Plant Ecol (2022) 223:1275–1288
https://doi.org/10.1007/s11258-022-01273-2

Climate change alters future distribution of mountain plants, a case study of *Astragalus adscendens* in Iran

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Received: 19 March 2021 / Accepted: 30 October 2022 / Published online: 10 November 2022

Abstract Climate is one of the most important elements affecting the distribution of species, and it is expected that the distribution of species will be widely influenced by climate change. In plants, edaphic factors also play a special role along with climate in determining the distribution range. The current study aimed to predict the future distribution of the Persian manna (*Astragalus adscendens*), an endemic perennial shrub in Zagros Mountains of Western Iran. For this purpose, two sets of static (i.e. edaphic and physiographic) and dynamic (i.e. climatic) data and an ensemble approach were used to develop two edaphic-physiographic and climatic models. Current and future suitability maps are representative of the climatic and the edaphic-physiographic niches of *A. Adscendens* that were obtained based on climatic suitable areas filtered by edaphic-physiographic model. The filtered map has less suitable habitats compared to the climatic model. Three dynamic variables (mean temperature of wettest quarter, temperature seasonality, temperature annual range) and two static variables (altitude and volumetric fraction of coarse fragments) were identified as the most important factors in determining the habitat of *A. Adscendens*. The importance of altitude was greater than latitude in maintaining or losing suitable habitats under different climate change scenarios, suggesting that the species will not have range expansion or northward shift due to no significant shift in latitude and longitude. Results revealed a sharp decline in the suitable habitats in such that 67% and 91% of the current habitat may be lost by the year 2050 and 2070, respectively. Area reduction was more extreme in future scenarios with the higher level of CO_2 emission. Range contraction of *A. Adscendens* will increases the risk of extinction. This study provides insights into the response of mountain plants, especially range restricted species, to climate change, revealing major dimensions of plant niche. Therefore, developing habitat management and conservation plans to preserve the predicted habitats of such species are required to preserve the predicted sustainable habitats.

Keywords Habitat suitability · Species distribution models · Climate change scenarios · General circulation models · Extinction risk

Communicated by Robert A. Washington-Allen.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11258-022-01273-2.

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Introduction

Climate change is recognized as one of the main drivers of biodiversity decline worldwide, with significant biological, spatial and temporal effects on species and habitats. The Intergovernmental Panel on Climate Change (IPCC) reported that even in the most optimistic scenario, the past decades trend of rising carbon dioxide in the atmosphere will continue for several decades, and this is expected to have major effects on animal and plant species (Ferrarini et al. 2014). Thus predicting the distribution of suitable habitats for species under climate change is essential for conservation planning.

Species distribution models (SDMs) are widely used to predict the geographic range of a species under the current condition and future projected climate change scenarios, using occurrence data and climatic variables (e.g. Anderson and Martinez-Meyer 2004; Franklin and Miller 2009; Peterson et al. 2011; Wilson et al. 2011). Climate has been widely known as the most important factor influencing plant distribution (Box 1981; Woodward 1987). Plant physiological variables may also change in the future climatic conditions (Becklin et al. 2016). Changes in the concentrations of greenhouse gases in the atmosphere (e.g. Gray and Brady 2016), rising temperatures and changes in precipitation patterns (e.g. Hui et al. 2018) have profound impacts on the physiological functioning of plants. Static factors (e.g. edaphic) along with dynamic factors (e.g. climatic) have been used to predict the distribution of plant species under climate change (e.g. Beauregard and de Blois 2014; Chauvier et al. 2021; Hageer et al. 2017; Zuquim et al. 2020). The importance of static variables in habitat modelling, especially, in predicting the impact of climate change has been shown (e.g. Stanton et al. 2012). Since the climate condition is a key factor in soil formation, the confounding effect between climate and soil variables would occur, if both variables are simply included into a single SDM (Feng et al. 2020). A two-step modelling approach (see method section) is recommended to consider both climate and soil effects.

SDMs determine the statistical relationships between the presence/ absence data of a species and a set of climatic variables and find areas for which a species may be able to occupy in the future (Elith and Leathwick 2009). It has been predicted that many species (including plants) are not able to migrate or adapt quickly enough to the projected climate change pace and scale, increasingly vulnerable to extinction (e.g. Lenoir et al. 2010; Rumpf et al. 2018). Plants are highly sensitive to rapid changes in climate due to their sessile, long lived and slow reacting to environmental changes. Several SDMs have been developed to assess the response of plant communities, forest ecosystems and individual species (Guisan and Thuiller 2005). Research have demonstrated differences in the results obtained from several single models in simulating the shift in the range of species (Pearson 2006). Therefore, it has been suggested to improve the accuracy of species distribution prediction by using ensemble models (Araújo and New 2007).

An ensemble approach improves results by combining multiple models, differing in structure, and allows inferences that are robust to uncertainties associated with any single model (Meller et al. 2014). Ensemble models combine the strength and avoid the inherent biases of a range of SDM algorithms. For example, models describing linear versus nonlinear relationships with a particular habitat feature could fit available data equally well, in which case either could represent the species true relationship with that feature. Furthermore, differences among models may be most apparent when applied to novel environments (Heikkinen et al. 2012).

SDMs have been used in numerous studies to predict plant species response to change in climate parameters (Bakkenes et al. 2002; Franklin et al. 2013; Randin et al. 2009; Rumpf et al. 2018). By combining models differing in structure, explanatory variables and data sources, ensemble predictions allow inferences that are robust to uncertainties associated with any individual model.

