New Forests (2025) 56:25
https://doi.org/10.1007/s11056-025-10092-y

RESEARCH

Prediction of the shift of the distribution of *Pinus brutia* Ten. Under future climate model

E. Seda Arslan[1,2] · Ömer K. Örücü[1] · Süleyman Gülcü[3] · Samet Dirlik[4] · Ecem Hoşgör[5]

Received: 3 May 2024 / Accepted: 11 January 2025 / Published online: 24 January 2025

Abstract
This study uses presence data and bioclimatic variables to predict distribution areas of the *Pinus brutia* Ten., the pine species with the most significant natural distribution in Turkey. The modeling was performed using the SSP2-4.5 and SSP5-8.5 scenarios based on the HadGEM3-GC31-LL model, both current and future distributions. In addition, change analysis was conducted to determine the changes that will occur over the years in the potential distribution areas of the species. In addition to bioclimatic variables, the model incorporated elevation, NDVI, human footprint, slope, and aspect as environmental layers. The model's performance was evaluated to determine its effectiveness, and the values in the area under the curve (AUC) from the receiver operating characteristics (ROC) were analyzed. A Jackknife test was conducted to assess the contribution of each variable included in the study to the model's performance. The study found that, the SSP2-4.5 scenario shows a slight increase in suitable areas over time, with "not suitable > suitable" regions increasing from 8.91 to 9.11%, while the SSP5-8.5 scenario indicates a net gain of suitable areas by 1.07% despite a 1.94% increase in unsuitable areas from 2081 to 2100. Consequently, Red Pine might experience less competition and have better expansion opportunities.

Keywords *Pinus brutia* Ten. · Climate change · Species distribution model · MaxEnt

E. Seda Arslan
sedaarslan@sdu.edu.tr

Ecem Hoşgör
ecembhosgor@gmail.com

1 Faculty of Architecture Department of Landscape Architecture, Süleyman Demirel University, Isparta, Turkey

2 Süleyman Demirel University Center for Water Resources of Lakes Region, Isparta, Turkey

3 Isparta University of Applied Sciences Faculty of Forestry, Isparta, Turkey

4 Isparta University of Applied Sciences Atabey Vocational School, Isparta, Turkey

5 Ankara University, Ankara, Turkey

Introduction

Climate encompasses the long-term weather patterns of a region, acting as a primary driver of species distributions by influencing their physiological limits and shaping the ecosystems they inhabit (Thomas 2010). Climate change, driven by human activities, is causing significant alterations to these patterns, leading to shifts in species ranges and potential disruptions to ecological communities (Thomas 2010). It is widely recognized as the preeminent environmental issue of our time (Huggel et al. 2022), manifesting as shifts in average temperatures, altered precipitation regimes, and increased frequency of extreme weather events (Misiou and Koutsoumanis 2022; IPCC 2022b). These changes impact the living conditions of all organisms, threatening the ecological and biological assets of natural ecosystems (Barik et al. 2023; Pecchi et al. 2020). As forest ecosystems play a crucial role in mitigating these impacts (Bellard et al. 2012; IPCC 2022a). Understanding how tree species distributions might respond to future climate change is essential for developing effective conservation strategies.

According to the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC), temperatures are rising on a global scale (IPCC 2022a). In addition to adversely impacting species distributions, climate change—the most significant environmental challenge we face today—threatens both species and genetic diversity, putting many species at risk of extinction (HamadAmin and Khwarahm 2023; Zhao et al. 2020). The increasing global temperatures could result in the extinction of crucial species native to forest regions (Friend et al. 2014). In these circumstances, it is crucial to identify the changes species may undergo due to the likely impacts of global warming, in order to develop sustainable strategies for their conservation and prevent their extinction (Ncube et al. 2020). Turkey, distinguished by its diverse climatic and ecological attributes, serves as the natural habitat for flora from three significant phytogeographical zones: Mediterranean, Euro-Siberia, and Irano-Turanian (Sıvacıoğlu and Öner 2010; Türkeş 1998). Semi-humid Aegean and Mediterranean regions, which lack sufficient water, are expected to be among the worst affected by the rise in temperature (Sıvacıoğlu and Öner 2010; Türkeş 1998).

Mediterranean forests offer numerous essential ecosystem services and goods that are crucial for human societal resilience. Therefore, protecting them from the impacts of climate change is vital (Mechergui et al. 2021). Species in Turkey will respond in various ways and to different extents to changes in climate and shifts in climatic regimes—such as precipitation, evaporation, and temperature patterns—which is likely to disrupt the structure, composition, productivity, and geographical distribution of many ecosystems (Kumar 2012; Marchant and Hooghiemstra 2004; Y. L. Wang 2012). The evolution and growth of trees, species distributions, seasonal variations, invasive species issues, and the relative decline or even extinction of specific species are all considered as consequences of climate change (IPCC 2022a). However, most of these ecological changes may only become visible in the decades and centuries following climate change (Chiarenza et al. 2023; Neale et al. 2023).

It is possible to identify potential distribution areas of a species by machine-learning methods and bioclimatic data (Arslan et al. 2020; Climent et al. 2021). Several species distribution models (SDMs) are used to predict distribution areas or understand ecological issues. Forest management strategies can be more realistic using climate-based SDMs to understand which tree species will tolerate the effects of climate change (Sandoval-Martínez et al. 2023). Recent studies evaluating species distribution models (SDMs) confirm that flexible, nonparametric algorithms like MaxEnt, Random Forest (RF), and Boosted Regression Trees (BRT), which deliver high AUC scores and spatial adaptability crucial for mapping species under climate variability, consistently outperform simpler traditional regression-based methods such as Generalized Linear Models (GLM) and Generalized Additive Models (GAM) in presence-only data scenarios (Ahmadi et al. 2023; Yudaputra, Astuti, and Cropper 2019; Valavi et al. 2023). To control model complexity and prevent overfitting, MaxEnt employs regularization parameters such as feature classes and regularization multipliers to reduce biases in occurrence datasets effectively and makes geographic extrapolation easier (Amindin et al. 2024; Valavi et al. 2021; Soley-Guardia, Alvarado-Serrano, and Anderson 2024). This capability is crucial for species with restricted distributional data. For this reason, the MaxEnt program was employed in the present study.

According to Turkey's forest inventory data, the Turkish Red Pine *(Pinus brutia* Ten.*)* is the species that have the most extensive distribution in Turkey, with a natural distribution over 5.215.292 hectares. The species accounts for almost 40–50% of the afforestation work carried out in the country (OGM 2021). A member of the Pinaceae family, the *Pinus brutia* Ten. is naturally distributed in Turkey, Greece, Syria, Lebanon, Iraq, and Cyprus where the Mediterranean climate predominates with its arid, semi-arid, humid, and semi-humid characteristics (Yaltırık and Efe 2000). The species is also encountered in certain parts of the Western Black Sea region which have microclimates that show similarities with the Mediterranean climate. Also, its high-quality timber, rapid growth, and resilience to drought, the many uses of its wood, the limited demands it makes on its surroundings, its ability to resist fires, and other similar qualities have made the *Pinus brutia* Ten. one of the most used species in afforestation efforts in Turkey (Öktem 1987; Yaltırık and Boydak 1993).

