Online ISSN: 2588-3526

Journal of Wildlife and Biodiversity

Volume 5 (4): 28-43 (2021) (http://www.wildlife-biodiversity.com/)

Research Article

Predicting the Potential Distribution of *Crataegus azarolus* L. under Climate Change in Central Zagros, Iran

Ali Asghar Naghipour[1*], Sima Teimoori Asl[1], Mohammad Reza Ashrafzadeh[1], Maryam Haidarian[2]

[1]Faculty of Natural Resources and Earth Sciences, Shahrekord University, 8818634141, Shahrekord, Iran

[2]Faculty of Natural Resources, Sari Agricultural Sciences, and Natural Resources University, Sari

*Email: aa.naghipour@sku.ac.ir

Received: 16 May 2021 / Revised: 01 June 2021 / Accepted: 12 June 2021 / Published online: 09 December 2021. Ministry of Sciences, Research, and Technology, Arak University, Iran.

How to cite: Naghipour, A.A., Teimoori Asl, S., Ashrafzadeh, M.R., Haidarian, M (2021). Predicting the Potential Distribution of *Crataegus azarolus* L. under Climate Change in Central Zagros, Iran, Iran. Journal of Wildlife and Biodiversity, 5(4), 28-43. **DOI: 10.22120/jwb.2021.530532.1229**

Abstract

Global climate change has had a significant impact on biodiversity and altered the geographical distribution of many plant species. In this study, ensemble modeling based on seven species distribution models was used to predict the effect of climate change on the spatial distribution of *Crataegus azarolus* L. in Chaharmahal-Va-Bakhtiari province, located in the Central Zagros region, Iran. We used 113 presence points of the species and physiographic, land cover, and bioclimatic variables. Predicting the geographical distribution of the *C. azarolus* in the future (years 2050 and 2070) was made based on four scenarios of the increase in the greenhouse gases (RCPs: Representative Concentration Pathways) in the general circulation model of MRI-CGCM3. Based on the results, about 20% (3292.192 km^2) of the study area can be considered as the suitable habitat of *C. azarolus*. Precipitation Seasonality, Isothermality, and Mean Temperature of the Wettest Quarter had the highest contribution to the species distribution model. The decline of suitable habitats will be 31.13% to 89.87% by 2050 and 2070 due to climate change, respectively. Assessments showed that the Random Forest was found to be the most reliable model for species prediction. Our results can provide reliable information on preparing adaptive responses for the sustainable management of the species.

Keywords: Ensemble modeling, habitat suitability, Random Forest, species distribution modeling

Introduction

Environmental factors, particularly air temperature and water availability, have considerable influences on the distribution of species (Fortunel et al., 2014). Global climate change has had a significant impact on biodiversity and altered the geographical distribution of many plant species (Kosanic et al., 2018). Extinctions at the lower elevation limit, shifts in geographic distribution, and range contractions of plant species may be the result of changes in the natural patterns of temperature and precipitation. These patterns of changes are among the expected effects of future climate change (Zomer et al., 2015; Ladányi et al., 2015). One of the most difficult challenges faced by conservation planners is adapting these shifts to effectively conserve biodiversity in the context of climatic regimes (Watson et al., 2012).

To elucidate the specific effects of climate change on species and reduce the negative impacts of climate change on ecosystems and biodiversity, we should integrate conservation strategies with species distribution modeling to identify suitable habitats (Kumar, 2012; Akhter et al., 2017; Guisan & Zimmermann, 2000). Species Distribution Models (SDMs) are applied to predict the spatial distribution of species from field data and environmental variables (Guisan & Zimmermann, 2000). In these models, the response variable is mainly the presence and absence of the species, and the predictor variables are environmental parameters, and the relationships between the variables are presented as mathematical functions. When climate change is due to a particular scenario, these statistical relationships are considered constant and are used as a hypothesis to determine changes in species distribution (predicting future conditions) (Guisan et al., 1998). We can use a range of SDM algorithms to predict the potentially suitable habitats for plant species (Tarkesh & Jetschke, 2016). The choice of a specific model may be complex; hence, an alternative is to run different modeling methods on the same dataset and for the same initial geographic area of analysis. It is then possible to compare the results to select the approach giving the most consistent results in terms of objectives or to combine the various results into one ultimate model. BIOMOD is a platform for an ensemble forecasting of species distributions that overcomes the uncertainties caused by different models and thus allows the study of species relationships with the environment (Thuiller et al., 2016).

Iran is one of the most important countries in the Middle East for biodiversity. Iranian ecosystems include 8000 plant species (Farashi et al., 2017). The forests of the Zagros are vital in terms of water conservation and climate change and are, therefore, important in the socio-economic balance of the whole country. Remarkable decline and dieback in Zagros forests (mostly *Quercus brantii*) have occurred in recent years and each day increases (Bashari et al. 2016). Also, this issue in other trees like *Crataegus* has occurred. One of the most important reasons for this might be a change within the climatic factors over a brief period (Attarod et al., 2016).

The genus *Crataegus* relates to the family Rosaceae; it contains about 280 species of deciduous spiny shrubs and little trees (Hyam & Pankhurst, 1995). This genus is distributed throughout the northern temperate regions, including North America, Europe, and Asia. *Crataegus azarolus* L. is a tree with a small round crown that is about 6 m high, primarily, growing on rocky mountainsides (Sagheb-Talebi et al., 2014).

The genus *Crataegus* L. is largely applied in the food industry while it can also be used for landscaping goals. Because it can grow in sandy, stony, shallow, and dry soils; can help with erosion control efforts. This genus is very valuable for different purposes, including food, medicinal, ornamental, and as a shelter for wildlife, soil conservation applications, and erosion control (Ahmadloo et al., 2015).

A few studies showed precipitation and temperature have played the most important role in the habitat suitability of the *Crataegus* genus. For example, Jafari et al. (2019) determined the potential habitat for *Crataegus azarolus* in Chaharmahal-va-Bakhtiari Province, Iran. They concluded that elevation, mean relative humidity and average annual rainfall have the greatest effects on the geographical distribution of this species. In another, similar study Rafiee et al. (2020) investigated the current potential distribution of *Crataegus pontica* in Lorestan Province. They concluded that the geographical distribution of the species is affected by Precipitation of the Coldest Quarter, Annual Precipitation, and elevation.

