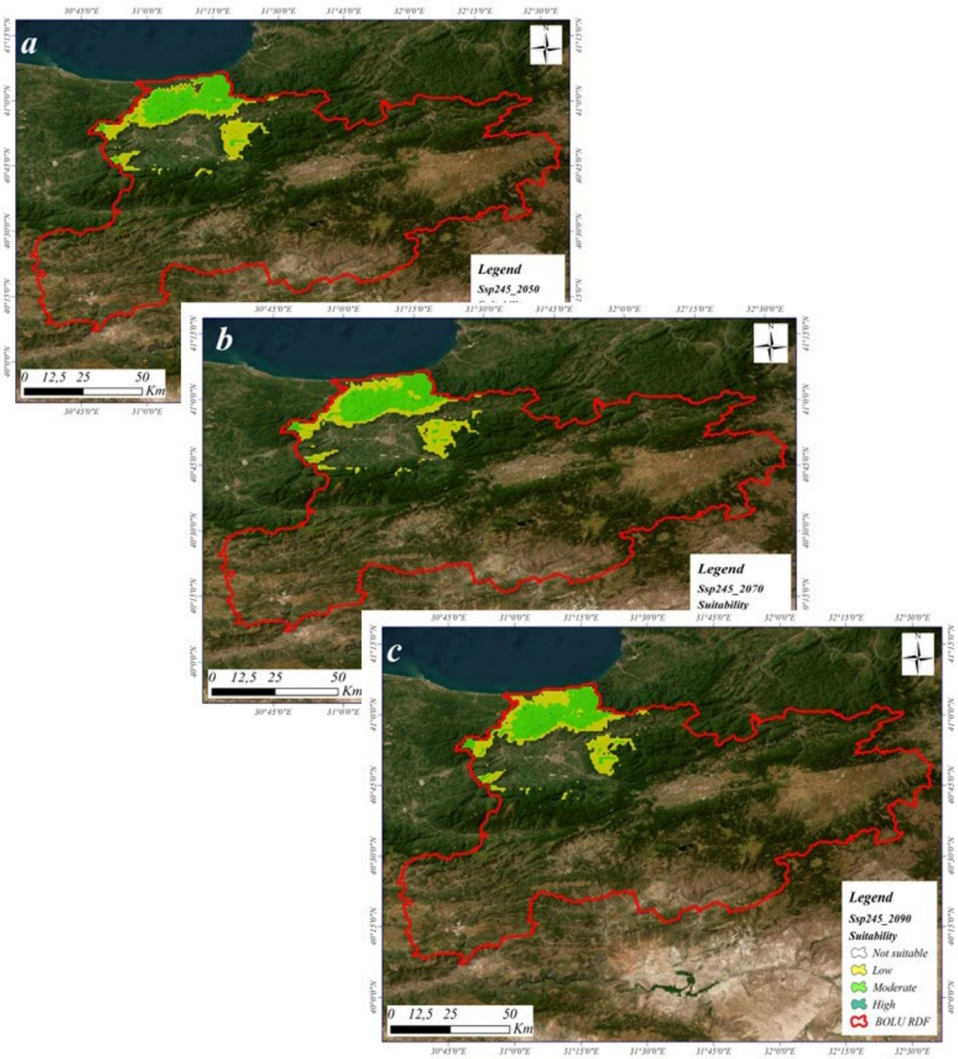

Figure 8. Habitat suitability maps of the tree species C. sativa according to SSP2-4.5 climate scenario and MaxEnt model a) 2050 b) 2070 and c) 2090.

