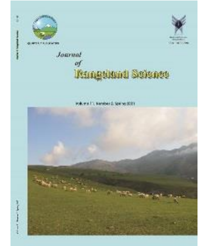

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Research and Full Length Article:

The Effects of Climate Changes on the Future Distribution of *Astragalus adscendens* in Central Zagros, Iran

Maryam Haidarian [A]*, Reza Tamartash [A], Zeinab Jafarian [A], Mostafa Tarkesh [B], Mohammad Reza Tatian [A]
[A] Sari Agricultural Sciences and Natural Resources University, Sari, Iran *(Corresponding author), Email: ma_haidarian@yahoo.com
[B] Faculty of Natural Resources, Isfahan University of Technology, Isfahan, Iran

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Abstract. Iran is one of the principal centers of *Astragalus* genus. *Astragalus adscendens* is a valuable endemic plant. There is less information about the effect of climate change on *Astragalus* genus especially *A. adscendens*. In this study, we used the ensemble modeling based on seven species distribution models to predict the spatial distribution of *A. adscendens.* The presence of *A. adscendens* points was recorded from our field surveys in Chaharmahal-va-Bakhtiari province as a semi-arid part of Central Zagros, Iran between 2015 and 2016. The future projections were made for the year 2050 and 2070 with two Representative Concentration Pathways (RCPs) scenarios (4.5 and 8.5). Also, in this approach, species occurrence data (140 points), 19 bioclimatic predictors from HadGEM2-CC (Hadley Centre Global Environmental Model, version two - Carbon Cycle), MRI-CGCM3 (Meteorological Research Institute Coupled Global Climate Model Version three) and three physiographic variables were used. According to the ensemble model, 33.58% of the study area (548678 ha) was suitable for the *A. adscendens.* This research showed annual precipitation, Isothermality, temperature annual range and slope have played the most important role in habitat suitability of this species. The response curves showed that occurrence probability of *A. adscendens* mostly exists in habitats with annual precipitation from 380 mm to 630 mm, Isothermality from 35.7 to 36.8 (dimensionless), temperature annual range from 40.5 to 43°C and slope of 0.1 to 30 degree. The decline of suitable habitats will be 59.3% to 89.7% by 2050 and 2070. In contrast, 18.1% to 56.2% of currently unsuitable habitats can become suitable with climate changes. Evaluations showed that Random Forest was found to be the most reliable model for species prediction. Predicting the potential future changes in suitable habitat for *A. adscendens* will allow more reliable planning and management of this valuable species for experts.

Key words: Chaharmahal-va-Bakhtiari province, Species distribution modeling, Biomod2, Ensemble modeling

Introduction

Climate is the statistics of weather over long periods of time (Planton, 2013). It has been identified as a primary control of the geographic distribution of plants (Forman, 1964; Box, 1981). A significant change in the mean state or the temporal variability of the climate due to natural variation of anthropogenic changes and external forcing in the atmosphere's composition or changes in land use is called climate change (IPCC, 2007). The recent emission rates of it are at the highest level in the documented history (Lüthi *et al*., 2008). According to the IPCC (2013), over the last century, the global temperature rose by 0.78 °C (Stocker *et al*., 2014) and is projected to rise by 0.3–4.8 °C by 2090–2099 (Priti *et al*., 2016).

Climate change has significant impacts on the potential distribution of species range shifts, and some species' potential habitat will be forecast to disappear (Anderegg *et al*., 2015). Predicting and measuring the accurate potential distribution of species under climate change are important to undertake urgent and effective conservation action (Dawson *et al*., 2011). Considering midrange climate warming scenarios for 2050, Thomas *et al*. (2004) predicted that 15–37% of species in their sample of regions and taxa would be committed to extinction.

Species Distribution Modeling (SDM) is statistical algorithms predicting the spatial distribution of species from field observations and environmental data (Guisan and Zimmermann, 2000; Hengl *et al*., 2009). They have become an important tool in biogeography, natural resource management, ecosystem management, and biodiversity conservation (Guillera-Arroita *et al*., 2015; Elith and Leathwick, 2009). As well, they have been used to project the potential effect of climate change on species distributions for more than a decade now (Eeley *et al*., 1999; Neilson *et al*., 2005; Renwick *et al*., 2012).

Iran is one of the most significant countries in the Middle East for biodiversity conservation. The ecosystems of Iran include 8,000 plant species (Farashi *et al.*, 2017). Central Zagros is important for ecological value and biodiversity (Hunnam, 2011; Bashari *et al*., 2016). In recent decades, Zagros biodiversity has suffered severe dangers (Arvahi *et al*., 2016). This area is modified largely by land-use changes (e.g., conversion of forest and rangelands into rain-fed agricultural fields) and livestock grazing (Naghipour *et al*., 2016). With its landscapes, receiving 250 mm of rainfall on average each year, Iran faced warming about 0.5°C during the 1961–2000 (Rahimzadeh *et al*., 2005; Babaeian *et al*., 2015). Habibi (2016) revealed that annual rainfall declined and mean annual air temperature increased during the past 15 years in the central part of the Zagros Range in southwestern Iran.

Astragalus L. (Fabaceae) is a genus widely distributed throughout the temperate regions (Rios and Waterman, 1997). Iran is one of the principal centers for various species of *Astragalus* genus and based on the latest information, there are more than 804 species, with an endemism rate of more than 60% including more than 11% of Iran's flora (Massoumi, 1998; Ghahremaninejad *et al*., 2012).

Astragalus adscendens Boiss. & Hausskn. Ex Boiss is a valuable perennial, spiny shrub and important for soil conservation (Azimi *et al*., 2005). The main habitat of this species has been introduced in Iran (Zohary 1973; Podlech 1986) although its limited presence has been reported in Iraq (Townsend and Guest, 1974) and may be found sporadically in Turkey (Khajeddin, 2001). Ecotone communities of this species with oaks are visible in many areas (Khajeddin, 2001). It produces gum tragacanth which is a kind of natural gum used in many industries such as pharmacy, confections, calico printing, dressing fabrics, making glues, papermaking and for preparing culture medium (Phillips and Williams, 2009). The occurrence of this species has been reported by Hauss Knecht from the mountains of southwestern Iran since 1870 (Grami, 1998).

