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Will *Ferulago glareosa* Kandemir and Hedge (Apiaceae) be extinct in the near future?

İdris SARI[1,*], **Ali KANDEMİR**[2]
[1]Erzincan Social Sciences High School, Erzincan, Turkey
[2]Department of Biology, Faculty of Art and Science, Erzincan Binali Yıldırım University, Erzincan, Turkey

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Abstract: Turkey is one of the most important temperate countries on Earth in terms of plant diversity. There is a growing interest in understanding habitat suitability and future distributions of species in the scientific world. Because climate change has impacted ecosystems with major consequences, species are shifting and declining much faster than in the past. Some global climate models used for predicting climate in the future better represent and have higher reliability for some climate types. *Ferulago glareosa,* which lives in Turkey, is a rare endemic plant species. In this study, we investigated current and future distributions of the species determined to be habitat-specific to lead to future studies on conservation. The Maxent model was used to map the current and future potential distribution of the species for Turkey. HadGEM2-ES and MPI-ESM-LR global climate models based on predicted future suitability of *F. glareosa* for 2050 and 2070 were examined. Models were constructed based on 20 presence points of the species and 2 abiotic variables. The current species distribution modeling of *Ferulago glareosa* predicted by the model produced very high success rates with training and test AUC values of 0.970 and 0.968, respectively. The true skill statistics value of the model (0.8245) indicated excellent model performance. In the end, we have demonstrated how predictions obtained from a highly reliable global climate model for a region's climate could provide more dependable insights into the future distribution of narrow-spread endemic species.

Key words: Climate change, *Ferulago glareosa*, habitat suitability, plant conservation, species distribution, Red List

1. Introduction

Only a green world, rich in plants, can sustain us and millions of other species. However, in an era of global change, many plant species are becoming rarer, threatened even to the point of extinction (Blackmore and Oldfield, 2017). Chen et al. (2011) and Dobrowski et al. (2013) remarked that there is a scientific consensus today that species are shifting and declining much faster than in the past due to drastic changes in climatic conditions.

Ecological niche models/habitat suitability models/ species distribution models (SDMs hereafter) have been useful for conservation studies and other purposes in the scientific world. Species distribution modeling is an efficient tool foranswering a variety of questions related to species' geographic distributions (Guisan and Thuiller, 2005; Elith and Leathwick, 2009; Peterson et al., 2011; Peterson and SoberoÂn, 2012). We have a long list of questions, which is why attention from the scientific community continues to be drawn to the topic (De Marco and Nóbrega, 2018).

The representative concentration pathways (RCPs), which are used for making projections, are the latest scenarios developed under the Intergovernmental Panel on Climate Change (IPCC) (Pachauri et al., 2014). Based on all of these scenarios, climate models are designed to demonstrate the effect of political decision-making and other influences on the environment of the future. The Coupled Model Intercomparison Project Phase 5 (CMIP5) now includes more than 50 global climate models (GCMs hereafter). Although there are several quantitative model skill scores that can be calculated for the models, different models tend to perform well on some metrics and poorly on others. In consequence, the IPCC avoids ranking models and treats each equally (Solomon et al., 2007; IPCC, 2014).

In their review evaluating 163 climate change modeling studies carried out from 1983 to 2013, Porfirio et al. (2014) expressed that only 10% of these models stated which GCM was chosen, only 40% of them used 2 or more GCMs and 1 or 2 emission scenarios, and only 7 studies performed more than 10 GCMs. They also criticized that each of these 7 articles focused on testing SDM methods, rather than applying predictions obtained from SDMs to practical conservation problems.

Although one of the most powerful tools for species-level conservation assessments in more recent years,

* Correspondence: botanical24@gmail.com

SDMs are not free from drawbacks. For example, the results of SDMs under future climatic conditions are affected by a range of factors, including the choice of the statistical model, variable selection, climate model range, and emission scenarios (Thuiller, 2004; Araújo et al., 2005; Diniz-Filho et al., 2009). Because predicted suitable environments for species would differ among predictions obtained from various GCMs, Porfirio et al. (2014) proposed some suggestions to researchers that would model future distributions of species. One of these recommendations is to consider multiple models in order to capture a reasonable range for future distributions of species.

On the other hand, although IPCC considers all climate models to be equal, certain GCMs better represent some climate types. For example, among the GCMs, BCC-CSM1.1 (Beijing Climate Centre, China Meteorological Administration) has higher reliability and has been better studied for regions with significant monsoonal precipitation (Jena et al., 2016; Sriniyasa and Kumar, 2016; Pramanik et al., 2018). In order to find a highly reliable GCM for Turkey under the ongoing "Determination of the Impact of Climate Change on Snow Melts and Flows Project", by which Regional Climate Model (RegCM4.3) was driven by 3 different GCMs, researchers demonstrated that MPI-ESM-MR was the most reliable GCM among the 3 GCMs (CNRM-CM5.1, HadGEM2-ES, and MPI-ESM-MR). Among these tested models, MPI-ESM-MR appeared to be little affected by systematic errors in climate projections and showed the highest performance in general.[1] *Ferulago glareosa* Kandemir and Hedge (Apiaceae), which is a rare endemic plant species, lives only in young soils and bedrock cracks in Kemah, Erzincan, Turkey (Kandemir and Hedge, 2007); reproductive success of the species is quite low in some years (Kandemir and Sarı, 2019) (Figure 1). Although some researchers have so far proposed multimodel approaches in modeling future distributions of species, in this study, we attempt to show how vital the predictions obtained from highly reliable GCM would be for any region's climate in the modeling of narrow-spread endemic species' future distribution.

2. Materials and methods

2.1. Study area and collecting presence points of the species

The study site is located between 39°22′31.70″E and 39°9′32.03″E longitude and 39°41′51.14″N and 39°39′10.42″N latitude on the hill slopes in the town of Kemah. Presence points (records hereafter) of the species' individuals were obtained using GPS in all distribution areas of *F. glareosa*. A total of 159 collected records were converted to shape files (.shp). Extent of occurrence (EOO hereafter) of the species (in line form) was drawn and converted to raster data, and again converted to shape data to obtain EOO (in the form of a grid) (Figure 2). All work was executed using ArcGis 10.5.1.[2]

2.2. Preparing and choosing predictor variables

The study used 19 bioclimatic and 4 terrain predictor variables for *F. glareosa*'s species distribution modeling. Data for different climate scenarios and years (current version 1.4; 2050 and 2070 version 1.4) were downloaded from the Worldclim database in the form of 19 bioclimatic variables at a resolution of 30 arc-seconds (~1 km × 1 km grid resolution). To create terrain variables (altitude, aspect, topographic position index, percentage of slope) used in modeling, elevation data was downloaded from DIVA-GIS data[3], then we created terrain data by using Spatial Analysis Tools in ArcGis 10.5.1 (Hijmans et al., 2005; Fick and Hijman, 2017).

Because Maxent performs best with the least number of records in comparison with several other models (Elith et al., 2006; Phillips et al., 2006; Pearson et al., 2007; Kumar et al., 2009), we used the Maxent 3.4.1 (Maximum Entropy) model[4] to map the current and future potential distribution of *F. glareosa* for Turkey. Spearman rank correlation was calculated using omnibus, satisfactory, legendary, and enmSDM packages in R 3.6.1 for Windows to evaluate multicollinearity among all predictor variables.[5] A cross-correlation value (r) > 0.70 was selected as a cut-off threshold to remove strongly correlated variables leading to the selection of strong variables (Philips et al., 2006; Philips and Dudik, 2008). If correlations among variables were greater than 0.7, lines between variable names were drawn in black; if they were smaller than –0.7, lines were drawn in red[6] (Figure 3).

The decision to exclude and include one from each set of highly correlated variables was made based on their inherent ecological significance to *F. glareosa*. Because large-scale screening studies revealed that germination requirements and timing of seedling emergence in a large number of Apiaceae species in the northern temperate climate have

[1] Ballı C (2019). Analysis of climate projection data [online]. Website https://www.tarimorman.gov.tr/SYGM/Belgeler/Ta%C5%9Fk%C4%B1n%20SON/%C4%B0klim%20Projeksiyonlar%C4%B1-Veri%20Analizi_CBalli.pdf [accessed 26 12 2019].

