

CHAPTER 8

MODELING THE DISTRIBUTION OF CRIMEAN *JUNIPER* (*JUNIPERUS EXCELSA* M. BIEB.): RANGE SHIFTS IN CURRENT AND POTENTIAL FUTURE DISTRIBUTION

Assoc. Prof. Dr. Ali Uğur ÖZCAN¹ &

Assoc. Prof. Dr. Derya GÜLÇİN² & Prof. Dr. Kerim ÇİÇEK^{3,4}

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¹Faculty of Forestry, Department of Landscape Architecture, Çankırı Karatekin University, Çankırı 18200, Turkey; auezcan@karatekin.edu.tr Orcid: 0000-0002-9046-8074

²Faculty of Agriculture, Department of Landscape Architecture, Aydın Adnan Menderes University, Aydın 09100, Turkey; derya.yazgi@adu.edu.tr Orcid: 0000-0001-7118-0174

³Section of Zoology, Department of Biology, Faculty of Science, Ege University, İzmir 35040, Turkey; kerim.cicek@ege.edu.tr Orcid: 0000-0002-6753-0757

⁴Natural History Application and Research Centre, Ege University, İzmir 35040, Turkey Orcid: 0000-0002-6753-0757

INTRODUCTION

The primary factors that determine a species' geographical range primarily encompass abiotic variables, such as climate, geology, and topography (Cox et al., 2016). Biotic interactions, including competition, disease, and dispersal capabilities, also play a crucial role (Svenning and Skov, 2007; Wisz et al., 2013). While it is widely recognized that biological interactions significantly influence species distributions at local scales, there is a growing need to better comprehend their importance on broader scales (Wisz et al., 2013). Notably, the capacity for seed dispersal holds exceptional significance as a determinant of postglacial tree diversity in Central and Northern Europe (Svenning and Skov, 2007).

When assessing the relationships between habitats within a landscape matrix, the potential alterations in land cover over time and how species might disperse in response to bioclimatic factors are often ignored (Albert et al., 2017; Foltête et al., 2012; Yang et al., 2020). However, species' responses in the context of global climate change have gained recognition as the pivotal ecological determinant shaping characteristics and distribution ranges of plant communities (Günel, 2013; Pecl et al., 2017). This understanding of species' reactions holds significance for their conservation and sustainability (Elsen et al., 2020; Wan et al., 2017). Climate change brings about shifts in species' bioclimatic requirements, consequently leading to changes in their geographical distributions (Bellard et al., 2018; Li et al., 2020; Zhang et al., 2018). These changes are closely linked to elevated temperatures and reduced precipitation during growing seasons (IPCC, 2014). Remarkably, each degree Celsius of temperature change translates to around 160 km of movement in ecological regions globally. For instance, a 4 °C warming over the coming century could necessitate a northern movement of approximately 500 km for species in the northern hemisphere (or an ascent of 500 m in altitude) (Thuiller, 2007).

Numerous studies addressing the impact of climate change on species have emphasized the consequences of rising global temperatures, indicating that species will migrate poleward (towards

higher latitudes) and to higher altitudes (Abdelaal et al., 2019; Sharma et al., 2022). Additionally, projections suggest that species' geographic ranges might expand, shift, or contract (Petitpierre et al., 2016). While some studies suggest that specific species could bolster their climate resilience in the future, others predict habitat loss, potentially leading to adverse impacts on biodiversity (Du et al., 2021; Rana et al., 2020). Furthermore, it has been noted that rapid climate shifts could exert pressure on relict or residual species, potentially driving species towards extinction (Fragnière et al., 2020; Tang et al., 2017). Temperature and precipitation, as climate-related variables, play a crucial role in influencing the survival, distribution, and other characteristics of plant species, along with shaping the composition of forest biomes and the future trajectory of terrestrial ecosystems (Garza et al., 2020; Taleshi et al., 2019). The rapid temperature fluctuations and other climatic changes experienced at higher elevations are expected to have substantial impacts on plant communities (Beniston et al., 1996; Guisan et al., 1995; Guisan and Theurillat, 2000; Walther et al., 2002).