Despite the critical role of *Pinus brutia* Ten. in Turkey's forest ecosystems, there is limited knowledge on how its distribution might shift under future climate conditions, especially in response to diverse climate scenarios. This study fills a gap by using species distribution modeling (SDM) to provide high-resolution projections of *Pinus brutia* Ten.'s potential habitat across varying climate futures. This study intends to map current and projected distributions using the MaxEnt algorithm and climate data. This will provide new information on species resilience in the Mediterranean and semi-humid Aegean regions most vulnerable to climate impacts.

The species' distribution areas were modeled for 2041–2060 and 2081–2100 under SSPs scenarios. The research questions are as follows:

1) What is the current and future potential distribution of *Pinus brutia* Ten in Turkey?
2) How can the future distribution of *Pinus brutia* Ten. be altered?

Materials and methods

Occurrence and environmental data

The coordinates of 108 points selected to represent the natural geographical distribution area of the *Pinus brutia* Ten. in Turkey were obtained from the Biological Diversity and Non-Wood Forest Products Database, GBIF, and previous literature records (OGM 2021; Davis 1965; GBIF 2024). These points were then indicated in the WGS84 coordinate system using Google Satellite Hybrid base maps with a high spatial resolution of 5 m to clarify the presence data accuracy accessed in ready form via the latest version of the QGIS program, version 3.34.11 (QGIS 2024) (Fig. 1).

The WorldClim version 2 database was used to model the current and predicted potential distribution areas for the future (Fick and Hijmans 2017). The bioclimatic variables with a spatial resolution of 30 s (about 1 km^2), Wordclim data, and Digital Elevation Model (DEM) obtained with the exact resolution used to identify the current distribution were downloaded from https://worldclim.org/data/bioclim.html (Hijmans et al. 2005). The slope and aspect were created from the DEM and used as an environmental layer. Accordingly, the human footprint map was used to develop the prediction model. These maps provide insights into human pressures, aiding in monitoring environmental changes and highlighting factors that can disrupt ecological systems (Venter et al. 2016; Örücü et al. 2023). The human footprint data was sourced from the NASA Socioeconomic Data and Applications Center (SEDAC) in GeoTIFF (.tif) format, featuring a resolution of 1 km² (Venter et al. 2018). In addition, the Normalized difference vegetation index (NDVI) was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) and used to improve the model.

The latest version of HadGEM, the HadGEM3-GC31-LL climate model, was used to predict *Pinus brutia* Ten's future distribution area. The present study uses SSPs climate change scenarios referred to in the AR6 for potential future predictions of the species. According to the purposes of the study, the SSP2-4.5 and SSP5-8.5 scenarios for the periods 2041–2060 and 2081–2100 were selected.

Modelling

To resolve the issue of multicollinearity (Zhang and Liu 2017), R was used to apply the Pearson correlation test to 19 bioclimatic and environmental variables for the presence data and background locations. Based on the result of this test, one of those variables with a correlation coefficient of (r) ± 0.8 was removed from the model (Cao et al. 2016; Yang et al. 2013) according to the ecological relevance.

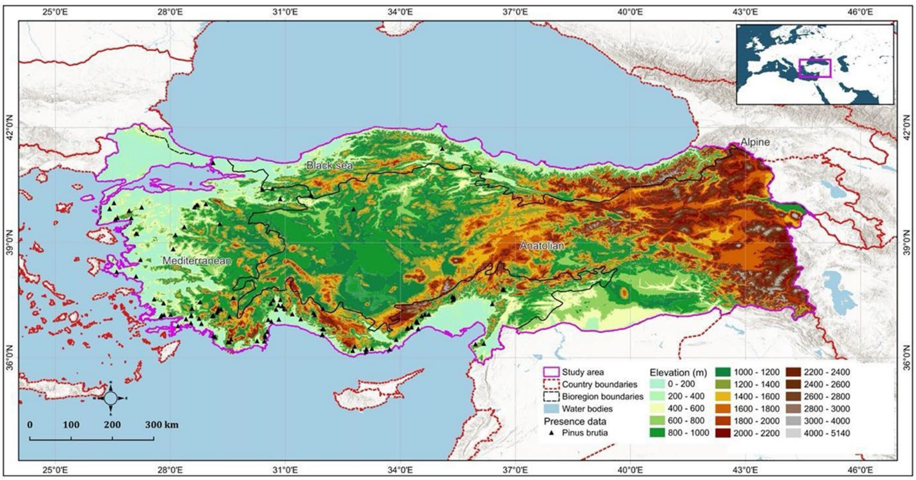

Fig. 1 Study area and presence data for the species

MaxEnt 3.4.1 version was performed with the occurrence data of *Pinus brutia* Ten. The random test percentage was defined as 25% (27 items), and the training data represented 75% (81 items) of the occurrence data. The replicated run type was chosen as a 'crossvalidate'. The number of replicates was set as 10. 'Linear,' 'quadratic,' threshold, and 'hinge' modeling procedures using 10,000 background points as random selection to create the best performance to model current and future distribution (Barry and Elith 2006; Pearson et al. 2007; Elith et al. 2011). Response curves were created, and the regularization multiplier value was set as 0.5. The model's performance was evaluated to determine its effectiveness, and the values in the area under the curve (AUC) from the receiver operating characteristics (ROC) were analyzed (Y. Wang et al. 2007). The AUC value derived can be interpreted as the estimated probability of selecting a random grid cell within a properly adjusted model. AUC measures model success across thresholds. If AUC > 0.5, it outperforms random estimation (Phillips and Elith 2010). AUC values closer to 1 indicate better model sensitivity and separation (Zhao et al. 2018). AUC ≥ 0.9 shows excellent performance, 0.9 > AUC ≥ 0.8 signifies good performance, and AUC < 0.8 reflects poor performance (Gassó et al. 2012; Çoban, Örücü, and Arslan 2020). In this study, the Jackknife Test, which enables assessing the significance levels for each independent variable, was used to assess the contributions of various environmental variables (Shcheglovitova and Anderson 2013).

The presence of a species is indicated by a value between 0 and 1 for the prediction model. The value is closer to 1 represent the higher potential habitat for the species in the area. Choosing thresholds involves three factors: discriminative capacity, comparability, and objectivity, as exemplified by prediction studies rely on specificity, sensitivity, and mission error to set thresholds, with current errors including omission and commission, while the former excludes commission errors. The current has been performed by the MTTS (maximum training sensitivity plus specificity) corporate with three factors of criteria selection (Bai et al. 2022; Liu et al. 2019). MTTS, projected area, threshold value, and balance training omission were applied to reclassify the MaxEnt outputs into not suitable and suitable habitats using the 'Reclassify tool' of 3.34.11 software. Then, the current and future optimal habitats were examined as km^2 under the climate change scenarios. In the potential distribution maps developed for the present and the future, the areas were classified according to their suitability for the distribution of the species as represented in MTTS.