[2] Environmental Systems Research Institute (ESRI) (2019) [online]. Website https://www.arcgis.com/index.html [accessed 15 09 2019].

[3] DIVA-GIS [online]. Website https://www.diva-gis.org/gdata [accessed 15 09 2019].

[4] Steven JP, Miroslav D, Robert ES (2019) [online]. Website https://biodiversityinformatics.amnh.org/open_source/maxent/ [accessed 10 10 2019].

[5] EnmSdm [online]. Website https://github.com/adamlilith/enmSdm [accessed 10 10 2019].

[6] Smith AB (2019). A Hands-on Short Course in Species Distribution Modeling Using R: From Start to Finish [online]. Website http://www.earthskysea.org/workshops-classes/ [accessed 15 09 2019].

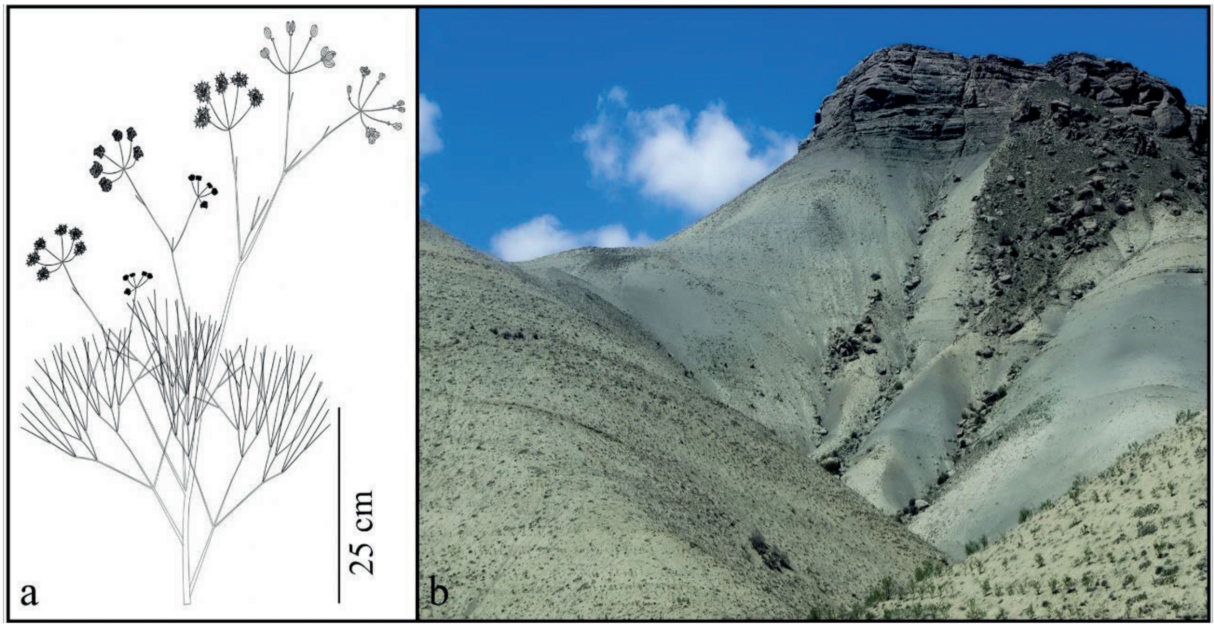

Figure 1. The illustration of *F. glareosa* (a); bare rocks and young soils in the species"habitat.

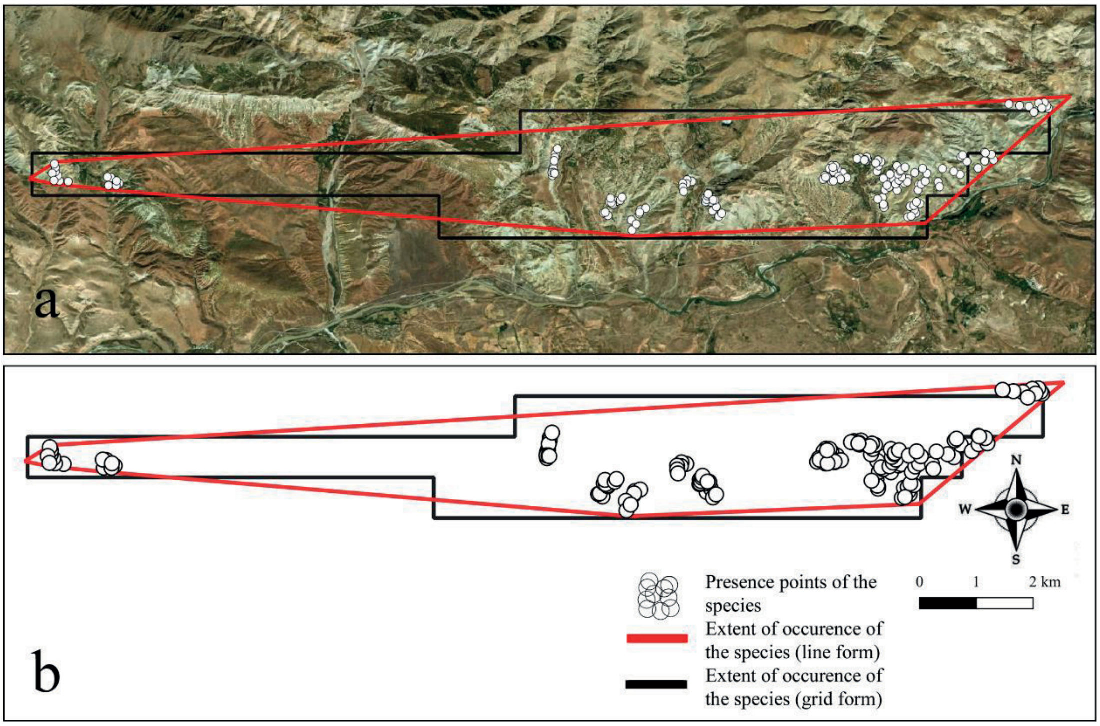

Figure 2. The records and EOO of the species' individuals [satellite view (a); simple view (b)].

a chilling requirement (Roberts, 1979; Grime et al., 1981; Baskin and Baskin, 1988; Vandelook et al., 2009), Mean Temperature of Coldest Quarter (Bio11) was chosen as the predictor variable among highly correlated variables. Other predictor variables which are not highly correlated with Bio11 were Mean Diurnal Range (Bio2), Isothermality (Bio3), Temperature Annual Range (Bio7), Precipitation of Driest Month (Bio14), Precipitation of Warmest Quarter (Bio18), Precipitation of Coldest Quarter (Bio19) Aspect, and Percentage of Slope (Percent of Slope hereafter).