Ecological niche modeling is experiencing a growing surge in popularity within the field of ecology. These models are widely utilized to generate maps illustrating the potential distribution of various plant and animal species. Grounded in geographic information systems, these models merge species data with a range of environmental variables, including bioclimatic conditions, remote sensing data, and topographical information. This integrated approach enables the forecasting, mapping, and visualization of anticipated species presence across extensive geographical areas (Adhikari et al., 2012; Brown, 2014; Cánovas et al., 2016; Khanum et al., 2013; Tripathi et al., 2017; Yang et al., 2015).

The genus *Juniperus* represented by seven valid species in Turkey: *J. drupacea* Ant. et Kotschy (the Syrian juniper), *J. oxycedrus* L. (known as Prickly cedar), *J. phoenicea* L. (Phoenician juniper), *J. sabina* L. (Savin juniper), *J. communis* L. (Common juniper), *J. foetidissima* Willd. (Stinking juniper), and *J. excelsa* M. Bieb. (referred to as Crimean or Greek juniper). Among these, *J. excelsa* has the

largest distribution (Ozkan et al., 2010). However, a history of poor resource management, silvicultural challenges, and extensive overgrazing by domestic animals has led to the significant degradation of most natural *J. excelsa* stands (Carus, 2004; Gezer et al., 2006). The estimation of potential future distribution for numerous species within the genus *Juniperus*, both globally and specifically in Turkey, has been conducted in light of the impacts of global climate change (Özkan et al., 2015; Salvà-Catarineu et al., 2021; Walas et al., 2019). A case study carried out in the mountainous regions of southern Greece, southern Turkey, as well as western Syria and Lebanon, has indicated that *J. drupacea* may face the risk of becoming endangered due to forthcoming climate changes (Walas et al., 2019). Another study, focused on modeling the historical, present, and prospective distribution of *J. phoenicea*, *J. turbinata*, and *J. canariensis*, leveraged bioclimatic variables through a maximum entropy model (Maxent) across the Mediterranean and Macaronesian regions. This study suggested that these species might experience a contraction in their current potential habitats due to the projected warming under the RCP2.6 and RCP8.5 scenarios (Salvà-Catarineu et al., 2021). Although numerous apprehensions exist regarding the repercussions of climate change on biodiversity, there remains a lack of understanding about its specific impact on certain plant species. The aim of this study is to identify the potential global distribution of the Crimean juniper and analyze the bioclimatic variables influencing its distribution. Furthermore, this study seeks to predict the future geographic range of the Crimean juniper in response to global climate change. The modeling and mapping of the species' potential distribution are crucial in identifying suitable locations for establishing new populations of this species. This information can then be used to develop effective strategies for the species' conservation in the coming years.

MATERIAL AND METHODS

Target species: This is a dioecious evergreen tree, capable of reaching heights between 20 to 25 meters. Initially pyramidal in its youth, the apex structure transition to a rounded shape as it matures.

The bark exhibits longitudinal fibrous strips that are cracked. Its shoots are notably slender, adopting a cylindrical or quadrangular form, and are adorned with bluish, dull-green, scaly leaves arranged diagonally. Distinguishing itself from the closely resembling *J. foetidissima*, this tree stands apart due to its thinner shoots and the tightly closed scaly leaves with flattened tips. During the initial 6-8 years of growth, needle leaves emerge in seedlings, forming a triple-circle arrangement. Within the berry cones, which take two years to mature, lie 4-10 seeds enclosed by 4-6 scales. These mature cones sport a black hue and emit a bluish smoke (Akkemik, 2018). In Turkey, two subspecies of the Crimean juniper [*J. excelsa* subsp. *excelsa* and *J. excelsa* subsp. *polycarpus* (K.Koch) Takht.] are present, naturally inhabiting altitudes ranging from 100 to 3950 meters across Europe, West Asia, and South Asia (Farjon, 2010). Thanks to its remarkable resistance to cold and drought, this species has established a widespread presence throughout Turkey, even encroaching into the steppe regions. With the exception of Thrace and Southeastern Anatolia, it displays a broad distribution spanning altitudes of 150 to 3000 meters (Anşın and Özkan, 1993).

Occurrence data: A comprehensive dataset comprising 1691 occurrence records for *J. excelsa* subsp. *excelsa* was collected from multiple sources: the Global Biodiversity Information Facility (www.gbif.org/), available literature, and the current study. These records were meticulously georeferenced using the WGS84 coordinate system and their accuracy was verified using ArcGIS (v10.7, ESRI, California, USA). Minimization of sampling bias and assurance of homogeneous sampling effort (Merow et al., 2013; Boria et al., 2014; Fourcade et al., 2014; Sillero et al., 2021), a buffer zone of 5 kilometers was applied around each occurrence point. This buffer was generated using the spThin ver. 0.2.0 package (Aiello-Lammens et al., 2015), resulting in a refined dataset of 221 records.