Despite a constant and continuous trend in global warming (between 3.3 and 4.5 °C by the end of the twenty-first century, IPCC (2022)), the proportion of rising temperatures has not been equal across the globe. For example, Iran may experience a more severe warming (a 2.6 °C increase in the average temperature and a 35% decrease in precipitation) in the coming decades (NCCOI 2017). An increase of 30% in temperature, by the end of the twenty-first century, has reported for Iran and West Asia (IPCC 2022; Rahimzadeh et al. 2009; Zhang et al. 2005). Studies have demonstrated the habitat loss, shift in the distribution range and even the possibility of species extinction under the climate change in Iran, using SDMs (e.g. Ahmadi et al. 2019; Malekian and Sadeghi 2020). In plant species, for example, slow shift to higher altitudes and habitat loss, in response to climate change, have been predicted for *Juniperus excelsa* (Fatemi et al. 2018) and *Acanthophyllum squarrsoum* (Mahmoudi Shamsabad et al. 2018).

The Persian manna (*Astragalus adscendens* Boiss & Haussk) is a valuable perennial shrub with wooden stems and inverted funnel shape ending at the root (Farahnaky et al. 2009). The main habitat of this species is in Zagros Mountains of Iran (Podlech 1986); however, its limited presence has been reported in Iraq (Townsend and Guest 1974), and it may be found sporadically in Turkey (Khajeddin 2001). The species counts as an important plant in Iran (Gerami 1998), which is used for a special manna production, a sweet exudate that is secreted by the puncture of an insect (*Cyamophila* sp).

In the current study, we modelled the current suitable habitats of *A. adscendens* and predicted the future distribution of the species under climate change scenarios. To avoid the uncertainty caused by different SDMs, we used an ensemble approach. We used two sets of edaphic-physiographic and climatic data to develop the models and integrate their predictions to represent both climatic and edaphic-physiographic effects, following (Feng et al. 2020). Since SDMs may overestimate the distribution of plant species if soil factors are not considered (Zuquim et al. 2020), current and future habitats of *A. adscendens* were obtained based on climatic suitable filtered areas by edaphic-physiographic model. For future distribution modelling, we used the fourth version of the Community Climate System Model (CCSM4) to project climate change scenarios and estimate shift in the *A. adscendens* distribution range. This climatic model has been widely used in distribution modelling studies in Iran (Esmaeili et al. 2018; Kafash et al. 2016; Yousefi et al. 2015).

Material and methods

Study area and sampling

The study site, with an area of 47,810 km^2, located in Zagros Mountains of western Iran (Fig. 1). The environment has a temperate climate with annual precipitation of about 400 to 800 mm, falling mostly in winter. Due to its special physiographic conditions, microclimates and different soil conditions, the study area supports unique biodiversity with relatively high plant diversity. The elevation ranges between 670 and 4350 m a.s.l. *Astragalus adscendens* is present at elevations between 1800 and 3600 m a.s.l. Other important trees and shrubs in the area include *Quercus brantii*, *Quercus infectoria*, *Acer monspessulanum*, *Pistacia atlantica*, *Pistacia khinjuk*, *Celtis australis*, *Daphne mucronata* and *Juniperus excelsa*. (Sagheb-Talebi et al. 2014).

We used propositional stratified random point method to collect the species presence data.

First, the distribution range of *A. adscendens* was identified from the Iranian Ecological Zones Recognition Project, Feizi (2018). Then the species range was classified into several homogeneous classes, based on physiographic factors such as slope, aspect and altitude (Hirzel and Guisan 2002). Three layers of slope, aspect and altitude were overlaid, and maximum effort was made to select at least one presence site in each homogenous class. To remove duplicates and homogenize the sample effort, the distance between the presence points was regulated based on the cell size of the environmental factors in SP package (Bivand et al. 2008) in R 3.4 (R Development Core Team 2017). The location of points was checked and verified in Google Earth 7.0 (https://www.google/earth.com). In total, 200 occurrence points were selected and used as model input.

Environmental variables for the climatic model

To consider both climate and soil effects, we adopted the two-step modelling approach (Feng et al. 2020). We first modelled the climatic suitable habitats and the soil conditional suitable habitats, respectively. We then incorporated the soil effect into our habitat prediction using the soil suitable habitat to filter the climatic suitable habitat. Thus, the final (filtered) suitable habitats were suitable in term of both climate and soil conditions.

To model climatic niche of *A. adscendens*, 19 bioclimatic factors at 30-arcsec resolution (approximately 1 km), derived from WorldClim website, were used (Hijmans et al. 2005). These bioclimatic factors for the current (average climate condition for 1991–2000) and for two time periods of 2050 (average climate condition for 2041–2060) and 2070 (average climate condition for 2061–2080) were downloaded from the worldclim website (www.worldclim.org). These factors are known to

