

Possible extinction of *Eversmannia subspinos* in Eastern Alborz by 2060 due to climate change: A MaxEnt study

Amir Zaheri

Damghan University

Reza Naderi

rezanaderia@du.ac.ir

Damghan University

Atefe Amirahmadi

Damghan University

Research Article

Keywords: legumes, species distribution models, Maximum Entropy, Iran SDMs, Global warming

Posted Date: March 8th, 2024

DOI: <https://doi.org/10.21203/rs.3.rs-3988262/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Theoretical and Applied Climatology on June 8th, 2024. See the published version at <https://doi.org/10.1007/s00704-024-05047-w>.

Abstract

Climate change has altered ecosystems by affecting the suitability of environments for different species. Species distribution models provide insights regarding these changes, which could be valuable in conservation planning. In this study, we model the current and projected future distribution of *Eversmannia subspinoso*, a shrub from the Fabaceae family, across the Eastern Alborz area. This plant is endangered in Iran and is only found in the study area. We used the Maximum Entropy (MaxEnt) method and trained the model with the least correlated and most important bioclimatic and topographic variables. CMCC-ESM2 and HadGEM3 climate models, in conjunction with IPCC Representative Concentration Pathways RCP2.6, RCP4.5, and RCP8.5, were used to predict the distribution of the species in 2040 and 2060. Our results suggest that the current habitats of *E. subspinoso* are mainly in southern parts of Eastern Alborz. Elevation (54.9%) and annual mean temperature (24.5%) were the main contributors to the model. CMCC-ESM2 model predicts significant habitat loss up to 2040 and almost complete disappearance of high probable habitats ($0.5 \leq$ probability of presence) up to 2060. It also suggests a distribution shift toward higher elevations in Northern and North-Eastern areas of the study area. The model trained by HadGEM3 predicts extinction of *E. subspinoso* across the study area up to 2040. Filling the gaps between protected areas and national parks and limiting road construction, which blocks its migration to higher elevations in response to global warming, could delay the extinction of this rare species in Iran.

Introduction

Climate change has been identified as a significant driver of shifts in species distribution. The ongoing changes in climate have led to alterations in the habitats and geographic ranges of numerous species (Bonebrake et al., 2018; A. Dhyani et al., 2021; Gervais et al., 2021; Parmesan et al., 2015; Warren et al., 2018). Recent studies have further substantiated these findings. While marine species are shifting poleward in response to ocean warming (Sunday et al., 2012), terrestrial species are undergoing range shifts at varying rates, depending on their specific thermal tolerances and habitat requirements (Pech et al., 2017). Many plant species are moving uphill and towards the poles in response to rising temperatures. This uphill and poleward migration is a survival strategy, as plants seek cooler temperatures and more suitable conditions for growth (Chen et al., 2011; Couet et al., 2022; Lenoir et al., 2015; Zu et al., 2021). Moreover, these shifts in species distribution have significant implications for biodiversity and ecosystem functioning. As species move to new areas, they can alter the composition and structure of communities, potentially leading to changes in ecosystem processes and services (Bellard et al. 2012; Sharma et al. 2021).

Species distribution modeling (SDM) is a powerful tool used in ecology to predict the geographic distribution of species based on environmental conditions at locations where they are known to occur (Elith et al., 2009). SDMs are based on the fundamental ecological principle that organisms are adapted to specific environmental conditions and thus their geographic distributions can be predicted by identifying these conditions (Anderson et al., 2011). The models use presence-only or presence-absence

data of species along with environmental predictor variables (such as temperature, precipitation and altitude) to predict suitable habitats for the species (Elith et al., 2009). These models can also forecast potential range shifts of species under different climate change scenarios, providing valuable information for conservation planning (Elith et al., 2006).

In this study, we focused on modeling the current and projecting the future distribution of *Eversmannia subspinos*a (Fisch. Ex DC.) B. Fedtsch, (Fabaceae Hedysareae), an endemic species distributed in Iran, Afghanistan, Central-Asia, North-East China, South-East Russia, Caucasias and Europe (Amirabadizadeh et al., 2023; Mironov et al., 2000). The populations of *E. subspinos*a in Iran, primarily observed along roads, are limited to Northern area of Semnan province, thriving in seasonal waterways and areas with short-term rainwater accumulation. Due to the very low occurrence of these populations and the threats they face from human factors such as road construction, we classify the species *E. subspinos*a as endangered in Iran, based on the International Union for Conservation of Nature classifications (Jalili et al., 1999; Mehrabian, 2013). Therefore, it is necessary to understand the changes in *E. subspinos*a distribution as it could affect the biodiversity and ecosystem functioning of Eastern Alborz which is one of the biologically richest areas of South-East Asia (Noroozi, 2020). Our primary objective in this SDM was to employ the MaxEnt method to map the present distribution of *E. subspinos*a and forecast the future distributions of this species up to 2060. To the best of our knowledge, this is the first SDM study conducted on a species belonging to the *Eversmannia* genus.

Materials and Methods

Study area

The study was conducted in Semnan province, Iran, spanning an area of approximately 96,816 square kilometers, located within the geographical coordinates of approximately 36.7° N (northernmost point), 34.6° N (southernmost point), 52.3° E (westernmost point) and 56.4° E (easternmost point) (Fig. 1). This region encompasses the southern slopes, hills and plains of the Eastern Alborz, a mountain range in northern part of Iran (Noroozi et al., 2008).

The climate of the study area is predominantly shaped by the hot and dry air currents originating from the desert plain (Ganjaeian, 2023). However, several other factors contribute to the region's climate, including its distance from the sea, the orientation and extent of the mountains, the altitude and prevailing wind patterns.

The precipitation is notably scarce, predominantly falling as rain during the colder seasons. The annual average precipitation is approximately 145 mm. The humidity levels increase from west to east across the area and from south to north.

Species

E. subspinoso is a type of short spinose shrub with a height of 10 to 40 centimeters (Fig. 2). It has upright, thin divergent branches, with almost opposite thorns up to 19 millimeters long. The leaves are imparipinnate, 1.5-5 cm long and 7-15-foliolate. The flowers are arranged in many-flowered, oblong racemes measuring up to 15 cm long. The dark brown calyx is covered with trichomes, measured 3.5-5.5 mm long with lanceolate teeth and an acute apex. The corolla is purple. The standard is oblong-obovate, measuring 13.5 to 15.5 mm long, with a retuse apex. The wings are dark brown and lanceolate, measuring around 5 mm long, with elongate oblong auricles at the base. The legume is brown, elongate, measuring approximately 4 cm, curved and tuberculate-granular. The seeds are 3 mm long, ovate, brown, smooth, shiny, more or less flat. The flowering season is from late April to mid-June (Amirabadizadeh et al., 2023).

In Iran, populations of *E. subspinoso* are found in seasonal waterways and puddles, mostly along the main roads in the northern part of Semnan province (Fig. 1). They grow in slightly alkaline (pH = 7.0-8.0) loamy soils with low to moderate salinity (EC = 2-8 dS/m).

Data Collection and Preprocessing

Presence Data: To initiate the study, field surveys were conducted in the study area between the years 2007 and 2021 to record occurrences of *E. subspinoso* (Fig. 1). Geographical coordinates of these occurrences were recorded using a GPS device.

Environmental Layers: Bioclimatic data including 19 bioclimatic variables, primarily utilized for ecological purposes (Merkenschlager et al., 2023) and elevation data (Table 1), at a 30-second resolution were obtained from WorldClim2.1 (<https://www.worldclim.org/>) (Fick et al., 2017). Additionally, "land use" and "soil quality" data, which are considered static in SDM studies (Stanton et al., 2012), were sourced from Harmonized World Soil Database v 1.2 (<https://www.fao.org/>) (Fischer et al., 2008). QGIS software v 3.30.3 (www.qgis.org) was employed to extract study area-specific data from all the above-mentioned data in projection system EPSG:4326, to serve as environmental layers. Static variables (e.g. topographic data) including elevation, slope and aspect derived from the elevation data that was obtained from WorldClim2.1 using raster analysis tool in QGIS software in projection system EPSG:4326, further enhancing the environmental dataset (Table 1) (Stanton et al., 2012).