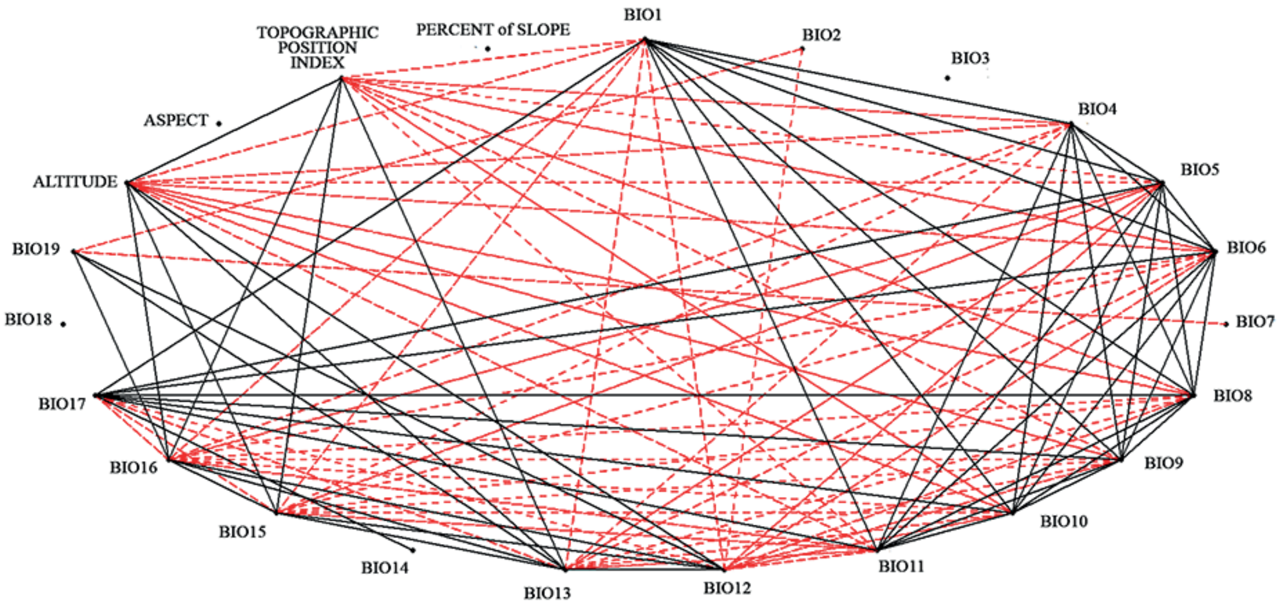

Figure 3. The correlation lines among the variables used in the modeling study.

2.3. Maxent modeling and assessment of the accuracy of predicted models

When constructing the model in Maxent settings, we chose random seed, write plot data, write background predictions, and replicated run type subsample; random test percentage was set to 25, replicates were set to 15, maximum iterations were set to 5000. We also chose threshold features, create response curves, and do Jackknife to measure the variables' importance; remaining settings were left at their default values in the Maxent interface (Philips et al., 2006; Philips and Dudik, 2008; Baldvin, 2009; Süel et al., 2018). After the initial model was run using 8 variables (Bio2, Bio3, Bio11, Bio14, Bio18, Bio19, Aspect, Percent of Slope), variables with low contributions to the model were eliminated by looking at the jackknife test and analysis of variable contribution results. Because it was understood that it could not be modeled with these 8 variables, we continued the process until 2 variables remained (Süel et al., 2018). Therefore, in the final model, we used Bio11 and Percent of Slope as predictor variables. Maxent discarded redundant records that occurred within the same grid cell; thus, 15 records were used for training and 5 records for testing. The area under the Receiver Operating Curve (AUC) and True Skill Statistic (TSS) were used to estimate the model's performance. The AUC is a single threshold-independent technique of model performance to differentiate presence from absence (Thuiller et al., 2005). AUC values vary from 0 to 1; higher AUC values suggest superiority. Hence, a value of 0.5–0.7 represents poor performance, 0.7–0.9 represents high performance, more than 0.9 signifies very high performance, and a value of 1.0 signifies perfect discrimination (Fielding and Bell, 1997; Swets, 1988; Peterson et al., 2011). TSS is the threshold-dependent measure of model performance. A value closer to +1 signifies an agreement between observations and prediction; lower value signifies agreement no better than random. TSS values >0.8 suggest excellent, 0.4–0.8 useful, and <0.4 poor model performance (Allouche et al., 2006). TSSs were executed using an Excel sheet. Factor analysis based on all predictor variables for all records of the species was conducted using IBM SPSS 25[7] (Hirzel et al., 2002).

In the choice of representative models, models with higher training AUC values and with little difference between training and test AUC values were preferred in each set of the 15 models obtained (Süel et al., 2018).

2.4. Preparation of image files

Current and future potential distribution maps and 3D maps of the species' habitats were created using the 3D map generator plugin for Adobe Photoshop CC 2019[8] and ArcGis 10.5.1. All cartography was created using QGIS 3.4.4.[9]

3. Results

The current species distribution model of *F. glareosa* predicted by the model produced very high success rates with training and test AUC values of 0.970 and 0.968,

[7] IBM Corporatiton (2019) [online]. Website https://www.ibm.com/tr-tr/products/spss-statistics [accessed 10 10 2019].

[8] Adobe Photoshop CC (2019) [online]. Website https://www.adobe.com/tr/ [accessed 07 08 2019].

[9] QGIS Development Team (2019) [online]. Website https://www.qgis.org/en/site/ [accessed 15 09 2019].

respectively. This signifies that the predictor variables used for the species distribution modeling were appropriately selected, therefore leading to very high prediction success. That there were few differences in the test and training AUC values indicates very little overfit in the predicted results. The TSS value of the model (0.8245) indicated excellent model performance. The results of the AUC curves in developing *F. glareosa* SDM under current conditions are shown in Figure 4.

The TSS and AUC values for *F. glareosa* under future conditions can be found in the Table.

According to the results obtained from the model, about 79.822% of the current potential distribution of the species was explained by 2 variables. The higher the

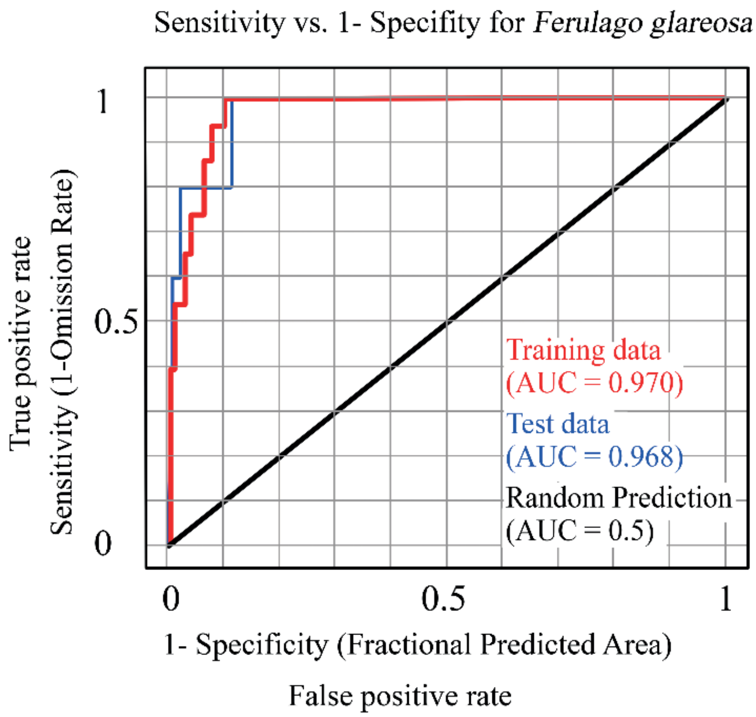

Figure 4. The ROC curve and AUC values for *F. glareosa*'s current potential distribution.

Table. TSS and AUC values and their assessments (bold) for *F. glareosa* under future conditions.

Climate Change Scenarios						
Global climate models - Year	RCP 2.6 TSS values	RCP 2.6 AUC values	RCP 4.5 TSS values	RCP 4.5 AUC values	RCP 8.5 TSS values	RCP 8.5 AUC values
HadGEM2-ES-2050	0.7781 Useful	Training data: 0.973 Test data: 0.964 Very high	0.7768 Useful	Training data: 0.972 Test data: 0.971 Very high	0.7831 Useful	Training data: 0.966 Test data: 0.960 Very high
MPI-ESM-LR-2050	0.7922 Useful	Training data: 0.965 Test data: 0.965 Very high	0.83 Excellent	Training data: 0.973 Test data: 0.970 Very high	0.7748 Useful	Training data: 0.969 Test data: 0.963 Very high
HadGEM2-ES-2070	0.7716 Useful	Training data: 0.973 Test data: 0.960 Very high	0.8319 Excellent	Training data: 0.973 Test data: 0.970 Very high	0.7625 Useful	Training data: 0.971 Test data: 0.950 Very high
MPI-ESM-LR-2070	0.8244 Excellent	Training data: 0.972 Test data: 0.966 Very high	0.8545 Excellent	Training data: 0.971 Test data: 0.966 Very high	0.7842 Useful	Training data: 0.969 Test data: 0.969 Very high

contribution, the more impact that a variable has on predicting the occurrence of the species. In this study, Bio11 had the highest predictive contribution of 67.9%; Percent of Slope had a predictive contribution of 32.1%.