Assessing the current situation of both climate scenarios and the projections for 2090, in the SSP5-8.5 scenario, where economic and social inequalities are evident and climate policies are limited, an increase of 2357 ha in not suitable areas and 315 ha in areas of moderate suitability is expected, while a decrease of 2627.7 ha in areas of low suitability and 44.5 ha in areas of high suitability are predicted. According to the SSP5-8.5 climate scenario, especially low suitability areas in the distribution of *C. sativa* will become not suitable areas (Table 9). In the SSP2-4.5 climate scenario, which is based on the assumption of unbalanced global development and partial implementation of climate policies, a higher increase of 2859.4 ha in not suitable areas is expected compared with the SSP5-8.5 scenario. Overall, for Ssp2-4.5, not suitable areas are expected to increase by 5216.5 ha and moderate areas by 1677.5 ha, while low suitability areas are expected to decrease by 6716.3 ha and high suitability areas by 177.6 ha (Table 9). When analysing the general table, it is estimated that the low suitability areas of the C. sativa tree species distribution areas will decrease significantly, and the high suitability areas will transition into moderately suitable areas. However, it is important to note that a significant portion of this decrease in low suitability areas shifts to moderate areas, while a larger portion shifts to not suitable areas.

Table 9. Current and 2090 land conditions and transitions according to SSP5-8.5 and SSP2-4.5 scenarios.

Suitability		**SSP5-8.5_2090 (Area-ha)**				
		Not suitable	Low	Moderate	High	Total
Present	Not suitable	902191.70	5357.18	37.04		907585.92
	Low	7115.56	29631.17	4673.66		41420.40
	Moderate	635.74	3804.28	29998.69	145.29	34584.00
	High			189.74	121.18	310.92
	Total	**909943.00**	**38792.63**	**34899.14**	**266.47**	**983901.24**
	SSP2-4.5_2090 (Area-ha)					
	Not suitable	904908.74	2660.52	16.66		907585.92
	Low	7828.84	28447.30	5144.25		41420.40
	Moderate	64.83	3596.29	30910.79	12.08	34584.00
	High			189.74	121.18	310.92
	Total	**912802.41**	**34704.11**	**36261.46**	**133.26**	**983901.24**

According to the probable distribution scenarios of the current situation and climate scenarios for the year 2090, 53 different regions in the SSP2-4.5 scenario and 52 different regions in the SSP5-8.5 scenario will move from Not Suitable to Low Suitable areas (Table 10). It is estimated that 44 different regions in the SSP2-4.5 scenario and 40 different regions in the SSP5-8.5 scenario will move from low to not suitable areas. It is predicted that 43 different areas will move from low to moderate suitability under SSP2-4.5 and 44 different areas under SSP5-8.5. From the moderate suitability areas, 45 areas were predicted to change to Low suitability areas under both scenarios. Although the same number of areas are changed, the different sizes and locations of the pieces result in different areas. In other suitability classes, transitions were expected to occur in small areas. In the SSP2-4.5, areas maintaining their current suitability status in 2090 represent 98% of the total area, whereas in the SSP5-8.5, this proportion is 97.8%. In summary, according to the scenarios, changes in suitability classes in *C. sativa* distribution areas were expected at rates corresponding to 2-2.5% of the total area. Of course, the rate of 2% may seem very low here, but in the BRDF, the proportion of areas that are not suitable at all for *C. sativa* distribution is approximately 92% (Figure 9).

Table 10. Expected land transitions according to climate scenarios.

Suitibility Transitions (Present to 2090)		SSP2-4.5		SSP5-8.5	
		Count	Area (ha)	Count	Area (ha)
Present	Not suitable to Low	53	2660.52	52	5357.18
	Not suitable to Moderate	3	16.66	2	37.04
	Low to Not suitable	44	7828.84	40	7115.56
	Low to Moderate	43	5144.25	44	4673.66
	Moderate to Not suitable	2	64.83	6	635.74
	Moderate to Low	45	3596.29	45	3804.28
	Moderate to High	1	12.08	4	145.29
	High to Moderate	5	189.74	5	189.74
	Unchange	166	964388	164	961942.72
	Total	362	983901.21	362	983901.21