Many studies have been conducted on the effect of climate change on the distribution of shrub and tree species (Ahn et al., 2015; Blach-Overgaard et al., 2015; Périé & de Blois, 2016; Shirk et al., 2018; Rajpoot et al., 2020). For example, Moustafa et al. (2019) reported a steady decline of habitat quality for *Crataegus sinica* over recent years. This decrease observed in this species is probably due to climate change over the past few decades and human activities. Also, several studies have predicted the effects of climate change on the geographical distribution of tree species in Iran (Haidarian et al., 2017a; Alavi et al., 2019; Naghipour et al., 2019a; Taleshi et al., 2019). These studies predict that future climate change (by 2050 and 2070) will significantly reduce the suitable habitat of different species.

The present study aimed to evaluate the effects of climate change on the geographical distribution of *C. azarolus* located in the Central Zagros. This study was conducted to accomplish the subsequent objectives: 1) to determine the most important environmental factors, which affect the distribution of the study species; 2) to spot suitable habitats and determine the geographical distribution of *C. azarolus* in the Central Zagros under the current climate; 3) to predict the results of climate change by 2050 and 2070 under different scenarios on the geographical distribution of *C. azarolus*.

Materials and Methods

Study area

Our study area includes Chaharmahal-va-Bakhtiari Province with an area of 16,532 km^2 in the central Zagros. This area is mostly mountainous, with dominating elevations over 2000 m and altitudes between 783 and 4178 m above sea level (asl). Annual rainfall varies between 250 mm in the east and southeast and 1400 mm in the northwest of the province. The average rainfall in the province is 560 mm. The average annual temperature of the province is 10 °C (Jaafari et al., 2017).

Occurrence data

Field studies were included to record the occurrence points across the study area between 2019 and 2020 with Global Positioning System (GPS). To reduce spatial autocorrelation, duplicate occurrence, less than one kilometer away, was removed. We used 113 occurrences points of *C. azarolus* for modeling (Fig. 1).

Bioclimatic and environmental data

Physiographic, land cover and bioclimatic variables were used as predictors of *C. azarolus* distribution. Bioclimatic variables derived from temperature and precipitation (Bio1-Bio19) and the digital elevation model layer (DEM) were received in downscaled with an accuracy of 30 arc-seconds (~1 km) from the Worldclim database (www.worldclim.org). The digital elevation model (DEM) was used to generate physiographic variables including slope and aspect. Land cover data were used that extracted from a map produced by the Iranian Forests, Ranges, and Watershed Management Organization (IFRWMO, 2014).

All environmental layers became similar in terms of spatial accuracy, dimensions, and geographic coordinate system in the ArcGIS 10.3 (ESRI Inc., http://www.esri.com/) environment. Before modeling, Pearson's correlation analysis (R^2 <0.8) and variance inflation index (VIF <3) were used to examine the collinearity between different environmental variables (Zuur et al., 2010). Finally, after removing the highly correlated layers, nine variables were used in distribution modeling (Table 1). The importance (%) of each environmental variable in the distribution modeling is shown in Table 1.

Table 1. The importance (%) of each environmental variable in the models for studying *C. azarolus* geographic distribution is shown.

Abbreviations	**Variables**	**Relative importance**	Unite
Bio15	Precipitation Seasonality (Coefficient of Variation)	60.74	dimensionless
Bio3	Isothermality (BIO2/BIO7) (* 100)	14.05	dimensionless
Bio8	Mean Temperature of the Wettest Quarter	11.10	°C
Bio17	Precipitation of the Driest Quarter	4.84	mm
Bio12	Annual Precipitation	3.73	mm
Bio4	Temperature Seasonality (standard deviation *100)	2.78	°C
Land use/Landcover	-	1.39	dimensionless
slope	Slope	1.09	**%**
aspect	Aspect	0.28	degree

Modeling

We used an ensemble model approach to model *C. azarolus* distribution within the BIOMOD2 (Thuiller et al. 2016) in R v. 3.1.2 (R Development Core Team, 2014). Ensemble methods were applied to forecast *C. azarolus* distribution including the Generalized Linear Model (GLM), Maximum Entropy (MaxEnt), Artificial Neural Network (ANN), Flexible Discriminant Analysis (FDA), Generalized Boosting Method (GBM), Multivariate Adaptive Regression Splines (MARS), and Random Forest (RF).

Since all models used require background data (such as pseudo-absence points), the number of background points equal to the species presence points in the study area was randomly generated outside the presence cells (Senay et al., 2013). Pseudo-absence points were prepared in the desired area and at a distance of one kilometer from each other (Arenas-Castro et al., 2018).

To calibrate the models, 80% of the presence points were used as training data, and the remaining 20% to evaluate the predictions of the models. We repeated this split-sample procedure ten times. Representative concentration pathways (RCPs: 2.6, 4.5, 6, and 8.5) and general circulation model MRI-CGCM3 were used to predict the future distribution of *C. azarolus* in the years 2050 and 2070. The consensus probability map, which shows suitable habitats for *C. azarolus* in response to current environmental conditions, was calculated using the averaging of predictions made by different algorithms (Marmion et al., 2009).

The performance of the models was evaluated using the true skill statistic (TSS) and the area under the receiver operating curve (AUC). AUC is a measure of overall accuracy, independent of threshold and prevalence (Manel et al., 2001), and TSS is independent of prevalence (Allouche et al., 2006). Based on receiver operating characteristic (ROC) criteria, we found the essential levels of predictor variables to divide habitats into two classes: suitable habitats and unsuitable habitats (Sangoony et al., 2016) and used differences in each class to produce habitat suitability maps. The approach suggested by Hessl et al., (2007) was used for the evaluation of AUC values: AUC < 0.7 (poor); 0.7 <AUC < 0.9 (moderate); and AUC > 0.9 (good). The approach suggested by Eskildsen et al. (2013) was used for the evaluation of TSS values: TSS > 0.75 (very good); 0.40 < TSS < 0.75 (good); and TSS < 0.40 (poor).

Results

All models used in this study attained an AUC > 0.89 and TSS > 0.65, showing good prediction accuracy (Table 2). The Random Forest (RF) algorithm provides the highest accuracy values (AUC = 0.99 and TSS = 0.98) (Table 2).

Table 2. Estimated values of the true skill statistic (TSS) and the area under the curve (AUC) were implemented in different models.

Model	**MARS**	**FDA**	**GBM**	**ANN**	**MaxEnt**	**GLM**	**RF**	**Average**
AUC	0.92	092	0.98	0.95	0.93	0.89	0.99	0.94
TSS	0.69	0.69	0.88	0.83	0.88	0.65	0.98	0.7

The relative contribution of environmental variables to the distribution models is shown in Table 1. Our results clearly showed that Precipitation Seasonality (60.74%), Isothermality (14.05%), and Mean Temperature of the Wettest Quarter (11.10%) had the largest contribution to the species distribution models.