Table 1 All the environmental variables initially considered in the modeling process and the selected variables considered for the final modeling.	
Environmental variable	Description
Bio1	Annual Mean Temperature (°C)
Bio2	Mean Diurnal Range (Mean of monthly (max temp - min temp)) (°C)
Bio3	Isothermality (BIO2/BIO7) (×100)
Bio4	Temperature Seasonality (standard deviation ×100)
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
Bio14	Precipitation of Driest Month (mm)
Bio15	Precipitation Seasonality (Coefficient of Variation)
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 above mean sea level (m)
Slope	Degrees
Aspect	Direction of slope with respect to north (degrees)
Soil quality	Soil properties
Land cover	Land cover

Projection layers: CMIP6 Future data (Eyring et al., 2016; Haarsma et al., 2016) based on CMCC-ESM2 (Cherchi et al., 2019; Vichi et al., 2011) and HadGEM3 (Andrews et al., 2020) climate models paired with three IPCC Representative Concentration Pathways RCP2.6, RCP4.5 and RCP8.5 (Meinshausen et al., 2020) for years 2040 and 2060 sourced from WorldClim2.1. Again, QGIS software was applied to extract study area-specific data in projection system EPSG:4326 to serve as projection layers in MaxEnt modeling.

Variable Selection and Correlation Analysis: To optimize the model, the R package v 4.3.2 was used to generate a correlation matrix using the Pearson method, identifying and removing highly correlated variables (correlation ≤ 0.8) (Hanberry, 2024; Harisena et al., 2021; Stanton et al., 2012). Finally, only five variables including elevation, bio1, bio19, bio15, and slope were considered for the modeling process as they were the most influential environmental variables with correlation ≤ 0.8 (Table 2).

Table 2 Environmental variables selected for the final modeling. Values over occurrence locations, percent contribution and permutation importance are also provided.			
Selected Environmental variable	Value over occurrence locations	Percent contribution	Permutation importance
Bio1	12.78-15.49	21.2	75.6
Bio15	53.93-70.68	5.1	3.6
Bio19	61-78	6.8	8.3
Elevation	1289-1718	62.3	12.3
Slope	0	4.6	0.2

Species Distribution Modeling

Species distribution modeling was performed using the Maximum Entropy (MaxEnt) approach, specifically utilizing version 3.4.4 of the MaxEnt software (S. J. Phillips et al., 2019). MaxEnt is a popular tool for modeling species distributions (Elith et al., 2011; S. B. Phillips et al., 2006). It expresses a probability distribution where each grid cell has a predicted suitability of conditions for the species (S. B. Phillips et al., 2006). Maxent distribution maps are interpreted as the predicted probability of species presence across the geographical area of interest (Elith et al., 2011). Areas with higher predicted probabilities are considered more suitable for the species based on the environmental conditions (S. B. Phillips et al., 2006).

To model the habitat suitability of *E. subspinosus* in the study area, the selected set of environmental variables including elevation, slope and bioclimatic variables bio1, bio15 and bio19 were loaded in MaxEnt 3.4.4 visual interface as environmental layers. To anticipate the potential impacts of climate change on the distribution of *E. subspinosus*, projection layers were loaded in MaxEnt 3.4.4 visual interface.

The model was trained using 16 out of the total 19 presence records, with the remaining 3 records used for validation. In addition, we utilized 10,000 background points, randomly selected by the model across the study area. The replication type was bootstrap and we generated ten replicates of the model with random selection of the presence data. This approach was taken to reduce uncertainty and create an ensemble model.

The Area Under the Curve (AUC) was used to assess accuracy of the model as it is a widely used metric for measuring the accuracy of models in MaxEnt modeling (Morales et al., 2020). The AUC value ranges from 0 to 1, where an AUC of 1 indicates a perfect model and an AUC of 0.5 suggests that the model performs no better than random guessing. In MaxEnt modeling, maximum AUC of a well-tuned model is $1 - a/2$, where “a” is the prevalence of the species (proportion of the study area occupied by the species) (S. B. Phillips et al., 2006). Maximum training sensitivity plus specificity was used as the threshold rule as the occurrence locations were scarce and the study conducted presence-only (A. Dhyani et al., 2021).

The habitats were grouped into three categories based on the probabilities (p) determined by the ensemble model. These are: (a) Potential habitats where $p \geq \text{threshold}$, (b) Less probable habitats where $\text{threshold} \leq p < 0.5$ (c) High probable habitats where $0.5 \leq p \leq 1$ (A. Dhyani et al., 2021; S. Dhyani et al., 2020). The area of these habitats was calculated for both current and future scenarios across the study area using R package v 4.3.2.

The jackknife test was applied to show the importance of each environmental variable in the modeling process (Kalle et al., 2013; Wang et al., 2024). In addition, response curves were generated to determine the effect of each environmental variable on the predicted probability of presence of *E. subspinoso* over the study area (Labarca-Rojas et al., 2022; S. B. Phillips et al., 2006; Tesfamariam et al., 2022).

Results and discussion

Based on the occurrence data, *E. subspinoso* is found to favor flat lands as the value over occurrence is 0 degrees (Table 2). This is consistent with the known ecology of the species, which is found in seasonal waterways and areas where rainwater accumulates for a short period of time.

Our findings also indicate that *E. subspinoso* prefers the annual mean temperature ranges from 12.78°C to 15.49°C and it thrives in areas where the precipitation during the coldest quarter of the year is between 61–78 mm. Precipitation seasonality, expressed as the coefficient of variation, is deemed suitable for this species when it lies between 53.93% and 70.68% (Table 2).

The species distribution modeling was performed using the MaxEnt approach, which has been widely recognized as one of the most accurate and reliable techniques for presence-only studies such as this one (Valavi et al., 2022). We also chose MaxEnt due to its popularity in distribution modeling of rare and endemic plants (Qazi et al., 2022).

The ensemble model achieved an AUC value of 0.981 which suggests high accuracy of the model (Fig. 3) (Anderson et al., 2011; Araújo et al., 2005; Yackulic et al., 2013). The maximum training sensitivity plus specificity categorical threshold was determined to be 0.256. Table 3 and Fig. 4 present the areas of potential habitats ($p \geq \text{threshold}$), less probable habitats ($\text{threshold} \leq p < 0.5$) and highly probable habitats ($0.5 \leq p \leq 1$).

Table 3

The predicted potential, less probable and high probable habitat area of *E. subspinosus* over the area of Semnan province, Iran (the study area) in the present time compared to that in 2040 and 2060 based on CMCC-ESM2 and HadGEM2 climate models under RCP2.6, RCP4.5 and RCP8.5 pathways.

Climate model	IPCC Representative Concentration Pathways	Year	Potential habitats (km ²) and changes respect to present area (%)	Less probable habitats (km ²) and changes respect to present area (%)	High probable habitats (km ²) and changes respect to present area (%)
		Present	8070.496	4184.65	3885.846
CMCC-ESM2	RCP2.6	2040	7656.071 (94.87%)	4209.028 (100.58%)	3447.043 (88.71%)
		2060	67.56176 (0.84%)	67.56176 (1.61%)	0
	RCP4.5	2040	6680.256 (82.75%)	4368.529 (104.39%)	2311.727 (59.50%)
		2060	690.24431(8.55%)	673.528 (16.09%)	16.71631 (0.43%)
	RCP8.5	2040	5244.742 (64.98%)	3500.674 (83.66%)	1744.068 (44.88%)
		2060	978.60074 (12.12%)	954.9193 (22.82%)	23.68144 (0.61%)
HadGEM3	RCP2.6	2040	0	0	0
		2060	0	0	0
	RCP4.5	2040	0	0	0
		2060	0	0	0
	RCP8.5	2040	0	0	0
		2060	0	0	0

The present time model suggests that this species could be found mainly in the North and Northern-East areas of the study area in elevations spanning from 1117 m to 2154 m. The probability of presence

increases from Southern desert lands with lower elevations, lower precipitation and higher temperatures toward Alborz mountains in the North but it starts to decrease again when the elevation gets higher (Fig. 2 and Fig. 4) and flat lands become scarce. According to this model, the area of potential habitats for *E. subspinosus* could be 8070.496 km² (Table 3 and Fig. 4).

Projections based on the CMCC-ESM2 climate model, in conjunction with all three IPCC Representative Concentration Pathways used in this study, indicate a significant decrease in potential habitats for *E. subspinosus* by 2040 compared to the present time. These projections indicate that by 2040, less probable habitats are not expected to change significantly. However, highly probable habitats are predicted to decrease to 88.71% and 59.50%. According to the SDM predicted using CMCC-ESM2 and RCP8.5, even less probable habitats would decrease to 83.66% by 2040 (Table 3 and Fig. 4).