Recent droughts, increasing temperatures in the winter, aerial dust, pests and diseases have threatened some part of the province's rangelands, especially where *A. adscendens* dominant, leading to dieback and declining to them (Fouladi, 2014). One of the most important reasons for this could be a change in the climatic factors over a short period (Attarod *et al*., 2016). Climate change also could negatively influence the survival of this species.

Ardestani *et al*. (2015) analyzed potential habitat modeling for the reintroduction of three native species of the *Astragalus* genus in central Iran. They identified the most suitable potential habitat distributions of the three species were predicted in the western and southwestern parts of rangeland in Isfahan province. Tarkesh and Jetschke (2016) investigated the current and future potential distribution of *Astragalus gossypinus* in central Iran. The model showed that *A. gossypinus* is expected to move north-eastwards to a decreasing area of distribution. Safaei *et al*. (2018) determined the potential habitat for *Astragalus verus* Olivier and compared three correlative models. They concluded that Ecological-Niche Factor Analysis (ENFA) delivers better performance to predict species distribution mapping in areas manipulated by humans. Mousazade *et al*. (2019) compared between frequency ratio and Maxent models for predicting the potential distribution of *Astragalus fasciculifolius*. They concluded that the Maxent model showed a better result compared to the frequency ratio approach.

There is limited published scientific data about the effects of climate change on the *Astragalus* genus distribution. It becomes an urgent priority to study how the *A. adscendens* distribution is affected by climate change in its habitat in Iran.

In this study, we used species distribution modeling to recognize the currently suitable habitats of *A. adscendens* and predict whether its range is likely to expand or contract under predicted climate change scenarios in Central Zagros (Iran). We explore for answers to the latter questions: i) which areas are predicted in current as suitable habitats for *A. adscendens* in Central Zagros, Iran? ii) Will the distribution of the species likely expand or contract under different climate change scenarios by 2050 and 2070?

Materials and Methods

Study Area

The studied region had an area of 1.6 million hectares in total Chaharmahal-va-Bakhtiari province situated in Central Zagros (Fig. 1). The province was too mountainous, with most of its range placed at more than 2000 m above sea level and altitudes between 783 and 4178 m. The annual rainfall ranges between 250 mm in the east and southeast and 1400 mm in the northwest of the province, with a provincial mean of 560 mm. The mean annual weather temperature is 10 °C is reported (Jaafari *et al*., 2017; Ashrafzadeh *et al*., 2019a, b).

Field studies were included in the harvest of geographical coordinates of the presence point of this species in total Chaharmahal-va-Bakhtiari Province between 2015 and 2016. Presence points were collected with Global Positioning System (GPS). To reduce spatial autocorrelation, all multiple occurrences of sites within a minimum distance of 1 km were eliminated. We used 140 presence point *A. adscendens* for modelling (Fig. 1).

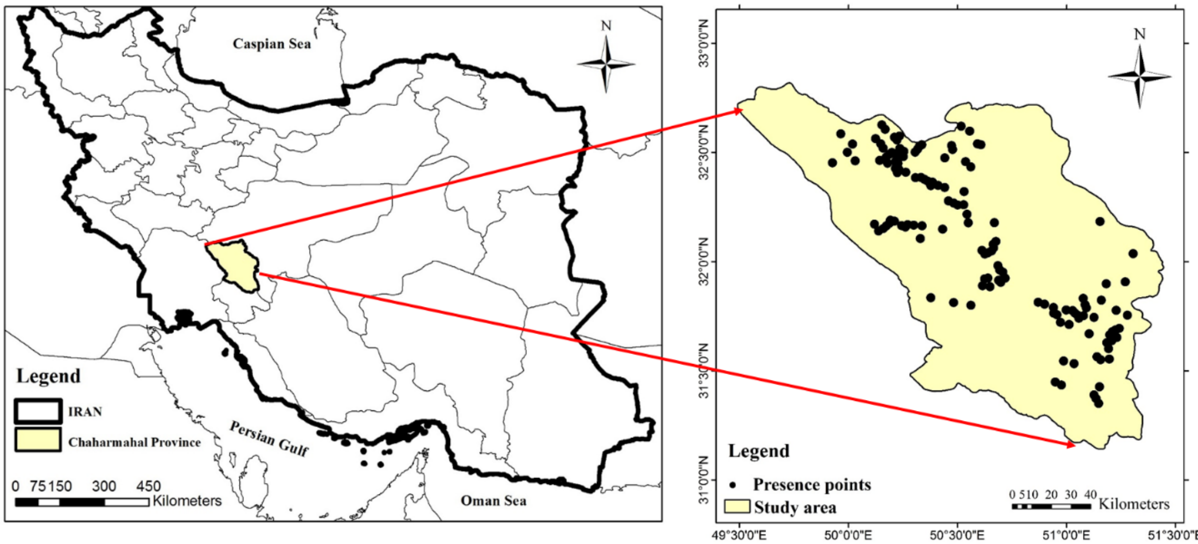

Fig. 1. Location of Chaharmahal-va-Bakhtiari Province in Iran (left) and distribution of *A. adscendens* occurrence sites used in this study (right)

Bioclimatic and environmental data

Physiographic (elevation, aspect, and slope) and bioclimatic variables (bio1–bio19) as the predictors of *A. adscendens* distribution were used. We obtained physiographic variables from the Digital Elevation Model. We used a Digital Elevation Model to produce topographic variables (slope and aspect). The bioclimatic variables and Physiographic variables were extracted (bio1-bio19) from a 30 arc-seconds (~1 km) resolution dataset in WorldClim-Global Climate data (http://www.worldclim.org).