The jackknife test results for the current distribution of the species are shown in Figure 5.

The occurrence probability of *F. glareosa* in its EOO rapidly increases at the Mean Temperatures of Coldest Quarter ranging between –0.1 °C and –1.8 °C; it decreases when temperatures drop toward –3.5 °C and rise toward 1.5 °C. As can be seen from the Percent of Slope graph of the species, the species does not prefer terrain with low slopes (below 7%) or high slopes (above 34%) (Figure 6).

In the below maps, red areas indicate highly suitable areas for the species, and blue areas denote areas that the species does not prefer. Current potential distribution of *F. glareosa* is shown in Figure 7.

HadGEM2-ES and MPI-ESM-LR GCMs-based models predicting future habitat suitability of *F. glareosa* for 2050 and 2070 are shown in Figures 8 and 9.

Future habitat suitability status of the species' EOO is shown in Figures 10 and 11.

When we take a look at the above figures, while the overall predictions obtained from the HadGEM2-ES model show us that the species may have difficulties in its current EOO in the near future, the overall predictions which can be obtained from the MPI-ESM-LR model argue against this.

4. Discussion

The HadGEM2 family of climate models represents the second generation of HadGEM configurations. Members of the HadGEM2 family were used in the IPCC Fifth Assessment Report (AR5). The ENSEMBLES project also uses members of this model family.[10] MPI-ESM is a new version of the global Earth system model developed at the Max Planck Institute for Meteorology. It has 3 configurations: MPI-ESM-LR (Low Resolution), MPI-ESM-P (Paleo), MPI-ESM-MR (Mid Resolution). Even though there are resolution-dependent differences between the LR and MR configurations, it is also worth noting that the MPI-ESM setups behave rather similarly in many respects (Jungclaus et al., 2013). Because only MPI-ESM-LR was available for making future modeling among these setups, we had to model the species' distribution using this configuration. We do not think that the resolution differences between MPI-ESM-LR and MPI-ESM-MR configurations would be important in our modeling study.

If we were to benefit from predictions obtained only from HadGEM2-ES GCM to guide *F. glareosa*'s future conservation efforts, our most optimistic approach would be that the current EOO of the species may not be suitable in the future (even in the 2050s). However, if we were to rely on the predictions obtained only from MPI-ESM-LR GCM, our most optimistic approach would be that the current EOO of the species will continue to be suitable for many years (at least until the 2070s) (see Figures 10 and 11). So, will *F. glareosa* be extinct in the near future? To answer this question only with some projections obtained from SDMs would depend on our predictions obtained from GCM, which can represent Turkey's climate more strongly than MPI-ESM-LR GCM. We find any urgent conservation action on behalf of the species to be unnecessary, as we rely on the predictions that we have from MPI-ESM-LR GCM. However, a more precise answer to the question can be given using data on abiotic and biotic factors (especially with reproductive ecology data of the species) affecting the species' survival. We would like to draw attention to the fact discussed below about how we can obtain more precise insights into the future distribution of plants on our planet.

It has been emphasized by many researchers that it may be difficult to find suitable new areas for endemic plants as the climate changes, because they have narrow tolerance ranges for many abiotic factors (Primack, 2006; Işık, 2011; Wamelink et al., 2014) and they may be able to grow only under certain conditions (Kempel et al., 2018). As stated by Blackmore and Oldfield (2017), only by looking at species-level conservation assessments across the board are we able to get a larger picture of the status of plants on our planet. We had 2 reasons for taking a closer look at the species' EOO. The first is that because the species belongs to the Apiaceae family, its dormant seeds are hard to germinate. Therefore, future habitat suitability of the species' current EOO is very important for breaking seed dormancy. The second reason is that the species never lives in the clay soils adjacent to the species' current EOO. Thus, if the species loses its current EOO for any reason and cannot adapt to new edaphic conditions, it will probably become extinct. The following map shows that the current EOO of the species is seen usually in the areas that are gray (due to the colors of bare rocks and young soils), and unsuitable areas on account of soil quality for the species are usually in the green and brown areas (due to the colors of clay soils and other plants that live there) (Figure 12). Briefly, it is unlikely that areas adjacent to the species' current EOO will be suitable in the near future from the results of many GCMs for the species, because it needs specialized habitat conditions.

Although Akçakaya et al. (2014) stated that climate change is quantitatively considered in Red List assessments for only a small number of species, Attorre et al. (2018)

[10] Collins WJ (2008). Evaluation of the HadGEM2 model [online]. Website https://www.metoffice.gov.uk/research/approach/modelling-systems/unified-model/climate-models/hadgem2 [accessed 26 12 2019].

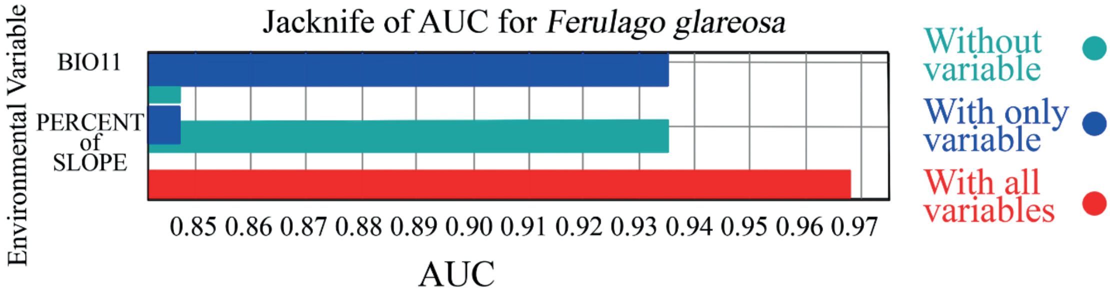

Figure 5. The jackknife test result for indicating the relative contribution of predictor variables for the current distribution of *F. glareosa*.

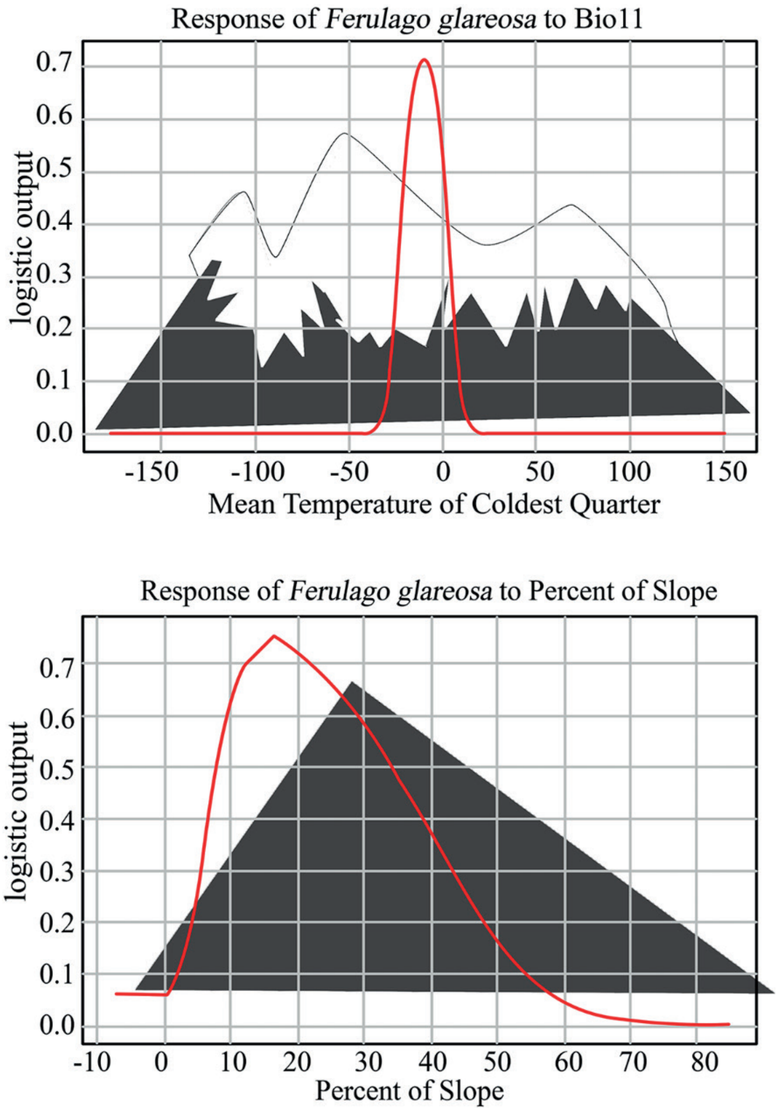

Figure 6. The response of *F. glareosa* to two predictor variables [Temperature unit: C° (Values/10)].