Consistent with the optimism of RCP2.6, the moderation of RCP4.5 and the pessimism of RCP8.5, the potential habitats predicted by the CMCC-ESM2-RCP4.5 model would cover fewer area than those predicted by the CMCC-ESM2-RCP2.6 model, but more area compared to the potential habitats predicted by the CMCC-ESM2-RCP8.5 model (Table 3, Fig. 4). In addition, high probable habitats would become more rare in lower elevations, where high potential habitats would be replaced by low probable habitats and non-suitable areas. Conversely, higher elevations would become more suitable for *E. subspinosus* (Fig. 2 and Fig. 4), which could be interpreted as the impact of global warming. However, probably as the flat lands suited for the species are less common in higher elevations of the Eastern-Alborz mountain range, the potential habitats would cover fewer area in 2040 in comparison to the present time.

Projections from the CMCC-ESM2 climate model, in conjunction with the RCP2.6, RCP4.5 and RCP8.5, suggest that by 2060, the potential habitat areas could decrease to 0.84%, 8.55% and 12.12% of the current potential habitat area, respectively. In addition, models based on CMCC-ESM2 predict that high probable habitats would decrease to less than 1% and less probable habitats would reduce to under 22.82% by 2060, if any of these pathways come to pass (Table 3 and Fig. 4). These projections show that almost all the high probable habitats would disappear and only some parts of the less probable habitats would remain in higher elevation in the north of the study area.

Interestingly, based on the CMCC-ESM2-RCP4.5 model, the area of potential habitats of *E. subspinosus* in 2060 would be significantly more than that projected by CMCC-ESM2-RCP2.6 model and slightly less than that projected by CMCC-ESM2-RCP8.5 (Table 3 and Fig. 4), which seems to be inconsistent with expectancy of the RCPs. Since the species would migrate to higher elevations, one reason for that inconsistency could be the presence of suitable flat lands (plateaus) on highest elevations of Eastern-Alborz mountain range, which would fall into suitable temperature range of *E. subspinosus* if harsher pathways come to pass and temperatures get higher.

The projections based on the HadGEM2 climate model indicate a more severe potential impact, suggesting the complete extinction of this legume species in the study area by 2040, if either RCP2.6, RCP4.5 or RCP8.5 come true (Table 3). So, these projections leave no room for further discussion.

Without a direct comparison of the two models over the study area, it is challenging to definitively determine which model is more suitable for this specific study and which projection is more accurate. To the best of our knowledge, our study is the first Species Distribution Modeling (SDM) study conducted in Iran using CMCC-ESM2 climate model.

Older versions of HadGEM have been used in several studies in Iran. Ahmadi et al. (2020) conducted a study on the potential impact of future climate on the distribution of *Taxus baccata* L. in Hircanian forests of Northern Iran, using six climate models including HadGEM2, HadGEM2-CC and MIRI-CGCM3. They concluded that *T. baccata* would lose the majority of its habitats by 2050 due to global warming (Ahmadi et al., 2020). In another study, Ghehsareh Ardestani and Heidari Ghahfarrokhi used HadGEM2-CC to project the future distribution of *Salvia hydrangea* in the Central Zagros mountain range, Western Iran. They found out that the area of good habitat suitability ($0.5 < p < 0.75$) and moderate habitat suitability ($0.25 < p < 0.50$) of *S. hydrangea* in the study area would significantly increase but area of low habitat suitability ($0 < p < 0.25$) and high habitat suitability ($0.75 < p < 1$) would decrease under HadGEM2-CC-RCP4.5 and HadGEM2-CC-RCP8.5 models by 2050 and 2070. Conversely, MIRI-CGCM3 climate model suggested significant loss of the habitats of this species (Ghehsareh Ardestani et al., 2021). Tarnian et al. (2021) used HadGEM2-AO, CCSM4 and MIROC5 to predict the future distribution of *Daphne mucronata* across Iran, under RCP4.5 and RCP8.5. They reached the conclusion that this species would lose 35% and 61% of its habitats in Iran and almost would disappear in elevations lower than 1500 m and 2000 m, under RCP4.5 and RCP8.5 pathways, respectively (Tarnian et al., 2021). To the best of our knowledge, our study is the first to use HadGEM3 for SDM in Iran.

There are not many SDM studies conducted on plants across Eastern-Alborz mountain range in Iran. In one study similar to ours, Fatemi et al. (2018) predicted the future distribution of *Juniperus excelsa* across Central- and Eastern-Alborz mountain range by MaxEnt modeling up to 2070. They found that *J. excelsa* is projected to lose some of its habitats and is expected to gradually migrate to higher elevations in response to rising temperatures (Fatemi et al., 2018).

Many SDM studies have projected a shift in distribution of plants toward higher elevations due to global warming in recent years. A 2022 study by Auld et al. found that climate change is causing rapid elevational shifts among Australian alpine plants. Some species are moving upslope, but continued warming could deplete suitable habitats within a century, emphasizing the need for ongoing conservation efforts (Auld et al., 2022). A recent study on alpine species in Norrbotten County, Northern Sweden, has shown varied responses to climate change, with some species increasing and others decreasing in population size. This finding highlights the complex interplay between climate change and species distribution, underscoring the need for continued research and conservation efforts (Rostö, 2020).

The Jackknife of AUC test yielded an AUC of over 0.93 for the Bio1 environmental variable when used in isolation in the Maxent model. This was followed by elevation, which resulted in an AUC between 0.92 and 0.93 and slope, which had an AUC of less than 0.8. The omission of both Bio1 and Bio15 variables

led to an AUC of less than 0.96. However, the omission of other variables did not significantly affect the model's AUC (Fig. 5).

These results suggests that temperature plays a significant role in determining habitat suitability of the species. Interestingly, despite having a lower contribution percentage (24.5%) compared to elevation (54.9%), the Bio1 variable showed a higher permutation importance (71.2%) that underscores the sensitivity of the species to temperature variations, implying that it may have specific temperature requirements for survival and reproduction, which is in alignment of narrow range of Bio1 variable (12.78°C-15.49°C) over occurrence locations (Table 2) and Bio1 response curve of the model (Fig. 6).

On the other hand, the elevation variable, while contributing the most (54.9%) to the model, did not demonstrate as high a permutation importance as Bio1. This could suggest that while elevation plays a role in distribution of the species, its influence is more generic and less sensitive to specific changes in value. Elevation has the most percent contribution to the model with 54.9%, followed by Bio1 with 24.5% contribution to the model. However, Bio1 variable with a permutation importance of 71.2% is the most influential variable when considering the effect of permuting the values of each variable across the training presence and background data (Table 2).

Many factors contribute to the way the distribution of plants shifts in response to raising temperatures. In their comprehensive 2021 study, Steven R. Beissinger and Eric A. Riddell highlight the crucial role of physiological traits of species and the availability of suitable habitats in determining the speed and direction of species range shifts (Beissinger et al., 2021). Chardon et al. (2023) found that microhabitat variables weakly predict recruitment and seedling survival, with varied responses to environmental factors across species and life stages (Chardon et al., 2023). Adding to this complexity, a recent research has highlighted the importance of considering intraspecific ecological variation when predicting species distributions for conservation and climate change impact assessment (Varaldo et al., 2023).

Conclusion

The present study aimed to model the current and future distribution of *E. subspinoso* which is an endangered species in Iran, found only in rare locations on the Southern side of the Eastern Alborz mountain range in Semnan province. Alborz mountains are in high priority for conservation efforts since they are home to many rare species as one of the areas in the South-East Asia with highest biodiversity. However, they have been under intensive human activities like road construction, recently (Noroozi, 2020).

Our presence-only SDM study suggested a significant loss in the area of the habitats of *E. subspinoso*, an endangered species in Iran, across the study area based on the CMCC-ESM2 climate model by 2060 due to global warming. In addition, the CMCC-ESM2 model suggests that this legume plant would migrate to higher elevations seeking flat lands with suitable temperatures. The HadGEM3 climate model suggests an even more severe impact of climate change on the future distribution of *E. subspinoso*,

predicting its complete extinction by 2040 under RCP2.6, RCP4.5 and RCP8.5 pathways in Semnan province, Iran.