Change analysis was conducted to compare the current potential distribution area with the predicted distribution areas using the intersection tool of QGIS 3.34.11 software. Distribution areas were calculated in km^{2,} and change maps were created. In this way, the extent and direction of the changes in the predicted distribution areas were calculated by comparing them against current suitability.

Results and discussion

According to the Pearson correlation test, BIO3, BIO7, BIO8, BIO10, BIO16, BIO17, BIO 18 and elevation, aspect, slope, NDVI and human footprint were used in the model (Fig. 2).

In Fig. 3, the AUC values indicate that the training data achieved a high result of 0.968, while the test data yielded an acceptable score of 0.931. This suggests that the model is both sensitive and descriptive.

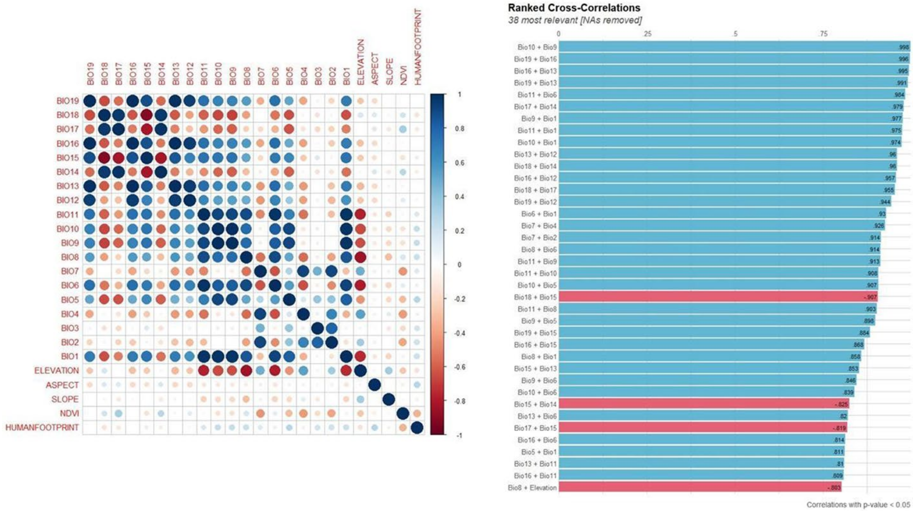

Fig. 2 Correlation matris and ranked cross-correlation for *Pinus bruita* Ten

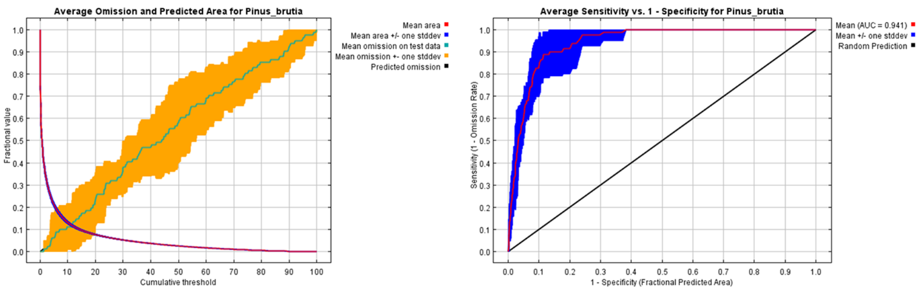

Fig. 3 Average omission and reliability of the prediction of *Pinus brutia* Ten

Table 1 presents the replicated MaxEnt model results, including training and test data metrics, as well as the MTTS values. The MaxEnt model was executed with 10 replicates for *Pinus brutia* Ten., and the results were averaged to minimize variability and provide robust predictions.

Figure 4 illustrates that the Jackknife test demonstrates the annual temperature range (BIO7) achieved the most substantial gain when considered independently. As a result, it is regarded as the most informative variable. On the other hand, the environmental variable that most significantly reduces the gain when excluded is NDVI, suggesting it holds unique information not captured by other variables.

The model results show that MTSS was calculated as 0.108 for the thresholds for identifying suitable and not suitable habitats for *Pinus brutia* Ten. The suitable habitat is 1–0.108, the not suitable habitat is 0.108–0. The predicted current potential distribution map for the *Pinus brutia* Ten. is shown in Fig. 5A. An analysis of the current distribution map derived from the model outputs indicates a strong resemblance to natural distribution areas. (https:

Table 1 Replicated MaxEnt results values

Replicates	Training AUC	Test AUC	MTSS
1	0.9673	0.9521	0.087
2	0.9692	0.9444	0.101
3	0.9673	0.9379	0.0934
4	0.9672	0.9664	0.1425
5	0.9674	0.954	0.106
6	0.9725	0.8673	0.1057
7	0.967	0.9444	0.0928
8	0.9673	0.9582	0.1006
9	0.9668	0.9522	0.1285
10	0.967	0.9317	0.124
Average	0.9679	0.9409	0.1082