All nineteen bioclimatic variable climate factors were used, which had been applied in many kinds of research as the base for monitoring impacts of climate change on the plant (e.g., Chhetri *et al*., 2018; Tanaka *et al*., 2012). These nineteen bioclimatic layers must be obtained from the three primary climatic variable monthly maximum temperatures, monthly minimum temperatures and monthly precipitation. Monthly precipitation was corrected by average monthly precipitation collected from weather stations across the province. Station values were considered as Y and values in pixels were considered as X. Then, using CurveExpert software, the best equation that showed the relationship between the amount in pixels and the value recorded in each station was determined. After correcting the monthly rainfall data with the help of this data and temperature data, nineteen bioclimatic variables were created in DIVA-GIS7.5 (http://www.diva-gis.org). 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. We used Pearson test in the IBM SPSS 23 (http://www.ibm.com) to check the correlation between the explanatory variables and exclude highly correlated ones (Pearson's correlation coefficient, r>±0.8) (Rana *et al*., 2017). Two topographic and six bioclimatic variables were applied to model its distribution based on correlation analysis.

Modeling

We applied an ensemble model approach to model *A. adscendens* distribution. Ensemble methods were used to predict *A. adscendens* distribution including the Generalized Linear Model (GLM), Classification Tree Analysis (CTA), Artificial Neural Network (ANN), Generalized Boosting Method (GBM), Flexible Discriminant Analysis (FDA), Multivariate Adaptive Regression Splines (MARS) and Random Forest (RF).

All models were generated using default Biomod parameters where appropriate Biomod2 package (Thuiller *et al*., 2016) in R v. 3.1.2 (R Development Core Team, 2014). The ensemble forecasting approach can produce a more robust model and overcome the uncertainties emerging from the interpretation of results from individual models (Araújo and New, 2007; Hao *et al*., 2019). We chose the number of pseudo-absences equivalent to the presence points (Senay *et al*., 2013). Random pseudo-absences were elected exclusively in the species identified range with the least distance of 1 km within pseudo-absences (Arenas-Castro *et al*., 2018). We used 80% of the occurrence points as training data for model calibration and the remaining 20% to evaluate the model's predictive performance. We repeated this split-sample procedure ten times and have simulated the suitability of habitat for 2050 and 2070. A total of 280 probabilities (ten repetitions- seven modelling techniques– two Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5 and two global circulation model HadGEM2-CC (Hadley Centre Global Environmental Model, version two-Carbon Cycle) and MRI-CGCM3 (Meteorological Research Institute Coupled Global Climate Model version three) of habitat suitability for this species were generated. We applied the variable importance criterion to estimate changes in modeling by accumulating the reduction in model statistics with the addition of each variable to the model (Kuhn, 2008). The consensus probabilistic map indicating suitable habitats for *A. adscendens* in response to current environmental conditions were generated by averaging the projections made by the different algorithms (Marmion *et al*., 2009). We used ArcGIS 10.3 (ESRI Inc., http://www.esri.com/) and the extension Spatial Analysis to reclassify the outputs of models for both current and future climatic conditions. Framework shows the main parts of the ensemble modeling (Fig. 2).

Model performance was assessed using the area under the receiver operating curve (AUC) and the true skill statistic (TSS) because both criteria are autonomous of prevalence in the species data (Allouche *et al*., 2006; Zipkin *et al*., 2012). Models generating presence-absence predictions are usually evaluated by comparing the predictions with a set of validation sites and constructing a confusion matrix that records the number of true positive (a), false positive (b), false negative (c) and true negative (d) cases predicted by the model (Allouche *et al*., 2006).

The receiver operating characteristic (ROC) curve provides an alternative technique for assessment of the accuracy of ordinal score models (Fielding and Bell, 1997). The construction of ROC curves uses all possible thresholds for classifying the scores into confusion matrices, obtaining each matrix' sensitivity and specificity; then, comparing sensitivity against the corresponding proportion of false positives (equal to 1 − specificity). (McPherson *et al.*, 2004; Thuiller *et al.*, 2005). Allouche *et al.* (2006) have shown that TSS is an intuitive method of performance measurement of SDMs in which predictions are expressed as Presence–absence maps (Table 1).

Table 1. Measures of predictive accuracy as: Sensitivity is the probability that the model will correctly classify a presence. Specificity is the probability that the model will correctly classify an absence.

Measure	Formula
Sensitivity	$\frac{a}{a+c}$
Specificity	$\frac{d}{b+d}$
TSS	Sensitivity+ Specificity-1

The result of AUC differs from 0.5 to 1.0, being recognized as poor if below 0.7, moderate if between 0.7 and 0.8, and good if > 0.8 (Hessl *et al*., 2007). Models by TSS > 0.75 were very good, 0.40–0.75 well, and < 0.40 poor (Eskildsen *et al*., 2013).