E. subspinoso is not only vulnerable to global warming across our study area, but human activities like road construction could also affect the future distribution of this endangered plant. Despite the tendency of this species to migrate to higher elevations due to rising temperatures, new roads may limit its capability to do so. While there are some protected areas and natural parks across the main habitats of *E. subspinoso*, the gaps between these areas could hinder the response of the species to global warming and accelerate its probable extinction over the study area (Noroozi, 2020). Therefore, filling these gaps with defining new protected areas and national parks is highly recommended to not only delay the extinction of this species, but also to protect other rare and endemic species of the study area (Noroozi, 2020; Noroozi et al., 2023).

Finally, we concluded that temperature, elevation and slope are the most important environmental variables affecting *E. subspinoso* distribution. Moreover, we should not ignore the role of other factors like ecological relationships with other species, the main way of propagation and seed germination and also human activities like road constructions, to plan conservation efforts more effectively. We suggest further studies using more occurrence locations or presence-absence data over a wider study area which could span from Western China to Eastern Europe. Using citizen science data (Hutchinson et al., 2017) could be useful due to the rarity of this species. We also suggest future studies to consider reproduction traits of the plant and human activities affecting its habitats.

Declarations

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

Ethical Approval

Not applicable

Funding

Not applicable

Author Contribution

Amir Zaheri: Methodology, data analysis, writing — original draft. Reza Naderi: Conceptualization, investigation, data collection, writing — original draft, review and editing, supervision. Atefe Amirahmadi: Conceptualization, data collection, formal analysis, methodology, writing — review and editing. All authors read and approved the final paper.

Acknowledgements

We express our gratitude to the World Climate Research Programme for coordinating and advocating for CMIP6 via its Working Group on Coupled Modelling. Our thanks also extend to the climate modeling groups for their production and provision of model output, the Earth System Grid Federation (ESGF) for their role in data storage and access and the numerous funding bodies that back CMIP6 and ESGF.

We also wish to acknowledge the organizations that contributed to the Harmonized World Soil Database v 1.2. This includes the Food and Agriculture Organization of the United Nations (FAO), the International Institute for Applied Systems Analysis (IIASA), ISRIC-World Soil Information, the Institute of Soil Science, Chinese Academy of Sciences (ISSCAS), and the Joint Research Centre of the European Commission (JRC). Their collaborative efforts have been instrumental in our research.

Availability of data and materials

Climate and elevation datasets used in this study were obtained from WorldClim version 2.1 (available at <https://www.worldclim.org/>). Soil data were obtained from Harmonized World Soil Database v 1.2 at the FAO website (available at <https://www.fao.org/>).

References

1. Ahmadi, K., Alavi, S. J., Amiri, G. Z., Hosseini, S. M., Serra-Diaz, J. M., & Svenning, J. C. (2020). The potential impact of future climate on the distribution of European yew (*Taxus baccata* L.) in the Hyrcanian Forest region (Iran). *International Journal of Biometeorology*, 64(9), 1451–1462. doi: 10.1007/s00484-020-01922-z
2. Amirabadizadeh, H., Assadi, M., Nemati Peykani, M., Janighorban, M., Jalilian, N., Maasoumi, A. ., Small, E., Zaeifi, M., Abbassi, M., Naanaie, S. ., Jafari, A., Pooyan, P., Ghahremaninejad, F., Chaghamirzaei, E., Amirkosaravi, A., & Mehregan, I. (2023). Fabaceae p.p. *Flora of Iran*, 177, 551–553.
3. Anderson, R. P., Martínez-Meyer, E., Nakamura, M., Araújo, M. B., Peterson, A. T., Soberón, J., & Pearson, R. G. (2011). Ecological Niches and Geographic Distributions (MPB-49). In Ecological Niches and Geographic Distributions (MPB-49) (Issue December). doi: 10.1515/9781400840670
4. Andrews, M. B., Ridley, J. K., Wood, R. A., Andrews, T., Blockley, E. W., Booth, B., Burke, E., Dittus, A. J., Florek, P., Gray, L. J., Haddad, S., Hardiman, S. C., Hermanson, L., Hodson, D., Hogan, E., Jones, G. S., Knight, J. R., Kuhlbrodt, T., Misios, S., ... Sutton, R. T. (2020). Historical Simulations With HadGEM3-GC3.1 for CMIP6. *Journal of Advances in Modeling Earth Systems*, 12(6), 1–34. doi: 10.1029/2019MS001995
5. Araújo, M. B., Pearson, R. G., Thuiller, W., & Erhard, M. (2005). Validation of species-climate impact models under climate change. *Global Change Biology*, 11(9), 1504–1513. doi: 10.1111/j.1365-2486.2005.01000.x

6. Auld, J., Everingham, S. E., Hemmings, F. A., & Moles, A. T. (2022). Alpine plants are on the move: Quantifying distribution shifts of Australian alpine plants through time. *Diversity and Distributions*, 28(5), 943–955. doi: 10.1111/ddi.13494
7. Beissinger, S. R., & Riddell, E. A. (2021). Why Are Species Traits Weak Predictors of Range Shifts? *Annual Review of Ecology, Evolution, and Systematics*, 52, 47–66. doi: 10.1146/annurev-ecolsys-012021-092849
8. Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W., & Courchamp, F. (2012). Impacts of climate change on the future of biodiversity. *Ecology Letters*, 15(4), 365–377. doi: 10.1111/j.1461-0248.2011.01736.x
9. Bonebrake, T. C., Brown, C. J., Bell, J. D., Blanchard, J. L., Chauvenet, A., Champion, C., Chen, I. C., Clark, T. D., Colwell, R. K., Danielsen, F., Dell, A. I., Donelson, J. M., Evengård, B., Ferrier, S., Frusher, S., Garcia, R. A., Griffis, R. B., Hobday, A. J., Jarzyna, M. A., ... Pecl, G. T. (2018). Managing consequences of climate-driven species redistribution requires integration of ecology, conservation and social science. *Biological Reviews*, 93(1), 284–305. doi: 10.1111/brv.12344
10. Chardon, N., Mcburnie, L., Goodwin, K., Pradhan, K., Hille, J., Lambers, R., & Angert, A. L. (2023). *Variable species establishment in response to microhabitat indicates different likelihoods of climate-driven range shifts*. 1–22.
11. Chen, I. C., Hill, J. K., Ohlemüller, R., Roy, D. B., & Thomas, C. D. (2011). Rapid range shifts of species associated with high levels of climate warming. *Science*, 333(6045), 1024–1026. doi: 10.1126/science.1206432
12. Cherchi, A., Fogli, P. G., Lovato, T., Peano, D., Iovino, D., Gualdi, S., Masina, S., Scoccimarro, E., Materia, S., Bellucci, A., & Navarra, A. (2019). Global Mean Climate and Main Patterns of Variability in the CMCC-CM2 Coupled Model. *Journal of Advances in Modeling Earth Systems*, 11(1), 185–209. doi: 10.1029/2018MS001369
13. Couet, J., Marjakangas, E. L., Santangeli, A., Kålås, J. A., Lindström, Å., & Lehikoinen, A. (2022). Short-lived species move uphill faster under climate change. *Oecologia*, 198(4), 877–888. doi: 10.1007/s00442-021-05094-4
14. Dhyani, A., Kadaverugu, R., Nautiyal, B. P., & Nautiyal, M. C. (2021). Predicting the potential distribution of a critically endangered medicinal plant *Lilium polyphyllum* in Indian Western Himalayan Region. *Regional Environmental Change*, 21(2). doi: 10.1007/s10113-021-01763-5
15. Dhyani, S., Kadaverugu, R., & Pujari, P. (2020). Predicting impacts of climate variability on Banj oak (*Quercus leucotrichophora* A. Camus) forests: understanding future implications for Central Himalayas. *Regional Environmental Change*, 20(4). doi: 10.1007/s10113-020-01696-5
16. Elith, J., H. Graham, C., P. Anderson, R., Dudík, M., Ferrier, S., Guisan, A., J. Hijmans, R., Huettmann, F., R. Leathwick, J., Lehmann, A., Li, J., G. Lohmann, L., A. Loiselle, B., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., McC. M. Overton, J., Townsend Peterson, A., ... E. Zimmermann, N. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, 29(2), 129–151. doi: 10.1111/j.2006.0906-7590.04596.x

