Ecological Indicators 137 (2022) 108752

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Review

The current and future potential geographical distribution of *Nepeta crispa* Willd., an endemic, rare and threatened aromatic plant of Iran: Implications for ecological conservation and restoration

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A R T I C L E I N F O

Keywords:
Maximum entropy model
Climate models
Environmental variables
Rare plant

A B S T R A C T

Nepeta crispa Willd. is a very rare medicinal plant that grows in a very limited habitat in western Iran. In recent years, due to climate change, many plants have become endangered, which poses a very serious threat to very rare species such as *N. crispa* Willd. In the present study, we aimed to model the current and future potential geographical distributions and identify the most relevant environmental factors influencing the distribution of *N. crispa* Willd. an endemic plant species in west of Iran. The species distribution was modeled with the maximum entropy model by using presence data (160 sampling points) and a total of 15 climatic and environmental variables. To predict possible shifts in the geographical distribution due to climate change, we used the Representative Concentration Pathway (RCP) 2.6 and RCP 8.5 for 2050 and 2070 for two Global Climate Models (GCMs). The jackknifing method was used to evaluate the contribution of the environmental variables to the model. We found that elevation, annual mean temperature, geology and precipitation of the driest quarter were the most important variables in determining the habitat of *N. crispa*. The species habitat suitability maps and models were efficient in predicting the habitat suitability distribution for *N. crispa* in the current conditions with an Area Under the ROC Curve (AUC) of 0.983. Our modeling approach also demonstrated that climate change would expand the habitat range of *N. crispa* in the Alvand mountain areas in Iran towards higher elevation (above 2000 m.a.s.l). Conservation measures should therefore predominantly concentrate on the elevation range between 2000 and 3500 m.a.s.l. Knowledge of current distribution of the *N. crispa* and predicting its potential future geographical distribution under different climate change scenarios provide useful information for conservation actions in Iran.

1. Introduction

Growth of human populations, land-use change, habitat destruction and fragmentation, over-exploitation of natural lands, and invasion of alien plant species are important factors that lead to species extinction at worldwide level (dos Santos et al., 2021; Heydari et al., 2012; Kumi et al., 2021; Ramachandran et al., 2018; Waddell et al., 2020). As a result, one-fifth of plant species are at risk of extinction and habitat loss (Brummitt and Bachman, 2010). Nowadays, one of the biggest global challenge is climate change and its effects on natural ecosystems (Chapin and Díaz, 2020; Vale et al., 2021). Climate change is known to influence extinction and geographical distributions of various species due

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https://doi.org/10.1016/j.ecolind.2022.108752
Received 15 December 2021; Received in revised form 2 March 2022; Accepted 3 March 2022

to temporal reproductive isolation (Ebrahimi et al., 2017; Meynecke, 2004; Monzón et al., 2011). The loss of any species could have significant negative effects on ecosystem functions and stability (Worm and Duffy, 2003). On the other hand, changes in the distribution ranges of plant species and vegetation patterns will affect how climate change is experienced across the landscape (Lawler et al., 2009; Roberts et al., 1997; Tang et al., 2018).

Understanding how species will respond to climate change (e.g. how they are distributed under future climate change scenarios), is critical to effective management and conservation of biodiversity (Çoban et al., 2020; Mendoza-González et al., 2013; Naudiyal et al., 2021). This is particularly noteworthy, as future climate predictions demonstrate a rising trend in temperature and greenhouse gas emissions. For example, based on the Fifth Assessment Report (AR5) produced by the Intergovernmental Panel on Climate Change (IPCC), global warming is anticipated to average 0.3–4.5° C by 2100 with a continuous upward trend (Stocker et al., 2013). Habitat restoration, one of the basic measures for plant species protection, requires accurate information on the current and future distributions of species (i.e. under climate change circumstances) in each habitat (Cao et al., 2016; Panwar and Tarafdar, 2006; Zhang et al., 2019). Thus, understanding the relationships of species with environmental factors and predicting their changes have become one of the fundamental challenges for ecologists (Dai et al., 2013; Kong et al., 2021; Lundholm and Larson, 2003). Climate change has major effects on the diversity of vegetation around the world, especially for arid and semi-arid regions in southwestern Asia such as Iran with high diversity and richness of vegetation (Talebi et al., 2014).

In the west of Iran, the Zagros forest ecosystem is a region of high ecological significance. This area of about 6 million ha is spread on the western and southern slopes of the Zagros Mountains from northwest to southeast of Iran with an elevation range of 200 to 4500 m.a.s.l. Forests of the Zagros region cover 44% of Iran's forests but in the recent decades, disturbances associated with climate change (e.g. drought, fires, pathogens outbreaks) have largely impacted the dynamics and stability of this ecosystem (Haidarian et al., 2021; Karami et al., 2018; Naghipour Borj et al., 2019). The high ecological value of Zagros is linked to the presence of endemic plant species in the mountainous areas. One of these species is *Nepeta crispa* Willd. which grows in Alvand mountain areas in Hamadan Province in western Iran. Because this species has significant medicinal properties (Alizadeh and Salimi, 2018; Sonboli et al., 2017); its habitat is highly vulnerable to destruction and extensive human exploitation, and its survival is greatly threatened Conservation of this species has to take into account how its distribution may be affected by various environmental and anthropogenic factors under different climate change scenarios. In this context, species distribution modeling (SDM) is a key tool to develop predictions to understand the future distribution of plant communities (Qin et al., 2020; Zhang et al., 2016). SDM is based on suitability indices to describe the relationships of diverse ecological attributes and evaluate the appropriateness of the habitat for a particular species. There are several modeling algorithms such as CLIMEX (Sutherst and Maywald, 1985), maximum entropy (Maxent) (Phillips et al., 2006), and BIOMAPPER (Hirzel et al., 2002) to study species ecological requirements and distribution areas and to predict habitat quality and spatial distribution of plant species under the influence of environmental factors (Borthakur et al., 2018; Eshetae et al., 2021; Hirzel and Guisan, 2002; Yang et al., 2013). In principle, these algorithms identify the predictor variables as well as their relationships with the response variables and predict the habitat suitability for a given species in its distribution area. Modeling algorithms of these models are continually improved to favor the widespread use of habitat utility models in the study of environmental, biogeographical, conservation, and species management issues (Bradley et al., 2012; Tsiftsis and Djordjević, 2020).