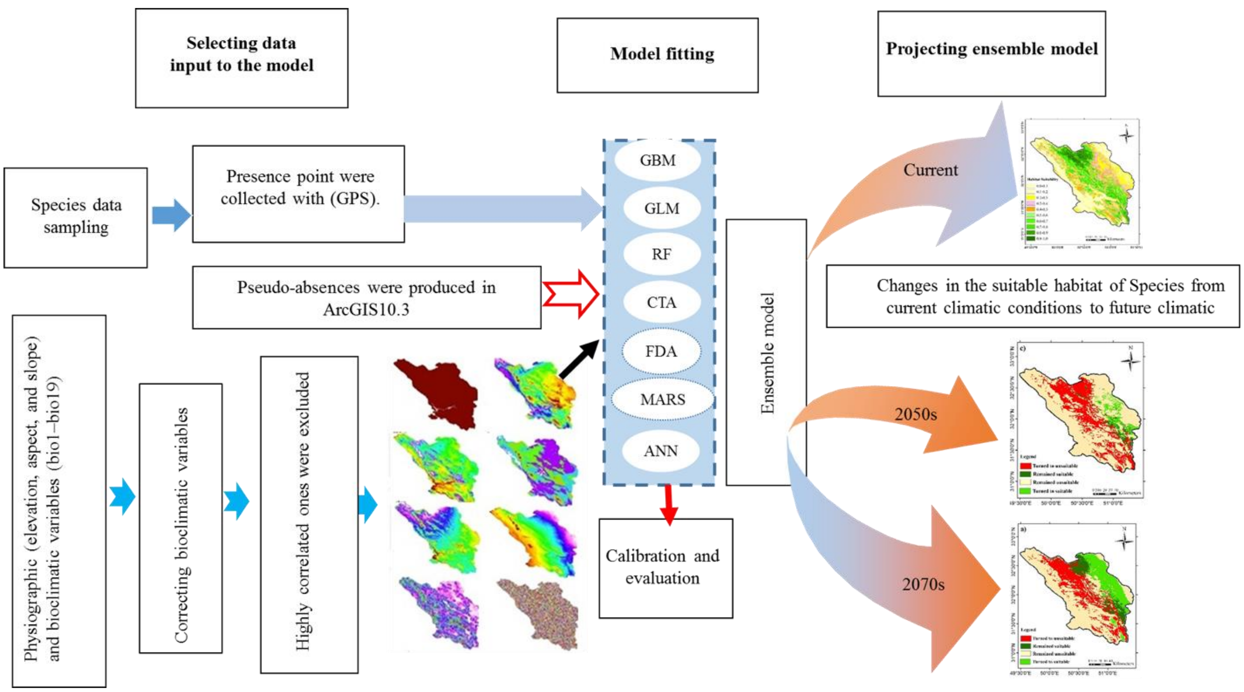

Fig. 2. Framework showing the main parts of the ensemble modeling, climate change effects on the future distribution of *A. adscendens* in Central Zagros, Iran

Results

Following conducting Pearson's correlation testing and eliminating layers with a high correlation, it was found that 8 layers (bio9, bio 7, bio 3, bio 4, bio 12, and bio 17, slope and aspect) were not correlated with one another and can enter to the final model (Table 2).

Table 2. The subset of uncorrelated variables used to develop the models of *A. adscendens* distribution

	Abbr.	Variables	Unite
1	slope	Slope	degree
2	aspect	Aspect	degree
3	bio3	Isothermality (mean diurnal range/bio7)*100	dimensionless
4	bio4	Temperature seasonality (standard deviation*100)	°C
5	bio7	Temperature annual range (maximum temperature of the warmest month – the minimum temperature of the coldest month)	°C
6	bio9	Mean temperature of the driest quarter	°C
7	bio12	Mean annual precipitation	mm
8	bio17	Precipitation of the driest quarter	mm

Source: www.worldclim.com

All the models used in this study reached an AUC > 0.85 and TSS > 0.55, showing good prediction accuracy (Table 3). The accuracy of Random Forest was the highest (AUC=0.99), followed by Generalized Boosting Method (0.98), Classification Tree Analysis (0.89), Multivariate Adaptive Regression Splines (0.88), Artificial Neural Network (0.86), Flexible Discriminant Analysis (0.86), Generalized Linear Model (0.85).

Table 3. The measures of the area under the curve (AUC) and the true skill statistic (TSS) in the studied models

Abbr.	Model's name	Models prediction accuracy	
		AUC	TSS
ANN	Artificial Neural Network	0.86	0.70
CTA	Classification Tree Analysis	0.89	0.69
GBM	Generalized Boosting Method	0.98	0.86
GLM	Generalized Linear Model	0.85	0.55
RF	Random Forest	0.99	0.97
FDA	Flexible Discriminant Analysis	0.86	0.57
MARS	Multivariate Adaptive Regression Splines	0.88	0.63

The relative contribution of the input variables to the models in predicting suitable habitats for the species presence is shown (Table 4). Our results revealed that Annual precipitation for GBM, FDA, CTA and RF models, Isothermality for FDA model, Temperature annual range for MARS model and Precipitation of the driest quarter for ANN, had the greatest effects on the species' distribution in the study area (Table 4). This research showed Annual precipitation (25.03%), Isothermality (22.23%), Temperature annual range (17.82%), and Slope (12.96%) have played the most important roles in habitat suitability of this species (Table 4).

Table 4. Relative contribution (%) of each environmental variable in the models for studying *A. adscendens* geographic distribution is shown (Abbreviations as in Table 3).

Variables#	ANN	CTA	GBM	GLM	RF	FDA	MARS	Relative importance
bio12	14.96	<u>34.46</u>	<u>39. 21</u>	13.16	<u>31.91</u>	<u>36.15</u>	5.36	25.03
bio3	1.38	26.15	27.10	30.29	19.20	<u>35.30</u>	16.20	22.23
bio7	21.42	5.89	6.54	27.33	10.76	10.76	<u>42.05</u>	17.82
Slope	20.21	17.87	17.87	5.71	15.66	0	13.42	12.96
bio4	9.36	0.00	4.18	7.43	8.75	9.21	23.23	8.88

bio9	10.3	15.89	1.96	15.24	6.23	0	0	7.09
bio17	21.64	0.00	1.70	0.00	4.21	8.84	0	5.20
Aspect	0.99	0.00	1.70	1.10	3.54	0	0	1.05

The underlined values are environmental variable with the highest relative contribution in each model

According to the ensemble model, 33.58% (548678 ha) of the study area is suitable for the *A. adscendens* (Fig. 3). According to species response curves (probability values equal to or greater than 0.4), this species occurs in the habitat with annual precipitation (bio12) of 380 mm to 630 mm and Isothermality (bio3) from 35.7 to 36.8, temperature annual range (bio7) from 40.5 to 43°C and slope of 0.1 to 30 degree (Fig.4). The range of elevation for species was determined from 1600 to 3360 m. The average elevation of suitable areas based on the modeling results was 2250 m above sea level. By studying climate change in the selected periods, species distribution maps in these periods were developed based on the climatic demands. These maps were produced for the current condition (Fig. 3) and two time periods, 2050 and 2070 (Figs. 5 and 6).