17. Elith, J., & Leathwick, J. R. (2009). Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, 40, 677–697. doi: 10.1146/annurev.ecolsys.110308.120159
18. Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, 17(1), 43–57. doi: 10.1111/j.1472-4642.2010.00725.x
19. Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–1958. doi: 10.5194/gmd-9-1937-2016
20. Fatemi, S. S., Rahimi, M., Tarkesh, M., & Ravanbakhsh, H. (2018). Predicting the impacts of climate change on the distribution of *juniperus excelsa* M. Bieb. in the central and eastern ALBORZ mountains, IRAN. *IForest*, 11(5), 643–650. doi: 10.3832/for2559-011
21. Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, 37(12), 4302–4315. doi: 10.1002/joc.5086
22. Fischer, G., Nachtergaele, F. O., Prieler, S., Teixeira, E., Tóth, G., Velthuizen, H. van, Verelst, L., & Wiberg, D. (2008). Global Agro-ecological Zones (GAEZ v3.0). *IIASA and FAO*, 196.
23. Ganjajanian, H. (2023). *Evaluation of desertification risk potential using DVI model (Case study: northern regions of Semnan province)*. October. doi: 10.22034/JARGS.2023.397791.1032
24. Gervais, C. R., Champion, C., & Pecl, G. T. (2021). Species on the move around the Australian coastline: A continental-scale review of climate-driven species redistribution in marine systems. *Global Change Biology*, 27(14), 3200–3217. doi: 10.1111/gcb.15634
25. Ghehsareh Ardestani, E., & Heidari Ghahfarrokhi, Z. (2021). Ensemblspecies distribution modeling of *Salvia hydrangea* under future climate change scenarios in Central Zagros Mountains, Iran. *Global Ecology and Conservation*, 26, e01488. doi: 10.1016/j.gecco.2021.e01488
26. Haarsma, R. J., Roberts, M. J., Vidale, P. L., Senior, C. A., Bellucci, A., Bao, Q., Chang, P., Corti, S., Fučkar, N. S., Guemas, V., von Hardenberg, J., Hazeleger, W., Kodama, C., Koenigk, T., Leung, L. R., Lu, J., Luo, J.-J., Mao, J., Mizielinski, M. S., ... von Storch, J.-S. (2016). High Resolution Model Intercomparison Project (HighResMIP~v1.0) for CMIP6. *Geoscientific Model Development*, 9(11), 4185–4208. doi: 10.5194/gmd-9-4185-2016
27. Hanberry, B. B. (2024). Practical guide for retaining correlated climate variables and unthinned samples in species distribution modeling, using random forests. *Ecological Informatics*, 79(December), 102406. doi: 10.1016/j.ecoinf.2023.102406
28. Harisena, N. V., Groen, T. A., Toxopeus, A. G., & Naimi, B. (2021). When is variable importance estimation in species distribution modelling affected by spatial correlation? *Ecography*, 44(5), 778–788. doi: 10.1111/ecog.05534
29. Hutchinson, R. A., He, L., & Emerson, S. C. (2017). Species distribution modeling of citizen science data as a classification problem with class-conditional noise. *31st AAAI Conference on Artificial Intelligence, AAAI 2017*, 4516–4523. doi: 10.1609/aaai.v31i1.11177

30. Jalili, A., & Jamzad, Z. (1999). *Red data book of Iran. A preliminary survey of endemic, rare and endangered plant species in Iran*. Research Institute of Forest and Rangeland, Tehran.
31. Kalle, R., Ramesh, T., Qureshi, Q., & Sankar, K. (2013). Predicting the distribution pattern of small carnivores in response to environmental factors in the Western Ghats. *PLoS ONE*, 8(11). doi: 10.1371/journal.pone.0079295
32. Labarca-Rojas, Y., Hernández-Bermejo, J. E., Quero, J. L., & Herrera-Molina, F. (2022). Bioclimatic habitat limitations for argan trees (*Argania spinosa* (L.) Skeels) in Northern Africa and Spain. *Regional Environmental Change*, 22(1). doi: 10.1007/s10113-021-01869-w
33. Lenoir, J., & Svenning, J. C. (2015). Climate-related range shifts - a global multidimensional synthesis and new research directions. *Ecography*, 38(1), 15–28. doi: 10.1111/ecog.00967
34. Mehrabian, A. (2013). *Principles of plant conservation, challenges and methods*. Shahid Beheshti University Press, Tehran.
35. Meinshausen, M., Nicholls, Z. R. J., Lewis, J., Gidden, M. J., Vogel, E., Freund, M., Beyerle, U., Gessner, C., Nauels, A., Bauer, N., Canadell, J. G., Daniel, J. S., John, A., Krummel, P. B., Luderer, G., Meinshausen, N., Montzka, S. A., Rayner, P. J., Reimann, S., ... Wang, R. H. J. (2020). The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500. *Geoscientific Model Development*, 13(8), 3571–3605. doi: 10.5194/gmd-13-3571-2020
36. Merckenschlager, C., Bangelesa, F., Paeth, H., & Hertig, E. (2023). Blessing and curse of bioclimatic variables: A comparison of different calculation schemes and datasets for species distribution modeling within the extended Mediterranean area. *Ecology and Evolution*, 13(10), 1–18. doi: 10.1002/ece3.10553
37. Mironov, E. M., & Sokoloff, D. D. (2000). A carpological study of *Eversmannia subspinosa* (Fisch. ex DC.) B.Fedtsch. (Leguminosae, Hedysareae). *Feddes Repertorium*, 111(1–2), 1–8. doi: 10.1002/fedr.20001110102
38. Morales, N. S., & Fernández, I. C. (2020). Land-cover classification using maxent: Can we trust in model quality metrics for estimating classification accuracy? *Entropy*, 22(3). doi: 10.3390/e22030342
39. Noroozi, J. (2020). *Plant Biogeography and Vegetation of High Mountains of Central and South-West Asia*.
40. Noroozi, J., Akhiani, H., & Breckle, S. W. (2008). Biodiversity and phytogeography of the alpine flora of Iran. *Biodiversity and Conservation*, 17(3), 493–521. doi: 10.1007/s10531-007-9246-7
41. Noroozi, J., Minaei, M., Khalvati, S., Kaveh, A., Nafisi, H., Nazari, B., Zare, G., Vitek, E., Hülber, K., & Schneeweiss, G. M. (2023). Hotspots of (sub)alpine plants in the Irano-Anatolian global biodiversity hotspot are insufficiently protected. *Diversity and Distributions*, 29(2), 244–253. doi: 10.1111/ddi.13656
42. Parmesan, C., & Hanley, M. E. (2015). Plants and climate change: Complexities and surprises. *Annals of Botany*, 116(6), 849–864. doi: 10.1093/aob/mcv169