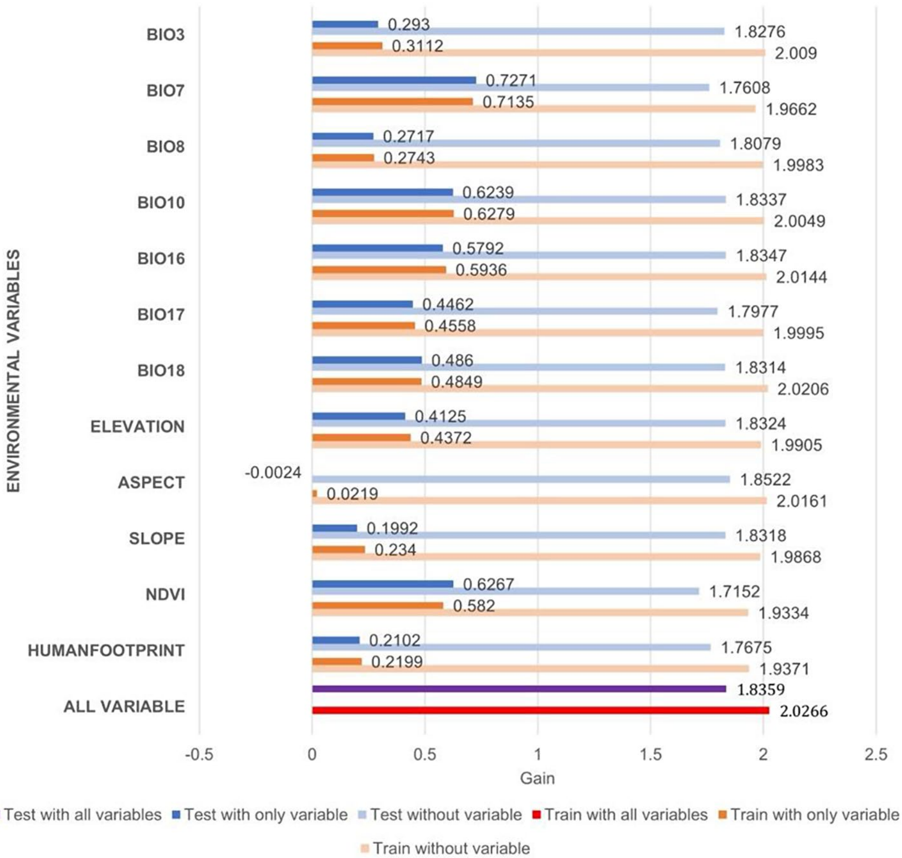

Fig. 4 Jacknife graph

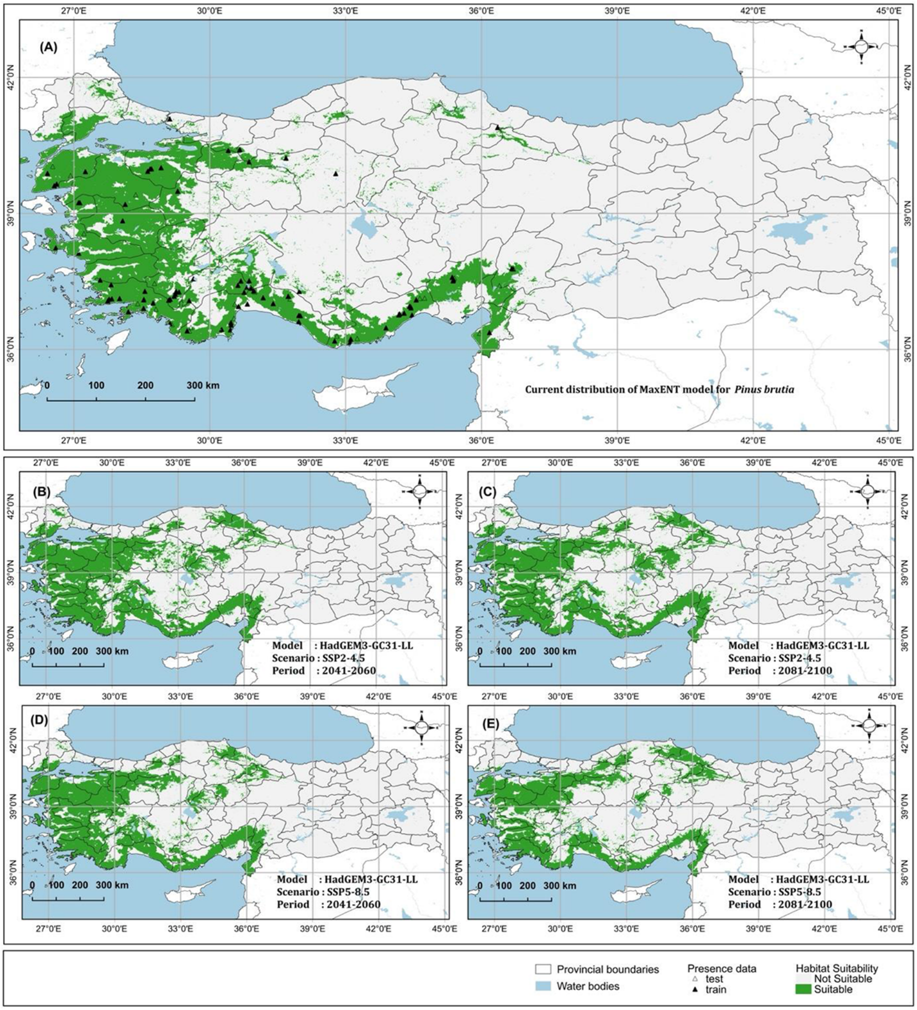

Fig. 5 Current and future potential distribution areas of *Pinus brutia* Ten

//www.euforgen.org/species/pinus-brutia/). Indeed, the distribution of *Pinus brutia* Ten. in Turkey is observed to extend across extensive territories.

Examining the predicted geographical distribution illustrated in the model maps for SSP2-4.5 during 2041–2060 (Fig. 5B) and 2081–2100 (Fig. 5C). The prediction indicates that the distribution of the species is projected to expand towards the north, whereas suitable habitats in the western region are likely to diminish. Currently, identified suitable areas, encompassing an expanse of 130,333 km^2, are projected to increase to 191,562 km^2 by 2060. However, it is anticipated that these areas will subsequently decrease to 186,310 km^2 by 2100 under the SSP2-4.5 scenario.

In the context of the SSP5-8.5 scenario, Fig. 5D illustrates the period spanning from 2041 to 2060, whereas Fig. 5E depicts the time frame from 2081 to 2100. The areas classified as suitable are estimated at 180,650 km^2 for 2041–2060 and 157,031 km^2 for 2081–2100.

Figure 6 shows the current and future distribution areas as percentages. The graph demonstrates that the suitable areas are projected to expand in alignment with climate change scenarios over time. Whereas, when examining suitable areas in the future, a reduction is anticipated between the years 2081 and 2100.

In summary, projections indicate that the distribution area of the species is expected to expand relative to the currently suitable regions under the climate change scenarios. Conversely, it appears that the areas deemed unsuitable will encompass a larger expanse under the SSP5-8.5 scenarios during the periods of 2081–2100. Predictions indicate that the appropriate areas are projected to shift northward under climate change conditions.

Change analysis

The results illustrate the magnitude and direction of the anticipated alterations in the projected potential distribution of the species for the periods from 2041 to 2060 and from 2081 to 2100 under the SSP2-4.5 and SSP5-8.5 climate change scenarios (Fig. 7). The calculations for the period between 2041 and 2060 under the SSP2-4.5 scenario indicate a gain of 69,552 km², coupled with a loss of 8,323 km². Similarly, from 2081 to 2100, there is a reported gain of 71,103 km² and a loss of 15,127 km².

The calculations for the period between 2041 and 2060 under the SSP2-8.5 scenario indicate a gain of 60,456 km², coupled with a loss of 10,140 km². Similarly, from 2081 to 2100, there is a reported gain of 55,488 km² and a loss of 28,791 km².

Figure 8 illustrates the percentage change across all climate change scenarios and time frames. For the SSP2-4.5 scenario, the regions classified as "not suitable>suitable" increased from 8,91% during 2041–2060 to 9.11% in 2081–2100. Additionally, the "suitable>not suitable" areas rose from 1.07% in 2041–2060 to 1.94% in 2081–2100. In the SSP5-8.5 scenario, the areas gained between 2041 and 2060 account for 7.75%, while the areas lost a total of 1.30%. When examining the period from 2081 to 2100, the increase in unsuitable areas is 3.69%, compared to a gain of 7.11%.