Maxent model is one of the models mostly used for predicting the distribution of species due to the numerous advantages it offers such as the use of categorical data and a good performance in predicting the distribution of species even with an incompleted dataset and limited sample size (Çoban et al., 2020; Marini et al., 2010; Pearson et al., 2007). Maxent uses only presence points and compares values of environmental layers for occurrence points with these values in background points to create a habitat suitability map (Phillips et al., 2006). In this study, we have used the Maxent model to (i) predict the current and future potential geographical distributions of *N. crispa* in the west of Iran; and (ii) identify the most significant environmental factors influencing the distribution of the species. To achieve these aims, we have used presence data of the species, environmental variables (i.e. bioclimatic (current and future), edaphic and topographic variables), and two climate change scenarios of the Representative Concentration Pathway (RCP) 2.6 and RCP 8.5 for 2050 and 2070 for two Global Climate Models (GCMs). The results of this study could help to better understand the trends and mechanisms of species adaptation and distribution in uncertain environmental futures. They could also provide conceptual foundations and a basis for more adapted management measures of endemic vegetations highly endangered by climate change.

2. Materials and methods

2.1. Study area and sampling

The study area (19,368 km2) is located in Hamadan Province in west of Iran (47°45′39″-49°29′ 31″ N, 34°00′39″-35°42′ 35″ E) (Fig. 1), elevation ranges from 1448 to 3475 m.a.s.l. The climate is cold and semi-arid with heavy snowfall in winter and mild sunny summer. The average precipitation is 350 mm and the long-term average temperature is 12 °C. To locate the sites with *N. crispa*, we used information obtained from local experts and natives, followed by a field survey. Sampling (recording of presence points of *N. crispa*) was done by the stratified random sampling method in spring 2019. In total, 160 sampling points of presence records of the species were collected (Fig. 1). To minimize spatial-autocorrelation, a cell of 1×1 km was considered to exclude any occurrence points of >1 km with another occurrence points by the Spatially Rarify Occurrence Data tool in the SDMtoolbox (Almasieh et al., 2019; Brown, 2014). Finally, 134 occurrence points were considered for modeling.

2.2. Environmental variables

We initially used 15 environmental variables that may affect the species distribution (Parra and Monahan, 2008). They include: slope (percent), aspect (degree), elevation (m.a.s.l.), type of soil, solar radiation (W/m^2), geology, distance from river (m), annual mean temperature (°C) (bio1), mean temperature diurnal range (°C) (bio2), isothermality (bio3), temperature seasonality (bio4), annual precipitation (mm) (bio12), precipitation of the driest month (mm) (bio14), precipitation seasonality (bio15) and precipitation of the driest quarter (mm) (bio17) (Jiang, 2018; Choudhary et al., 2019) (Table 1).

The SRTM (Shuttle Radar Topography Mission data) (see https://earthexplorer.usgs.gov/) was used to prepare the digital elevation model (DEM) and then slope and aspect maps were extracted from the DEM (Almasieh et al., 2018; Hosseini et al., 2013). Spatial analyst tool in ArcGIS 10.4 software was used to generate slope and aspect variables. Climatic variables were obtained from the WorldClim Database (http://www.worldclim.org) (Jayasinghe and Kumar, 2019) (Table 1). The data in this database is in raster format at a scale of 30 s with a spatial resolution of 1 km^2 and in the coordinate system CGS_WGS_1984. Due to the spatial resolution of 1 km^2 of climate data, other data including topography and geology data with a pixel size of 1 km^2 were used (Jayasinghe and Kumar, 2019). High correlation between the enviromental variables may cause errors in the model (Ahmadzadeh et al., 2013; Boria et al., 2014; Jayasinghe and Kumar, 2019). Therefore, the correlations between the bioclimatic variables were studiedto identify highly correlated variables (i.e. Pearson