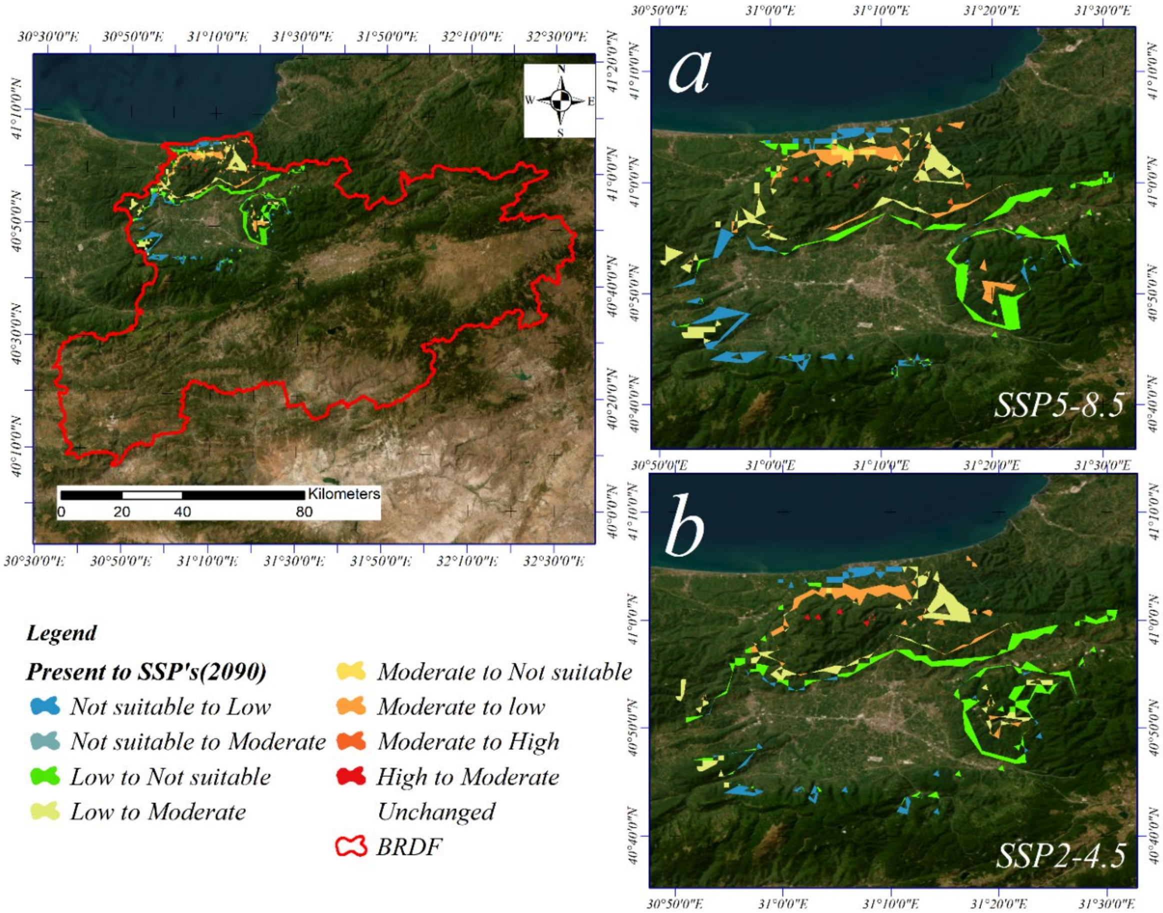

Figure 9. Changes in suitability status according to the current situation and the a) SSP5-8.5 b)SSP2-4.5 2090 scenarios.

3.4. Findings related to vertical distribution

When analyzing the vertical distribution of the tree species *C. sativa* in the BRDF, it can be seen that it extends from sea level to 1000 m altitude. In the current situation, it can be seen that areas of low and medium suitability are generally concentrated at altitudes of 0-800 m. The high suitability areas were small and were distributed between 300-800 m (Figure 10).