The climate models used in this study predict a rise in surface temperatures of 3.8–4.2 °C under the SSP2 scenario and 4.7–5.1 °C under the SSP5 scenario by 2100 (Riahi et al. 2017). This further emphasizes the importance of temperature variations in influencing

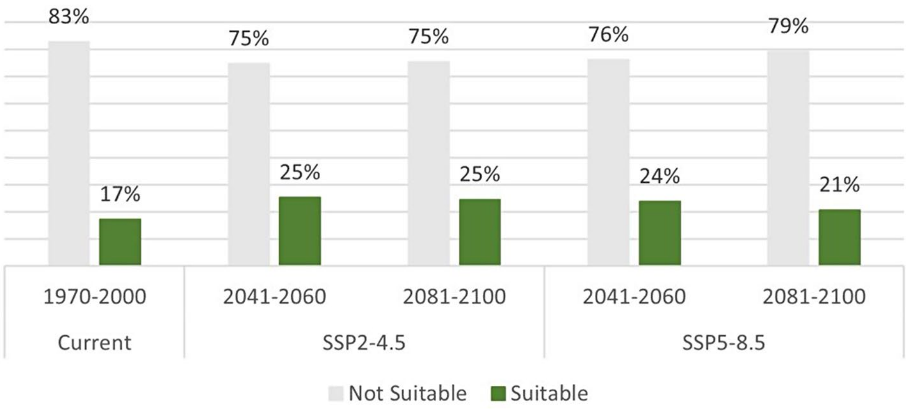

Fig. 6 Current and future distribution areas of *Pinus brutia* Ten. (%) according to climate change scenarios

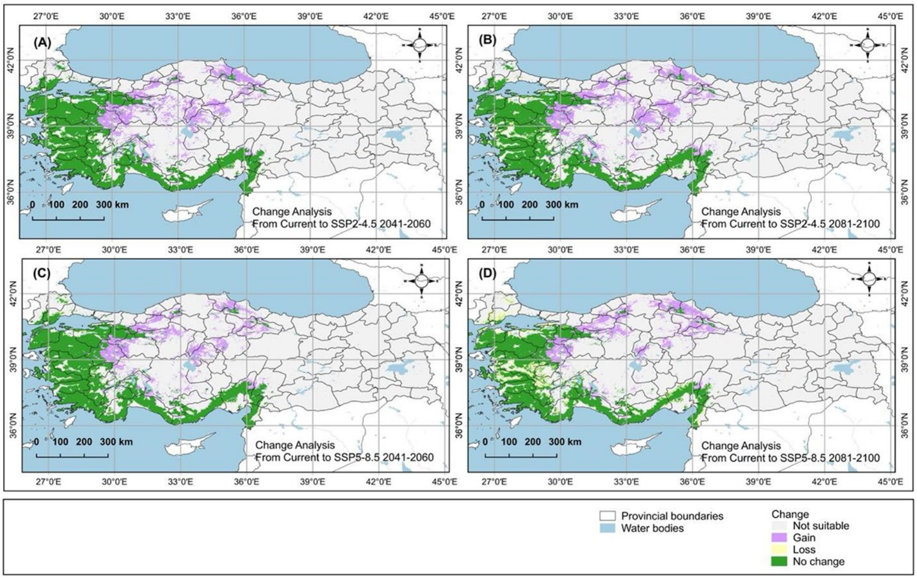

Fig. 7 Changes between the predicted distribution areas of *Pinus brutia* Ten. (**A**) 2041–2060 (**B**) 2081–2100, SSP2-4.5 scenario (**C**) 2041–2060 (**D**) 2081–2100, SSP5-8.5 scenario

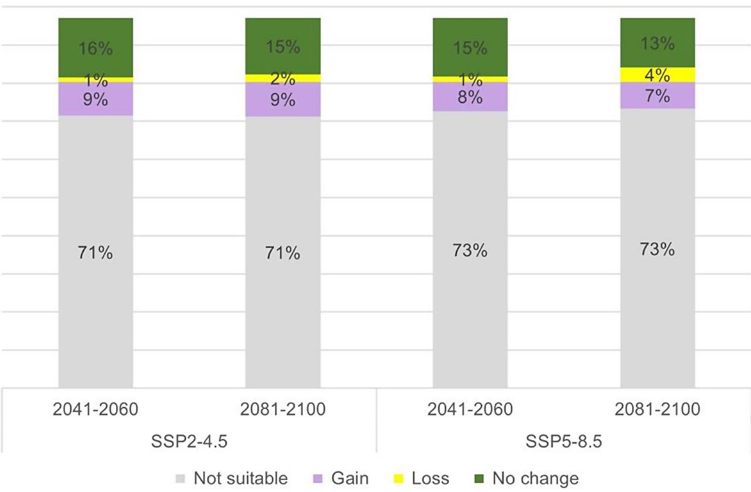

Fig. 8 Changes in *Pinus brutia* Ten. The area between current, 2041–2060, and 2081–2100 under SSP2-4.5 and SSP5-8.5 scenarios (%)

shifts in species distribution. A related study indicated that by 2050, there will be a significant reduction in the Turkish Red Pine, Cedar, Black Pine, and Juniper found in the Seyhan Basin (Zeydanlı et al. 2011). According to the findings of the community models examined by Yalcin (2012), the regions that are climatically suitable for *Pinus brutia* Ten. are projected to migrate toward the northern and northeastern areas of Turkey. Furthermore, it is anticipated that a substantial proportion of the current habitats of *Pinus brutia* Ten. could become unsuitable in the future, and climate change is expected to impact the *Pinus brutia* Ten. forests in Turkey profoundly.

P. asperata will move northward from its present distribution area, whereas *P. chinensis* will have a small effect on Yuan et al. (2022) predicted the future distribution of two *Pinus* species: *P. asperata* and *P. chinensis*. Their research indicated that *P. asperata* is expected to migrate north from its current range, while *P. chinensis* will experience minimal changes to its distribution due to climate change effects. Martinez-Sifuentes et al. (2020) noted in their study that the conservation of *P. greggii* populations is vital for in situ restoration efforts under future climate conditions, as projected by the HadGEM2-ES climate model. Additionally, a study by Petrenko et al. (2022) examined the potential future impacts of climate change on *Pinus koraiensis*, revealing that optimal conditions for this species may disappear in various parts of its distribution under both pessimistic and optimistic climate scenarios. This study is consistent with prior research regarding plant migration due to global warming (Abdelaal et al. 2019; Arslan et al. 2020; Li et al. 2020). These studies indicate that plants are likely to migrate to higher latitudes and altitudes. Likewise, our research suggests that *Pinus brutia* Ten. habitat changes are likely to occur in the mountainous areas to Turkey's north, west, and east.