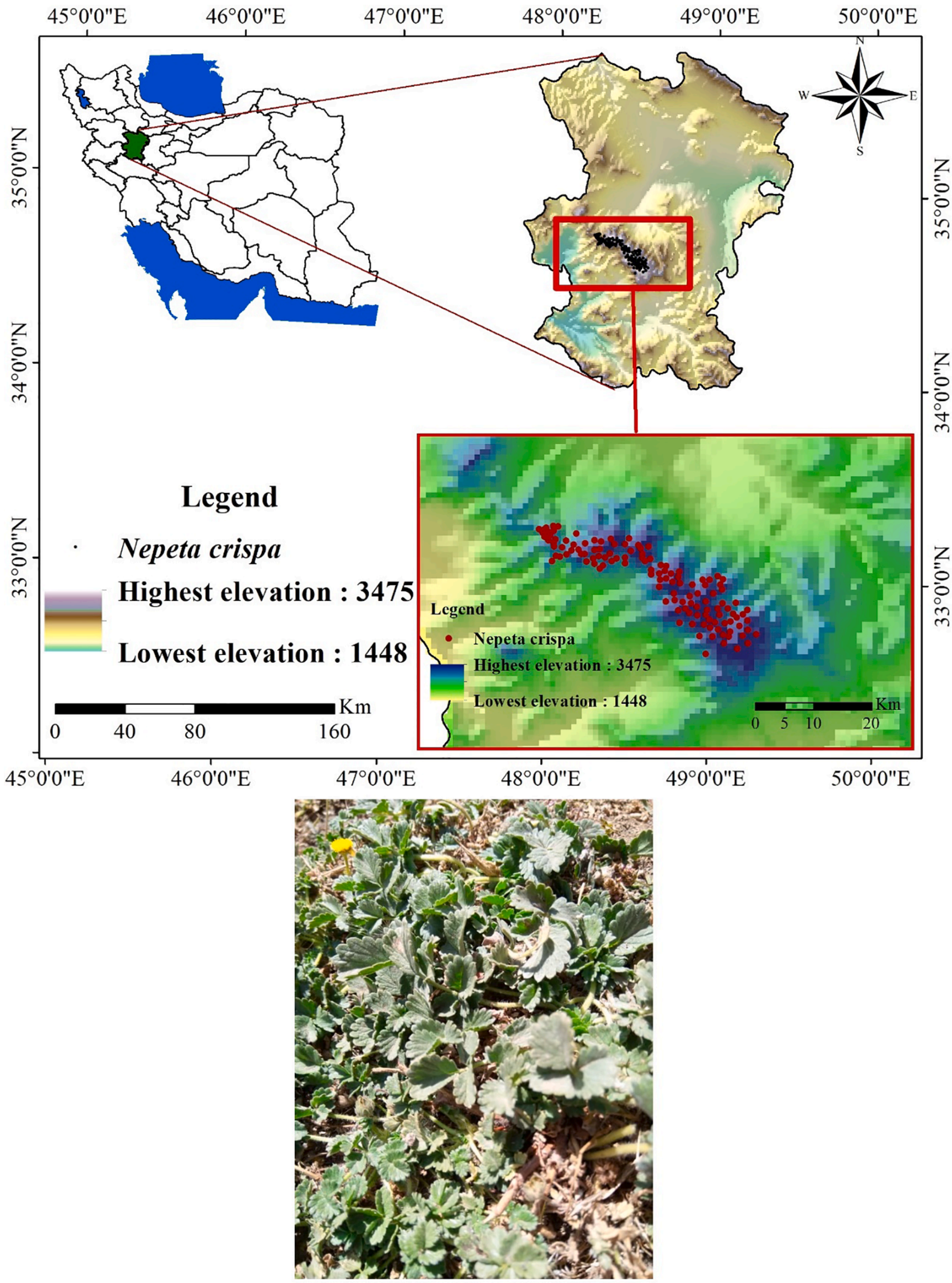

Fig. 1. Location of the studied habitat in Hamadan Province and picture of the plants.

correlation coefficient | r | >0.75). Finally, out of 19 bioclimatic variables, 8 variables that were slightly correlated with each other (| r | <0.75) were selected for model processing (Table 1). These 8 climatic variables are: annual mean temperature (bio1), mean diurnal range (bio2), isothermality (bio3), temperature seasonality (bio4), annual precipitation (bio12), precipitation of the driest month (bio14), bio15 (Precipitation Seasonality and precipitation of the driest quarter (bio17) (Choudhary et al., 2019; Jiang, 2018).

Eventually, the provided layers were transformed to ASCII format for subsequent processing in Maxent (Jayasinghe and Kumar, 2019). Annual daily solar radiation (kJ m^{-2} day^{-1}) computed over the period 1970–2000 was also used for habitat modeling. Due to importance of water resources for plant species, distance from rivers was obtained using Euclidean Distance tool in ArcGIS.

2.3. Modeling the effect of climate on the distribution of N. Crispa

We model *N. crispa* future distribution using two different climate

Table 1
correlation test of explanatiory variables.

Layer	Bio1	Bio12	Bio14	Bio15	Bio17	Bio2	Bio3	Bio4	srad	Elevation	Dis_river	Slope
Bio1	1.0											
Bio12	0.05	1.0										
Bio14	−0.45	0.10	1.0									
Bio15	0.25	0.26	−0.49	1.0								
Bio17	−0.68	0.05	0.55	−0.24	1.0							
Bio2	0.52	0.14	−0.40	0.27	−0.47	1.0						
Bio3	0.44	0.02	−0.07	−0.20	−0.22	0.38	1.0					
Bio4	−0.22	−0.17	0.51	−0.21	0.47	−0.51	0.10	1.0				
srad	−0.22	−0.17	0.51	−0.31	0.47	−0.51	0.10	0.58	1.0			
Elevation	−0.55	−0.05	0.19	0.11	0.30	−0.24	−0.43	−0.06	−0.06	1.0		
Dis_river	−0.27	−0.12	0.27	−0.51	0.54	−0.27	−0.04	0.45	0.45	0.08	1.0	
Slope	−0.41	0.18	−0.06	0.42	−0.06	−0.30	−0.58	−0.27	−0.27	0.58	−0.16	1.0

Table 2
Environmental variables used used for habitat modeling of *N. crispa* in the study area.

Type	Abbreviations	Description	Unit	Source
Bioclimatic	Bio1	Annual mean temperature	°C	https://www.worldclim2.org (Fick & Hijmans, 2017)
	Bio2	Mean Diurnal Range (Mean of monthly (max temp – min temp))	°C	
	Bio3	Isothermality (BIO2/BIO7) (×100)	°C	
	Bio4	Temperature Seasonality (standard deviation ×100)	°C	
	Bio15	Precipitation Seasonality (Coefficient of Variation)		
	Bio12	Annual precipitation	Mm	
	Bio14	Precipitation of the driest month	Mm	
	Bio17	Precipitation of the driest quarter	Mm	
Topography	SLP	Slope	Percentage	(DEM)
	ASP	Aspect	Class	(DEM)
	DEM	Elevation	m.a.s.l.	(https://earthexplorer.usgs.gov/)
solar radiation	SRAD	Solar radiation	(kJ m-2 day-1)	Fick & Hijmans, 2017
soil	SOIL	Types of soil	CLASS	(DoE, 2018)
Distance from rivers	DISR	Distance from rivers	M	(FRWMO, 2010)
Geology	GEO	Geology	CLASS	(DoE, 2018)