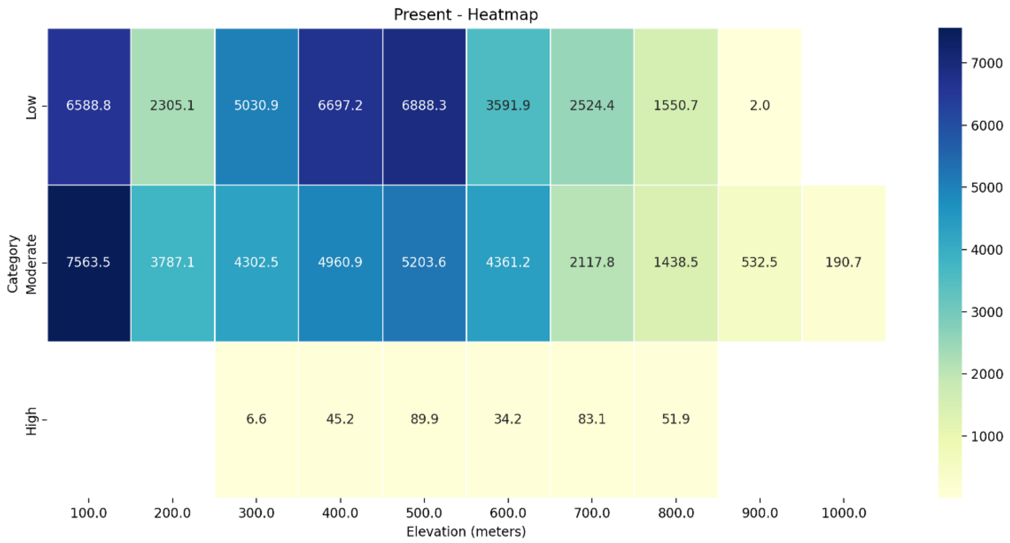

Figure 10. Current vertical distribution of C. sativa tree.

The vertical distribution in 2090 for the SSP5-8.5 climate scenario is predicted to be intensively distributed at altitudes of 0-700 metres. It is predicted that the distribution areas will increase, especially at lower altitudes, compared with the current situation. The most striking aspect of the vertical distributions in the SSP5-8.5 climate scenario is the prediction that there will be areas in the high suitability class in the 0-100 metre altitudes compared to the other scenarios and the current situation. It can also be seen that in this scenario the high distribution areas are distributed between 0-100 m, but the general distribution area is between 300-800 m (Figure 11).

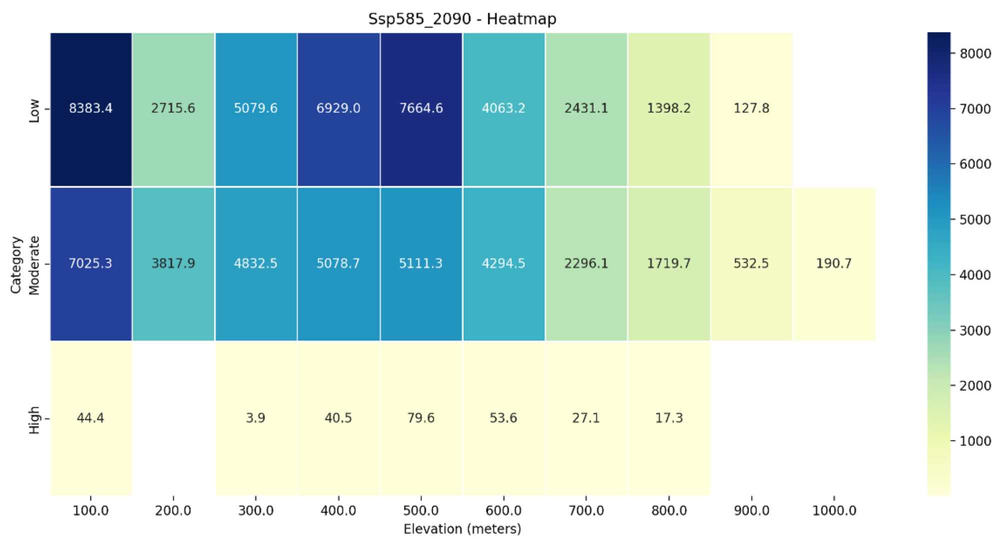

Figure 11. Vertical distribution of C. sativa tree in 2090 according to SSP5-8.5 scenario.

When analyzing the vertical distribution in 2090 for the SSP2-4.5 climate scenario, it can be seen that low and medium suitability areas are generally distributed at altitudes of 0-700 m. According to this climate scenario, although the densest area of distribution is at altitudes of 0-100 m, it is predicted to be extremely dense at altitudes of 300-600 m. In paritcular, high suitability areas are expected to be distributed at altitudes of 300-800 m, although they are distributed as small areas (Figure 12).