Finally, it is essential to recognize the assumptions and limitations inherent in SDMs when interpreting these results. For instance, SDMs generally assume that species are in equilibrium with their current environments, potentially leading to lag effects where actual distributions do not reflect environmental suitability (Schatz, Kramer, and Drake 2017). Additionally, the exclusion of biotic interactions—such as competition and predation—can significantly impact species distributions, as these models often focus solely on abiotic factors (Kissling et al. 2012). The accuracy of SDM outputs heavily depends on the quality of input data; biased or incomplete occurrence data can result in misleading predictions (Soley-Guardia, Alvarado-Serrano, and Anderson 2024). Furthermore, predicting distributions under novel environmental conditions can yield unreliable projections, particularly when extrapolating beyond the training data's range (Porfirio et al. 2014). Lastly, many SDMs assume unlimited dispersal capabilities, disregarding geographic barriers and species' inherent limitations in tracking suitable habitats, which can lead to underestimations of habitat loss (Thomas 2010).

Conclusions

The analysis includes predictions for the years 2041–2060 and 2081–2100, revealing that the potential natural distribution areas of *Pinus brutia* Ten. are expected to expand significantly. The maximum entropy method has revealed important insights into this species' potential adaptations to shifting climate conditions. Considering these predictions, it becomes crucial to focus on the ecological sustainability of the species. To safeguard the continued existence of *Pinus brutia* Ten., carefully examining the intersections between current and future habitats. Identifying populations and genotypes that are most resilient to potential climate changes can support conservation efforts. In-situ and ex-situ gene conservation techniques should be employed as precautionary measures to ensure the species' survival.

A combination of factors may explain the spread of red pine to a larger area in Turkey between 2041 and 2060. Rising temperatures and improved climatic conditions are among the crucial drivers of this change. In the SSP2-4.5 scenario, rising temperatures from 2041 to 2060 may create favorable conditions for red pine to thrive in areas that once experienced colder or more restrictive climates. This species can adapt to warm climates, and increasing temperatures may expand its range.

The potential for dispersal in high altitudes and inland areas might influence its distribution. Rising temperatures may enable red pine to expand into higher altitudes and cooler regions of Turkey's interior. Currently, these areas have restricted ranges because of unfavorable climate conditions. Nonetheless, anticipated temperature rises could enhance the suitability of these regions for red pine.

In the SSP2-4.5 scenario, changes in precipitation patterns may occur in the Mediterranean region and Turkey. Red pine, known for its resilience to arid and semiarid environments, is likely to adapt more effectively to heightened drought and shifting precipitation distribution. As a result, more sensitive species could face decline or displacement, while red pine may expand its distribution area.

Furthermore, red pine is a fire-resistant species that regenerates well after fires. With climate change likely escalating the frequency and intensity of fires, creating, more prominent openings in burned areas could enhance opportunities for red pine to establish itself in these spaces.

Climate change could hinder the survival of certain tree species or restrict their distribution. Consequently, red pine might experience less competition and have better expansion opportunities. Species more vulnerable to rising temperatures and drought conditions may find themselves at a disadvantage compared to red pine. In summary, this study highlights the possible challenges *Pinus brutia* Ten. might encounter over the next few decades due to climate change. By gaining insight into the expected changes in the species distribution and emphasizing ecological conservation, we can strive to alleviate the impacts and maintain the natural diversity of this important tree species.

Author contributions E.S.A. has performed the first draft of the manuscript with S.D. S.G. and Ö.K.Ö. performed data collection and analysis, created maps, and calculated the results. E.S.A., Ö.K.Ö. and E.H. improved the structure and revised the manuscript. All authors reviewed the manuscript.

Funding Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK).

Data availability The datasets generated during and/or analyzed during the current study are available on https://sekizgenacademy.com/database/.

Declarations

Competing interests The authors declare no competing interests.

References

Abdelaal M, Fois M, Fenu G, and Gianluigi B (2019) Using MaxEnt modeling to predict the potential distribution of the Endemic Plant Rosa Arabica Crép. In Egypt. Ecol Inf 50:68–75

Ahmadi M, Hemami M-R, Kaboli M, and Farzin S (2023) MaxEnt brings comparable results when the input data are being completed; Model parameterization of four species distribution models. Ecol Evol 13(2):e9827. https://doi.org/10.1002/ece3.9827

Amindin A, Pourghasemi HR, Safaeian R, Rahmanian S, Tiefenbacher JP, Naimi B (2024) Predicting current and future habitat suitability of an endemic species using data-fusion approach: responses to climate change. Rangeland Ecol Manag 94:149–162. https://doi.org/10.1016/j.rama.2024.03.002

Arslan ES, Akyol A, Örücü ÖK, Sarıkaya AG (2020) Distribution of rose hip (Rosa canina L.) under current and future climate conditions. Regional Environ Change 20(3):107. https://doi.org/10.1007/s10113-020-01695-6

Bai J, Hou P, Jin D, Zhai J, Ma Y, Zhao J (2022) Habitat Suitability Assessment of Black-Necked Crane (Grus Nigricollis) in the Zoige Grassland Wetland ecological function zone on the Eastern Tibetan Plateau. Diversity 14(7):579

Barik S, Kanta MD, Behera S, Shrotriya and Vladimir Likhovskoi (2023). Monitoring climate change impacts on agriculture and forests: trends and prospects. Environ Monit Assess 195(1):174. https://doi.org/10.1007/s10661-022-10754-w

Barry S, Elith J (2006) Error and uncertainty in habitat models. J Appl Ecol 43(3):413–423. https://doi.org/10.1111/j.1365-2664.2006.01136.x

Bellard Céline, Bertelsmeier C, Leadley P, Thuiller W, Franck C. (2012) Impacts of climate change on the future of biodiversity. Ecol Lett 15(4):365–377. https://doi.org/10.1111/j.1461-0248.2011.01736.x

Cao B, Bai C, Zhang L, Li G, and Mingce M (2016) Modeling Habitat Distribution of Cornus Officinalis with Maxent modeling and fuzzy logics in China. J Plant Ecol 9(6):742–751

Chiarenza A, Alessandro AM, Waterson DN, Schmidt PJ, Valdes C, Yesson PA, Holroyd ME, Collinson A, Farnsworth DB, Nicholson, Varela S (2023) 100 million years of Turtle Paleoniche ynamics enable the prediction of atitudinal ange shifts in a warming world. Curr Biol 33(1):109–121

Climent José, Alizoti P, Rodriguez-Quilón I, Kurt Y, Ducci F, Fady B, Alía R (2021) Conservation and breeding of Mediterranean Pines. Pines Their Mixed for Ecosyst Mediterranean Basin, 33–70

Çoban, H. O., Örücü, Ö. K., & Arslan, E. S. (2020) MaxEnt modeling for Predicting the current and future potential geographical distribution of Quercus Libani Olivier. Sustainability 12(7):2671

Davis PH (ed.) (1965-1985). Flora of Turkey and the East AegeanIslands. Vol. 1-9. Edinburgh: University Press.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. Divers Distrib 17(1):437–57. https://doi.org/10.1111/j.1472-4642.2010.00725.x

Fick SE, and Hijmans RJ (2017) WorldClim 2: New 1-km spatial resolution climate surfaces for Global Land Areas. Int J Climatol 37(12):4302–4315. https://doi.org/10.1002/joc.5086