change scenarios: RCP2.6 and RCP8.5 for 2050 and 2070 respectively. These scenarios were performed in the form of two Global Climate Models (GCMs), namely Hadley Centre Global Environmental Model, version 2-Carbon Cycle (HadGEM2-CC) and the Community Climate System Model, version 4 (CCSM4) (Ramos et al., 2019). The accuracy and efficiency of the HadGEM2-CC model in the Northern Hemisphere has been recognized (Sutton et al., 2014). It has also been reported that the CCSM4 model was efficient in modelling temperature and precipitation variables for Asia (Chaturvedi et al., 2012). These scenarios include: 1) RCP 2.6 named peak scenario, which indicates that the radiative forcing level reaches 3.1 W/m^2 by mid-century however returns to 2.6 W/m^2 by 2100., and 2) RCP 8.5, which radiative forcing reaches >8.5 W m^{-2} by 2100 and continues to increase for a certain amount of time (Cabrera and Selvaraj, 2020). In the present study, in order to reduce the uncertainty duo to future climate, we used two main GCMs (CCSM4 and HadGEM2-CC) that have been used in other studies in Iran (Alavi et al. 2019; Taleshi et al. 2019; Ahmadi et al. 2020).

The Maxent model (Maxent software version 3.4.1) was used to model the habitat of *N. crispa*. This model requires the presence records of the species and predictive environmental variables (Phillips et al., 2006; Zamora-Gutierrez et al., 2021). In this study, 70 percent of the species presence points were randomly selected for the modeling and the remaining 30 percent were used to evaluate the model (Evcin et al., 2019). The important source of uncertainty in SDM is uncertainty due to model specification. In the case of MaxEnt, the method for generating background samples from presence-only data is a source of variability (Merow et al. 2013). in order to reduce uncertainty, we tried to generate background points 10 times and run the model for each dataset.

The jackknifing method was used to evaluate the contribution of the various bioclimatic variables to the model. Predictors that produced the most training gains were selected as the most important bioclimatic attributes (Jayasinghe and Kumar, 2019). The response curves that demonstrate the relationships between the probability of the plant presenceand the environmental variables were evaluated. In a jackknife method, the model is obtained from each factor that indicates which attributes have the best information independent from other variables (Jayasinghe and Kumar, 2019; Kalle et al., 2013). The receiver operating characteristic (ROC) curve and the area under the curve (AUC) were produced to examine model efficiency (Elith et al., 2006). The model was run 10 times with 1000 repetitions each time. The performance of the model was evaluated using the AUC, which is a quantitative indicator that shows the performance and strength of the model. A value of 0.5 indicates a poor performance of the model, values between 0.5 and 0.7 are appropriate, between 0.7 and 0.9 are good and a value >0.9 is excellent (Elith, 2000). Eventually, the quantitative and continuous habitat map became a binary map based on the maximum logistics threshold to the Maxent feature in the model (Jiménez-Valverde and Lobo, 2007).

3. Results

3.1. Importance of environmental variables

The results of jackknife method show that among the various variables, elevation, annual mean temperature (Bio1), geology and precipitation of the driest quarter (Bio17) are the most important variables in determining the habitat of *N. crispa*. Among the input environmental variables, elevation is the most influential and account for 26.4 % of the distribution model while annual mean temperature (Bio1) and geography account for 19% and 18.1%, respectively (Table 3).

The variable ‘precipitation of the driest month’ (Bio14) has a share of 0.2, which is the lowest contribution. The variable importance result indicates that the habitat of this species was inversely related to the average annual temperature as the species was more abundant at higher elevations where the temperature was lower than at lower elevations.

Table 3
Percentage contribution and permutation importance of the predictor variables. Abbreviations are indicated Table 2.

Variable	Percent contribution	Permutation importance
bio1	19	14.7
bio2	1.8	10.4
bio3	1.9	8.7
bio4	0.5	3.2
bio12	6.6	4.9
bio14	0.2	0.3
bio15	6.8	6.6
bio17	0.2	2.3
Aspect	3	0.2
DEM	26.4	21.9
Geo	18.1	11.6
Distance from River	0.9	1.8
Slope	6.9	7.1
Soil	3.1	0.5
SRAD	4.6	5.8

The Maxent model's jackknife procedure of variable importance indicates that annual mean temperature (coefficient of variation) (Bio1), geography and elevation are the key predictors of *N. crispa* habitat distribution (Fig. 2). According to the response curves, higher probabilities of *N. crispa* presence are obtained when the annual mean temperature (Bio1) is below 4.5 °C, while its distribution is limited at >4.5 °C. For the variables bio2 (mean annual temperature), bio3 (isothermality) and elevation (DEM), the optimal habitat suitability is <12 °C, <31.54 °C and between 2000 m and 3500 m.a.s.l respectively. Outside these ranges, the suitability of the habitat decreases (Fig. 3).

The response curves are shown Fig. 3. For aspect, the numbers 1 to 9 represent the flat area and the directions north, northeast, east, southeast, south, southwest, west and northwest, respectively. The probability of presence is the highest in the northern, northeastern and eastern aspects and the lowest in flat and western positions. For geology, each of the numbers 1 to 43 indicates a specific class, a peak of presence was detected in class 5 (i.e. metamorphic rocks: two mica Hornfels; cordierite Hornfels; andalusite-sillimanite Hornfels and locally metamorphosed carbonate rocks (skarn)) and in class 23 (i.e., limestone, argillaceous limestone; tile red sandstone and gypsiferous marl). In the soil diagram, the numbers 1 to 5 represent the Rock Outcrops/Entisols (1), Rock Outcrops/Inceptisols (2), Aridisols (3), Entisols/Inceptisols (4) and Inceptisols (5), respectively. The highest distribution of the species is in the first class (Parra and Monahan, 2008) (Fig. 3).

3.2. The species distribution model and its accuracy

Results on the accuracy of the models implemented in this study showed that the species habitat map is efficient to determine the habitat suitability distribution for *N. crispa* with an AUC of 0.983 (Fig. 4). The models produced to predict the species distribution under different climate change scenarios are also very accurate (AUC values >0.9). These results indicate that the distribution maps (Fig. 5) under different RCP scenarios have sufficient accuracy and reliability.