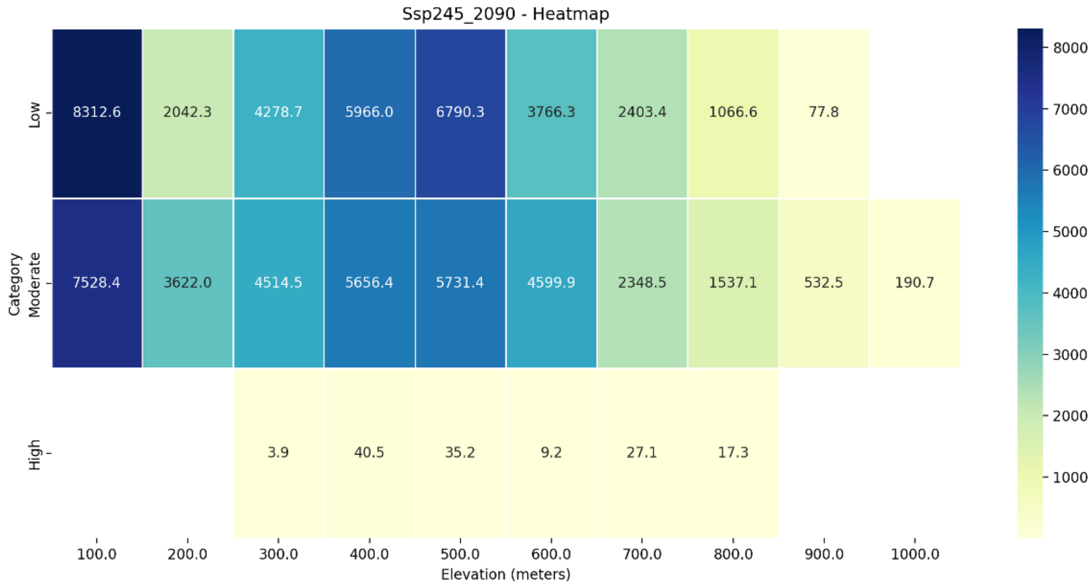

Figure 12. Vertical distribution of C. sativa tree in 2090 according to SSP2-4.5 scenario.

In terms of vertical distribution, when the current situation and the situation of the scenarios in 2090 are evaluated together, it is seen that the densest distribution areas are in areas between 0-100 meters altitude. About 1/5 of all suitable areas were distributed in areas up to 100 m. Although *C. sativa* trees are densely distributed up to an altitude of 700 m, the distribution areas decrease above 700 m. The areas with the highest suitability are currently and according to the SSP2-4.5 scenario between 300-800 m, whereas according to the SSP5-8.5 scenario, an area of 44.4 ha at an altitude of 0-100 m is estimated to have a high distribution area. Low suitability areas at 900 m are estimated to increase, although by a greater amount compared to the SSP5-8.5 scenario. It is predicted that the distribution of moderate suitability areas above 900 m will not change according to the scenarios. It is also seen that there will be a shift towards lower altitude areas over time in areas with high suitability classes. Based on the current distribution of suitable areas in terms of vertical distribution and the scenarios for the year 2090, it is estimated that *C. sativa* species will continue to spread to lower altitude areas in the following years (Table 11).

Table 11. Vertical distribution of suitability areas according to the current situation and scenarios.