Friend AD, Lucht W, Rademacher TT, Keribin R, Betts R, Cadule P, Ciais P et al (2014) Carbon Residence Time Dominates Uncertainty in Terrestrial Vegetation Responses to Future Climate and Atmospheric CO_2. Proc Natl Acad Sci 111(9):3280–85. https://doi.org/10.1073/pnas.1222477110

Gassó Núria, Thuiller W, Pino J, Vilà M (2012) Potential Distribution Range of Invasive Plant Species in Spain. *NeoBiota* 12 (February):25–40. https://doi.org/10.3897/neobiota.12.2341

GBIF. (2024) Global Biodiversity Information Facility. https://www.gbif.org/occurrence/search

HamadAmin BA, and Khwarahm NR (2023) Mapping impacts oflimate change on the distributions of two endemic tree species under socioeconomic pathway scenarios (SSP). Sustainability 15(6):5469. https://www.mdpi.com/2071-1050/15/6/5469

Hijmans RJ, Susan E, Cameron JL, Parra, Peter G, Jones, and Andy Jarvis (2005) Very high Resolution Interpolated Climate surfaces for Global Land Areas. Int J Climatol 25:1965–1978. https://doi.org/10.1002/joc.1276

Huggel C, Bouwer LM, Juhola S, Mechler R, Muccione V, Orlove B, and Wallimann-Helmer I (2022) The existential risk space of Climate Change. ClimateChange 174(1):8. https://doi.org/10.1007/s10584-022-03430-y

IPCC (2022b) Global warming of 1.5°C: IPCC Special Report on impacts of global warming of 1.5°C above pre-industrial levels in context of strengthening response to Climate Change, Sustainable Development, and efforts to Eradicate Poverty, 1st edn. Cambridge University Press. https://doi.org/10.1017/9781009157940
IPCC (2022a) Climate Change 2022: Mitigation of Climate Change. https://www.ipcc.ch/report/ar6/wg3/
Kissling WD, Carsten F, Dormann Jürgen, Groeneveld T, Hickler I, Kühn GJ, McInerny JoséM, Montoya et al (2012) Towards Novel approaches to Modelling biotic interactions in multispecies assemblages at large spatial extents. J Biogeogr 39(12):2163–2178. https://doi.org/10.1111/j.1365-2699.2011.02663.x
Kumar P (2012) Assessment of Impact of Climate Change on rhododendrons in Sikkim Himalayas using Maxent Modelling: limitations and challenges. Biodivers Conserv 21(5):1251–1266. https://doi.org/10.1007/s10531-012-0279-1
Li G, Huang J, Guo H, and Sheng Du (2020) Projecting species loss and turnover under Climate Change for 111 Chinese tree species. Forest Ecol Manag 477:118488. https://doi.org/10.1016/j.foreco.2020.118488
Liu Y, Huang P, Lin F, Yang W, Gaisberger H, Christopher K, and Yongqi Zheng (2019) MaxEnt Modelling for Predicting the potential distribution of a near threatened Rosewood species (Dalbergia Cultrata Graham Ex Benth). Ecol Eng 141:105612
Marchant R Hooghiemstra H. (2004) Rapid environmental change in African and South American tropics around 4000 years before present: a review. Earth Science Reviews 66(3):217–260. https://doi.org/10.1016/j.earscirev.2004.01.003
Martinez-Sifuentes AR, Villanueva-Diaz J, Manzanilla-Quinones U, Becerra-Lopez JL, Hernandez-Herrera JA, Estrada-Avalos J, Actin H, Velazquez-Perez (2020) Spatial modeling of the Ecological Niche of Pinus Greggii Engelm.(Pinaceae): a species conservation proposal in Mexico under climatic change scenarios. iForest-Biogeosciences Forestry 13(5):426
Mechergui K, Altamimi AS, Jaouadi W, and Naghmouchi S. (2021) Climate change impacts on spatial distribution, Tree-Ring Growth, and Water Use of Stone Pine (Pinus Pinea L.) forests in the Mediterranean Region and Silvicultural practices to limit those impacts. iForest-Biogeosciences Forestry 14(2):104
Misiou O, and Koutsoumanis K. (2022) Climate Change and its implications for Food Safety and Spoilage. Trends Food Sci Technol 126(August):142–152. https://doi.org/10.1016/j.tifs.2021.03.031
Ncube B, Shekede MD, Gwitira I, and Dube T. (2020) Spatial modelling the effects of Climate Change on the distribution of Lantana Camara in Southern Zimbabwe. Appl Geogr 117:102172. https://doi.org/10.1016/j.apgeog.2020.102172
Neale PJ, Williamson CE, Banaszak AT, Häder D-P, Hylander S, Ossola R, Rose KC, Wängberg S-Å, and Zepp R.(2023) The response of aquatic ecosystems to the interactive effects of Stratospheric ozone depletion, UV Radiation, and Climate Change. Photochem Photobiol Sci 22(5):1093–1127.
OGM. (2021) *2020 Türkiye Orman Varlığı*. 1st ed. Ankara, Türkiye: T.C. Orman Genel Müdürlüğü yayını. https://www.ogm.gov.tr/tr/ormanlarimiz-sitesi/TurkiyeOrmanVarligi/Yayinlar/2020%20T%C3%BCrkiye%20Orman%20Varl%C4%B1%C4%9F%C4%B1.pdf
Öktem E (1987) Kızılçam El Kitabı Dizisi 2. Ormancılık Araştırma Enstitüsü Yayınları Muhtelif Yayınlar Serisi 52:11–57
Örücü ÖK, Azadi H, Arslan ES, Kamer Aksoy, Choobchian S, Nooghabi SN, Stefanie HI (2023) Predicting the distribution of european hop hornbeam: Application of MaxEnt algorithm and climatic suitability models. Eur J Forest Res 142(3):579–91. https://doi.org/10.1007/s10342-023-01543-2
Pearson, R. G., Raxworthy, C. J., Nakamura, M., & Townsend Peterson, A. (2007). Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. J Biogeogr 34(1):102–117. https://doi.org/10.1111/j.1365-2699.2006.01594.x
Pecchi M, Marchi M, Moriondo M, Forzieri G, Ammoniaci M, Bernetti I, Bindi M and Gherardo C (2020) Potential Impact of Climate Change on the Forest Coverage and the Spatial Distribution of 19 Key Forest Tree Species in Italy under RCP4. 5 IPCC Trajectory for 2050s. Forests 11(9):934. https://www.mdpi.com/1999-4907/11/9/934
Petrenko TY, Kirill A, Korznikov DE, Kislov NG, Belyaeva, and Pavel V. Krestov (2022) Modeling of Cold-Temperate Tree Pinus Koraiensis (Pinaceae) distribution in the Asia-Pacific Region: Climate Change Impact. ForestEcosystems 9:100015
Phillips SJ, Elith J (2010) POC plots: calibrating species distribution models with Presence-only data. Ecology 91(8):2476–2484
Porfirio LL, Rebecca MB, Harris EC, Lefroy S, Hugh SF, Gould G, Lee NL, Bindoff, and Mackey B. (2014) Improving the use of species distribution models in Conservation Planning and Management under Climate Change. PLoS ONE 9(11):e113749. https://doi.org/10.1371/journal.pone.0113749
QGIS. (2024) QGIS Geographic Information System. Open Source Geospatial Foundation Project. www.qgis.org

Riahi K, van Vuuren DP, Kriegler E, Edmonds J, Brian C, O'Neill S, Fujimori N, Bauer et al (2017) The Shared Socioeconomic pathways and their energy, Land Use, and Greenhouse Gas emissions implications: an overview. Global Environ Change 42(January):153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Sandoval-Martínez, J., Badano, E. I., Guerra-Coss, F. A., Cano, J. A. F., Flores, J., Gelviz-Gelvez, S. M., & Barragán-Torres, F. (2023). Selecting tree species to restore forest under climate change conditions: Complementing species distribution models with field experimentation. J Environm Manag 329:117038.