Our hypothesis focused on identifying the viable study area for the Crimean Juniper across both current and future temporal contexts, as suggested by Soberón and Peterson (2005). To anticipate the species' potential distribution in the coming periods, we applied a five-degree buffer around occurrence data in the study area. This buffered

region was then refined into a polygon spanning from 09.90°N to 39.11°N latitude and 34.33°E to 60.74°E longitude, which effectively delineates the defined study area.

Environmental variables: Initially, we employed 19 bioclimatic variables and two topographic variables as predictors for the existing distribution of the species. These predictor variables were sourced from the CHELSA database (Karger et al., 2017, 2021) and underwent resampling to attain a spatial resolution of 2.5' (approximately 4.7 km). These data were derived from monthly temperature and precipitation values averaged over the period from 1979 to 2013. The CHELSA database operates on a monthly mean basis and is founded on a quasi-mechanistic statistical downscaling process of the ERA interim global circulation model, coupled with a GPCC bias correction (Karger et al., 2017). Furthermore, we integrated two topographic variables—specifically, the terrain roughness index and the topographic position index—at the same spatial resolution of 2.5' (around 4.7 km). These variables were generated from digital elevation model products, utilizing both the global 250 m GMTED2010 and the near-global 90 m SRTM4.1dev datasets (<https://www.earthenv.org/>, Amatulli et al., 2018).

We assessed the variance inflation factor (VIF) for all bioclimatic variables in order to quantify the degree of multicollinearity. This analysis was conducted using the *usdm* package developed by Naimi, (2015). Adhering to the suggestions of Guisan et al. (2017), we established a VIF value of 10 along with a correlation threshold of 0.75. Employing a stepwise approach, we deliberately selected and retained a mere eight bioclimatic variables. This selection was made to emphasize values aligning closely with the ecological prerequisites of the species. The selected variables were mean diurnal range [Mean of monthly (max temp - min temp)] (BIO2), temperature seasonality (BIO4), Mean Temperature of Warmest Quarter (BIO10), Precipitation of Wettest Month (BIO13), Precipitation of Driest Month (BIO14), Precipitation Seasonality [Coefficient of Variation] (BIO15), terrain roughness index (TRI), and topographic position index (TPI).

The prospective habitat suitability of Crimean Juniper was evaluated by projecting the calibrated models onto five distinct global circulation models: GFDLESM 4.1 (Dunne et al., 2020), UKESM1.0-LL (Sellar et al., 2019), MPI-ESM1-2-HR (Müller et al., 2018), IPSLCM6A-LR (Boucher et al., 2020), and MRI-ESM2.0 (Yukimoto et al., 2019). These projections encompassed three shared socioeconomic pathways (SSPs) representing varying levels of uncertainty in climate model forecasts: optimistic (SSP126), middle-of-the-road (SSP370), and pessimistic (SSP585), as outlined by Sanderson et al. (2015). The bioclimatic variables were sourced from the 6th Climate Model Intercomparison Project (available at: <https://chelsa-climate.org/cmip6/>), spanning three 30-year intervals (2011–2040, 2041–2070, 2071–2100). We employed Maximum Entropy Modelling (Maxent v3.4.1; Phillips et al., 2006, 2017) to predict habitat suitability and determine potential ranges for Crimean juniper under current climatic conditions as well as three projected future climate scenarios. To achieve this, we utilized the "random k-fold" method, which partitions occurrence localities randomly into a specified number of (k) bins (Hastie et al., 2009). Specifically, we divided the data into 10 random groups. The process of optimizing model complexity and balancing goodness-of-fit and predictive ability, as well as generating maximum entropy models, was executed using the R package ENMeval v2.0.0 (Kass et al., 2021; Muscarella et al., 2014). For model building, we considered a range of regularization multiplier values from 0.5 to 10 (in increments of 0.5) and employed six distinct combinations of feature classes (L, LQ, H, LQH, LQHP, and LQHPT), where L signifies linear, Q indicates quadratic, H represents hinge, P stands for product, and T refers to threshold. This comprehensive approach resulted in 120 individual model runs for each species. Model accuracy was assessed using four evaluation metrics within ENMeval (Kass et al., 2021; Muscarella et al., 2014). These metrics included:

1. **AUC_{TEST}** (area under the curve of the receiver operating characteristic plot for test localities), as proposed by Hanley and McNeil (1982) and Peterson et al. (2011).