Suitability		Elevation (meters)										
		100	**200**	**300**	**400**	**500**	**600**	**700**	**800**	**900**	**1000**	Total Area
PRESENT	Low	6588.8	2305.1	5030.9	6697.2	6888.3	3591.9	2524.4	1550.7	2.0		35179.1
	Moderate	7563.5	3787.1	4302.5	4960.9	5203.6	4361.2	2117.8	1438.5	532.5	190.7	34458.3
	High			6.6	45.2	89.9	34.2	83.1	51.9			310.9
	Total	**14152.2**	**6092.1**	**9340.0**	**11703.2**	**12181.8**	**7987.3**	**4725.3**	**3041.2**	**534.5**	**190.7**	**69948.3**
	Percent (%)	20.2	8.7	13.4	16.7	17.4	11.4	6.8	4.3	0.8	0.3	100.0
SSP5-8.5 2090	Low	8383.4	2715.6	5079.6	6929.0	7664.6	4063.2	2431.1	1398.2	127.8		38792.6
	Moderate	7025.3	3817.9	4832.5	5078.7	5111.3	4294.5	2296.1	1719.7	532.5	190.7	34899.1
	High	44.4		3.9	40.5	79.6	53.6	27.1	17.3			266.5
	Total	**15453.1**	**6533.6**	**9916.0**	**12048.2**	**12855.5**	**8411.4**	**4754.4**	**3135.2**	**660.3**	**190.7**	**73958.2**
	Percent (%)	20.9	8.8	13.4	16.3	17.4	11.4	6.4	4.2	0.9	0.3	100.0
SSP2-4.5 2090	Low	8312.6	2042.3	4278.7	5966.0	6790.3	3766.3	2403.4	1066.6	77.8		34704.1
	Moderate	7528.4	3622.0	4514.5	5656.4	5731.4	4599.9	2348.5	1537.1	532.5	190.7	36261.5
	High			3.9	40.5	35.2	9.2	27.1	17.3			133.3
	Total	**15841.0**	**5664.3**	**8797.2**	**11662.9**	**12557.0**	**8375.4**	**4779.1**	**2621.0**	**610.3**	**190.7**	**71098.8**
	Percent (%)	22.3	8.0	12.4	16.4	17.7	11.8	6.7	3.7	0.9	0.3	100.0

In assessing the impact of climate change on the distribution of *C. sativa* trees, particularly in the BRDF, the aim was to identify significant habitat changes by using different scenarios (SSP2-4.5 and SSP5-8.5). According to the scenario results, the not suitable areas increase to 909,943 ha in SSP5-8.5, and 912,802 ha in SSP2-4.5 by 2090. This shows that different climate scenarios can lead to conflicting results, particularly in terms of habitat suitability. In the fossil fuel dominated, high emission, climate scenario, more moderate results can be found, which is contrary to the expectations of climate change research. However, in these studies, it was more appropriate to evaluate the habitat suitability conclusions of climate change scenarios in the context of their associated environmental impacts (Gustafson et al., 2022; Sandercock et al., 2024). Hattab et al. (2014) found that the combination of climate change and habitat loss scenarios significantly altered species distributions. They also emphasized that habitat loss may occur even under low emission scenarios, which may negatively affect species richness. However, the magnitude and nature of these effects are complex and vary depending on the specific scenario (Hattab et al. 2014). Preston (2006) examined the impact of climate change on existing habitat loss and found that it was difficult to reduce existing habitat loss, even under low emission scenarios. This indicates that even low emission targets may not be sufficient to reduce habitat loss (Preston, 2006). Another study by Wilson et al. (2012) found that considering factors such as climate change and habitat loss together can reduce the risk of species extinction, and if these two threats are not addressed together, there will be great difficulties in conserving species (Wilson et al., 2012). In another study, Travis (2003) emphasised that climate change and habitat loss are interacting factors (Travis, 2003). Changes in species distribution and suitable habitats under current climate scenarios show the negative consequences of this interaction.

There were very small changes between 2050 and 2090 in the areas predicted to be highly suitable under the SSP5-8.5 climate scenario. This indicates that the scenario maintains relatively stable conditions. In contrast, areas of high suitability are expected to decrease in the SSP2-4.5, where habitat changes are predicted under low greenhouse gas emission scenarios (Stanton-Jones and Alexander, 2024; Martín et al., 2010). The SSP5-8.5 scenario showed some resilience in highly suitable habitats, suggesting that some ecoregions may be better able to withstand climate change (Sandercock et al., 2024). In moderately suitable areas, SSP2-4.5 is spread over a larger area than SSP5-8.5, and it has a greater capacity to support moderately suitable habitats. This suggests that although SSP2-4.5 performs poorly in high suitability areas, it has the potential to provide the flexibility needed for species that require such habitats under changing climatic conditions. Many studies have highlighted that moderately suitable habitats are essential for biodiversity conservation (Portela et al., 2014; Sohn et al., 2016). The results of this study highlight the need for targeted adaptation strategies in forest management, especially in areas with high habitat concentrations of moderate and low suitability. Increasing conservation efforts in these critical areas will increase resilience to adverse climate impacts and facilitate species migration and adaptation (Tabor et al., 2018). As studies in different regions hav shown, climate-induced changes highlight the increasing need to address habitat fragmentation and ensure the long-term sustainability of adapted plant communities (Petford and Alexander, 2021).