emphasized that determining the applicability of SDMs to Red Lists is difficult due to model uncertainties, as many biotic and abiotic factors cannot be included (or are difficult to include) in these models. For this reason, they suggested that SDMs and Red List assessments could play a complementary role in conservation efforts, such

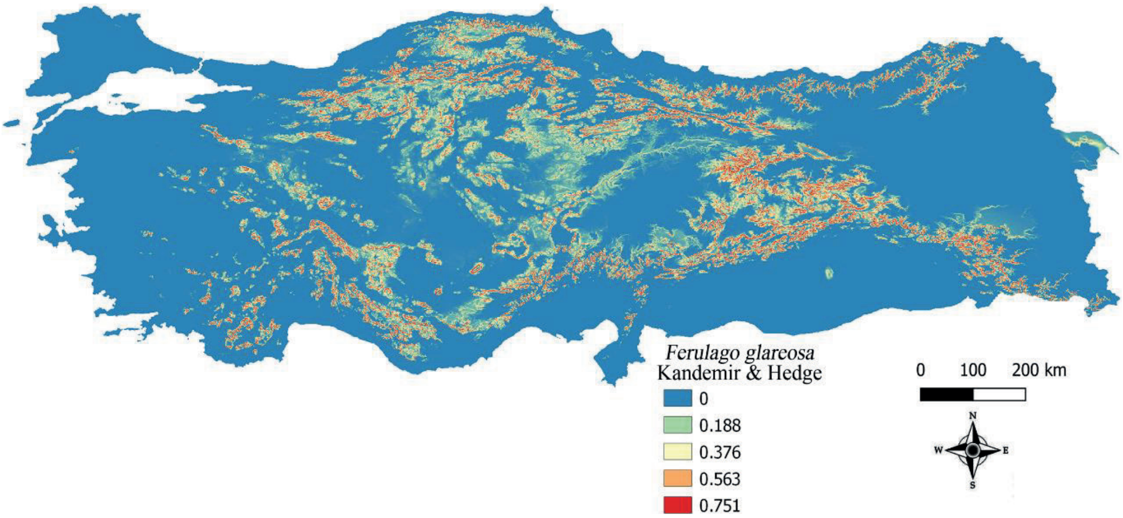

Figure 7. Current potential distribution of *F. glareosa*.

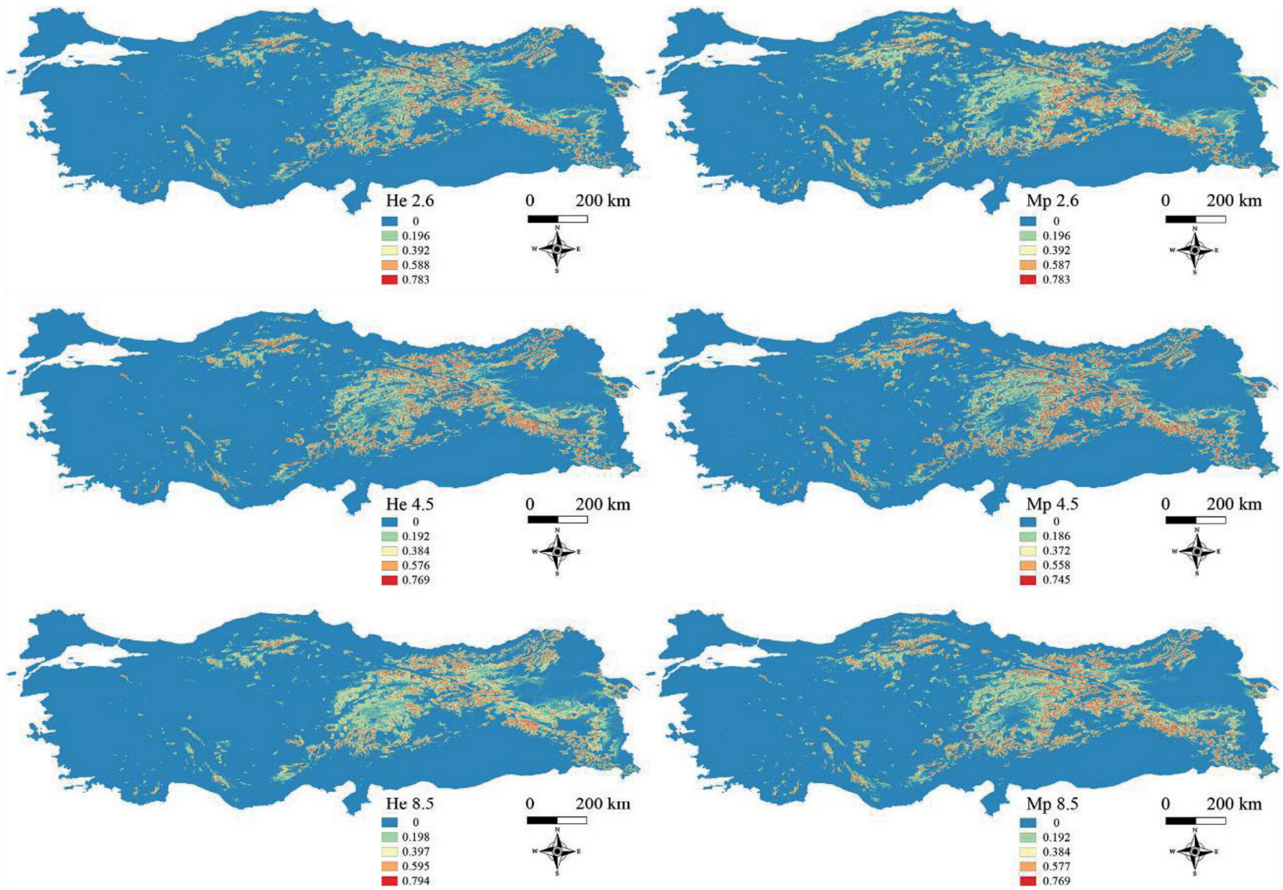

Figure 8. The maps show HadGEM2-ES (He) (left) and MPI-ESM-LR (Mp) (right) GCMs based predicted future suitability of *F. glareosa* for 2050.

as Red List categories providing information on both the current and future extinction risk for a target species, while SDMs may provide warnings on the magnitude of future extinction risk. Attore et al. (2018) also showed a good example of the studies performed in this direction by evaluating some ecological characteristics of Italian plant