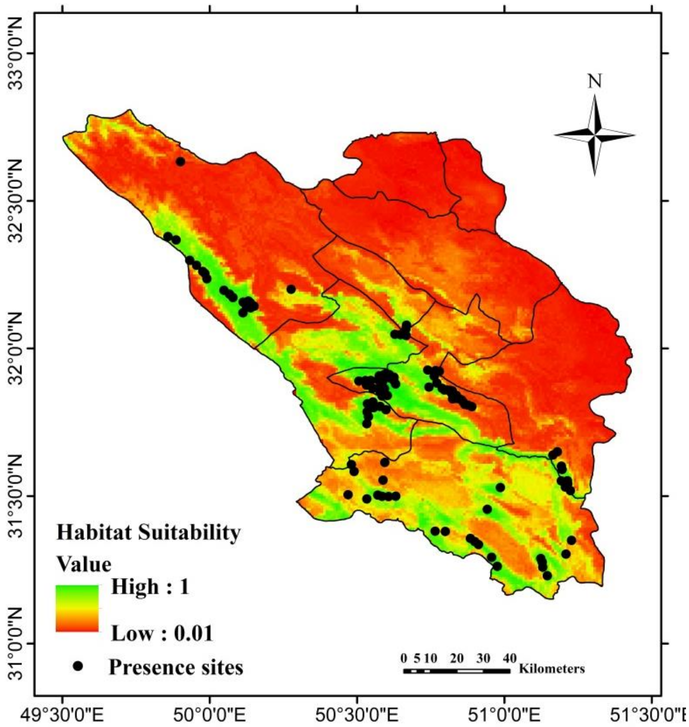

Figure 1. The ensemble map of current habitat suitability for *C. azarolus*

According to the ensemble model, 19.91% (3292.19 km^2) of the study area is currently suitable habitat for the *C. azarolus* (Fig. 1). The findings reveal the southern, central, and western parts of the province are the most suitable habitat for *C. azarolus*. The response curves indicate the species occurs in the habitats with a Precipitation Seasonality (bio15) of 88 mm to 100 mm, an Isothermality (bio3) of 34 to 37.7, and a Mean Temperature of the Wettest Quarter (bio8) between 0 to 4.8°C (Fig. 2).

Our results suggest that climate change can adversely affect the current distribution of *C. azarolus*. The results of all RCPs scenarios reveal an average increase of unsuitable habitats for *C. azarolus* by years 2050 and 2070 (Fig. 3 and 4). As illustrated in Fig. 3 and Fig. 4 dark green denotes nearly no changes in *C. azarolus* habitat distribution (habitat remained suitable), light green denotes an increase in suitable habitat areas (turned to suitable habitat), and red denotes a decrease in suitable habitat regions (turned to unsuitable habitat). The reduction of suitable habitats for *C. azarolus* will be 31.13% (RCP 2.6) to 89.87% (RCP 8.5) due to future climate change by 2050 and 2070 (Table 3). While in the same period, about 1.9% to 12.91% will be added to the suitable habitats of this species (unsuitable habitats will become suitable) (Fig. 3 and 4, and Table 3).

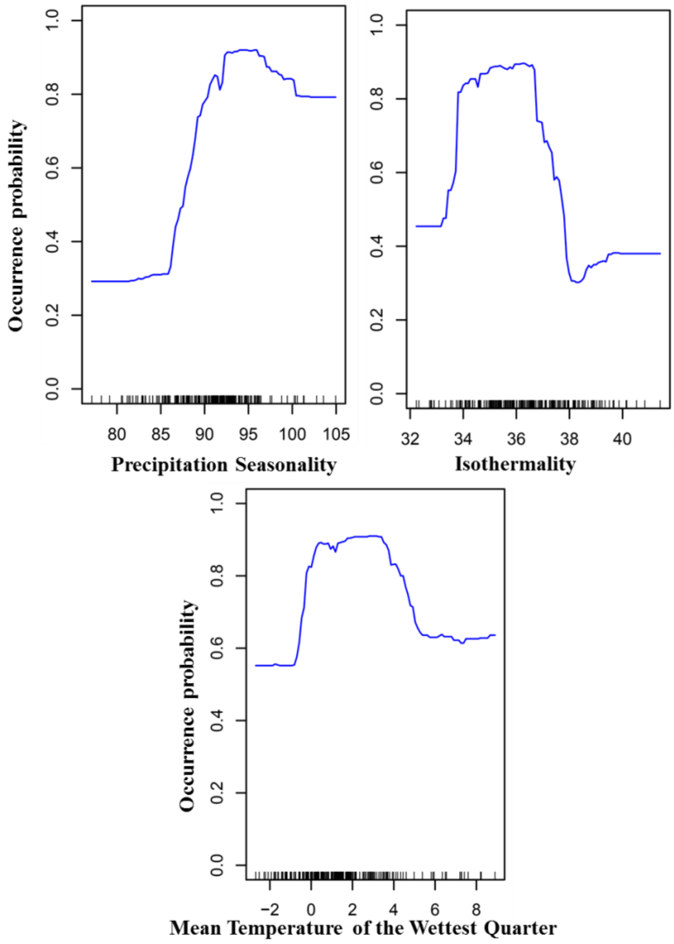

Figure 2. Probability of *C. azarolus* presence along effective variables based on the Random Forest (RF) model in Chaharmahal va Bakhtiari province

Table 3. Changes in the area of suitable habitats (km^2) of *C. azarolus* by 2050 and 2070 compared to the current distribution under different climatic scenarios and the MRI-CGCM3 model.