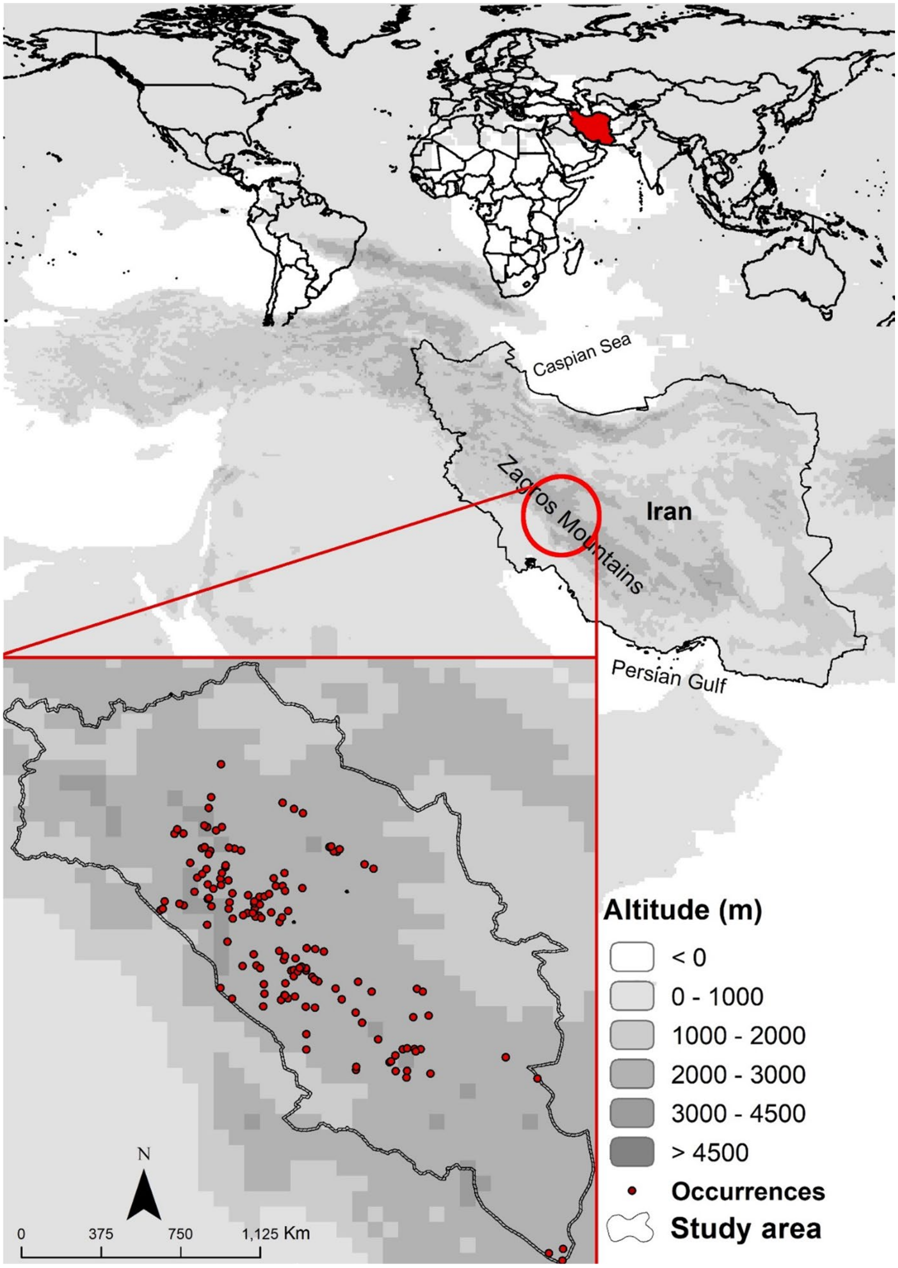

Fig. 1 Locations of the study area and occurrence points of the Persian manna in Western Iran

effectively affect the biological functions of plants (Riordan and Rundel 2014) and closely associated with growth and development of species. Thus, they are widely used in the assessment of species distribution (Elith et al. 2006; Graham et al. 2008).

Environmental variables for the edaphic-physiographic model

To model edaphic-phisiographic niche of *A. Adscendens*, Digital Elevation Model (DEM) with a pixel size of 90 m × 90 m derived from the SRTM web site (http://srtm.csi.cgiar.org) was used to generate physiographic factors (i.e. altitude, slope and aspect), using Arc GIS 10.5 (ESRI, Redlands, CA, USA). Edaphic factors were extracted from the ISRIC data product 'SoilGrids' (https://soilgrids.org) at a resolution of 250 m and at a depths of 0–30 cm (Batjes et al. 2020). Effect of these factors on plants distribution can be strong due to the interactions between factors such as altitude with temperature and precipitation (Körner 2003) in mountains and at the local scale and slope with the velocity of both surface and subsurface flow, and hence, with edaphic conditions (Pouteau et al. 2012). Finally, edaphic and physiographic factors re-sampled the cell size equal to climatic variables (approximately 1 km).

Environmental variables determination

To prevent model over-fitting and multicollinearity between factors for both climatic and edaphic-physiograghic models, we, first, randomly selected 10,000 points as pseudo-absence points across the study area and then extracted values of all factors (climatic and edaphic-physiograghic factors separately) for the presence and pseudo-absence points. Finally, we calculated the variance inflation factor (VIF) between the climatic and edaphic-physiograghic factors, using the usdm package (Naimi 2015). A value equal to 6 and a threshold of 0.75 was set for VIF.

Modelling procedure and statistical analysis

An ensemble modelling approach was employed to predict the distribution of *A. adscendens*, using the software package BIOMOD2 (Thuiller et al. 2021) with 10 replications. To create an ensemble model, we used the weighted average of individual models according to their AUC scores (Thuiller et al. 2021). We used four different SDMs including a regression method: generalized linear model (GLM), a machine learning method: random forest (RF), a recursive partitioning method: classification tree analysis (CTA) and a rectilinear envelope method: surface range envelop (SRE) to create an ensemble map.