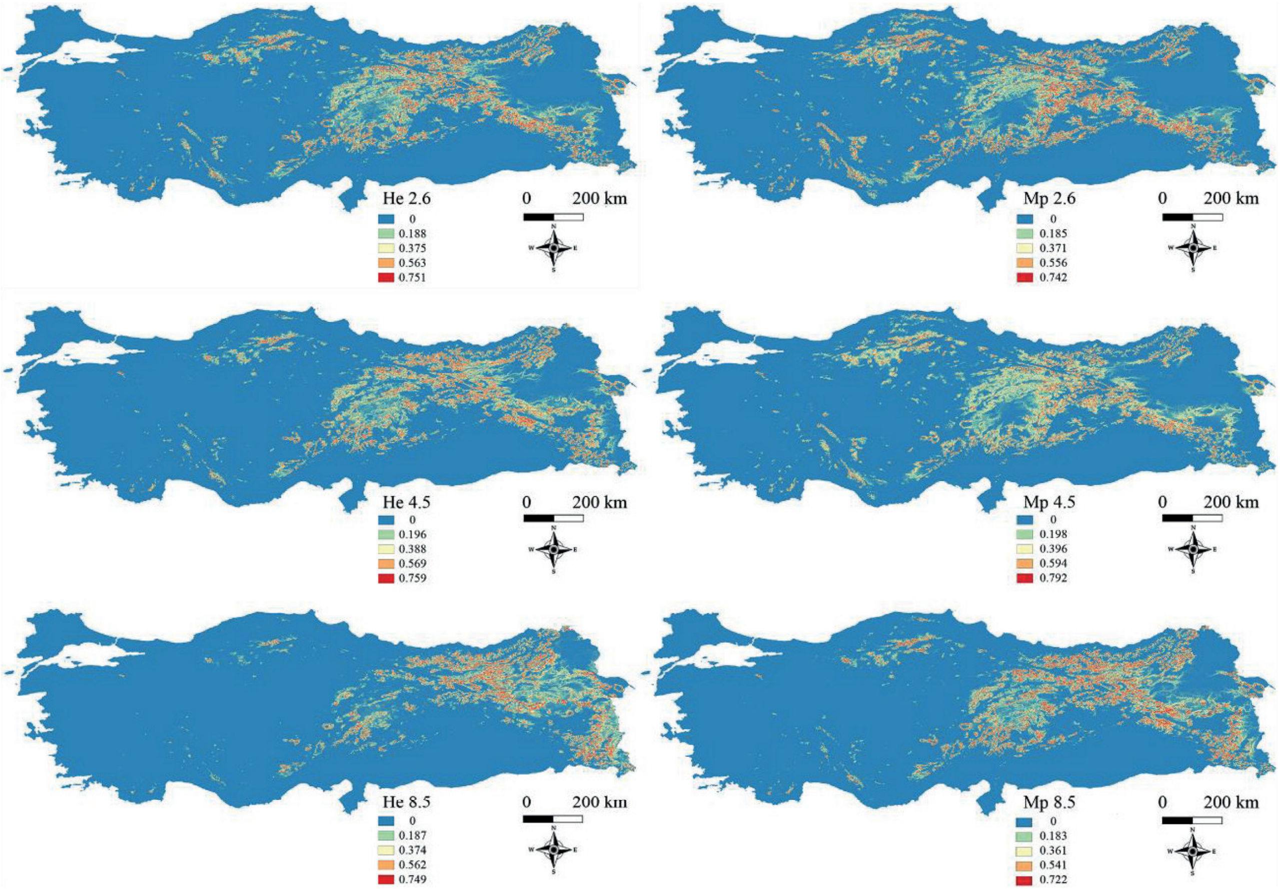

Figure 9. The maps show HadGEM2-ES (He) (left) and MPI-ESM-LR (Mp) (right) GCMs based predicted future suitability of *F. glareosa* for 2070.

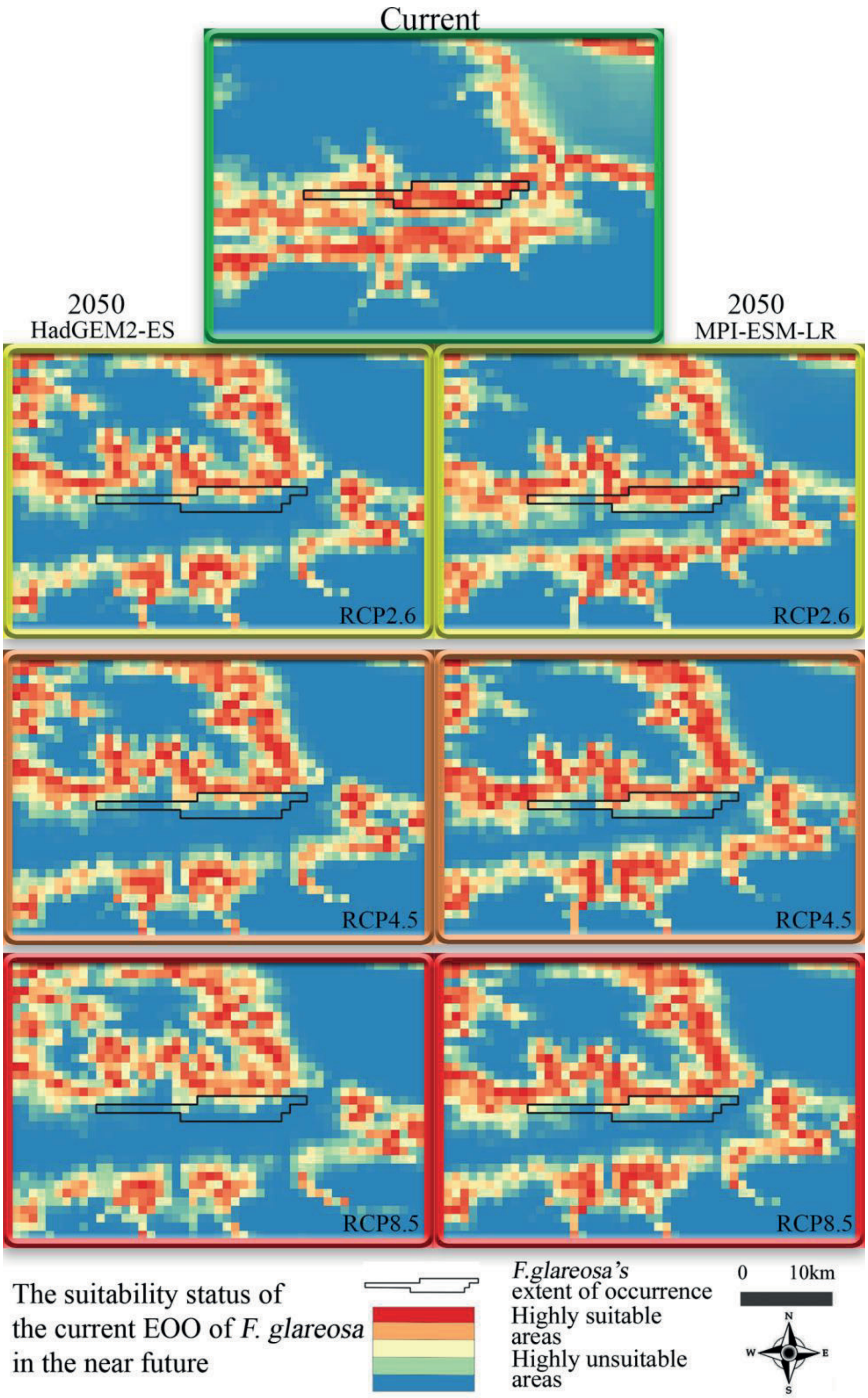

Figure 10. Future habitat suitability status of the species"EOO for 2050 according to predictions obtained from HadGEM2-ES (left) and MPI-ESM-LR (right) GCMs.