3.3. Current and future suitable habitats

The maps of the potential habitat of *N. crispa* under the current conditions and in 2050 and 2070 under different models and climat change scenarios are shown Fig. 5. The maps indicate that the potential habitat areas of the species is likely to increase in the Province. At the present time, 4.14% of the study area, which is equivalent to an area of 802.19 km^2, is suitable for the species habitat (Table 4).

In the future, the habitat area will increase under the changing climatic conditions (CCSM4 model and scenario RCP 2.6) to reach up to 9.69% in 2050 and 14.74% in 2070. Results are globally comparable between the two climate change scenarios and models althought species distribution will be larger with the HadGEM2-CC model than with the CCSM4 model (Fig. 5). A more detailed analysis of the maps, reveals that the species is likely to establish in the central areas of Hamedan Province where environmental conditions are more favorable to the species in particular due to a higher elevation and a lower air temperature, than in the other areas (Fig. 5).

The average elevation of the areas where the species is currently located is about 2501 m.a.s.l. and is expected to reach 2512 m.a.s.l for

Fig. 2. Results of jacknife evaluations of the relative importance of the predictor variables and their percentage contribution in *N. crispa* distribution. Abbreviations are indicated Table 2.

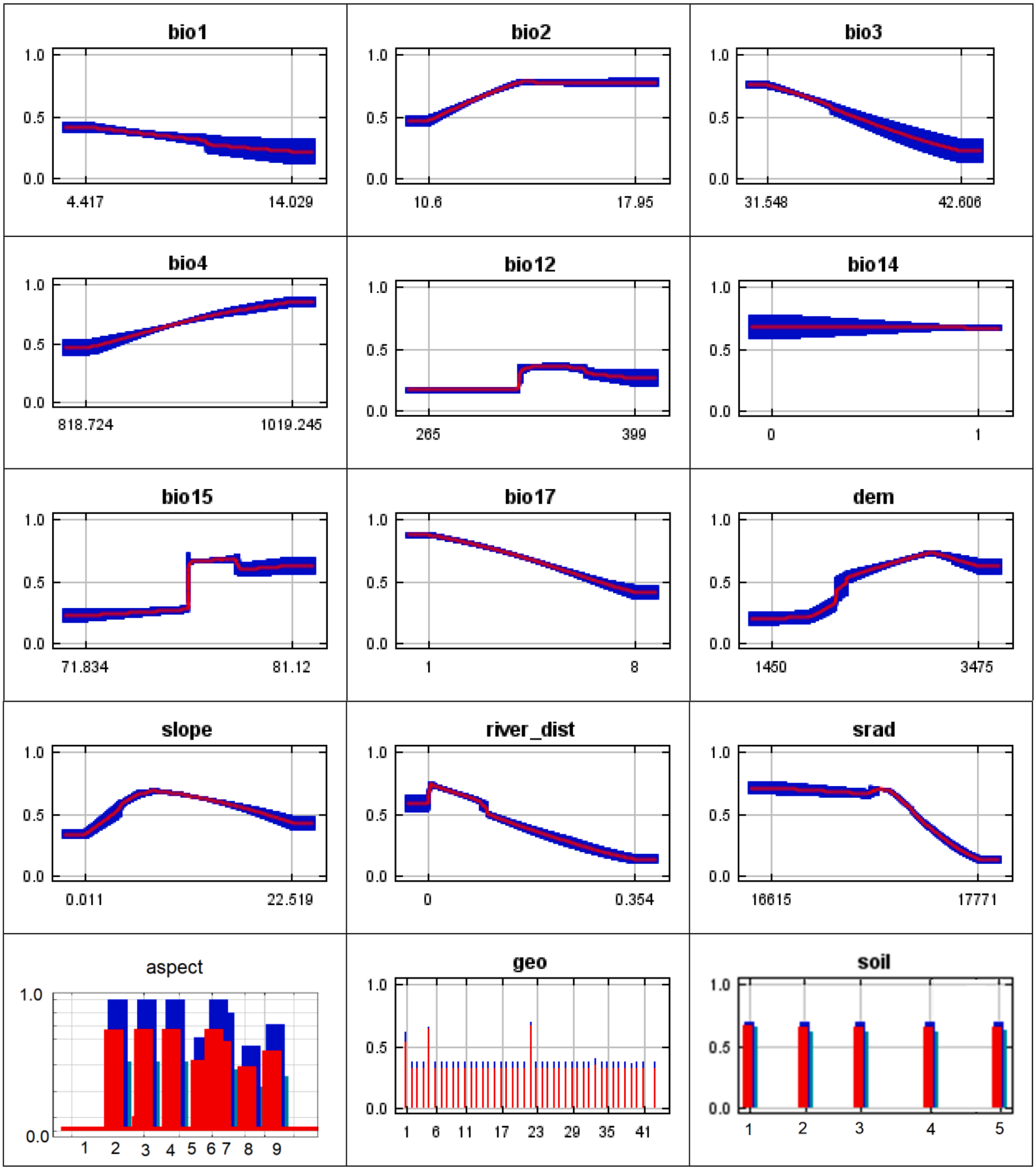

Fig. 3. Response curves for the major predictors of suitability habitats of *N. crispa*. Confidence intervals are shown in blue. Aspect: 1) flat, 2) North, 3) North-east, 4) East, 5) South-east, 6) South, 7) South-west, 8) West, 9) North-west. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

RCP8.5 (i.e. a 10 m.a.s.l. increase). In contrast, the average elevation is likely to decrease by 9–21 m.a.s.l. under CCSM4- RCP2.6 for 2050 and 2070, HadGEM2-CC- RCP2.6 and RCP8.5 for 2050 and HadGEM2-CC-RCP2.6 of 2070, respectively (Table 4).