2. **AUC_{DIFF}** (the difference between AUC values from training and testing), following the method of Warren and Seifert (2011).
3. **OR₁₀** (10% training omission rate) for test localities, based on the work of Fielding and Bell (1997) and Peterson et al. (2011).
4. **AIC_c** (Akaike Information Criterion corrected for small sample sizes), as described by Burnham and Anderson (2004) and Warren and Seifert (2011).

Furthermore, we adopted the null model concept (Raes and ter Steege, 2007) to assess the performance of our models. Bohl et al. (2019) recommended evaluating models on the same reserved occurrence data as the empirical model. To implement this, we conducted null Ecological Niche Models (ENMs) employing the method outlined by Bohl et al. (2019) with an extension by Kass et al. (2021), iterated over 100 times. We then employed ENMeval (Kass et al., 2021) to visualize and compare the performance of the empirical model against the averaged null model outcomes. For each species, each chosen model underwent 10 iterations. To transform the complementary log-log regression (cloglog) output, ranging from 0 (unsuitable) to 1 (suitable), into a continuous presence-absence distribution map, we applied the 10-percentile training presence logistic threshold approach as recommended by Liu et al. (2005). This transformation was conducted to estimate potential habitat size using the raster package in R (Hijmans et al., 2015). Subsequently, the results were imported and displayed using rasterVis (Lamigueiro and Hijmans, 2021) as well as ArcGIS v10.7.

RESULTS

The model chosen for each species was determined by its statistical performance and low complexity, with considerations based on four assessment metrics and null models (Table 1). Among the chosen models, all demonstrated notable performance, boasting an impressive average area under the curve concerning training data (average AUC 0.937, SD= 0.018). The eight environmental factors

were determined to impact the distribution of the Crimean juniper to different degrees [bio13 = 30%, bio15 = 17.9%, bio4 = 19.7%, bio14= 14.1%, bio10 = 8.3%, tri= 7.7%, bio2= 2.2%, tpi=0.1%].

Table 1. Parameters and performance statistics of the best models for an assessment of the Crimean juniper, using the following column abbreviations: feature class (FC); regularization multiplier (RM); areas under curves for “training” the model (AUC_{TRAIN}), the difference between training and testing (AUC_{DIFF}), and the training dataset value for the null model ($AUC_{TRAIN-NULL}$); the corrected Akaike Information Criterion ($AICc$); the 10% training omission rate (OR_{10}); the Z-value (Z); and the p-value (p). cbi: Continuous Boyce Index.

statistic	AUC_{TRAIN}	cbi.train	auc.val	AUC_{DIFF}	cbi.val	or.mtp	OR_{10}
emp.mean	0.955	0.996	0.944	0.014	0.807	0.01	0.116
emp.sd	NA	NA	0.013	0.011	0.13	0.021	0.048
null.mean	0.627	0.939	0.548	0.127	0.106	0.029	0.199
null.sd	0.016	0.045	0.017	0.017	0.096	0.024	0.033
Zscore	20.688	1.265	22.931	-6.762	7.279	-0.793	-2.534
pvalue	< 0.000	0.103	< 0.000	< 0.000	< 0.000	0.214	0.006

The precipitation of wettest month (bio13), precipitation seasonality (bio15), temperature seasonality (bio4), and precipitation of driest month (bio14) are mainly shaped by its distribution pattern. According to the known distribution of the species and the present-time prediction, the Anatolia constitutes an important part of its distribution (Figure 1).