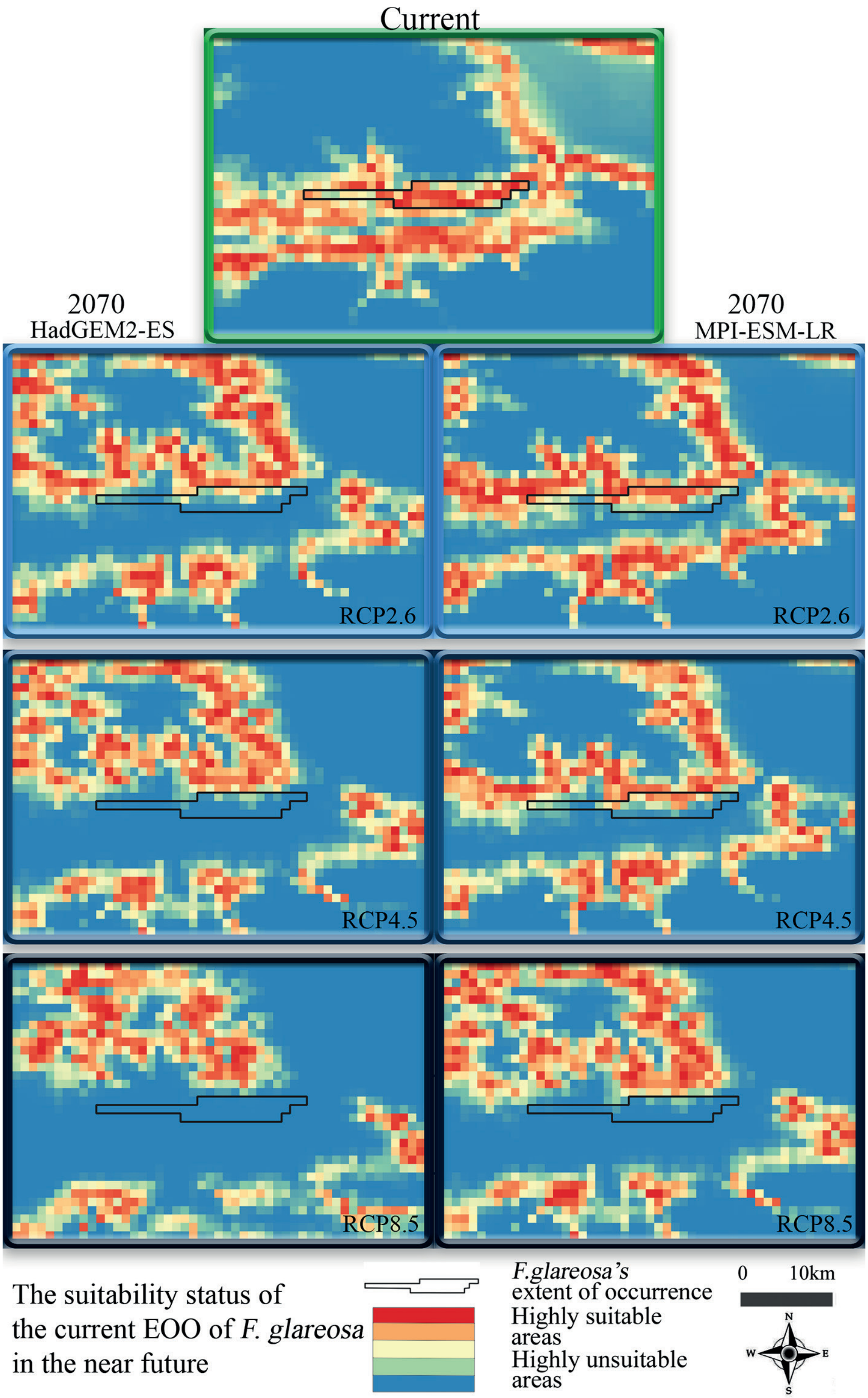

Figure 11. Future habitat suitability status of the species' EOO for 2070 according to predictions obtained from HadGEM2-ES (left) and MPI-ESM-LR (right) GCMs.

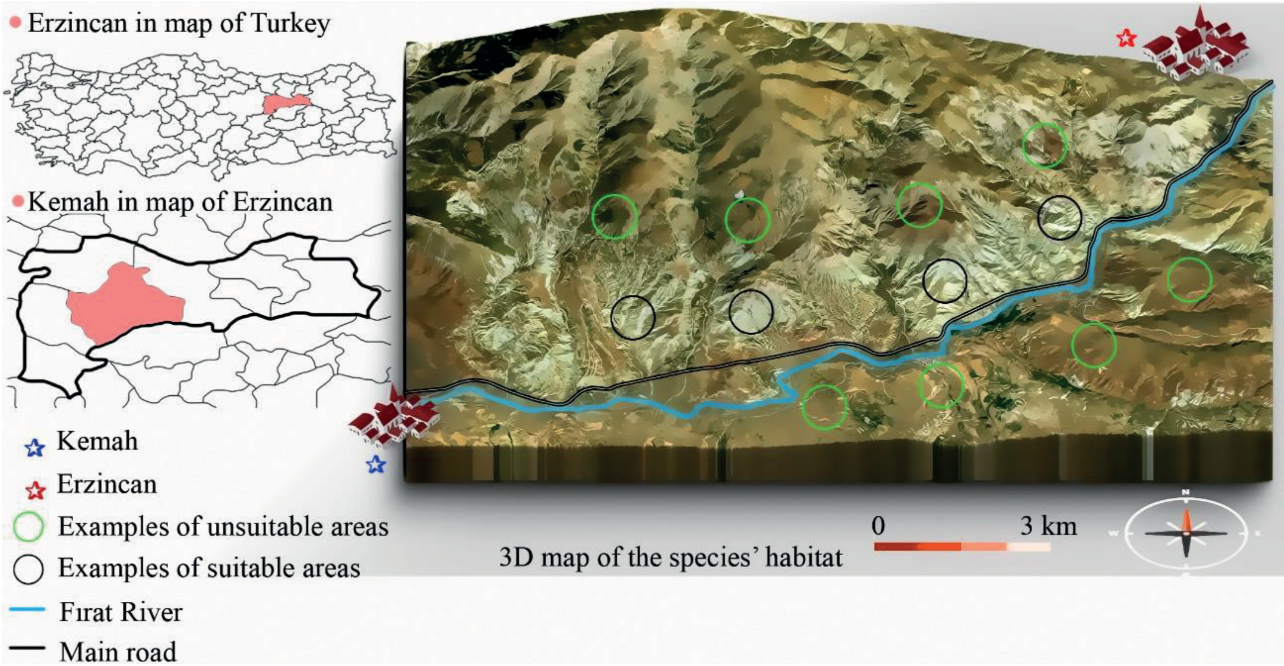

Figure 12. The 3D map shows suitable and unsuitable areas on account of soil factors for the species.

species policy together with the predictions they obtained about the future distributions of these species. Even though we share the same view on assessing species' vulnerability to climate change as Attorre et al. (2018), we also want to draw attention to the use of predictions obtained from GCMs, whose reliability for any region's climate has been analyzed/tested with the help of Regional Climate Models and meteorological data. We think that this is an overlooked but important point in assessing species' vulnerability to climate change. Thus, we recommend that conservationists should benefit from the best GCM by ranking many of the available GCMs according to their ability to simulate the climate of the region where the species to be modeled live. This may play a role in reducing uncertainties in future plant conservation studies.

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References

Akçakaya HR, Butchart SH, Watson JE, Pearson RG (2014). Preventing species extinctions resulting from climate change. Nature Climate Change 4 (12): 1048-1049. doi: 10.1038/nclimate2455

Allouche O, Tsoar A, Kadmon R (2006). Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). Journal of Applied Ecology 43 (6): 1223-1232. doi: 10.1111/j.1365-2664.2006.01214.x

Araújo MB, Whittaker RJ, Ladle RJ, Erhard M (2005). Reducing uncertainty in projections of extinction risk from climate change. Global Ecology and Biogeography 14 (6): 529-538. doi: 10.1111/j.1466-822x.2005.00182.x

Attorre F, Abeli T, Bacchetta G, Farcomeni A, Fenu G et al. (2018). How to include the impact of climate change in the extinction risk assessment of policy plant species? Journal for Nature Conservation 44: 43-49. doi: 10.1016/j.jnc.2018.06.004

Baldwin R (2009). Use of maximum entropy modeling in wildlife research. Entropy 11 (4): 854-866. doi: 10.3390/e11040854

Baskin CC, Baskin JM (1998). Seeds: ecology, biogeography, and evolution of dormancy and germination. San Diego, USA: Academic Press.