Predictions of the areas covered by the species in the different elevation classes and climat change scenarios for 2050 and 2070 are indicated Fig. 6. In all scenarios and years, the species is not established at an elevation <1500 m.a.s.l. The largest increase in species area in the future will occur in the elevation class of 2000–2500 m.a.s.l. in CCSM4-RCP2.6 for 2070 but an increase is also noted in all other scenarios and in both 2050 and 2070. In contrast, the change in the species area is expected to be negligible whatever the scenarios and climatic models in both 2050 and 2070 for all other elevation classes (Fig. 6 and Table 5).

4. Discussion

4.1. Performance of Maxent model for predicting potential species distribution

From our results, we can conclude that the Maxent model is a useful

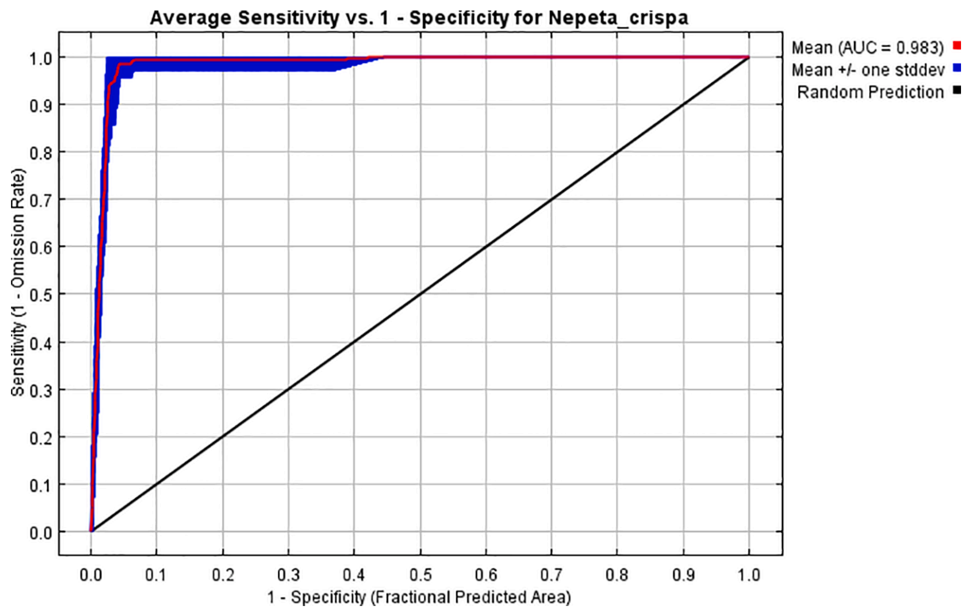

Fig. 4. Results of the AUC (area under ROC) curves in developing habitat suitability model in current climate.

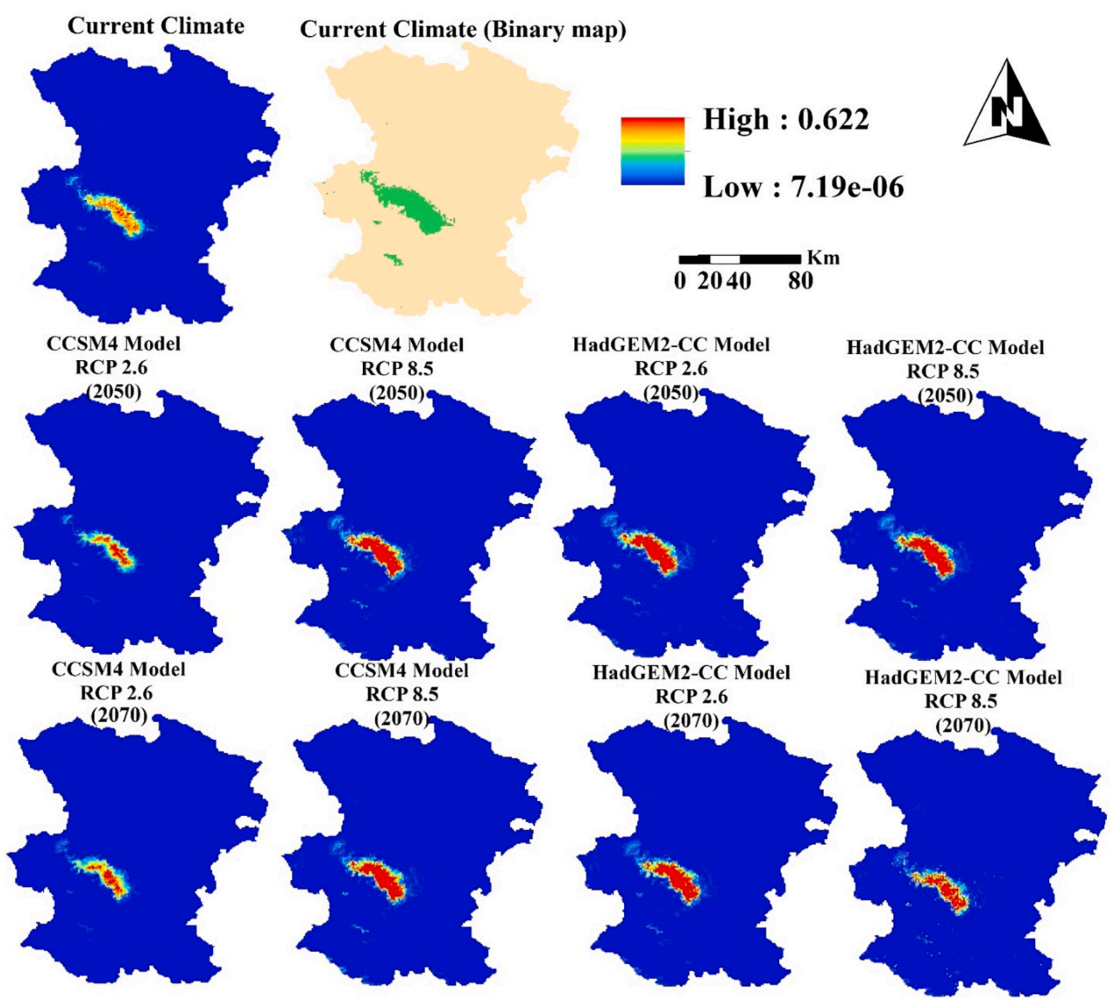

Fig. 5. Projected distribution maps of *N. crispa* showing likely suitable areas under RCP 2.6, and RCP 8.5 in 2050 and 2070 with respect to the current time period.