Year/Scenario	**Remained unsuitable (km^2)**	**Remained suitable (km^2)**	**Habitat loss (km^2)**	**Habitat loss (%)**	**Habitat gain (km^2)**	**Habitat gain (%)**	**Habitat change (%)**
MRI-CGCM3							
2050							
RCP2.6	2267.32	12814.92	1024.87	31.13	424.89	12.91	-18.22
RCP4.5	1954.51	12950.40	1337.68	40.63	289.37	8.79	-31.84
RCP6	1627.05	13028.10	1665.14	50.58	211.71	6.43	-44.15
RCP8.5	1316.44	13058.13	1975.75	60.01	181.68	5.52	-54.5
2070							
RCP2.6	1429.60	11865.26	1862.59	56.58	1374.56	10.38	-46.19
RCP4.5	971.13	12767.28	2321.06	70.50	427.53	3.57	-66.93
RCP6	432.17	12962.31	2860.02	86.87	277.51	2.1	-84.74
RCP8.5	333.40	12988.26	2958.79	89.87	251.56	1.9	-87.97

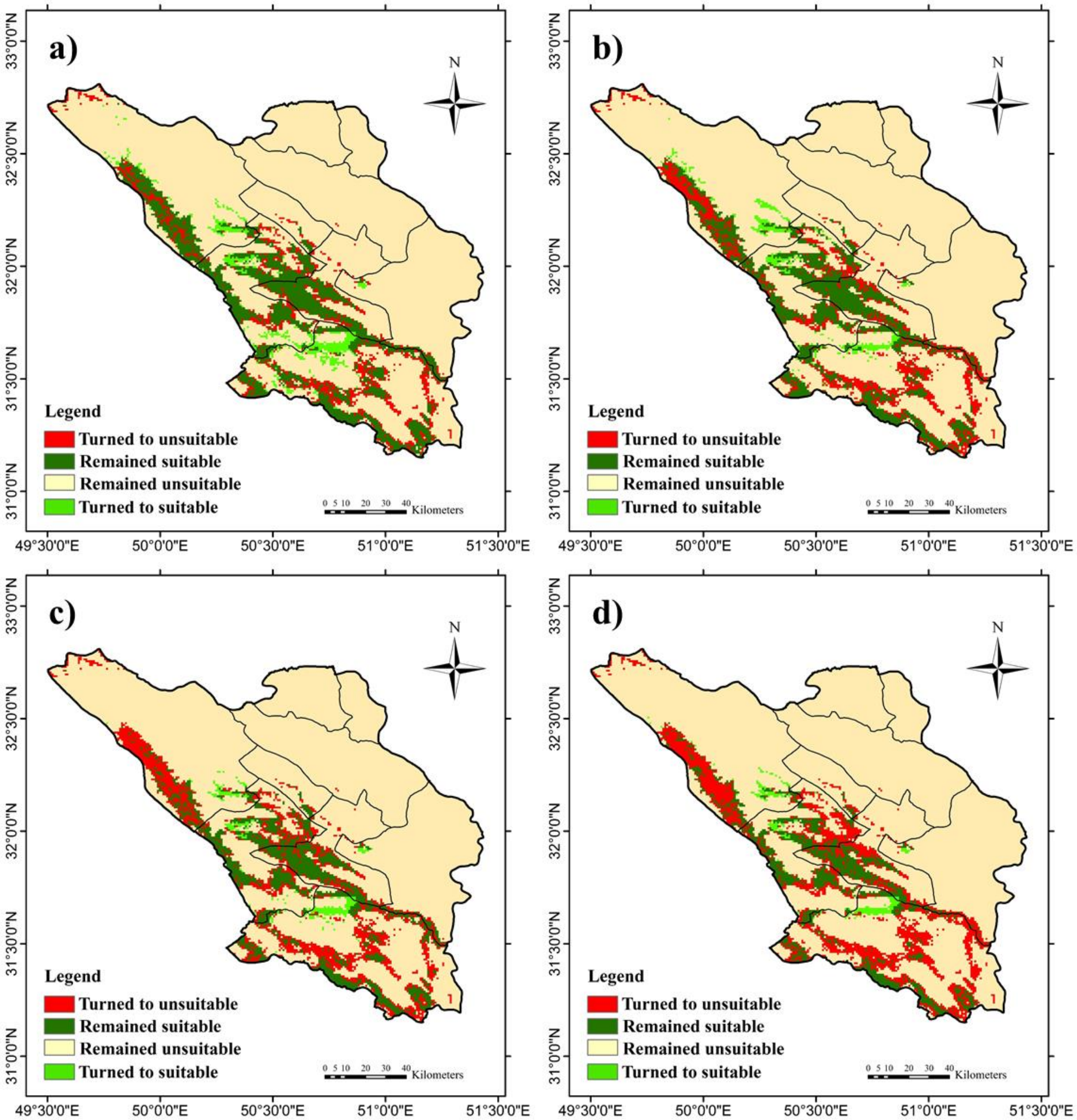

Figure 3. Changes in the suitable habitats of *C. azarolus* from current to future climatic conditions (2050) resulting from the ensemble model and based on the MRI-CGCM3 model with four RCP scenarios: (a) RCP2.6, (b) RCP4.5, (c) RCP6, and (d) RCP8.5