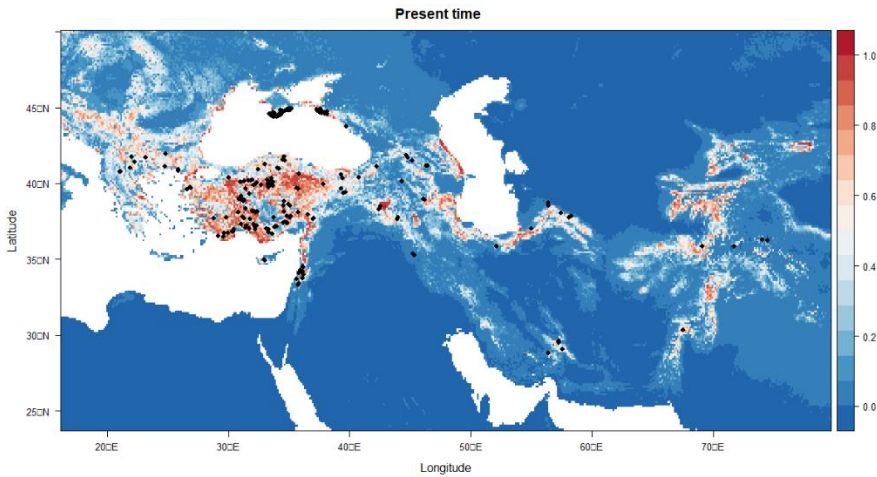


Figure 1. Average climate habitat suitability maps for the Crimean juniper projected to the present day. Black dots show occurrence records. The probability of occurrence ranges from 0 (dark blue, low probability) to 1 (red, highest probability).

The species holds a significant presence across Eastern and Southern Europe, and it is noteworthy for its widespread distribution in Western Asia, particularly along the Elburz Mountain range along Iran's northern border. Furthermore, this species can be found in various regions across Southern, Eastern, and Central Asia. Notably, there are expectations of its expansion, particularly towards the western part of the Pamir Range (Himalayas) in Tajikistan and in the northern and northeastern reaches of the Hindu Kush Range in Afghanistan. Within the hills and mountainous terrain of the Eastern Mediterranean Basin, the Black Sea area, and a mountain range curving around the western and southern extremity of the Caspian Sea, this species is prevalent. However, its frequency diminishes notably as it is headed eastward along the latter mountain range. Furthermore, this species can be found along the Kopet Mountains, extending into Afghanistan. As it progresses northeastward, it extends its habitat into the Tian Shan and the mountains of Kyrgyzstan.

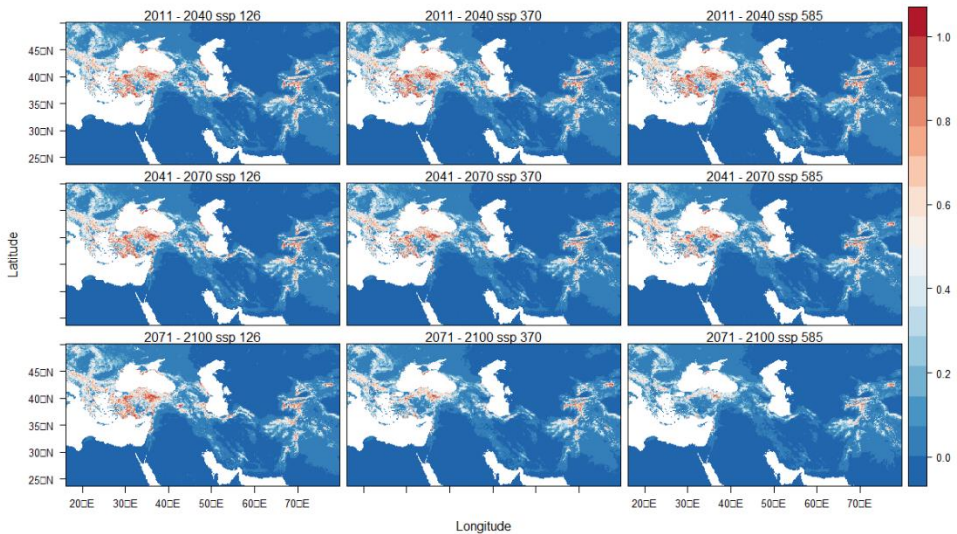


Figure 2. Average prediction of climate habitat suitability maps for the Crimean juniper under future climate scenarios. Average projections are presented for each of three time periods (2011–2040, 2041–2070, 2071–2100) and three shared socioeconomic pathways (optimistic - SSP126, middle of the road - SSP370 and worst - SSP585). The probability of occurrence ranges from 0 (dark blue, low probability) to 1 (red, highest probability).