For model calibration, 70% of the occurrence points was used for model training and the remaining 30% of dataset as test data. Two measures were used to evaluate the accuracy of ensemble models including, area under the curve (AUC) of a receiver operating characteristic (ROC) plot and true skill statistic (TSS). AUC is a threshold-independent index for evaluating the model predictions against actual observations (presence points) and tests whether the model classifies the species presence points more accurately than a random predictions (Fielding and Bell 1997). In perfect model, AUC is equal to 1; however, excellent performance is achieved when the AUC is greater than 0.8. In contrast, TSS is a threshold-dependent measure ranging from − 1 to 1, where 1 indicates perfect agreement between predictions and observations while zero or negative values represent model performance no better than random (Allouche et al. 2006). The relative contribution of each environmental variable to species distribution prediction was investigated by assessing the impact on predictions of variables randomizations (Thuiller et al. 2021).

The output of SDMs is in the form of continuous maps and a threshold is required to obtain a binary map of the habitat suitability (suitable /unsuitable). There is no agreement on an appropriate and constant method for adding thresholds to species range projections (Nenzén and Araújo 2011), maxSSS threshold (Liu et al. 2013) was used to create the potential distribution binary map and compare changes in the habitat suitability, under the climate change scenarios, to the current. This threshold is maximizing the sum of sensitivity and specificity and it is recommended as an appropriate method, when real absente data are not available (Liu et al. 2013). In addition, present and future suitability maps were classified into five categories of unsuitable (< 0.2), low (0.2–0.35), moderate (0.35–0.5), high (0.5–0.67) and very high (> 0.67) suitability to identify hotspots of habitat suitability in the studied area. To evaluate the species response to the variables, response curves were produced. The response curve was generated for the model with the highest performance, which here the GLM model showed the highest performance for both climatic and edaphic-physiographic models.

Projecting the future distribution of A. adscendens

Here, we used the fourth version of the Community Climate System Model (CCSM4) (Gent et al. 2011), created by Global Climate Models (GCMs) for two time periods of 2050 (average climate condition for

2041–2060) and 2070 (average climate condition for 2061–2080). For each GCM, two Representative Concentration Pathway (RCP) namely RCP 2.6 and RCP 8.5, the minimum and maximum CO_2 emission scenarios, respectively, were considered. Finally, to obtain the final projection of climate change, a weighted-averaging approach was used, and each statistic model was weighted according to its predictive accuracy on test data.

Changes in the habitat suitability of the species for two time periods of 2050 and 2070 were divided into three classes including gain, lost and stable. In addition, to evaluate the predicted changes in the habitat suitability of these classes, a scatter diagram, which plots the altitude versus latitude, was used. We also investigate latitude and longitude shift by comparing the average longitude and latitude in the future distribution with the current.

Results and discussion

Current climate niche of A. adscendens

All four models (GLM, RF, CTA and SRE) for climatic and edaphic-phisiographic models showed excellent predictive performance (AUC > 0.8, TSS > 0.6). However, the performance (AUC and TSS) of the climatic model was higher than the edaphic-physiographic model (Table 1). Most SDMs often produce good results; however, ensemble models produce better prediction compared to a single model (Araújo and New 2007; Breiner et al. 2015), by combining the strength of several models and avoid the inherent biases of different SDM algorithms. Many studies report increased accuracy using this approach (e.g. Chefaoui and Lobo 2008; Senay et al. 2013; Warton and Shepherd 2010).

The ensemble model for climatic (Fig. S1) and climatic-filtered models (Fig. 2) showed that current habitats were patchily distributed across the study area. In the climatic-filtered model, however, greater proportions of the study area were unsuitable (Table 2). Similar reductions in the area and spatial extents of suitable habitats were also observed in suitability classes (Table 3). Smaller percentage of very high suitability class (hotspots of habitat suitability) was obtained in the climatic-filtered model compared to the climate model under the climate change scenarios (RCP2.6 and RCP8.5 for 2050 and 2070, Table 3). Area reduction was more extreme in future scenarios with the higher level of CO_2 concentration. Zuquim et al. (2020) showed that the inclusion of soil variables affected the size and shape of predicted suitable areas, especially in future models. For nearly half of the studied species, the size of future suitable areas was smaller in climate + soil models than predicted by climate-only models (Zuquim et al. 2020).

Based on the contribution of variables, three bioclimatic variables including mean temperature of wettest quarter (BIO8), temperature seasonality (BIO4) and temperature annual range (BIO7) were identified as the most influencing variables in on the implementation of the model (Table 4). The response of *A. adscendens* to these variables indicates a decrease in habitat suitability with increasing BIO8 and BIO4 and an increase with increasing BIO7 (Fig. 3). Temperature determines the geographic distribution of organisms, both in the context of latitudinal and altitudinal gradients of thermal niches occupation (Hochachka and Somero 2002). Effects of temperature on the parameters of the natural history of plants have been shown in several studies (reviewed in

Table 1 Performance of discrimination capacity and accuracy of four different algorithms to map the distribution of *A. adscendens* for climatic and edaphic-phisiographic models