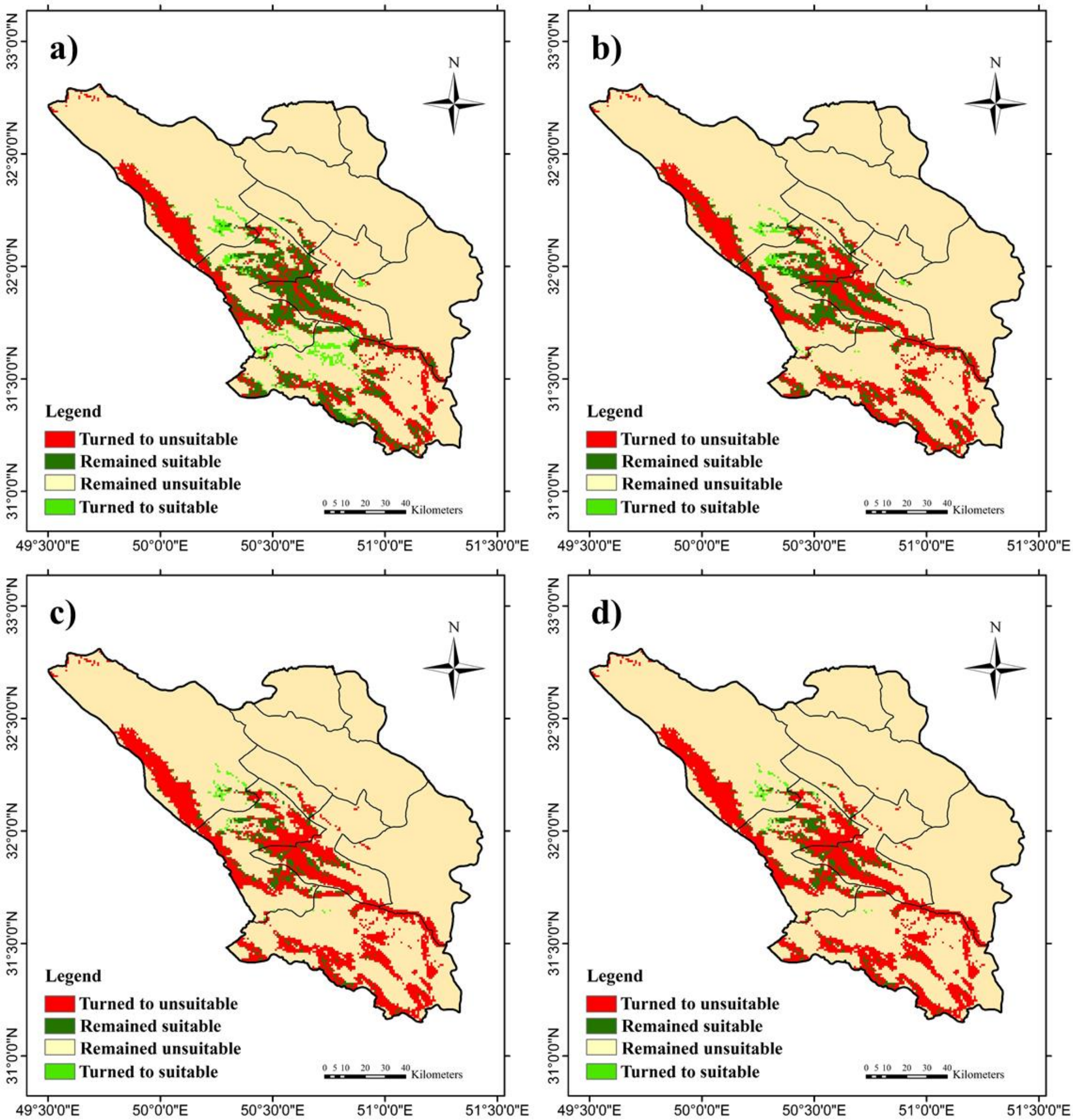

Figure 4. Changes in the suitable habitats of *C. azarolus* from current to future climatic conditions (2070) resulting from the ensemble model and based on the MRI-CGCM3 model with four RCP scenarios: (a) RCP2.6, (b) RCP4.5, (c) RCP6, and (d) RCP8.5

Discussion

Predicting the current and future distributions of species is essential for developing management strategies to maintain future suitable habitats (Porfirio et al. 2014). For this purpose, the species distribution modeling (SDM) is one of the essential tools to determine habitat suitability (Guisan et al., 2013), species demands, and ecological conservation (Jarvis & Robertson, 1999), as well as for recognizing biodiversity patterns (Williams & Hero, 2001).

In this study, we performed the modeling of current and future (2050 and 2070) distributions of *C. azarolus* using the ensemble approach, including seven species distribution models algorithm in Central Zagros. Our results, consistent with Jafari et al. (2019), indicate that southern, central, and western parts of the study area are the most important habitats for *C. azarolus*. The findings of the present study revealed that about 31% to 90% of currently suitable habitats of *C. azarolus* will become unsuitable due to climate change by 2050 and 2070. The foretold decline in the suitable habitats of this species was consistent with the results of other studies in the Central Zagros and Central Iran (Sangoony et al., 2016: *Bromus tomentellus;* Haidarian et al., 2017a: *Quercus brantii;* Naghipour et al., 2019a: *Pistacia atlantica;* Naghipour et al., 2019b: *Fritillaria imperialis;* Tarkesh & Jetschke, 2016: *Astragalus adscendens;* Amiri et al., 2019: *Artemisia sieberi* and Abolmaali et al., 2018: *Daphne mucronata*).

Nevertheless, the rate of such changes has accelerated significantly due to climate change, in which human communities play an important role. Humans have an important impact on changes in the natural environment, especially vegetation patterns, and are mainly responsible for habitat loss and species distribution (Ibáñez et al., 2014).

Furthermore, the suitable areas for *C. azarolus* were projected to shift towards higher elevations at an average of about 190 m in 2070. The effect of climatic conditions (rainfall and temperature) on the habitat of *C. azarolus*, which makes the lower elevation unsuitable for this species, is the reason for this shift (Al-Qaddi et al., 2016; Ashrafzadeh et al., 2019a; Attorre et al., 2011; Hodd et al., 2014). Our results indicate RCP8.5 could lead to a more severe impact on the distribution of *C. azarolus* than the other scenario. This was predictable given the intensity of climate change in this scenario. Consequently, the benefits of such species for human well-being are likely to decline in the future, and ecosystem services may be negatively affected (Arslan et al., 2020).

In this study, the SDMs applied have focused on macroecology (i.e., physiographic and climate variables). The SDM algorithms commonly involve some uncertainty resulting from climate models and available climatic data (Wang et al., 2012). It should also be emphasized that Climatic variables aren't only environmental variables influencing the species distribution, but also edaphic and biological variables that can affect the distribution of species. Therefore, a study on physiological plasticity is crucial to refining predictions about the impacts of changing climate on species distribution. The mechanism of seed dispersal, the presence of different plant and animal species, and human activities (e.g. invasive species, fire, and ecotourism) can also affect the spatial distribution of the target species (Holtmeier, 2009). However, it is important to emphasize that when modeling the species distribution in a large geographical area, the climate is usually the most important determinant of species presence (Pearson & Dawson 2003), and provides basic data on habitat suitability for the species (Marino et al., 2011).

Our results, inconsistent with other studies, indicate that precipitation seasonality (Kumar & Stohlgren, 2009; Uğurlu & Oldeland, 2012; Rajpoot et al., 2020), Isothermality (Arslan et al., 2020; Yang et al., 2013), and mean temperature of the wettest quarter (Xu et al., 2009; Jarnevich & Reynolds, 2011) are among the most important variables influencing the spatial distribution of different plant species.

Seasonal rainfall changes control the annual growth cycle (phenology) of plants, including shoot growth (vegetative growth), flowering, and leaf fall in trees (Borchert, 1994a, b) and synchronize tree phenology in forests and to some extent (Borchert, 1998). The precipitation seasonality has an important role in the response to forests to climate variability (Borchert, 1998). Additionally, measuring the precipitation seasonality is critical to setting the soil capacity to obtain water stock to be utilized by plants (Kosmas et al. 1999). Species distributions can be heavily influenced by variability in precipitation, precipitation seasonality presents a percentage of precipitation variability where greater percentages indicate higher variability of precipitation. (O’Donnel & Ignizio, 2012). According to the response curves, *C. azarolus* occurs in all types of habitats with a precipitation seasonality of 88 mm to 100 mm. Amiri & Mesgari (2009) reported that the central and southern parts of the study area had the highest precipitation seasonality.