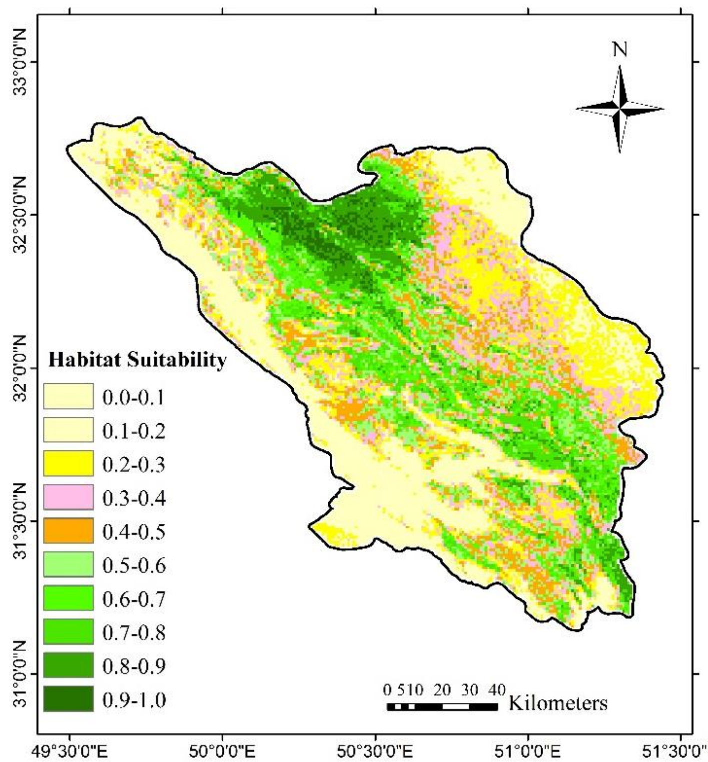

Fig. 3. The ensemble map of habitat suitability for *A. adscendens* based on current conditions

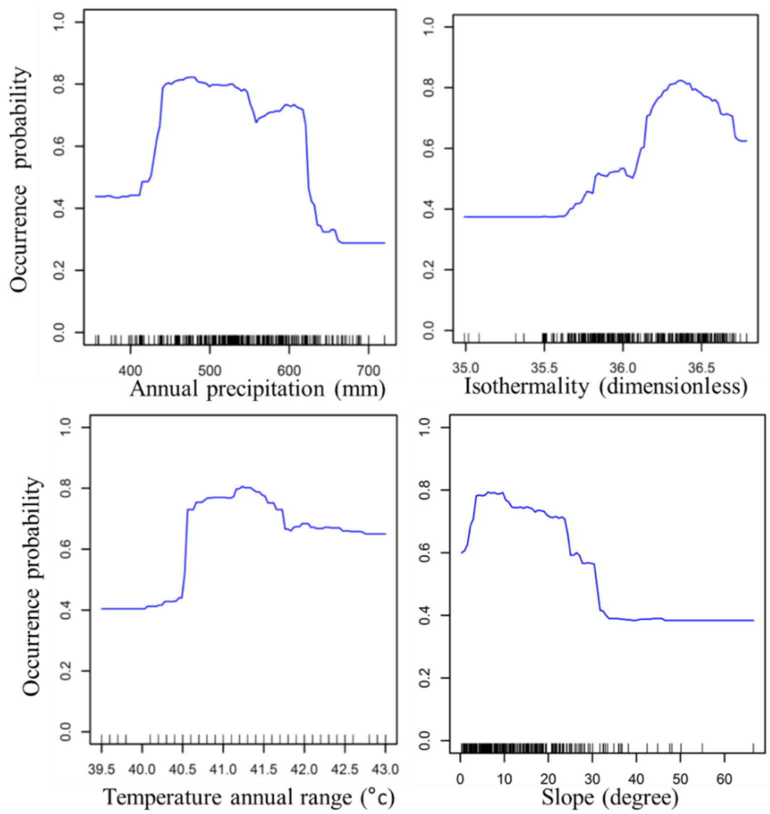

Fig. 4. Indicates species response curves of random forest that had had the most performance between models in relation to the four most important environmental factors used in the ensemble

The results suggest the future climate will adversely influence the predicted distribution. The model prediction for almost all scenarios (RCP 4.5 and 8.5) 2050 as well as 2070 revealed that areas unsuitable habitat for *A. adscendens* compared to the current potential distribution area would increase (Fig. 5 and 6). The reduction of suitable habitats for *A. adscendens* will be 59.3% to 88.7% under RCP 4.5 by 2050 and 2070. The decline of suitable habitats will be 65.4% to 89.7% under RCP 8.5 by 2050 and 2070 (Table 5). Compared with the area of the suitable habitat under current climate prediction, the predictions by 2050 (Fig. 5) and 2070 (Fig. 6) using the RCP4.5 and RCP8.5, ensemble model showed almost more than the present predictions (gain). For the RCP4.5 scenario, the gain of suitable habitats for the species will be 27.2% to 56.2% by 2050 and 2070. Further, habitat gains for *A. adscendens* will be 18.1% to 52.2% under RCP 8.5 by 2050 and 2070 (Table 5). Based on modeling of current conditions, center and southeast of the province were determined as most suitable regions for *A. adscendens*. Under climate change, the suitable regions of this species in the northeast and east of the province increases.

Altogether the decline of suitable habitats will be 59.3% to 89.7% by 2050 and 2070. In contrast, 18.1% to 56.2% of unsuitable habitats can become suitable with climate change (Table 5).