Table 4
Percentage of change of area of suitability for *N. crispa* by 2050 and 2070 under RCP 2.6, and 8.5 using GCMs models.

Year	Global Climate Models	RCPs	Area (Km2)	Area (%)	Percentage of habitat changes compared to the present
Current climate	–	–	802.19	4.14	0
2050	CCSM4	RCP 2.6	879.89	4.54	9.69
	CCSM4	RCP 8.5	830.09	4.29	3.48
	HadGEM2-CC	RCP 2.6	869.85	4.49	8.44
	HadGEM2-CC	RCP 8.5	869.13	4.49	8.35
2070	CCSM4	RCP 2.6	920.42	4.75	14.74
	CCSM4	RCP 8.5	805.89	4.16	0.46
	HadGEM2-CC	RCP 2.6	846.37	4.37	5.51
	HadGEM2-CC	RCP 8.5	810.99	4.19	1.1

tool for identifying the suitable habitat of *Nepeta crispa* Willd an endemic plant species in west of Iran with limited distribution. Besides, the model is also able to accurately predict the current and future distribution of this species. The use of species distribution models to identify suitable areas for the presence of medicinal plant species has been proven in many studies (Cahyaningsih et al., 2021; Kaky and Gilbert 2019Li et al., 2020; Li et al., 2018; Rana et al., 2020). There are nonetheless some limitations to the use of SDMs, in particular when available data are insufficient for the modeling process to be effective (Kadmon et al., 2003; Kaky and Gilbert 2019, 2008), or when forecasts include outsourcing of existing forecasters (Saupe et al., 2012). On the other hand, the use of only bioclimatic variables may cause bias in the results (Kaky and Gilbert 2019) because other factors such as human activities (Newbold et al., 2015), and dispersal limitations also play key roles in predicting the future distributions of such species (Ahmadi et al., 2020). Recent studies showed that despite some uncertainties, SDMs are reliable models to predict the geographic distribution of rare species even with consideration of future climate change (Ahmadi et al., 2020; Alavi et al., 2019). Of course, SDMs accurarydepends on the quality of the data in particular the consideration of human activity and species interactions although such data are often not available in regions such as our study area. Therefore, in order to increase the accuracy of MaxEnt model in this study, we have added various environmental variables to the traditional bioclimatic variables.

4.2. Influence of environmental variables on habitat suitability

Among the climatic parameters, temperature and precipitation, which greatly vary over space and time particularly in moutaneous areas, are well known main factors influencing the dynamics of plant communities (Körner et al., 2016). Our modelling approach indicates that annual precipitation (bio12) and mean annual temperature (bio1) contributed 6.6 % and 19%, respectively to the distribution of *N. crispa* in the Alvand mountain areas of western Iran. The higher contribution of temperature than precipitation emphasizes the preference of this species for cool areas, more specifically within the optimal range of 3 °C to 4.5 °C i.e. at elevations between 2000 and 3500 m. Alvand mountains offer a strong gradient of climatic conditions due to a large range of elevations (from 1448 to 3475 m.a.s.l), and contrasted seasons between cold winters with heavy snowfalls and mild sunny summers. The crucial role played by major bioclimatic factors in mountaineous areas is

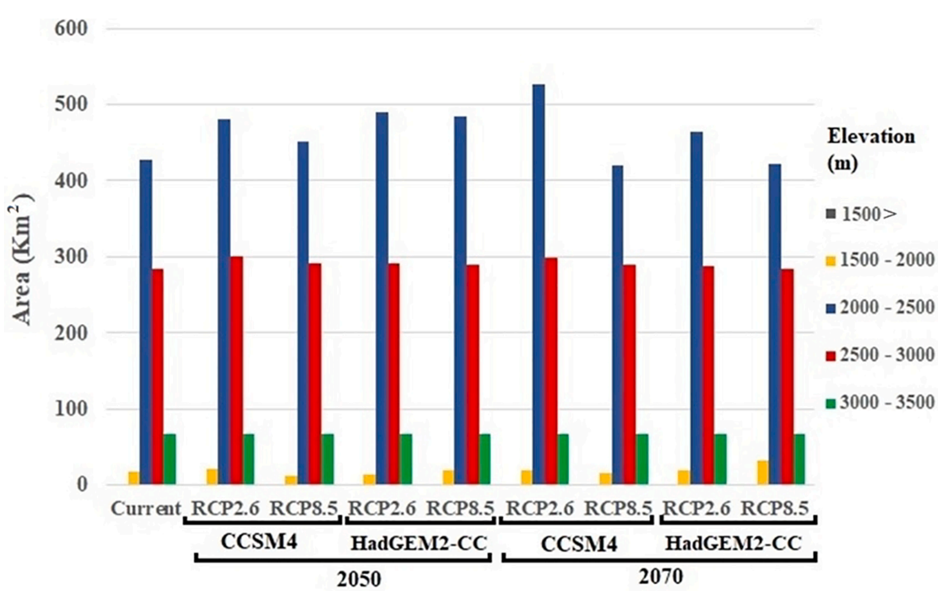

Fig. 6. Comparison of *N. crispa* area changes by elevation classes in current and future conditions predicted by the various climate change scenarios.

Table 5
Average elevation of the species habitat *N. crispa* under the current climate and different climate change scenarios for 2050 and 2070.