Isothermality quantifies how large the day-to-night temperatures oscillate relative to the summer to winter oscillations (O’Donnel & Ignizio, 2012). Based on results *C. azarolus* occurs in habitats with Isothermality values of 34 to 37. So this value indicates the habitat where the diurnal temperature range for *C. azarolus* is 34%-37% of the annual temperature range. Mean temperature of wettest quarter gives mean temperatures throughout the most humid three months of the year, which can be valuable for considering how such environmental factors may affect species seasonal distributions (O’Donnel & Ignizio, 2012). Results showed that *C. azarolus* occurs in habitats with a mean temperature of the wettest quarter (winter in the study area) between 0 to 4.8°C. Based on the results, the RF model had the highest accuracies (AUC: 0.99, TSS: 0.98). This algorithm is an efficient method for modeling the species distribution (Cheng et al., 2012; Haidarian et al., 2017b; Mi et al., 2017; Ashrafzadeh et al., 2019b; Naghipour et al., 2019b). Due to its non-parametric nature, the RF algorithm is flexible in using different explanatory variables and can show nonlinear relationships between response variables and explanatory variables as well as hierarchical interactions between explanatory variables (Henderson et al., 2014).

Conclusion

Species distribution modeling is an efficient predictive tool that helps to identify the conservation and restoration priority areas over time. In this study, the potential distribution of *C. azarolus* under the current and future climatic conditions was successfully modeled. The species is one of the major tree species in central Zagros of Iran and it is reported to have medicinal and soil protection values. Our results revealed that the distribution of *C. azarolus* in Zagros forests would be radically influenced by future climate change. It is suggested that the predicted effects of climate change should be considered for the conservation and management strategies of *C. azarolus* communities in the Zagros forest area. A high conservation priority area is the predicted suitable habitat that is occupied by the target species. The restoration areas are the modeled suitable area that has not been occupied by the species, where is likely to gain a suitable habitat under future climatic conditions. This study can provide reliable information on preparing adaptive responses for the sustainable management of the species.

References

Abolmaali, SM-R., Tarkesh, M., & Bashari, H. (2018). Maxent modeling for predicting suitable habitats and identifying the effects of climate change on a threatened species, Daphne mucronata, in central Iran. Ecological Informatics, 43, 116-123.

Ahmadloo, F., Kochaksaraei, M. T., Azadi, P., Hamidi, A., & Beiramizadeh, E. (2015). Effects of pectinase, BAP and dry storage on dormancy breaking and emergence rate of Crataegus pseudoheterophylla Pojark. New Forests, 46(3): 373-386.

Ahn, Y., Lee, D-K., Kim, H. G., Park, C., Kim, J., & Kim J-u. (2015). Estimating korean pine (pinus koraiensis) habitat distribution considering climate change uncertainty-using species distribution models and rcp scenarios. Journal of the Korea Society of Environmental Restoration Technology, 18, 51-64.

Akhter, S., Mcdonald, M. A., van Breugel, P., Sohel, S., Kjær, E. D., & Mariott, R. (2017). Habitat distribution modelling to identify areas of high conservation value under climate change for Mangifera sylvatica Roxb. of Bangladesh. Land Use policy, 60, 223–232.

Alavi, S. J., Ahmadi, K., Hosseini, S. M., Tabari, M., & Nouri, Z. (2019). The response of English yew (Taxus baccata L.) to climate change in the Caspian Hyrcanian Mixed Forest ecoregion. Regional Environmental Change, 19(5), 1495-1506.

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.

Al-Qaddi, N., Vessella, F., Stephan, J., Al-Eisawi, D., & Schirone, B. (2016). Current and future suitability areas of kermes oak (Quercus coccifera L.) in the Levant under climate change. Regional Environmental Change, 17, 143-156.

Amiri, M. A., & Mesgari, M. S. (2019). Spatial variability analysis of precipitation and its concentration in Chaharmahal and Bakhtiari province, Iran. Theoretical and Applied Climatology, 137(3-4), 2905-2914.

Amiri, M., Tarkesh, M., & Jafari, R. (2019). Predicting the distribution of Artemisia sieberi Besser under climate change in the steppe and semi-steppe of Iran-Touranian region. Desert Management, 7(13), 29-48. (In Persian)

Arenas-Castro, S., Gonçalves, J., Alves, P., Alcaraz-Segura, D., & Honrado, J. P. (2018). Assessing the multi-scale predictive ability of ecosystem functional attributes for species distribution modelling. PLoS One, 13(6), e0199292.

Arslan, E.S., Akyol, A., Örücü, Ö.K., & Sarıkaya, A.G. (2020). Distribution of rose hip (Rosa canina L.) under current and future climate conditions. Regional Environmental Change, 20(3), 1-13.

Ashrafzadeh, M. R., Naghipour, A. A., Haidarian, M., & Khorozyan, I. (2019a). Modeling the response of an endangered flagship predator to climate change in Iran. Mammal Research, 64(1), 39-51.

Ashrafzadeh, M. R., Naghipour, A. A., Haidarian, M., Kusza, S., & Pilliod, D. S. (2019b). Effects of climate change on habitat and connectivity for populations of a vulnerable, endemic salamander in Iran. Global Ecology and Conservation, 19, e00637.

Attarod, P., Sadeghi, S. M. M., Taheri Sarteshnizi, F., Saroyi, S., Abbasian, P., Masihpoor, M., kordrostami, F., & Dirikvandi, A. (2016). Meteorological parameters and evapotranspiration affecting the Zagros forests decline in Lorestan province. Iranian Journal of Forest and Range Protection Research, 13(2), 97-112. (In Persian)

Attorre, F., Alfò, M., De Sanctis, M., Francesconi, F., Valenti, R., Vitale, M., & Bruno, F. (2011). Evaluating the effects of climate change on tree species abundance and distribution in the Italian peninsula. Applied Vegetation Science, 14, 242-255.

Bashari, H., Naghipour, A. A., Khajeddin, S. J., Sangoony, H., & Tahmasebi, P. (2016). Risk of fire occurrence in arid and semi-arid ecosystems of Iran: an investigation using Bayesian belief networks. Environmental monitoring and assessment, 188(9), 531.