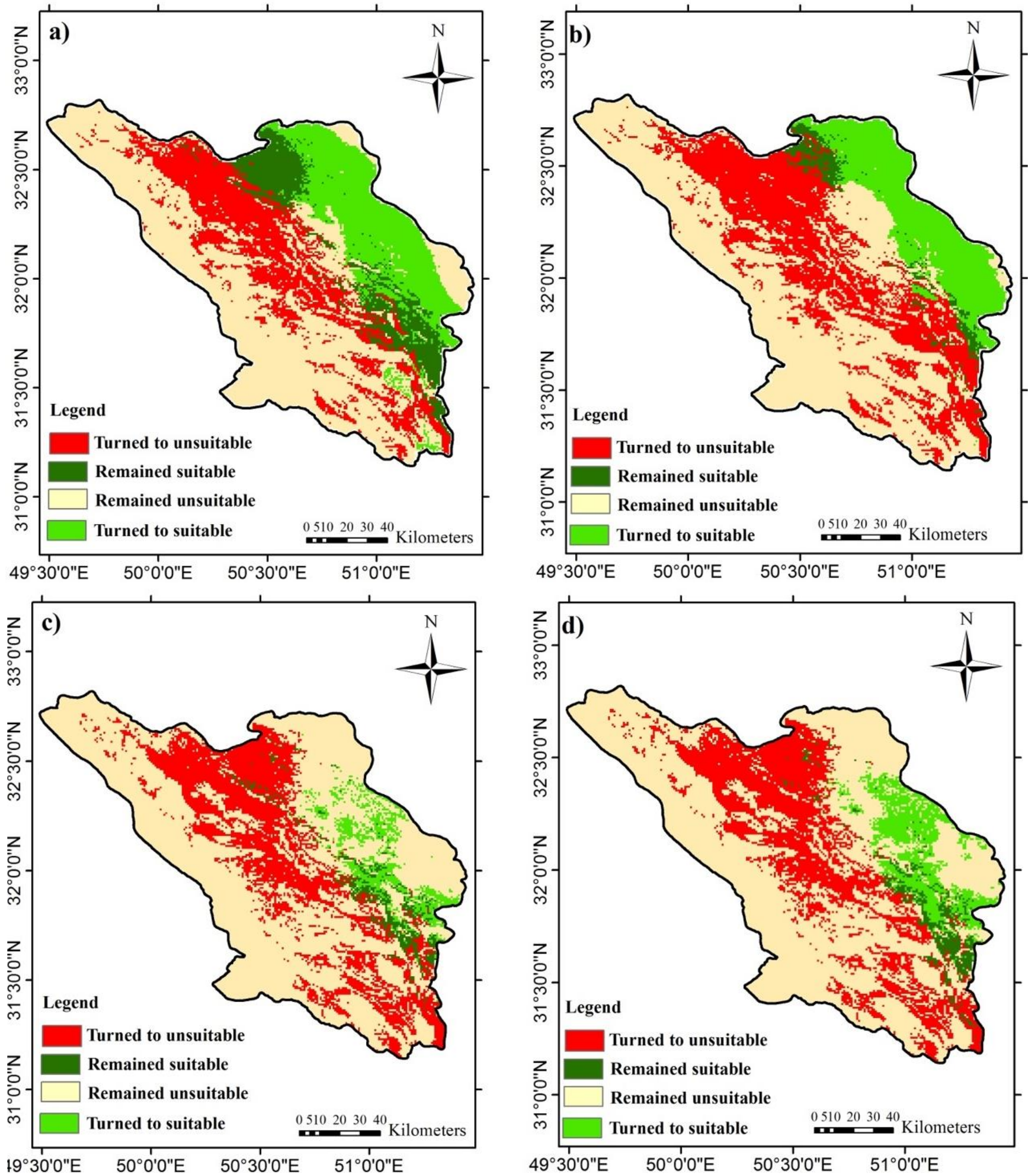

Fig. 5. Changes in suitable habitat of *A. adscendens* from current climatic conditions (1970-2000) to future climatic conditions (year 2050) based on HadGEM2-CC model (a, b) and MRI-CGCM3 model (c, d) with two RCP scenarios (RCP4.5 and RCP8.5)

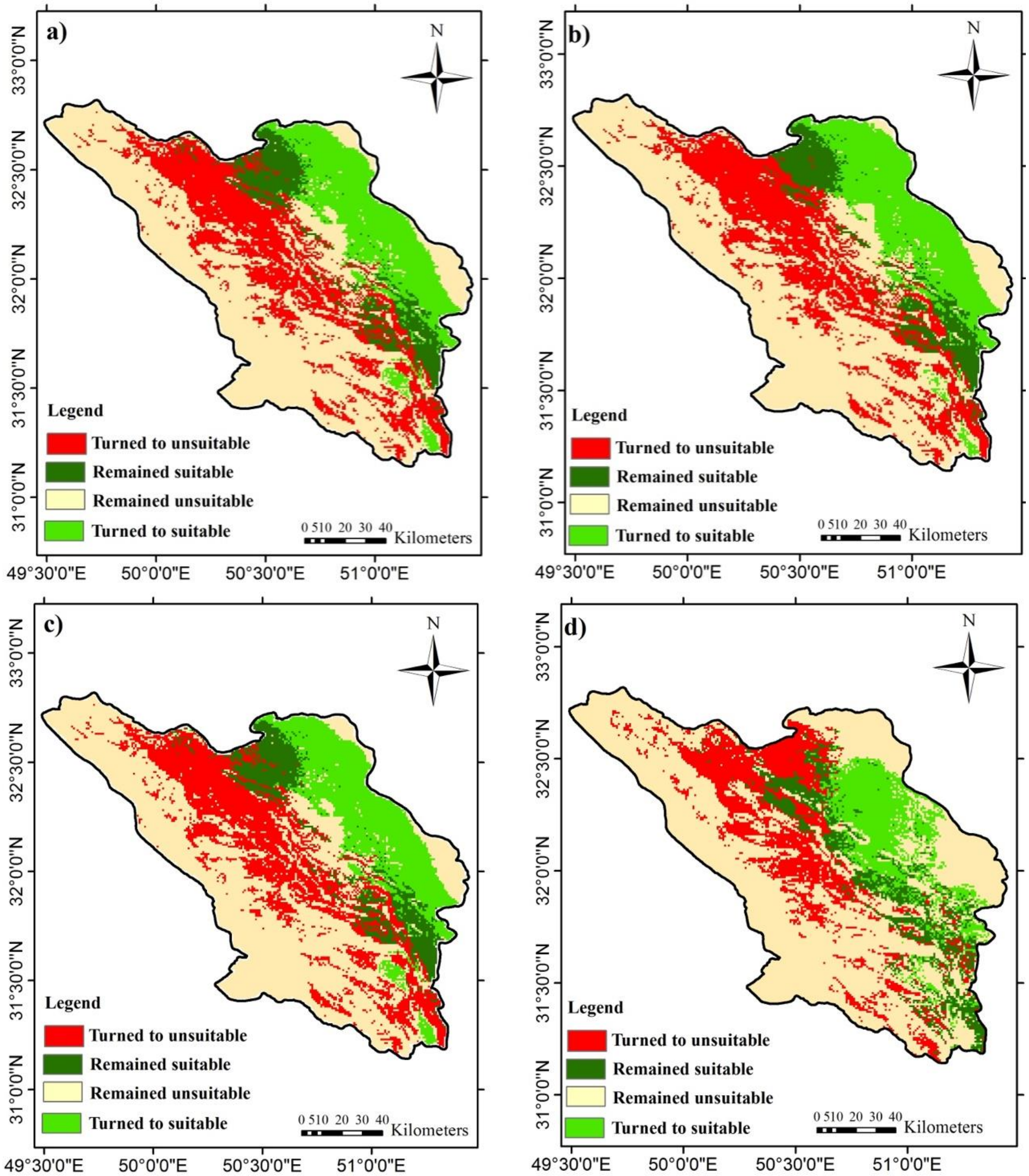

Fig. 6. Changes in suitable habitat of *A. adscendens* from current climatic conditions (1970-2000) to future climatic conditions (year 2070) based on HadGEM2-CC model (a, b) and MRI-CGCM3 model (c, d) with two RCP scenarios (RCP4.5 and RCP8.5)