Model	Current	2050				2070			
		CCSM4		HadGEM2-CC		CCSM4		HadGEM2-CC	
		RCP2.6	RCP8.5	RCP2.6	RCP8.5	RCP2.6	RCP8.5	RCP2.6	RCP8.5
Elevation (m.a.s.l.)	2501.44	2492.71	2503.86	2488.19	2480.8	2480.41	2512.17	2489.15	2500.5

commonly found in other studies on medicinal plants in such regions. For instance, Wang et al. (2014) found the distribution of *F. cirrhosa* in the Nepal Himalayas was related to isothermality. Similarly, Rana et al. (2017) showed that bioclimatic variables derived from temperature were the most important to define the distribution of *Fritillaria cirrhosa* and *Lilium nepalense* in mountainious areas of Nepal and Liao and Chen (2021) also emphasized the key role of temperature in their species distribution models. In this study too, temperature has a crucial effect on the distribution of *N. crispa*, although the role of precipitation and related bioclimatic variables cannot be ignored. The greater role played by temperature over precipitation is based on the fact that the former is more limiting than the latter on the distribution of plant species in the upper slopes of the mountaineous areas (Grabherr et al., 1994; Melanie et al., 2016).

These climatic characteristics can thus benefit to *N. crispa* development as the optimal elevation range for for this species is between 2000 and 3500 m.a.s.l. Elevation, annual mean temperature, annual precipitation, and geology all together contribute by 70.1% in explaining the spatial distribution of the species in the Alvand mountain areas. Elevation is an obvious factor affecting climatic variables such as temperature and precipitation but is less used directly in species distribution studies. However, in our study elevation is a factor of particular interest for modelling the distribution of this species found in high elevation areas. Oke and Thompson (2015) also put forward the role of elevation in mountainious species distribution modeling: they found that thedrop of this variable had a negative effect on SDMs whereas its inclusion greatly improved the models accuracy. Bazrmanesh et al. (2019), Almasieh et al. (2018) and Ardestani et al. (2015) also introduced the elevation as the most important variable in the habitat modeling of *Astragalus cyclophyllon*, *Bromus tomentellus* and *Centaurea pabotii* respectively in other parts of Iran. In line with these studies, we showed that elevation was the most significant variable in the habitat distribution of this endemic plant species in the study area.

4.3. Projected changes in coverage and distribution of N. Crispa

The effects of the climate change on the geographical distributions of a wide range of mountainous plant communities have been reported across the world (Buitenwerf et al., 2015; Hamid et al., 2019; Khwarahm, 2020; Palomo, 2017). Under the climate change scenarios of the CCSM4 and HadGEM2-CC models, the habitat range of the species will increase from 4.14 % of the total study area to 7.49 % and 5.45 % in 2050 and 2070, respectively. Climate change scenarios predict a marked increase of the temperature and a reduction of the precipitation. A logical consequence is a shift in the spatial distribution of the species towards higher elevations to benefit from higher precipitations and cooler temperatures more adapted the plant development. Therefore, the habitats located at low elevations are particularly thereathened in the future. Previous studies, particulary in mountain ecosystems, have also reported the elevational shift in the distribution of plant communities under climate change scenarios in Iran (Almasieh et al., 2018; Bazrmanesh et al., 2019; Naghipour Borj et al., 2019) and other parts of the world (Braunisch et al., 2014; Bertrand et al., 2011; Khwarahm et al., 2021; Walther et al., 2005). In our study, the distribution of *N. crispa* was accurately predicted but gain in accuracy could be obtained by using climate data with higher resolution as climate variability is huge in mountaineous areas like ours (Lembrechts et al., 2019).

4.4. Implications for ecological conservation and restoration

Medicinal plants play a very important role in human health and are significant components of ecosystems. In recent decades, restoration and conservation of medicinal plants have gained a strong foothold in the ecosystem management of terrestial ecosystems worldwide. Species distribution models are thus useful tools that help us achieve restoration (Wang et al., 2015) and conservation (Gibbons and Lindenmayer 2007; Kumar and Stohlgren 2009) of rare and endangered species. Therefore, this study recommends that the conservation and management actions should predominantly concentrate on the elevation range between 2000 and 3500 m.a.s.l. of the Alvand mountain areas in Hamadan Province in western Iran. Futhemore, developing new and/or updating ecosystem management guidelines should be considered as a preparatory step in understating the adaptibilty of the species under future climate change scenarios. For example, assisted migration could be an option for investigating the adaptibilty of the species in elevations higher than its current range.

It is clear that the negative effects of climate change are increasing and may be amplified by human disturbances, especially land-use change and grazing in mountainous areas. Recent studies have shown that in addition to climate, human activities also affect the distribution of plants and have to be considered before undertaking conservation operations. Unfortunately, SDMs are not currently fully capable of including all the factors linked to human activity that affect plant species distribution and the resulting uncertainty have to be considered in designing conservation and rehabilitation programs.

5. Conclusion

Reliable and accurate predictions on the suitable area distribution of *N. crispa* in the current and future climate conditions were performed by Maxent model. Distribution models under climate change scenarios predict a geographical shift in the distributions of *N. crispa* towards higher elevations (above 2000 m.a.s.l). Among the variables tested, elevation, annual mean temperature, geology and precipitation of driest quarter were the most important in determining the habitat of *N. crispa*. Therefore, conservation and management actions should predominantly concentrate on the elevation range between 2000 and 3500 m.a.s.l. There is a need for developing new and/or updating forest management guidelines as a preparatory step in understating the adaptability of the species in the wake of climate change. Correlation-based modeling, future climate projections, and GIS techniques provide useful information for conservation actions in Iran and in regions with similar climatic conditions. We highly recommend such studies to natural resources managers before planning conservation or restoration actions of rare endemic species in high elevation areas.

CRediT authorship contribution statement

Shirin Mahmoodi: Conceptualization, Methodology, Software. **Mehdi Heydari:** Writing – review & editing. **Kourosh Ahmadi:** Conceptualization, Methodology, Software. **Nabaz R. Khwarahm:** Writing – review & editing. **Omid Karami:** Writing – review & editing. **Kamran Almasieh:** Writing – review & editing. **Behzad Naderi:** Data curation. **Prévosto Bernard:** Writing – review & editing. **Amir Mosavi:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We are thankful to Ilam University for financial support.

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