Blach-Overgaard, A., Balslev, H., Dransfield, J., Normand, S., & Svenning, J-C. (2015). Global-change vulnerability of a key plant resource, the African palms. Scientific Reports, 5, 1-10.

Borchert, R. (1998). Responses of tropical trees to rainfall seasonality and its long-term changes. In A. Markham (Ed.), Potential impacts of climate change on tropical forest ecosystems (pp. 241-253). Dordrecht: Springer.

Borchert, R. (1994a). Soil and stem water storage determine phenology and distribution of tropical dry forest trees. Ecology, 75(5), 1437-1449.

Borchert, R. (1994b). Water status and development of tropical trees during seasonal drought. Trees, 8(3), 115-125.

Cheng, L., Lek, S., Lek-Ang, S., & Li. Z. (2012). Predicting fish assemblages and diversity in shallow lakes in the Yangtze River basin. Limnologica, 42 (2), 127–136.

Eskildsen, A., Roux, P. C., Heikkinen, R. K., Høye, T. T., Kissling, W. D., Pöyry, J., Wisz, M. S., & Luoto, M. (2013). Testing species distribution models across space and time: high latitude butterflies and recent warming. Global Ecology and Biogeography, 22(12), 1293–1303.

Farashi, A., Shariati, M., & Hosseini, M. (2017). Identifying biodiversity hotspots for threatened mammal species in Iran. Mammalian Biology, 87, 71-88.

Fortunel, C., Paine, C. T., Fine, P. V., Kraft, N. J., & Baraloto, C. (2014). Environmental factors predict community functional composition in Amazonian forests. Journal of Ecology, 102(1), 145-155.

Guisan, A., Theurillat, J. P., & Kienast, F. (1998). Predicting the potential distribution of plant species in an alpine environment. Journal of Vegetation Science, 9(1), 65-74.

Guisan, A., Tingley, R., Baumgartner, J. B., Naujokaitis-Lewis, I., Sutcliffe, P. R., Tulloch, A. I., et al. (2013) Predicting species distributions for conservation decisions. Ecology Letters, 16, 1424–1435.

Guisan, A., & Zimmermann, N. E. (2000). Predictive habitat distribution models in ecology. Ecological modeling, 135, 147-186.

Haidarian Aghakhani, M., Tamartash, R., Jafarian, Z., Tarkesh Esfahani, M., & Tatian, M. (2017a). Predicting the impacts of climate change on Persian oak (Quercus brantii) using species distribution modelling in Central Zagros for conservation planning. Journal of Environmental Studies, 43, 497-511. (In Persian)

Haidarian Aghakhani, M., Tamartash, R., Jafarian, Z., Tarkesh Esfahani, M., & Tatian, M. (2017b). Forecasts of climate change effects on Amygdalus scoparia potential distribution by using ensemble modeling in Central Zagros. Journal of RS and GIS for Natural Resources, 8(3), 1-14. (In Persian)

Hyam, R., & Pankhurst, R. (1995). Plants and their names: a concise dictionary. Oxford University Press.

Henderson, E. B., Ohmann, J. L., Gregory, M. J., Roberts, H. M., & Zald, H. (2014). Species distribution modelling for plant communities: stacked single species or multivariate modelling approaches? Applied Vegetation Science, 17(3), 516-527.

Hessl, A., Miller, J., Kernan, J., Keenum, D., & McKenzie, D. (2007). Mapping Paleo-Fire boundaries from binary point data: comparing interpolation methods. The Professional Geographer, 59(1), 87-104.

Hodd, R. L., Bourke, D., & Skeffington, M. S. (2014). Projected range contractions of European protected oceanic montane plant communities: Focus on climate change impacts is essential for their future conservation. PloS One, 9(4), e95147.

Holtmeier, F. K. (2009). Mountain timberlines: ecology, patchiness, and dynamics (Vol. 36). Springer Science & Business Media.

Ibáñez, I., Katz, D.S., Peltier, D., Wolf, S. M., & Connor Barrie, B. T. (2014). Assessing the integrated effects of landscape fragmentation on plants and plant communities: the challenge of multiprocess–multiresponse dynamics. Journal of Ecology, 102(4), 882-895.

Jafari, A., Alipour, M., Abbasi, M., & Soltani, A. (2019). Distribution Modeling of Hawthorn (Crataegus azarolus L.) in Chaharmahal & Bakhtiari Province using the maximum entropy method. Journal of Environmental Studies, 45(2), 223-235. (In Persian)

Jaafari, A., Mafi Gholami, D., & Zenner, E. K. (2017). A Bayesian modeling of wildfire probability in the Zagros Mountains, Iran. Ecological Informatics, 39, 32-44.

Jarnevich, C. S., & Reynolds, L. V. (2011). Challenges of predicting the potential distribution of a slow-spreading invader: a habitat suitability map for an invasive riparian tree. Biological Invasions, 13(1), 153-163.

IFRWMO. (2014). Iranian forests, range and watershed management organization national land use/land cover map. Forest, Range and Watershed Management Organization of Iran, Tehran. Available at: http://frw.org.ir/00/En/. (Accessed 20 July 2014).

Jarvis, A. M., & Robertson, A. (1999). Predicting population sizes and priority conservation areas for 10 endemic Namibian bird species. Biological Conservation, 88, 121– 131.

Kosanic, A., Anderson, K., Harrison, S., Turkington, T., & Bennie, J. (2018). Changes in the geographical distribution of plant species and climatic variables on the West Cornwall peninsula (South West UK). PloS One, 13(2), e0191021.

Kosmas, C., Ferrara, A., Briasouli, H., & Imeson, A. (1999). Methodology for mapping environmentally sensitive areas (ESAs) to desertification. The medalus project Mediterranean desertification and land use. Manual on key indicators of desertification and mapping Environmentally Sensitive Areas to desertification, 31-47.

Kumar, P. (2012). Assessment of impact of climate change on Rhododendrons in Sikkim Himalayas using Maxent modelling: limitations and challenges. Biodiversity and Conservation, 21(5), 1251-1266.

Kumar, S., & Stohlgren, T. J. (2009). Maxent modeling for predicting suitable habitat for threatened and endangered tree Canacomyrica monticola in New Caledonia. Journal of Ecology and the Natural Environment, 1, 094-098.

Ladányi, Z., Blanka, V., Meyer, B., Mezősi, G., & Rakonczai, J. (2015). Multi-indicator sensitivity analysis of climate change effects on landscapes in the Kiskunság National Park, Hungary. Ecological indicators, 58, 8-20.