43. Pecl, G. T., Araújo, M. B., Bell, J. D., Blanchard, J., Bonebrake, T. C., Chen, I. C., Clark, T. D., Colwell, R. K., Danielsen, F., Evengård, B., Falconi, L., Ferrier, S., Frusher, S., Garcia, R. A., Griffis, R. B., Hobday, A. J., Janion-Scheepers, C., Jarzyna, M. A., Jennings, S., ... Williams, S. E. (2017). Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science*, 355(6332). doi: 10.1126/science.aai9214
44. Phillips, S. B., Aneja, V. P., Kang, D., & Arya, S. P. (2006). Modelling and analysis of the atmospheric nitrogen deposition in North Carolina. *International Journal of Global Environmental Issues*, 6(2–3), 231–252. doi: 10.1016/j.ecolmodel.2005.03.026
45. Phillips, S. J., Dudík, M., & Schapire, R. E. (2019). *Maxent software for modeling species niches and distributions (Version 3.4.1)*. Available from url: http://biodiversityinformatics.amnh.org/open_source/maxent/. Biodiversity Informatics. Retrieved from http://biodiversityinformatics.amnh.org/open_source/maxent/
46. Qazi, A. W., Saqib, Z., & Zaman-ul-Haq, M. (2022). Trends in species distribution modelling in context of rare and endemic plants: a systematic review. *Ecological Processes*, 11(1). doi: 10.1186/s13717-022-00384-y
47. Rostö, E. (2020). *Changes in alpine plant population sizes in response to climate change*.
48. Sharma, S., Mishra, A., Shukla, K., Kumari, P., Jindal, T., Shukla, S. (2021). *Climate change and the microbiome sustenance of the ecosphere* (Issue October). doi: 10.1007/978-3-030-76863-8
49. Stanton, J. C., Pearson, R. G., Horning, N., Ersts, P., & Reşit Akçakaya, H. (2012). Combining static and dynamic variables in species distribution models under climate change. *Methods in Ecology and Evolution*, 3(2), 349–357. doi: 10.1111/j.2041-210X.2011.00157.x
50. Sunday, J. M., Bates, A. E., & Dulvy, N. K. (2012). Thermal tolerance and the global redistribution of animals. *Nature Climate Change*, 2(9), 686–690. doi: 10.1038/nclimate1539
51. Tarnian, F., Kumar, S., Azarnivand, H., Chahouki, M. A. Z., & Mossivand, A. M. (2021). Assessing the effects of climate change on the distribution of *Daphne mucronata* in Iran. *Environmental Monitoring and Assessment*, 193(9), 1–19. doi: 10.1007/s10661-021-09311-8
52. Tesfamariam, B. G., Gessesse, B., & Melgani, F. (2022). MaxEnt-based modeling of suitable habitat for rehabilitation of *Podocarpus* forest at landscape-scale. *Environmental Systems Research*, 11(1). doi: 10.1186/s40068-022-00248-6
53. Valavi, R., Guillera-Aroita, G., Lahoz-Monfort, J. J., & Elith, J. (2022). Predictive performance of presence-only species distribution models: a benchmark study with reproducible code. *Ecological Monographs*, 92(1), 1–27. doi: 10.1002/ecm.1486
54. Varaldo, L., Guerrina, M., Dagnino, D., Minuto, L., & Casazza, G. (2023). Dealing with disjunct populations of vascular plants: implications for assessing the effect of climate change. *Oecologia*, 201(2), 421–434. doi: 10.1007/s00442-023-05323-y
55. Vichi, M., Manzini, E., Fogli, P. G., Alessandri, A., Patara, L., Scoccimarro, E., Masina, S., & Navarra, A. (2011). Erratum to: Global and regional ocean carbon uptake and climate change: Sensitivity to a

- substantial mitigation scenario (Clim Dyn, 10.1007/s00382-011-1079-0). *Climate Dynamics*, 37(11–12), 2551. doi: 10.1007/s00382-011-1144-8
56. Wang, Z., Ma, Q., Liang, S., & Liu, Y. (2024). *Study on the distribution and habitat suitability of seagrass in the Northern Chinese Seas*. *January*, 1–15. doi: 10.3389/fmars.2023.1297137
57. Warren, R., Price, J., Graham, E., Forstenhaeusler, N., & VanDerWal, J. (2018). The projected effect on insects, vertebrates, and plants of limiting global warming to 1.5°C rather than 2°C. *Science*, 360(6390), 791–795. doi: 10.1126/science.aar3646
58. Yackulic, C. B., Chandler, R., Zipkin, E. F., Royle, J. A., Nichols, J. D., Campbell Grant, E. H., & Veran, S. (2013). Presence-only modelling using MAXENT: When can we trust the inferences? *Methods in Ecology and Evolution*, 4(3), 236–243. doi: 10.1111/2041-210x.12004
59. Zu, K., Wang, Z., Zhu, X., Lenoir, J., Shrestha, N., Lyu, T., Luo, A., Li, Y., Ji, C., Peng, S., Meng, J., & Zhou, J. (2021). Upward shift and elevational range contractions of subtropical mountain plants in response to climate change. *Science of the Total Environment*, 783, 146896. doi: 10.1016/j.scitotenv.2021.146896

Figures

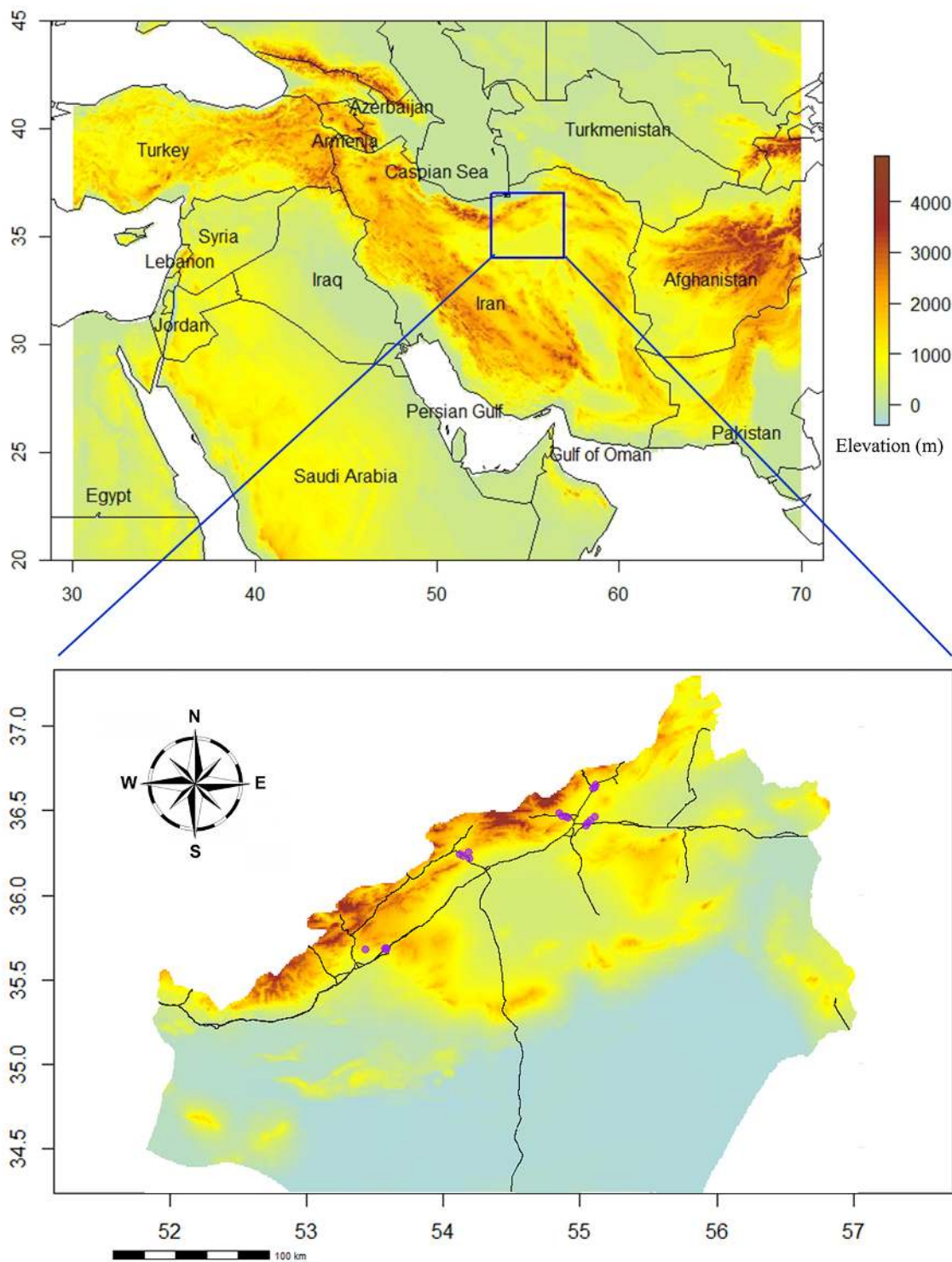


Figure 1

The elevation map of the study area (Semnan, Iran) showcasing the primary roads (black) and the occurrences of *E. subspinosus* that are shown as purple dots