It is important to highlight that the distribution of species exhibits both positive and negative fluctuations across various time periods, depending on different scenarios. (Figure 3). It is expected that 0.8% of suitable areas for the species will increase and 1.18% will decrease in the SSP126 scenario during the 2011–2040 periods. When examined spatially, it is seen that a large part of the decrease is in Anatolia. The species shifts northward in Anatolia. The same is true for Asia. Although there are decreases in Southern Asia, there are increases in Central and Eastern Asia and the species shifts northward. In addition, it is observed that suitable areas of the species are shifting southward in southern and eastern Europe. According to the SSP370 scenario and the optimistic scenario in the 2011–2040 periods, the suitability areas of the species show great similarity spatially. In the 2011–2040 periods, the amount of loss is more than the gain according to all scenarios. The same is true for the SSP126, SSP370 and SSP585 scenarios in the 2041–2070 periods.

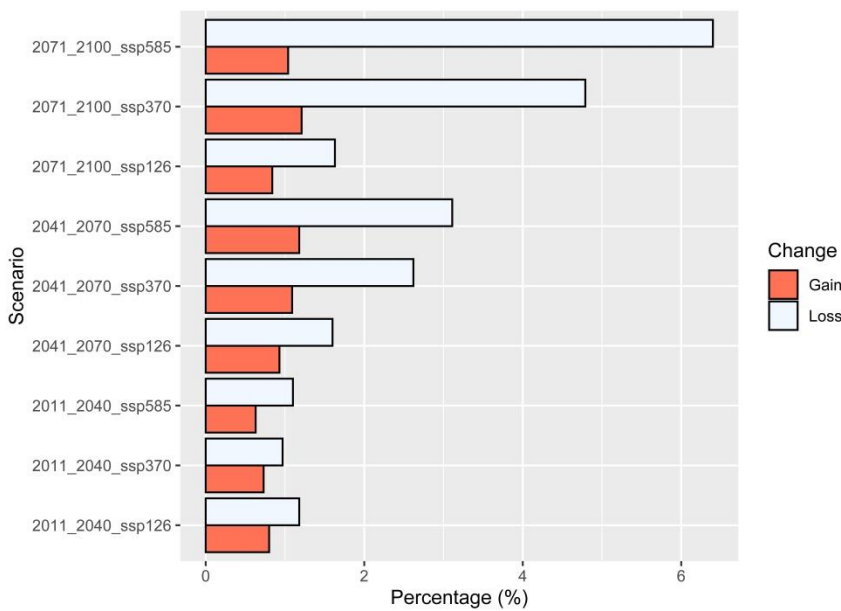


Figure 3. Change in suitable areas for the species by different scenarios

In the 2041–2070 periods, the amount of loss is less in the optimistic scenario (1.60%) and more in the pessimistic scenario (3.11%). When the spatial differences are examined, the most obvious change in this period is that the species decreased significantly in central and eastern Anatolia, increased its spread in Europe, and moved north in Southern Asia, especially in Afghanistan. In the 2071–2100 periods, it is expected that the species will spatially decrease its distribution outside northern Anatolia significantly, and move southward by narrowing its distribution in Europe. It is also predicted that it will reduce its distribution along the Elburz Mountains in the north of Iran in Southern Asia, and on the contrary, it will expand its distribution in China and Jammu Kashmir in Eastern Asia. Significantly, the distribution of the species undergoes varying trends across different timeframes and scenarios. Specifically, within the SSP126 scenario spanning from 2011 to 2040, there is an expected increase of 0.8% in suitable habitat areas for the species, counterbalanced by a decrease of 1.18%. Spatially, this decrease is

predominantly concentrated in Anatolia, resulting in a northward shift of the species within this region. A similar northward trend is observed in Asia, where despite declines in Southern Asia, Central and Eastern Asia witness increases in suitable habitat areas. Moreover, there is a notable southward shift in the species' suitable habitat areas across southern and eastern Europe. Strikingly, when comparing the SSP370 scenario with the optimistic scenario for the 2011–2040 timeframe, there is a remarkable spatial congruence in the suitability areas for the species. Across all scenarios in the 2011–2040 and 2041–2070 periods, losses in suitable habitat areas consistently outweigh gains. This pattern persists into the 2041–2070 period, where the optimistic scenario experiences a smaller loss (1.60%) compared to the pessimistic scenario (3.11%). Analyzing spatial disparities during this timeframe reveals a significant decline in the species' presence in central and eastern Anatolia, coupled with an expansion of its distribution in Europe and a northward migration in Southern Asia, particularly evident in Afghanistan. Looking ahead to the 2071–2100 period, the losses increase for the SSP126, SSP370, and SSP585 scenarios, amounting to 1.63%, 4.79%, and 6.40%, respectively. During this period, a substantial spatial decrease in the distribution of the species outside northern Anatolia is anticipated, accompanied by a southward shift and narrowing of its European distribution. Predictions also indicate a reduction in the species' presence along the Elburz Mountains in northern Iran within Southern Asia, contrasted with an expansion in China and Jammu Kashmir within Eastern Asia.