Manel, S., Williams, H. C., & Ormerod, S. J. (2001). Evaluating presence–absence models in ecology: the need to account for prevalence. Journal of Applied Ecology, 38(5), 921-931.

Marmion, M., Luoto, M., Heikkinen, R. K., & Thuiller, W. (2009). The performance of state-of-the-art modelling techniques depends on geographical distribution of species. Ecological Modelling, 220(24), 3512-3520.

Marino, J., Bennett, M., Cossios, D., Iriarte, A., Lucherini, M., Pliscoff, P., et al. (2011). Bioclimatic constraints to Andean cat distribution: a modelling application for rare species. Diversity and Distributions, 17(2), 311-322.

Mi, C., Huettmann, F., Guo, Y., Han, X., & Wen, L. (2017). Why choose Random Forest to predict rare species distribution with few samples in large undersampled areas? Three Asian crane species models provide supporting evidence. PeerJ, 5, e2849.

Moustafa, A., Zaghloul, M., Mansour, S., & Alotaibi, M. (2019). Conservation Strategy for protecting Crataegus x sinaica against climate change and anthropologic activities in South Sinai Mountains, Egypt. Catrina: The International Journal of Environmental Sciences, 18(1), 1-6.

Naghipour, A. A., Haidarian, M., & Sangoony, H. (2019a). Predicting the impact of climate change on the distribution of Pistacia atlantica in the Central Zagros. Journal of Plant Ecosystem Conservation, 6 (13), 197-214. (In Persian)

Naghipour, A. A., Ostovar, Z., & Asadi, E. (2019b). The Influence of Climate Change on distribution of an Endangered Medicinal Plant (Fritillaria Imperialis L.) in Central Zagros. Journal of Rangeland Science, 9(2), 159-171.

O'Donnell, M. S., & Ignizio, D.A. (2012). Bioclimatic predictors for supporting ecological applications in the conterminous United States. US Geological Survey Data Series, 691(10).

Périé, C., & de Blois, S. (2016). Dominant forest tree species are potentially vulnerable to climate change over large portions of their range even at high latitudes. PeerJ, 4, e2218.

Pearson, R. G., & Dawson, T. P. (2003). Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful?. Global Ecology and Biogeography, 12(5), 361-371.

Porfirio, L. L., Harris, R. M., Lefroy, E. C., Hugh, S., Gould, S. F., Lee, G., et al. (2014). Improving the use of species distribution models in conservation planning and management under climate change. PLoS One, 9(11), e113749.

Rafiee mo, G., Jafari, R., Matinkhah, S. H., Tarkesh isfahani, M., karimzadeh, H. R., & jafari, Z. (2020). Predicting the Potential Habitat Distribution of Crataegus Pontica C. Koch, Using a Combined Modeling Approach in Lorestan Province. Ijae, 9(2), 45-59

Rajpoot, R., Adhikari, D., Verma, S., Saikia, P., Kumar, A., Grant, K. R., et al. (2020). Climate models predict a divergent future for the medicinal tree Boswellia serrata Roxb. in India. Global Ecology and Conservation, 23, e01040.

R Development Core Team. (2014). R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna.

Sangoony, H., Vahabi, M., Tarkesh, M., & Soltani, S. (2016). Range shift of Bromus tomentellus Boiss. As a reaction to climate change in Central Zagros, Iran. Applied Ecology and Environmental Research, 14(4), 85-100.

Senay, S. D., Worner, S. P., & Ikeda, T. (2013). Novel three-step pseudo-absence selection technique for improved species distribution modelling. PLoS One, 8, e71218.

Shirk, A. J., Cushman, S. A., Waring, K. M., Wehenkel, C. A., Leal-Sáenz, A., Toney, C., et al. (2018). Southwestern white pine (Pinus strobiformis) species distribution models project a large range shift and contraction due to regional climatic changes. Forest Ecology and Management, 411, 176–186.

Sagheb-Talebi, K. S., Sajedi, T., & Pourhashemi, M. (2014). Forests of Iran. In A Treasure from the Past, a Hope for the Future. Dordrecht: Springer publication.

Taleshi, H., Jalali, S. G., Alavi, S. J., Hosseini, S. M., Naimi, B., & Zimmermann, N. E. (2019). Climate change impacts on the distribution and diversity of major tree species in the temperate forests of Northern Iran. Regional Environmental Change, 19(8), 2711-2728.

Tarkesh, M., & Jetschke, G. (2016). Investigation of current and future potential distribution of astragalus gossypinus in central iran using species distribution modelling. Arabian Journal of Geosciences, 9, 1-11.

Thuiller, W., Georges, D., Engler, R., Breiner, F., Georges, M. D., & Thuiller, C. W. (2016). Package ‘biomod2’. https://cran.r-project.org/package= biomod2.

Uğurlu, E., & Oldeland, J. (2012). Species response curves of oak species along climatic gradients in Turkey. International Journal of Biometeorology, 56(1), 85-93.

Wang, T., Campbell, E. M., O’Neill, G. A., & Aitken, S. N. (2012). Projecting future distributions of ecosystem climate niches: uncertainties and management applications. Forest Ecology and Management, 279, 128-140.

Watson, J. E., Rao, M., Ai-Li, K. & Yan, X. (2012). Climate change adaptation planning for biodiversity conservation: A review. Advances in Climate Change Research, 3(1), 1-11.

Williams, S. E., & Hero, J. M., (2001). Multiple determinants of Australian tropical frog biodiversity. Biological Conservation 98, 1–10.

Xu, Z., Zhao, C., & Feng, Z. (2009). A study of the impact of climate change on the potential distribution of Qinghai spruce (Picea crassifolia) in Qilian Mountains. Acta Ecologica Sinica, 29(5), 278-285.

Yang, X.Q., Kushwaha, S.P.S., Saran, S., Xu, J., & Roy, P.S. (2013). Maxent modeling for predicting the potential distribution of medicinal plant, Justicia adhatoda L. in Lesser Himalayan foothills. Ecological engineering, 51, 83-87.

Zomer, R. J., Xu, J., Wang, M., Trabucco, A., & Li, Z. (2015). Projected impact of climate change on the effectiveness of the existing protected area network for biodiversity conservation within Yunnan Province, China. Biological Conservation, 184, 335-345.

Zuur, A. F., Ieno, E. N., & Elphick, C. S. (2010). A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution, 1(1), 3-14.