Model	Measures	GLM	CTA	FDA	RF
Climatic	AUC	0.92 ± 0.02	0.84 ± 0.22	0.92 ± 0.01	0.89 ± 0.02
	TSS	0.75 ± 0.03	0.68 ± 0.04	0.73 ± 0.04	0.72 ± 0.03
Edaphic-phisiographic	AUC	0.88 ± 0.01	0.82 ± 0.03	0.87 ± 0.01	0.84 ± 0.01
	TSS	0.68 ± 0.03	0.64 ± 0.04	0.65 ± 0.04	0.66 ± 0.03

Higher values indicate better model performance for each metric. *AUC* the area under the curve of a receiver operating characteristic (ROC), *TSS* true skill statistic, *GLM* generalized linear model, *CTA* classification tree analysis, *SRE* surface range envelop and *RF* random forest. Values are given ± SD

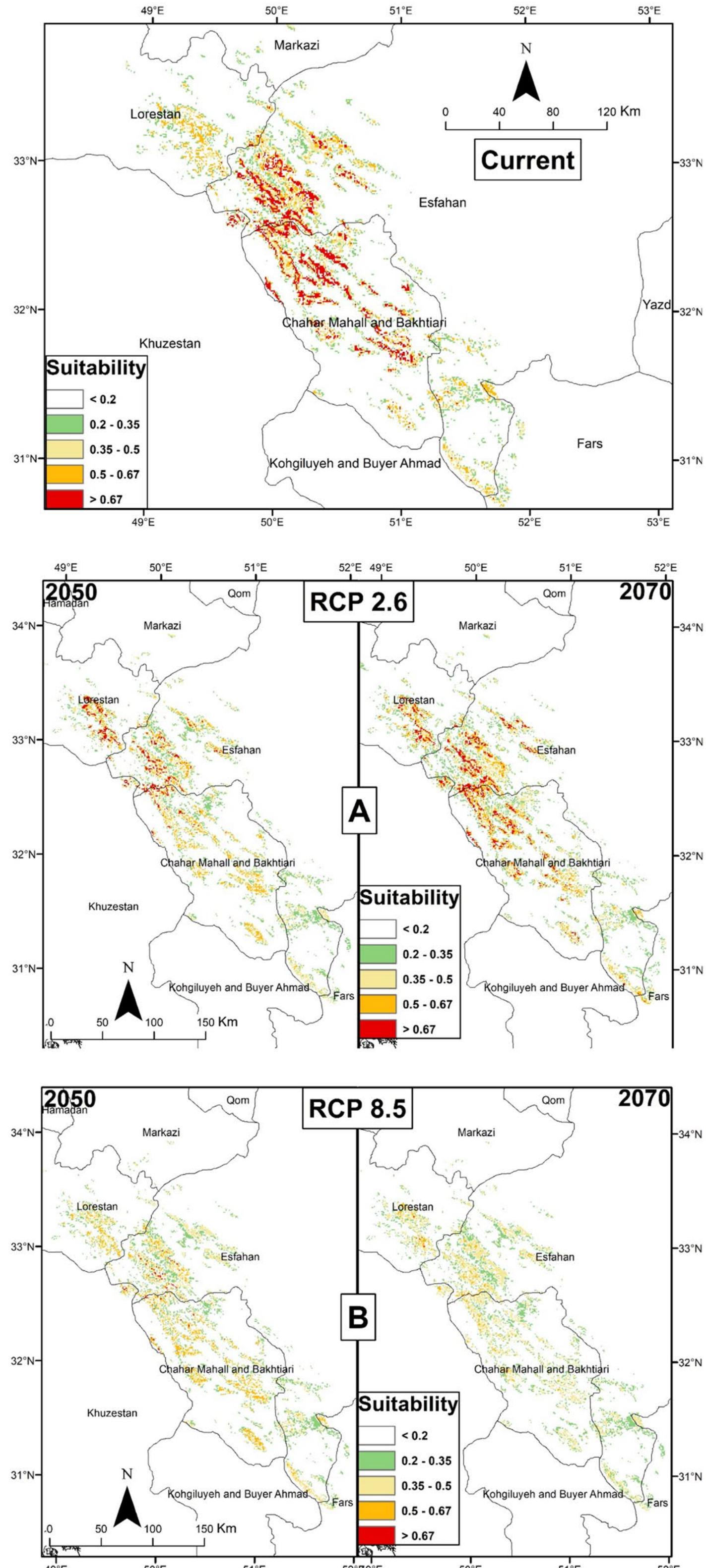

Fig. 2 Current (**A**) climatic-filtered suitable habitats of *A. adscendens* and model-based predictions of its habitat suitability under future climate change scenarios for two time periods of 2050 and 2070 and two Representative Concentration Pathways: RCP 2.6 (**B**) and RCP 8.5 (**C**). The red areas indicate hotspots of suitability

Table 2 Projected changes for climatic and climatic-filtered models in suitable habitats of *A. adscendens* for two time periods (2050 and 2070) and two concentration representative pathways (RCP 2.6 and RCP 8.5)

Models	Time periods	Number of habitat representative cells	Habitat reduction (%)
Climatic	Current	9850	0
	RCP 2.6 2050	4121	− 58
	RCP 8.5 2050	3037	− 69
	RCP 2.6 2070	6496	− 34
	RCP 8.5 2070	840	− 91
Climatic filtered	Current	8753	0
	RCP 2.6 2050	3966	− 55
	RCP 8.5 2050	2871	− 67
	RCP 2.6 2070	5816	− 34
	RCP 8.5 2070	790	− 91

Nievola et al. 2017). Considering that plants are sessile, their survival depends on the efficient activation of resistance responses to thermal stress (Ruelland and Zachowski 2010). Therefore, temperature is probably more important than any other factor in the physiology and natural history of plants (Nievola et al. 2017; Źróbek-Sokolnik 2012). Chauvier et al. (2021) used three sets of climatic, soil and land-use variables for distribution modelling of vascular plants. Results showed that climatic variables had more importance, in determining the spatial distribution of species, compared with other variables. In Beauregard and de Blois (2014), the relative importance of soil and climate varied with growth forms, with trees being more related to climate, while plants with shorter vegetative form were more related to soil conditions.