The results of this study showed that the SSP5-8.5 scenario was relatively more successful in conserving high suitability *C. sativa* habitats, whereas the SSP2-4.5 scenario was more successful in conserving moderately suitable habitats. The SSP2-4.5 medium and low emissions scenario is estimated to increase global temperature by approximately 2.0-3.0°C by 2090, while the SSP5-8.5 high emissions scenario is estimated to increase global temperature by about 4.0-5.5°C. This means that temperature increases are tolerable for *C.*

sativa, but warmer summers may lead to increased water stress and reduced survival (Conedera et al., 2021). The predicted reductions and changes in habitat suitability for *C. sativa* are consistent with the results of previous studies on this species. Atalay Dutucu (2023) modelled the distribution of *C. sativa* for the Anatolian region and its surroundings for the period 2081-2100. According to the results, it is predicted that there will be a decrease in areas with the highest habitat suitability and an increase in not suitable areas, especially in the SSP2-4.5 and SSP5-8.5. In the study by Sarıkaya and Orucu (2019), it is estimated that the potential suitable areas of *C. sativa* will decrease and reach critical ratios depending on RCP4.5 and RCP8.5 scenarios for the period 2050-2070. In addition, Cedano Giraldo and Küçüker (2023) modelled the future distribution of *C. sativa* for the years 2061-2080 under SSPs 1-2.6, 2-4.5 and 5-8.5 within the boundaries of the Trabzon Regional Directorate of Forestry using the predictions of the Hadley Centre Global Earth Model HadGEM-GC31-. According to the model results, there was a significant decrease in the suitable areas for *C. sativa*.

4. Conclusions

This study, which shows the effects of climate change on the potential distribution of *C. sativa* habitats under different SSP scenarios, highlights the need to consider multiple environmental factors when assessing the ecological potential. The results of the study show that areas of high suitability show very little change in the high emissions scenario (SSP5-8.5), but these areas are significantly reduced in the medium emissions scenario (SSP2-4.5). These contradictory results show the complexity of climate-induced changes in habitat areas and the possibility of nonlinear responses in ecological systems. An increase in not suitable habitats was expected under both scenarios, indicating the inevitability of climate change in habitats. However, the diversity of areas of high and moderate suitability under different climate scenarios indicates that conservation strategies should not be based solely on reducing emissions, and that habitat-specific adaptations should also be considered. The conservation of high suitability areas in the SSP5-8.5 scenario shows that ecological and topographical factors have a positive effect on coping with climate change. Despite the overall loss of habitat suitability, some ecological habitats can thrive, even under extreme climatic conditions. However, the reduction in habitat area associated with the SSP2-4.5 scenario shows that severe habitat fragmentation and loss can occur even under the moderate emissions and climate change scenarios. The larger the area of habitat of moderate suitability, the greater the capacity of these areas to act as transition zones and facilitate more rapid adaptation to climate change.

The results of this study highlight the need for greater consideration of climate change strategies in forest management and conservation planning. Given the expected habitat loss and changes, it is important to consider and implement measures that complement strategies, such as assisted migration, habitat restoration, and improving ecological connectivity. In addition, the high level of agreement with previous studies on climate-based habitat modelling demonstrates the validity of these predictions. Future research is extremely important, and habitat models should be improved, especially those that include ecological variables, such as soil structure, competition, and natural disturbance. In addition, the development of holistic strategies that combine ecological modelling, land-use planning, and economic components is essential to cope with the effects of climate change and conserve biodiversity.

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