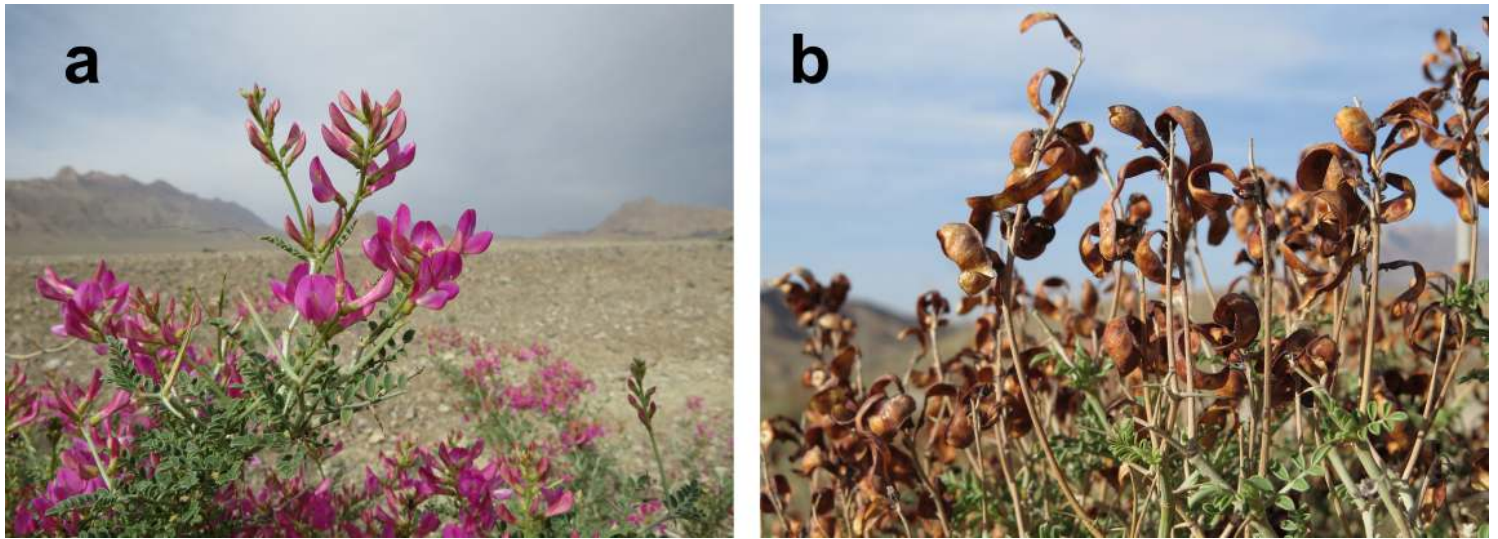


Figure 2

The habit of *E.subspinososa* in Eastern Alborz. Flowering stage (a) and fruiting stage (b)

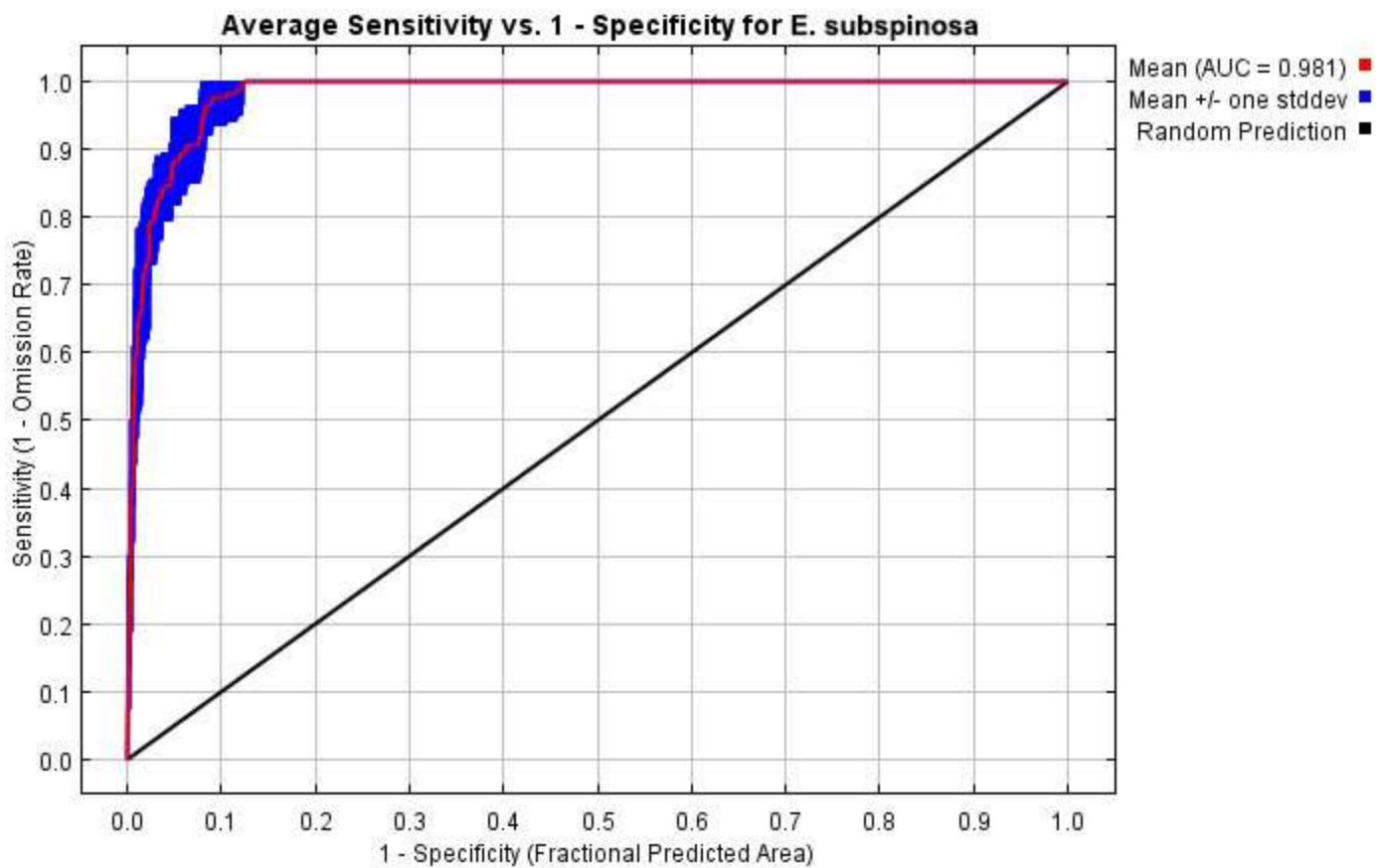


Figure 3

ROC (Receiver Operating Characteristic) curve for *E.subspinososa* ensemble model. The ROC curve, which plots the true positive rate against the false positive rate, demonstrates the model’s performance (Elith et al., 2011). The red line shows the mean value of “sensitivity against 1 – specificity” and the diagonal

black line shows sensitivity vs. 1 – specificity value for a random model. The Area Under the Curve (AUC) for the ensemble model is 0.981. Blue illustrates mean $\pm$ standard deviation