Temperature also affects the rate of plant development. Warmer temperatures, expected with climate change and the potential for more extreme

Table 3 Projected suitability classes change over the time periods (2050 and 2070) and scenarios of climate change (RCP 2.6 and RCP 8.5) for climatic and climatic-filtered models

Time period	Suitability classes	Suitability classes in climatic model (%)	Suitability classes in climatic-filtered model (%)
Current	Unsuitable (< 0.2)	71.94	84.35
	Low (0.2–0.35)	10.19	4.71
	Moderate (0.35–0.5)	8.28	4.17
	High (0.5–0.67)	4.53	3.57
	Very high (> 0.67)	5.06	3.2
RCP 2.6 2050	Unsuitable (< 0.2)	85.66	86.9
	Low (0.2–0.35)	8.52	5.37
	Moderate (0.35–0.5)	4.23	5.26
	High (0.5–0.67)	1.39	2.5
	Very high (> 0.67)	0.2	0.15
RCP 8.5 2050	Unsuitable (< 0.2)	87.82	87.03
	Low (0.2–0.35)	4.91	4.97
	Moderate (0.35–0.5)	3.78	4.34
	High (0.5–0.67)	2.03	2.68
	Very high (> 0.67)	1.46	0.98
RCP 2.6 2070	Unsuitable (< 0.2)	71.55	84.23
	Low (0.2–0.35)	15.9	5.6
	Moderate (0.35–0.5)	6.89	4.51
	High (0.5–0.67)	2.45	3.67
	Very high (> 0.67)	3.21	1.99
RCP 8.5 2070	Unsuitable (< 0.2)	90.79	86.79
	Low (0.2–0.35)	7.44	5.79
	Moderate (0.35–0.5)	1.6	6.7
	High (0.5–0.67)	0.1	0.71
	Very high (> 0.67)	0.07	0.01

Table 4 Contribution scores of variables included in climatic and edaphic-physiographic models to determine the habitat of *A. adscendens*

Model	Abbreviation of the variables	Description [conventional units]	VIF ± *SD*
Climatic	BIO3	Isothermality [-]	0
	BIO4	Temperature seasonality [°C *100]	0.36 ± 0.06
	BIO7	Temperature annual range [°C *100]	0.23 ± 0.06
	BIO8	Mean temperature of wettest quarter [°C *100]	0.85 ± 0.05
	BIO12	Annual precipitation [mm]	0
	BIO18	Precipitation of warmest quarter [mm]	0
Edaphic-physiographic	Or-Ca-Den	Organic carbon density [kg/m^3]	0
	So-Or-Cr-St	Organic carbon stocks [kg/m^2]	
	Clay-Con	Proportion of clay particles (< 0.002 mm) in the fine earth fraction [g/100 g (%)]	0
	Co-Frag	Volumetric fraction of coarse fragments (> 2 mm) cm3/dm3 (vol‰) [cm3/100cm3 (vol%)]	0.17 ± 0.02
	Silt	Proportion of silt particles (≥ 0.002 mm and ≤ 0.05 mm) in the fine earth fraction [g/100 g(%)]	0
	CEC	Cation Exchange Capacity of the soil [cmol(c)/kg]	0
	Nitrogen	Total nitrogen (N) [g/kg]	0
	So-Or-Cr	Soil organic carbon content in the fine earth fraction [g/kg]	0
	Soil-ph	Soil pH [pH]	0
	Dem	Altitude [m]	0.54 ± 0.05
	Slope	Slope [Degree]	0
	Aspect	Aspect [Degree]	0

Variance inflation factor (VIF) scores less than 0.1were considered as zero. Values are given as mean ± standard deviation (*SD*)

temperature events, will impact net primary productivity, phenology, and leaf and fruit developments (Źróbek-Sokolnik 2012). Pollination is one of the most sensitive phenological stages to temperature extremes across all species and, during this developmental stage, temperature extremes would greatly affect production (Dixon and Aldous 2014; Nievola et al. 2017).The hydrological cycle has also been predicted to become more intense in future climates, resulting fluctuations in soil water content, may dramatically affect plants (Zeppel et al. 2013).

For the edaphic-physiographic model, however, only altitude (DEM) and volumetric fraction of coarse fragments (Co-Frag) were important (Score > 0.1) in the model implementation (Table 4). Response curves also indicted an increase in the habitat suitability of *A. adscendens* with increasing DEM and Co-Frag (Fig. S2). In general, with increasing altitude in mountainous areas, the depth of the soil decreases and the size of soil particles becomes larger. In field surveys, the presence of *A. adscendens* in highlands with coarse-grained soils was evident.