Schatz AM, Kramer AM, and John M. Drake (2017) Accuracy of climate-based forecasts of Pathogen Spread. Royal Soc Open Sci 4(3):160975. https://doi.org/10.1098/rsos.160975

Shcheglovitova M, Anderson RP (2013) Estimating optimal complexity for ecological niche models: a Jackknife Approach for species with small sample sizes. Ecol Model 269:9–17. https://doi.org/10.1016/j.ecolmodel.2013.08.011

Sıvacıoğlu A, Öner N (2010) İklim Değişimi ve Sürdürülebilir Ormancılık. In III. Ulusal Karadeniz Ormancılık Kongresi, 20–22 Mayıs 2010, Bildiriler Kitabı, III, 1021–1029, Artvin. https://www.researchgate.net/profile/Nuri-Oener/publication/312176367_Iklim_Degisimi_ve_Surdurulebilir_Ormancilik_Climate_Change_and_Sustainable_Forestry/links/5874d5ed08ae8fce4927e2c2/Iklim-Degisimi-ve-Suerdueruelebilir-Ormancilik-Climate-Change-and-Sustainable-Forestry.pdf

Soley-Guardia, Mariano, Diego F, Alvarado-Serrano, Anderson RP (2024) Top Ten Hazards to Avoid When Modeling Species Distributions: A Didactic Guide of Assumptions, Problems, and Recommendations. Ecography 2024(4):e06852. https://doi.org/10.1111/ecog.06852

Thomas CD (2010) Climate, Climate Change and Range boundaries. Divers Distrib 16(3):488–495. https://doi.org/10.1111/j.1472-4642.2010.00642.x

Türkeş M (1998) Küresel Isınma Rekor Kırıyor. Bilim ve Teknik Dergisi 370:20–21

Valavi R, Guillera-Arroita G, Lahoz-Monfort JoséJ, and Elith J. (2021) Predictive performance of Presence-only species distribution models: a Benchmark Study with Reproducible Code. Ecol Monogr 92(1):e01486. https://doi.org/10.1002/ecm.1486

Valavi R, Elith J, Lahoz-Monfort JoséJ, and Guillera-Arroita G. (2023) Flexible species distribution modelling methods perform well on spatially separated Testing Data. Glob Ecol Biogeogr 32(3):369–383. https://doi.org/10.1111/geb.13639

Venter O, Sanderson EW, Magrach A, Allan JR, Beher J, Jones KR, Possingham HP et al (2016) Sixteen years of change in the global Terrestrial Human footprint and implications for Biodiversity Conservation. Nat Commun 7(1):12558. https://doi.org/10.1038/ncomms12558

Venter O, Sanderson EW, Magrach A, Allan JR, Beher J, Jones KR, Watson JE (2018) Last of the wild project, version 3 (LWP-3): 2009 human footprint, 2018 release. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC), 10, H46T0JQ4.

Wang Yun-sheng, Xie Bing-yan (2007) Fang-hao Wan, Qi-ming Xiao, and Liang-ying Dai. The Potential Geographic Distribution of *Radopholus Similis* in China. Agri Sci China 6(12):1444–49. https://doi.org/10.1016/S1671-2927(08)60006-1

Wang, Y. (2012). Predicting the potential geographic distribution of crofton weed (Ageratina adenophora) around the world using maxent modeling. Vegetos 25(2):324–335.

Yalcin S (2012) Modelling the Current and Future Ranges of Turkish Pine (Pinus Brutia) and Oriental Beech (Fagus Orientalis) in Turkey in the Face of Climate Change. Master Thesis, Middle East Technical University, The Graduate School of Natural and Applied Sciences, Department of Geodetic and Geographic Info. Technologies. https://acikbilim.yok.gov.tr/handle/20.500.12812/244018

Yaltırık F, and Boydak M. (1993) Türkiye Kızılçamlarında Genetik Çeşitlilik (Varyasyon)Uluslararası Kızılçam Sempozyumu.

Yaltırık F and Efe A (2000). Dendroloji. İstanbul Üniversitesi Yayın, no. 4265

Yang X, Kushwaha S, Saran S, Xu J, Roy P (2013) Maxent modeling for Predicting the potential distribution of Medicinal Plant, Justicia Adhatoda L. in Lesser Himalayan Foothills. Ecol Eng 51:83–87. https://doi.org/10.1016/j.ecoleng.2012.12.004

Yuan Y, Zuo J, Zhang H, Tang X, and Zu M(2022) Climate Change on potential suitable areas for typical Pinaceae species on the Western Sichuan Plateau. Geocarto International, 37(26):14739–14757

Yudaputra A, Astuti IP, and Cropper WP (2019) Comparing six different species distribution models with several subsets of environmental variables: Predicting the potential current distribution of Guettarda Speciosa in Indonesia. Biodivers J Biol Divers 20(8). https://doi.org/10.13057/biodiv/d200830

Zeydanlı Uğur, Turak Ayşe, Bilgin C, Kınıkoğlu Yeşim, Yalçın S, and Doğan H (2011). *İklim Değişikliği ve Ormancılık: Modellerden Uygulamaya Adana Orman Bölge Müdürlüğü Için Uyum Önerileri*. 1st ed. Ankara, Türkiye: Doğa Koruma Merkezi. https://dkm.org.tr/uploads/yayinlar/1585596904875.pdf

Zhang T, Liu G (2017) Study of methods to improve the temporal transfer ability of Niche Model. J China Agri Univ 22(2):98–105

Zhao D, He HS, Wen J, Wang L, Wang H, Du KL, and Zong S (2018) Predicting Wetland distribution changes under Climate Change and Human activities in a Mid- and high-latitude region. Sustainability 10(3):863. https://doi.org/10.3390/su10030863

Zhao H, Zhang H, Xu C (2020) Study on Taiwania Cryptomerioides under Climate Change: MaxEnt modeling for Predicting the potential geographical distribution. Glob Ecol Conserv 24:e01313. https://www.sciencedirect.com/science/article/pii/S2351989420308544