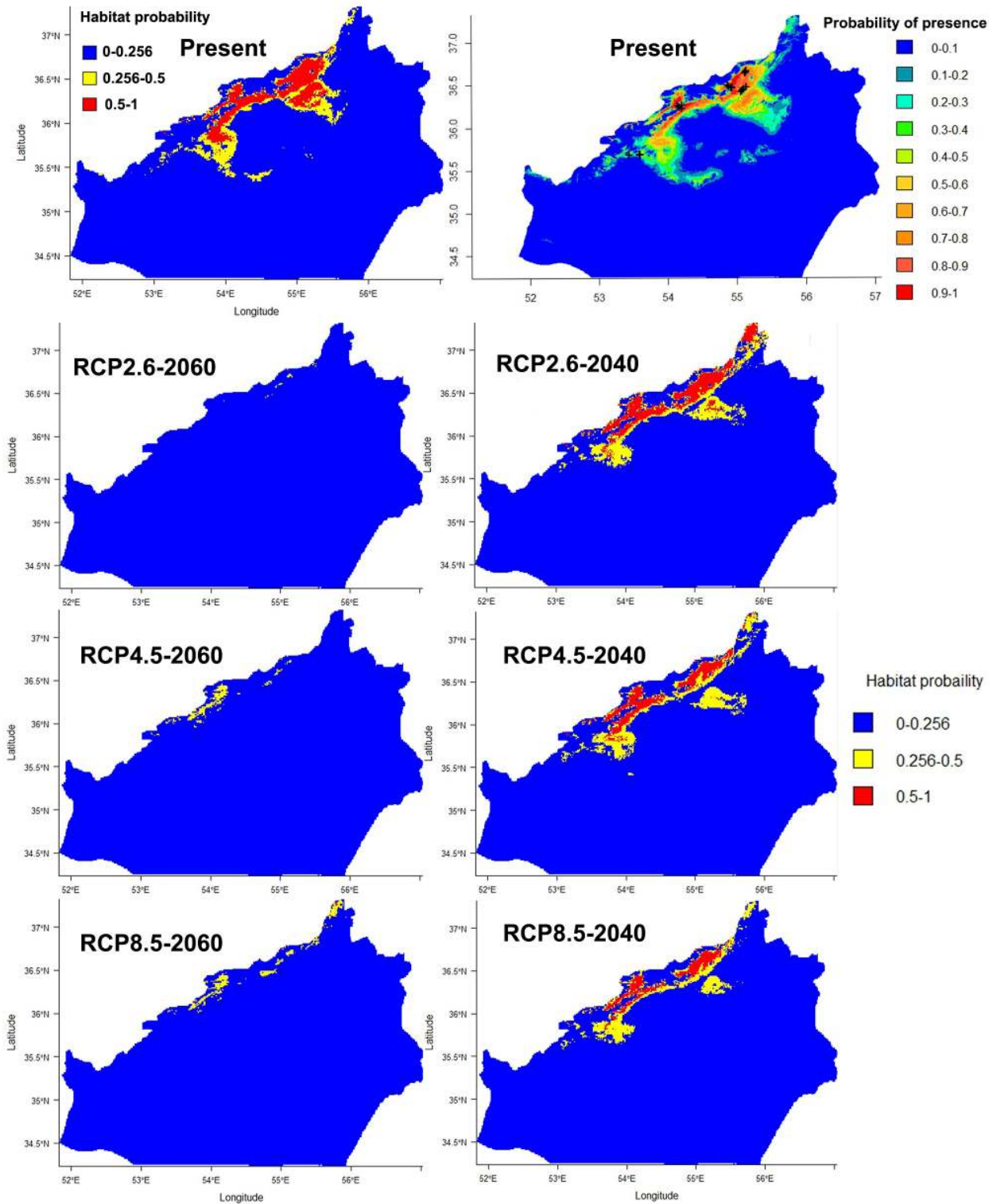


Figure 4

Present distribution model of *E. subspinosus* across the study area and occurrence locations (shown as '+') (upper right shape), categorization of the present habitats into less probable (threshold $\leq p < 0.5$; shown in yellow) and high probable ($0.5 \leq p \leq 1$; shown in red) (upper left shape), and predicted habitat

distribution of *E. subspinosabased* on CMCC-ESM2 model paired with RCP2.6, RCP4.5 and RCP8.5 for the years 2040 and 2060

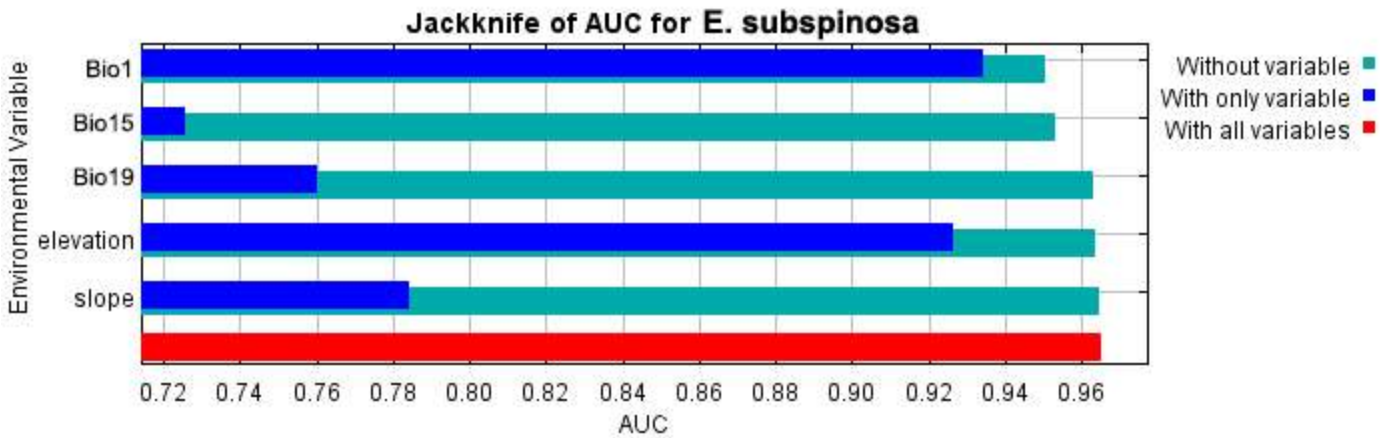


Figure 5

Results of Jackknife of AUC test for *E. subspinosabased*

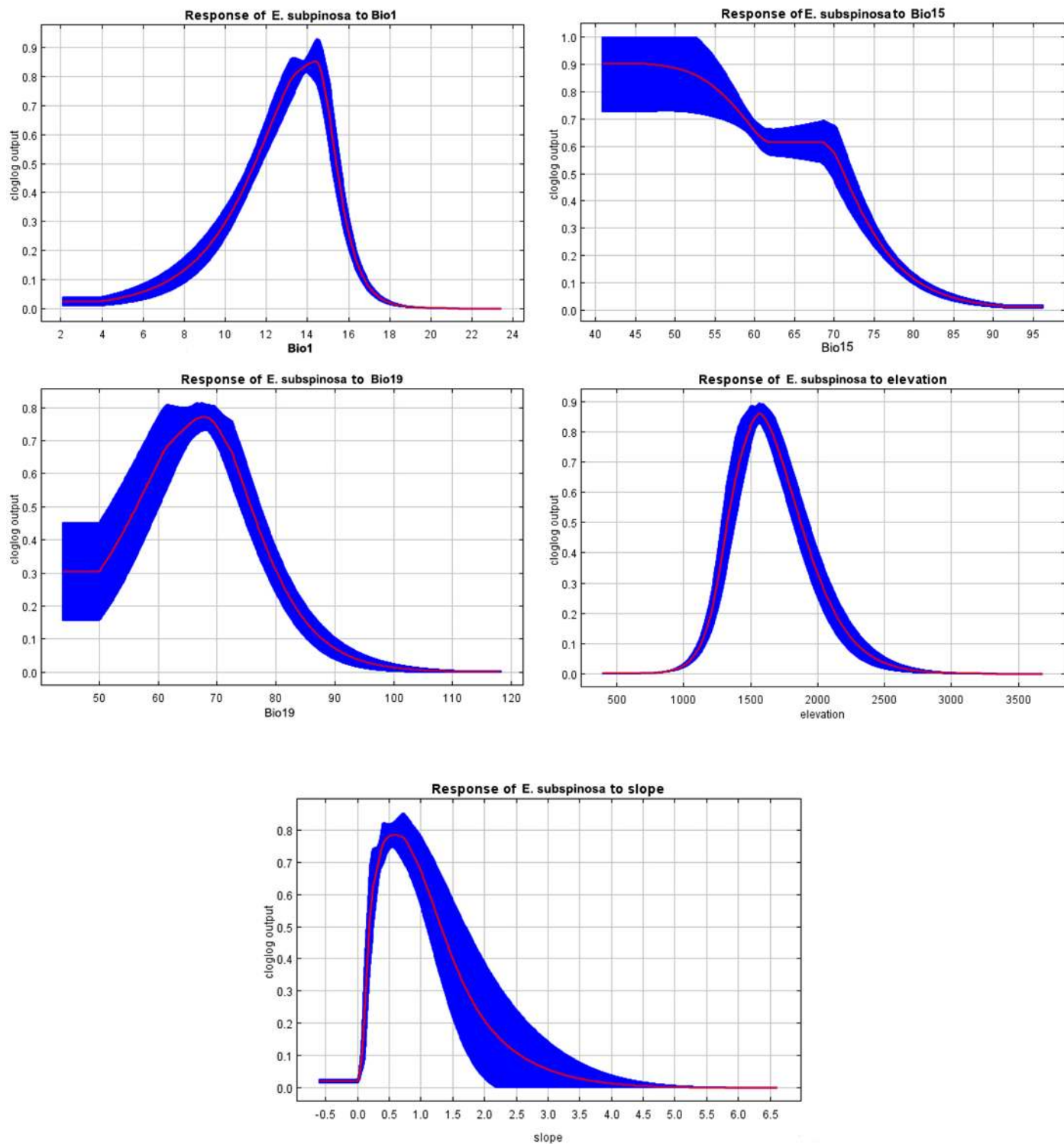


Figure 6

Individual variable response curves, which illustrate changes in the predicted suitability of a species when only a single specific environmental variable is used to construct the model. Each graph shows the response of *E. subspinoso* to a different environmental variable. The red line represents the mean response of the 10 replicate runs of the model and the blue shade shows standard deviation of the red line $\pm$ one