Blackmore S, Oldfield S (2017). Plant Conservation Science and Practice: The Role of Botanic Gardens. Cambridge, England: Cambridge University Press.

Chen I, Hill JK, Ohlemuller R, Roy DB, Thomas CD (2011). Rapid range shifts of species associated with high Llvels of climate warming. Science 333 (6045): 1024-1026. doi: 10.1126/science.1206432

De Marco P, Nóbrega CC (2018). Evaluating collinearity effects on species distribution models: an approach based on virtual species simulation. Plos One 13 (9): e0202403. doi: 10.1371/journal.pone.0202403

Diniz-Filho JA, Mauricio Bini L, Fernando Rangel T, Loyola RD, Hof C et al. (2009). Partitioning and mapping uncertainties in ensembles of forecasts of species turnover under climate change. Ecography 32 (6): 897-906. doi: 10.1111/j.1600-0587.2009.06196.x

Dobrowski SZ, Abatzoglou J, Swanson AK, Greenberg JA, Mynsberge AR et al. (2012). The climate velocity of the contiguous United States during the 20th century. Global Change Biology 19 (1): 241-251. doi: 10.1111/gcb.12026

Elith J, Graham CH, Anderson RP, Dudik M, Ferrier S et al. (2006). Novel methods improve prediction of species' distribution from occurrence data. Ecography 29 (2): 129-151. doi: 10.1111/j.2006.0906-7590.04596.x

Elith J, Leathwick JR (2009). Species distribution models: ecological explanation and prediction across space and time. Annual Review of Ecology, Evolution, and Systematics 40 (1): 677-697. doi: 10.1146/annurev.ecolsys.110308.120159

Fick SE, Hijmans RJ (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

Fielding AH, Bell JF (1997). A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24 (1): 38-49. doi: 10.1017/s0376892997000088

Grime JP, Mason G, Curtis AV, Rodman J, Band SR (1981). A comparative study of germination characteristics in a local flora. The Journal of Ecology 69 (3): 1017. doi: 10.2307/2259651

Guisan A, Thuiller W (2005). Predicting species distribution: offering more than simple habitat models. Ecology Letters 8 (9): 993-1009. doi: 10.1111/j.1461-0248.2005.00792.x

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A (2005). Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25 (15): 1965-1978. doi: 10.1002/joc.1276

Hirzel AH, Hausser J, Chessel D, Perrin N (2002). Ecological-niche factor analysis: how to compute habitat-suitability maps without absence data? Ecology 83 (7): 2027-2036. doi: 10.1890/0012-9658(2002)083[2027:enfaht]2.0.co;2

IPCC (2014). Climate Change 2013 – The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press. doi: 10.1017/CBO9781107415324

Jena P, Azad S, Rajeevan M (2016). CMIP5 projected changes in the annual cycle of Indian monsoon rainfall. Climate 4 (1): 14. doi: 10.3390/cli4010014

Jungclaus JH, Fischer N, Haak H, Lohmann K, Marotzke J et al. (2013). Characteristics of the ocean simulations in the Max Planck Institute Ocean Model (MPIOM) the ocean component of the MPI-Earth system model. Journal of Advances in Modeling Earth Systems 5 (2): 422-446. doi: 10.1002/jame.20023

Işık K (2011). Rare and endemic species: why are they prone to extinction? Turkish Journal of Botany 35: 411-417. doi: 10.3906/bot-1012-90

Kandemir A, Hedge IC (2007). An anomalous new *Ferulago* (Apiaceae) from eastern Turkey. Willdenowia 37 (1): 273-276. doi: 10.3372/wi.37.37115

Kandemir A, Sarı İ (2019). Impacts of insect herbivory on reproductive success of *Ferulago glareosa* (Apiaceae). Biological Diversity and Conservation 12 (1): 160-166. doi: 10.5505/biodicon.2019.21939

Kempel A, Rindisbacher A, Fischer M, Allan E (2018). Plant soil feedback strength in relation to large-scale plant rarity and phylogenetic relatedness. Ecology 99 (3): 597-606. doi: 10.1002/ecy.2145

Kumar S, Spaulding SA, Stohlgren TJ, Hermann KA, Schmidt TS et al. (2009). Potential habitat distribution for the freshwater diatom *Didymosphenia geminata* in the continental US. Frontiers in Ecology and the Environment 7 (8): 415-420. doi: 10.1890/080054

Pachauri RK, Allen MR, Barros VR, Broome J, Cramer W et al. (2014): Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change / R. Pachauri R, Meyer LA (editors). Geneva, Switzerland. ISBN: 978-92-9169-143-2.

Pearson RG, Raxworthy CJ, Nakamura M, Townsend Peterson A (2006). Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. Journal of Biogeography 34 (1): 102-117. doi: 10.1111/j.1365-2699.2006.01594.x

Peterson AT, Soberón J (2012). Species distribution modeling and ecological niche modeling: getting the concepts right. Natureza & Conservação 10 (2): 102-107. doi: 10.4322/natcon.2012.019

Peterson AT, Soberón J, Pearson RG, Anderson RP, Martínez-Meyer E et al. (2011). Ecological Niches and Geographic Distributions (MPB-49). Princeton, NJ, USA: Princeton University Press.

Phillips SJ, Anderson RP, Schapire RE (2006). Maximum entropy modeling of species geographic distributions. Ecological Modelling 190 (3-4): 231-259. doi: 10.1016/j.ecolmodel.2005.03.026

Phillips SJ, Dudík M (2008). Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31 (2): 161-175. doi:10.1111/j.0906-7590.2007.5203.x

Porfirio LL, Harris RM, Lefroy EC, Hugh S, Gould SF et al. (2014). Improving the use of species distribution models in conservation planning and management under climate change. Plos One 9 (11): e113749. doi: 10.1371/journal.pone.0113749

Pramanik M, Paudel U, Mondal B, Chakraborti S, Deb P (2018). Predicting climate change impacts on the distribution of the threatened *Garcinia indica* in the Western Ghats, India. Climate Risk Management 19: 94-105. doi: 10.1016/j.crm.2017.11.002

Primack RB (2006). Essentials of Conservation Biology. Sunderland, MA, USA: Sinauer Associates, Inc.

R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing.

Roberts HA (1979). Periodicity of seedling emergence and seed survival in some Umbelliferae. Journal of Applied Ecology 16 (1): 195. doi: 10.2307/2402738

Solomon S, Qin D, Manning M, Chen Z, Marquis M et al. (2007). Climate Change 2007: The Physical Science Basis. Working Group I Contribution to the Fourth Assessment Report of the IPCC. Cambridge, UK and New York, USA: Cambridge University Press.

Srinivasa RK, Nagesh Kumar D (2016). Selection of global climate models for India using cluster analysis. Journal of Water and Climate Change 7 (4): 764-774. doi: 10.2166/wcc.2016.112

Süel H, Şentürk Ö, Mert A, Özdemir S, Yalçınkaya B (2018). Habitat Suitability Modeling and Mapping. In: V. International Multidisciplinary Congress of Eurasia; Barcelona, Spain. p. 74.

Swets J (1988). Measuring the accuracy of diagnostic systems. Science 240 (4857): 1285-1293. doi: 10.1126/science.3287615

Thuiller W (2004). Patterns and uncertainties of species' range shifts under climate change. Global Change Biology 10 (12): 2020-2027. doi: 10.1111/j.1365-2486.2004.00859.x

Thuiller W, Lavorel S, Araujo MB (2005). Niche properties and geographical extent as predictors of species sensitivity to climate change. Global Ecology and Biogeography 14 (4): 347-357. doi: 10.1111/j.1466-822x.2005.00162.x

Vandelook F, Bolle N, Van Assche JA (2009). Morphological and physiological dormancy in seeds of *Aegopodium podagraria* (Apiaceae) broken successively during cold stratification. Seed Science Research 19 (2): 115-123. doi: 10.1017/s0960258509301075

Wamelink GW, Goedhart W, Frissel JY (2014). Why some plant species are rare. Plos One 9 (7): e102674. doi: 10.1371/journal.pone.0102674