DISCUSSION

The current study evaluates the susceptibility of *J. excelsa* to future climate change and its potential habitat reduction, which holds significant implications for the species' conservation status. To accomplish this, we employed an ensemble modeling approach known for its robustness in generating distribution models. The reliability of this method was confirmed through a thorough assessment using established performance metrics. This modeling technique has previously demonstrated its effectiveness in predicting species

distributions in other relevant studies (e.g., Dakhil et al., 2021; El-Barougy et al., 2023).

Furthermore, to enhance predictive accuracy, our study integrated data from five distinct climate models (GFDLESM 4.1, UKESM1.0-LL, MPI-ESM1-2-HR, IPSLCM6A-LR, and MRI-ESM2.0). This integration is expected to improve the precision of our species distribution models and future projections. By averaging the ensemble of climate scenarios, our aim is to reduce uncertainties in the model outputs, effectively accounting for variations among different future climate scenarios.

Climate change poses a significant threat to various *Juniperus* species, as highlighted by previous studies (Abrha et al., 2018; Adams et al., 2014; Arar et al., 2020; Dakhil et al., 2021; El-Barougy et al., 2023; Salvà-Catarineu et al., 2021; Walas et al., 2019). Specifically, *J. procera*, which is already endangered due to climate change in northern Ethiopia, is expected to lose nearly 90% of its suitable habitats (Abrha et al., 2018). *J. drupacea*, a vital juniper species found in the Eastern Mediterranean, had a distribution during the last ice age that was three times larger than its current range. However, in the future, the species is anticipated to face unfavorable conditions across most of its geographic range, except for Turkey, its distribution center (Walas et al., 2019). Regarding *J. phoenicea*, which forms forests in semi-arid and arid regions along the northern borders of the Sahara Desert in northern Africa, research by Arar et al. (2020) suggests that almost half of its potential habitat areas may be lost by 2070, according to the RCP8.5 scenario. While the distribution of this species is declining in Europe, there are predictions of expansion in northern Spain and central France (El-Barougy et al., 2023). In general, the most vulnerable regions in terms of vegetation are those located at the extremes of species' distribution areas, where climate change is causing shifts in both altitude and latitude (Coudun and Gégout, 2006).

The Crimean Juniper extends from the central and southern Balkans through Anatolia to the Crimea, central and southwestern Asia, and eastern Africa (Deligöz, 2012). The westernmost extent of this species' distribution is in the Balkans. Within the confines of the Prespa

National Park, located west of the primary *J. excelsa* distribution, this species can be found inhabiting limestone bedrock areas situated at elevations ranging from 840 to 1360 meters. In this habitat, it shares space with other vegetation including *Quercus macedonica*, *Juniperus oxycedrus*, *Quercus pubescens*, *Pyrus amygdaliformis*, *Carpinus orientalis*, *Acer monspessulanum*, and *Juniperus foetidissima* (Pavlidis, 1985). In the Nestos valley of northeastern Greece, *J. excelsa* is also observed on limestone bedrock, sandy-clay, rocky, and shallow soils (Maragos, 1998), coexisting with various mixed species such as *Quercus coccifera*, *Phillyrea latifolia*, *Fraxinus ornus*, *Paliurus spinachristy*, *Juniperus oxycedrus*, and *Quercus pubescens*, as reported by Milios et al. (2009). Notably, the Balkans region represents the lowest altitudes at which this species is found, and under even the most optimistic scenarios, it is expected to shift away from coastal areas towards higher elevations. Nevertheless, the limited elevation range in the Balkans presents a significant challenge, along with the presence of deciduous forests in the northern part of the Balkans that may hinder the species' competitive advantage. Moreover, it is anticipated to encounter difficulties expanding into forested regions like the Carpathians, where numerous coniferous species prevail. Interestingly, the species found in association with *J. excelsa* in this context is quite similar to those in the central region of Turkey. Thus, it is highly likely that the continuity of this species will persist in Karst Mountain running parallel to the sea.