Projecting the future distribution of A. adscendens

In both climatic and climatic-filtered models, a sharp decline was observed in the habitat suitability of *A. adscendens* for the two time periods of 2050 and 2070, showing low and moderate suitability compare to the current (Fig. 2B, C and Fig. S1B, S1C). The reduction of suitable habitats, in the climatic model, was greater than the climatic-filtered model (Table 2). Research showed that only considering climate variables in SDMs may overestimate specie's suitable areas (Sun et al. 2021). Under the condition of RCP 2.6, the predicted amounts of habitats loss were ~ 34% and ~ 55% for 2050 and 2070, respectively (Table 2). Under the maximum CO_2 emission scenarios (RCP8.5), 67% and 91% of the current habitat may be lost by the year 2050 and 2070, respectively (Table 2). As we expected, range contractions

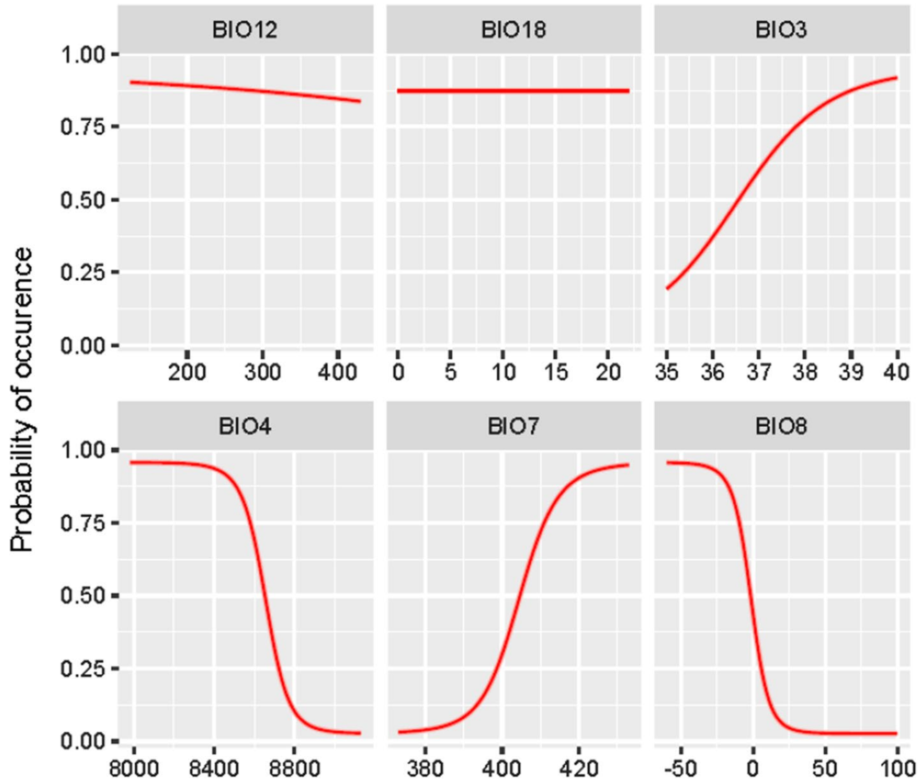

Fig. 3 Response curves of *A. adscendens* to the dynamic variables (climatic model) produced in accordance with the higher performance (AUC) of the GLM model. See Table 4 for the description of variables

increase over time and under the more severe emissions scenarios. Accordingly, the extent of projected habitats would get the most reduction by 2070. This indicates *A. adscendens* range contraction under changing climates during the twenty-first century (from the current to 2050 and to 2070). A reduction in range size and consequently extinction risk were also predicted for other mountain plants (Dullinger et al. 2012).

Projected changes in latitude and longitude for *A. adscendens* for two time periods (2050 and 2070) and two representative concentration pathways (RCP 2.6 and RCP 8.5), showed no significant shift (Table 5). However, a shift in the species range towards higher elevations may be expected under climate change scenarios (Fig. 4), as predicted suitable habitats includes altitudes from 2000 m to above 4000 m. Based on the field surveys, the altitude range of *A. adscendens* is from 1800 to 3600. Under climate change scenarios, areas that maintain stability during climate change are generally at altitudes above 3000 m and in all latitudes. Lost areas are generally less than 3000 m above sea level and in different latitudes (Fig. 4). In contrast, the gain habitats are very limited and are scattered in different latitudes and heights. An expansion to higher altitudes is usually expected for plants in mountainous areas under the context of climate

Table 5 Projected changes in latitude and longitude in climatic-filtered model for *A. adscendens* for two time periods (2050 and 2070) and two representative concentration pathways (RCP 2.6 and RCP 8.5)

	Longitude	Latitude
Current	50.3 ± 0.52	32.46 ± 0.59
RCP 2.6 2050	50.19 ± 0.55	32.47 ± 0.62
RCP 8.5 2050	50.32 ± 0.58	32.44 ± 0.6
RCP 2.6 2070	50.3 ± 0.59	32.45 ± 0.49
RCP 8.5 2070	50.31 ± 0.59	32.46 ± 0.62

The values reported are the average longitude and latitude. Numbers are given ± standard deviation (SD)