Table 5. Changes in *A. adscendens* distribution by 2050 and 2070 under two climate change scenarios, within the two general circulation models (HadGEM2-CC and MRICGCM3) compared with the current distribution of *A. adscendens* in Chaharmahal-va-Bakhtiari Province.

Climate models	Year/ Scenario	Stable presence (ha)	Stable absence (ha)	Habitat loss (ha)	Habitat loss (%)	Habitat gain (ha)	Habitat gain (%)	Habitat change (%)
HadGEM2-CC	2050							
	RCP4.5	174738	776667	373940	68.0	308353	56.2	-11.8
	RCP8.5	55899	808520	492779	89.7	276500	50.4	-39.3
	2070							
	RCP4.5	150691	795974	397987	72.5	289046	52.68	-19.82
	RCP8.5	406212	792977	142467	74.0	292043	52.2	-21.8
MRI-CGCM3	2050							
	RCP4.5	55133	1011974	431164	88.66	135427	27.84	-60.82
	RCP8.5	51648	1059440	434649	89.37	87961	18.08	-71.29
	2070							
	RCP4.5	191884	1033372	280124	59.34	128318	27.18	-32.16
	RCP8.5	163168	957817	308841	65.43	203872	43.19	-22.23

RCP4.5: RCP4.5 is a scenario that stabilizes radiative forcing at 4.5 W m−2 without ever exceeding that value in the year 2100

RCP8.5: RCP8.5 is a scenario that the greenhouse gas emission and concentrations in this scenario increase extremely over time, contributing to a radiative forcing of 8.5 W/m^2 at the end of the century.

Discussion

Species distribution models assume that a certain equilibrium with climate. Apart from climatic changes, other parameters such as soil, land use change and competition would be regarded as contributing factors (Iverson and Prasad, 1998). In addition, Pearson and Dawson (2003) noted that climatic and physiographic factors were sufficient for modeling at the regional scale. This is impossible and unnecessary to estimate all these processes when modeling the effects of climate change is performed on an extensive geographic scale (Hamann and Wang, 2006). Moreover, despite the deficiencies of species distribution models, the overall patterns of predicted species' range shift often match the detected biological tendencies (Parmesan *et al.*, 2005).

The potential distribution and suitability of *A. adscendens* in Chaharmahal-va-Bakhtiari province have reached an alarming condition and are a serious worry for the rangeland departments and policymakers. In this work, we applied the ensemble forecasting method to assess the spatial distribution of suitable habitats for *A. adscendens* in the semi-arid part of central Zagros, under climate change. The predictive modeling of *A. adscendens* helps to determine the suitable sites where the species can grow well. The present study modeled the climatic envelope of *A. adscendens* for the current and the future 2050 years (up to 2070) and remarking the potential areas for its conservation.

Under the scenario of RCP 4.5 and 8.5 for all the elected periods (2050 and 2070) and elected HadGEM2-CC and MRI-CGCM3 climate models, these variables are expected to show significant variations, instigating large area of the current distribution to become low potential by 2050 and 2070. When the habitats turn unsuitable for the occurrence of *A. adscendens*, other competitive species will become dominant in the area. This species is expected to gain some new suitable habitat under these mentioned circumstances. The decline of suitable habitats will be 59.3% to 89.7% by 2050 and 2070. As revealed by the model, in the future, the suitable habitat under the current climatic conditions would be rendered unsuitable, which leads to local extinction. Rcp8.5 had a more severe effect on the species habitat than the other scenario. This was predictable given the intensity of climate change in this scenario.

The foretold decline in the suitable habitats of this species was consistent with the results of similar studies in the central Zagros, on *Bromus tomentellus* (Sangoony *et al*., 2016), *Quercus brantii* (Haidarian *et al*., 2017a), *Fritillaria imperialis* (Naghipour Borj *et al*., 2019a), *Pistacia atlantica* (Naghipour Borj *et al*., 2019b). Also, for *A. adscendens* (Tarkesh and Jetschke, 2016), *Artemisia sieberi* (Amiri *et al*., 2019), and *Daphne mucronata* in central Iran (Abolmaali *et al*., 2018), this decline has been indicated in their study.

Our results show that annual precipitation and isothermally, temperature annual range made the highest contribution to performing our ensemble model. Annual precipitation had the highest influence on *A. adscendens* distribution, in agreement with previous studies in the Central Zagros region indicating this as the most important factor determining (Sangoony *et al*., 2017; Haidarian *et al*., 2017a). Result of studies in the west of Isfahan province, Iran *A. verus* (Safaei *et al.,* 2013) and *A.* gossypinus (Sangoony *et al.*, 2012) indicated that annual precipitation had the greatest effects on the species distribution of them.

According to the ensemble map of all models, this species occurs in the habitat with annual precipitation of 380 mm to 630 mm. This agrees with the experimental findings of Pakzad *et al*. (2013) who reported an optimal distribution for *A. adscendens* in areas with an annual rainfall of over 400 mm.

The response curves showed that *A. adscendens* occurs in all types of habitats with Isothermality (bio3) from 35.7 to 36.8 °C and temperature annual range (bio7) from 40.5 to 43 °C. Safaei *et al*. (2018) showed that *A. verus* occurs in the habitat with Isothermality (bio3) from 19.53 to 23.56 °C and temperature annual range (bio7) from 57.13 to 65.99 °C.