Turkey boasts one of the broadest distributions of *J. excelsa*, yet the climatic and geographical conditions for this species vary considerably across the country. While the Crimean juniper is prevalent in the Mediterranean and Iranian Caucasian ecosystems, it extends its range to the Black Sea region via the Gökırmak basin in Kastamonu and Sinop. This coniferous species forms a significant part of the central Turkish landscape and migrates toward the interior alongside *J. foetidissima* and *J. oxycedrus*. In Turkey, projections for the future suggest a northward and upward shift in the species' range. While optimistic future scenarios show relatively little change in its distribution, pessimistic scenarios paint a picture of the species

potentially retreating entirely behind the Black Sea and moving toward the Anatolian Diagonal, all while maintaining a presence in the central parts of the Mediterranean Taurus. In both scenarios, the species would need to contend with existing forests for space. An important impediment to its expansion is its inability to compete effectively with conifers such as *Pinus nigra*, *Pinus sylvestris*, *Cedrus libani*, and *Abies cilicica*. This limitation arises from its pyramid-like growth in youth, vulnerability to shade, and slow growth in later stages (Kırsal Çevre, 2021).

The Elburz Mountains, situated to the north of the country and south of the Caspian Sea, represent a crucial segment of the species' potential distribution in Iran. They play a pivotal role in facilitating its east-west expansion. Forecasts indicate an anticipated reduction in the species' future distribution within this region. An estimated decline of approximately 7% in areas with favorable and high potential for the species was reported in a regional study conducted within the Elburz Mountains (Fatemi et al., 2018). In the province of Chaharmahal and Bakhtiari in the Central Zagros region parallel to the Persian Gulf in southern Iran, 36.63% to 77.63% of suitable habitats for the species will be lost by 2050 (Naghipour et al., 2021). These findings align closely with our own results, demonstrating a consistent pattern of declining distribution in the region.

In addition to climate change, the speed at which species expand their range is of significant importance. *J. excelsa* and nearly all *Juniperus* species are expected to shift towards northern and higher altitudes. In the Himalayas, *J. macropoda* has been observed at elevations ranging from 3000 to 4260 meters and demonstrates an upward migration rate of 3.91 meters per year (Kumar et al., 2022). While this rate of expansion may appear relatively slow on a global scale, it is important to note that natural processes can accelerate in response to sudden changes. For instance, in Oman, *J. seravschanica* may need to undergo an upward range shift of 250 meters within just two decades to thrive in its optimal habitat (Adams et al., 2014). This equates to an approximate rate of 12.5 meters per year. The concept of rapid plant migration, initially elucidated by Reid (Reid, 1899), shed

light on the phenomenon where oaks spread at a pace faster than the natural dispersal rate of their seeds in northern England following the last glacial period. The primary reason behind this phenomenon, referred to as the Rapid Plant Migration Paradox (Clark et al., 1998), is the assumption that crows play a significant role in facilitating such rapid dispersal. The dispersal of seeds by birds is a widespread occurrence, and *J. excelsa* may be fortunate in this regard. Thrush species, particularly those belonging to the *Turdus* genus, now play a crucial ecological role in the germination and distribution of juniper seeds. These birds are increasingly being considered in the design of strategies aimed at protecting or restoring vegetation communities (Tellería et al., 2011).

CONCLUSIONS

This study suggests that, according to the Optimistic (SSP126) scenarios, the current distribution pattern of *J. excelsa* is likely to remain relatively stable between 2011 and 2100. Conversely, under the middle-of-the-road (SSP370) and pessimistic (SSP585) scenarios, it is anticipated that the species' range will contract significantly during the periods of 2041–2070 and 2071–2100 (refer to Figure 2). Notably, the prediction for the 2071–2100 period is particularly concerning, showing a substantial reduction in the species' distribution, especially in southern regions.

Currently, *J. excelsa* is classified as Least Concern. However, due to the escalating levels of greenhouse gas emissions and increased human activities disrupting its habitats, there is a growing apprehension that these habitats will face more significant threats in the near future. Our findings can offer valuable insights for the development of conservation strategies specifically tailored to address the expected changes in vegetation habitats resulting from shifting climate conditions. In this context, further investigations are necessary, with a particular focus on endangered species and the incorporation of alternative species distribution models, general circulation models, and various scenarios.

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