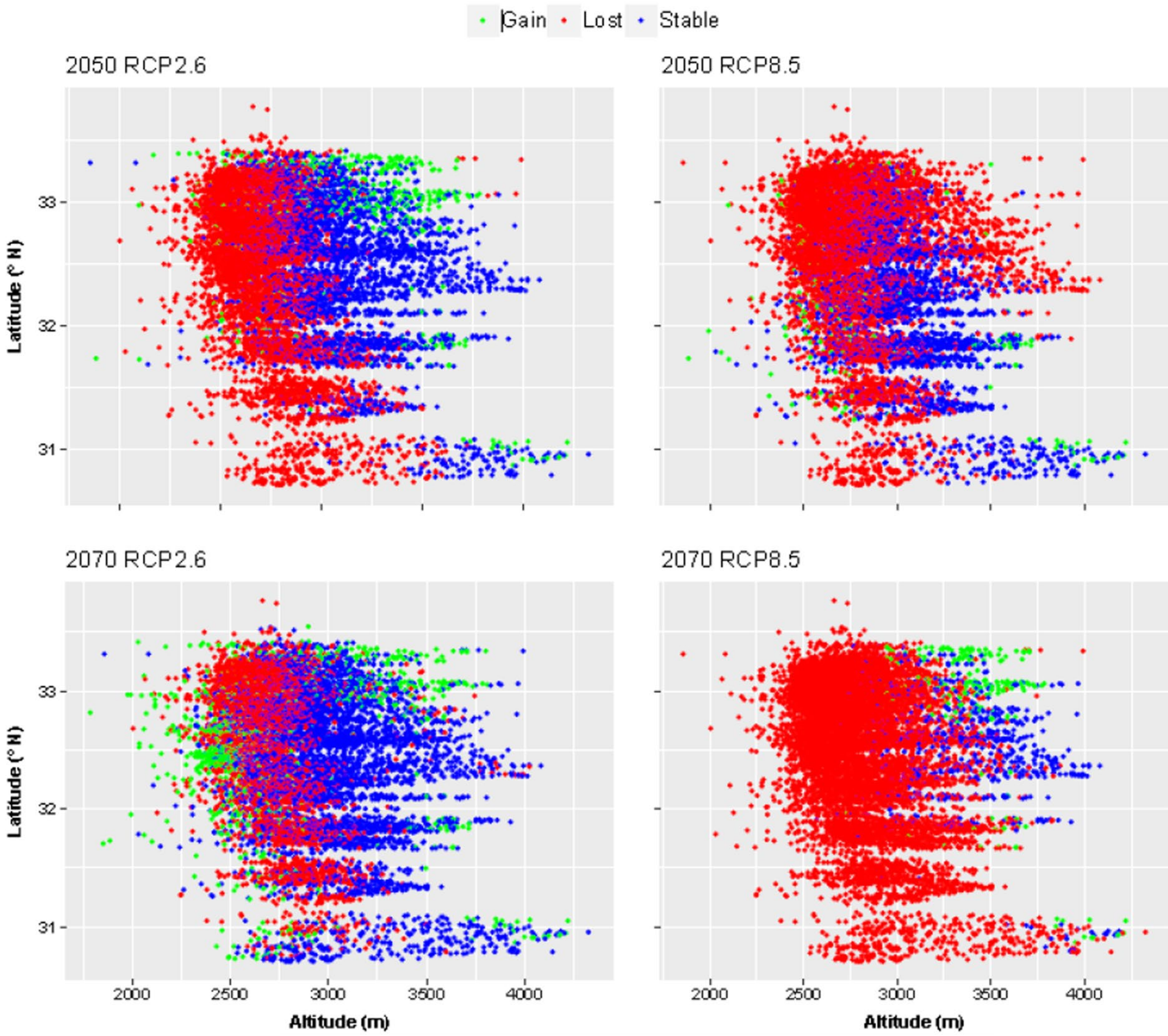

Fig. 4 Climatic-filtered suitability model changes in future distribution projecting of two RCPs (82.6 and 8.5) and two time periods (2050 and 2070) in altitude and latitude for *A. Adscendens*

change (Fatemi et al. 2018; Rumpf et al. 2018; Walther et al. 2002).

Conclusion

With the current trend of climate change, large parts of habitat of *A. adscendens* will be lost by 2070. Estimates of global climate change indicated that species may not be able to shift their distribution range fast enough to track suitable conditions (e.g. Burrows et al. 2014; Loarie et al. 2009). Thus, the distribution of plants and plant communities are likely to change and a subsequent reaction of climate sensitive species is expected. Climatic, physiographic and edaphic conditions of Zagros Mountains have led to a unique plant diversity (Zohary 1973). In this study, we focused on the habitat suitability of *A. adscendens* in its main habitat (Iran) and used the major environmental factors affecting the distribution of *A. Adscendens*. In general, our results demonstrated patchily distributed habitats for *A. Adscendens* with sharp declines under climate change. Other parameters such as human-induced factors, management parameters and the occurrence of extreme events (e.g. fires and floods), which may also lead to a further shrinkage of suitable habitats and even the risk of extinction. Management planning is required to maintain its highly suitable and stable habitats during climate change. This study provides insights into the response of mountain plants, especially range restricted species, to climate change. Therefore, developing habitat management and conservation plans for such species are required to protect the predicted sustainable habitats. Results can help in planning conservation strategies, tailored to the expected changes in habitats under the climate change conditions.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by SG, MM and MT. The first draft of the manuscript was prepared by SG and AR. MM led the writing with input from other authors. All authors read and approved the final manuscript.

Funding There has been no significant financial support for this research.

Data availability The data that support the findings of this study are available from the corresponding author, [MM], upon reasonable request.

Code availability Not applicable.

Declarations

Conflict of interest We wish to confirm that there are no known conflicts of interest associated with this manuscript.

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