In the present study, according to the forecast maps, the range of elevation for species was determined from 1600 to 3360 m and slope of 0.1 to 30 degree. Moghimi (2005) determined the elevation range of this species from 1500 to 3400 m. Azimi *et al.* (2005) determined the highest elevation range of this species from 1600 to 3360 m and the range of slope >40% and 25 to 40% on the northern and western slopes.

This research showed that ensemble modeling by Biomod could predict the current potential distribution of *A. adscendens* with good accuracy (AUC > 0.85 and TSS > 0.55). Among all the statistical approaches, random forest was discovered to be the most reliable model for this species prediction. It was not so surprising because it gives the predictions by producing thousands of trees and aggregated with an average (Breiman 2001; Elith *et al*., 2008). Random forest is an efficient method for modeling the prediction of species distribution (Cheng *et al*., 2012, Ashrafzadeh *et al.* (2019a), Haidarian *et al.* (2017b). According to studies, only a random forest model can have a function equal to the mean output of several modeling methods (Grenouillet *et al*., 2011). De Clercq *et al*. (2015) concluded that the random forest method had the best performance. Milanesi *et al*. (2016) also evaluated the efficiency of different models and concluded that the random forest model has the highest accuracy and has better performance than other models.

Conclusion

This research indicated that ensemble modeling by Biomod could predict the current potential distribution of *A. adscendens* with high accuracy. This research showed annual precipitation, Isothermality, temperature annual range and slope have played the most important roles in habitat suitability of this species. According to the results, *A. adscendens* is expected to decrease the area of current distribution under 2050 and 2070. This study highlights the importance of climate change on the geographical plant species distribution. *A. adscendens* is one of the most important range plant species in central Zagros of Iran, very crucial for soil conservation and people's economic life. Hence, the current and predicted map of habitat suitability and identification of suitable bioclimatic variables could be a significant guide for the government responsible for the management and conservation of important plants. Ensemble modeling can be a valuable technique that can produce significant evidence on the climate change impacts on the species suitability and distribution. The region mapped in the study as current and future 'suitable habitats' for the species could be effective for the re-establishment and re-introduction of *A. adscendens* species. Predicting the species' habitat suitable in the future will allow more reliable planning and management of conservation works and tactic and overall protection of the valuable species.

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اثر تغییر اقلیم بر پراکنش آینده گونه گون گزی (*Astragalus adscendens*) در زاگرس مرکزی

مریم حیدریان[الف*]، رضا تمرتاش[الف]، زینب جعفریان[الف]، مصطفی ترکش[ب]، محمدرضا طاطیان[الف]
[الف]گروه مرتع‌داری، دانشکده منابع طبیعی، دانشگاه علوم کشاورزی و منابع طبیعی ساری*(نگارنده مسئول)، پست الکترونیک:ma_haidarian@yahoo.com
[ب]گروه مرتع و آبخیزداری، دانشکده منابع طبیعی، دانشگاه صنعتی اصفهان

چکیده. ایران از مراکز اصلی گونه‌های مختلف جنس *Astragalus* است. گون گزی (*Astragalus adscendens*)، گونه با ارزش و بومی ایران است. اطلاعات اندکی درباره اثر تغییر اقلیم بر جنس گون، مخصوصاً گون گزی در دسترس است. در این مطالعه، به منظور پیش‌بینی پراکنش گون گزی از رویکرد مدل‌سازی اجماعی با تلفیق هفت مدل پراکنش گونه‌ای استفاده شد. نقاط حضور گون گزی بر اساس بازدیدهای میدانی در سال‌های ۱۳۹۴ و ۱۳۹۵، در استان چهارمحال و بختیاری واقع در زاگرس مرکزی برداشت شد. پیش‌بینی آینده بر اساس دو سناریوی انتشار (RCP4.5 و RCP8.5) و در دو دوره زمانی (۲۰۵۰ و ۲۰۷۰) انجام شد. همچنین در این رویکرد، داده‌های حضور گونه (۱۴۰ نقطه)، ۱۹ متغیر زیست اقلیمی، سه متغیر فیزیوگرافی و دو مدل گردش عمومی MRI-CGCM3 و HadGEM2-CC مورد استفاده قرار گرفتند. حدود ۳۳/۵۸ درصد (۵۴۸۶۷۸ کیلومتر مربع) از محدوده مورد مطالعه به عنوان رویشگاه‌های مطلوب گون گزی شناسایی شد. موثرترین متغیرها در مطلوبیت رویشگاه گونه مورد مطالعه، به ترتیب بارندگی سالانه، هم‌دمایی، دامنه دمای سالانه و شیب بودند. منحنی‌های عکس‌العمل نشان داد که احتمال وقوع گون گزی عمدتاً در رویشگاه‌هایی با مجموع بارندگی سالیانه ۳۸۰ تا ۶۳۰ میلی‌متر، هم‌دمایی ۳۵/۷ تا ۳۶/۸،دامنه دمای سالانه ۴۰/۵ تا ۴۳ درجه سانتیگراد و شیب ۰/۱ تا ۳۰ درجه وجود دارد. یافته‌ها نشان داد که ۵۹/۳۰ تا ۸۹/۷۰ درصد از رویشگاه‌های مطلوب گون گزی تا سال‌های ۲۰۵۰ و ۲۰۷۰ به واسطه تغییر اقلیم نامناسب خواهد شد. در مقابل، ۱۸/۱۰ تا ۵۶/۲۰ درصد از رویشگاه‌های نامناسب به علت تغییر اقلیم مناسب خواهد شد. ارزیابی‌ها نشان داد که مدل جنگل تصادفی، قابل‌اعتمادترین مدل برای پیش‌بینی پراکنش گونه می‌باشد. پیش‌بینی تغییرات آینده در رویشگاه مناسب گون گزی امکان تهیه طرح‌های حفاظتی و مدیریتی از این گونه با ارزش را در اختیار کارشناسان قرار می‌دهد.

کلمات کلیدی: استان چهارمحال و بختیاری، مدل‌سازی پراکنش گونه‌ای، Biomod2، مدل‌سازی اجماعی