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ARTICLE

Climate Change and Its Impact on Brown Bear Distribution in Iran

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ABSTRACT

Climate change is one of the threats in the recent century, affecting biodiversity directly and indirectly. Modeling the patterns of species distribution is one of useful tools for predicting the impacts of climate change on endangered species. Brown bear (Ursus arctos) plays an important role as a focal species in mountainous ecosystems. This study was aims to investigate the effects of future climate changes on the distribution of this species using an ensemble modeling method in R-software. For this purpose five algorithms including MAXENT, RF, MARS, GAM, GLM and BRT were used to predict the distribution of the species in the present climatic conditions as well as in the 2050s and 2070s. The results showed that temperature and precipitation were two main factors in the distribution of brown bears in Iran. Investigating the distribution of the brown bear in the future showed that suitability of its habitat will decrease in the western and central parts and increase in the northern parts. So a shift toward higher altitude will be expected for brown bear in the future. Therefore, in this condition it is imperative to upgrade the extent of protected areas for better conservation of brown bear.

1. Introduction

The consequences of the rapid changes in the global climate are still uncertain [1,2]. Since one of the most effective factors on distribution of the species is climate [3,8,35], species respond quickly to climate change [2]. Consequently, changing distribution patterns of species and/or reduction in species diversity can be expected [2,6].

In the recent years, prediction of species response to climate change has attracted much attention from scientists [4,7,8]. Predicting potential future risks play an important role in decision-making and can be used as a powerful tool to prevent the negative effects of climate change on species [4,7]. Although little evidence has been provided so far about the recent extinctions due

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to climate change, many studies have suggested habitat destruction as the major threat to global biodiversity and can be exacerbated by climate change in the upcoming few decades [4]. Nowadays, the application of species distribution models (SDMs) has been a growing increase in numerous studies in ecology, conservation biology and biogeography [9-11]. Among the various applications of the SDMs, habitat suitability of species along with the identification of factors affecting their distribution can be mentioned [11,12]. Moreover, SDMs can be used for prediction of changes in species future distribution under climate change [13,14] which plays an important role in the awareness of managers in order to better planning for the conservation of rare and endangered species [11].

There are various techniques for modeling the species distribution such as maximum entropy (Maxent) [12], artificial neural networks (ANNs) [15], multivariate adaptive regression splines (MARS) [16], random forest (RF) [17], generalized boosting model (GBM) [18], the generalized linear model (GLM) [19] and support vector machines (SVMs) [20]. However, they are considerably different in summarizing the relationships between response and the predictive variables and the projection either at the time of transferring the species distribution into different temporal or spatial contexts [21]. One of the newest SDMs techniques is the platform sdm in R. in which different implementations of the SDMs are integrated in a framework to eliminate the constraints of other methods [21].

Brown bear as a widespread species is small and often isolated populations in the Middle East countries such as Turkey, Iraq and Iran [22-24]. Brown bears live in Iran in the west of the country through the central Zagros Mountains, the Caucasus mountains in the north-west of the country, the Hyrcanian forests on the northern slopes of the Alborz mountains [25]. In recent years, the historical range of this species has declined and they are at risk of local extinction in Iran due to some reasons such as unplanned hunting and habitat loss [4,5].

Numerous studies have been carried out on brown bears that often focused on phylogeographic lineage [24], habitat suitability and connectivity [27], population genetic diversity and ecological isolation [26]. However, little is known about exact distribution and effect of climate change on the distribution of brown bear in Iran.

The aim of the present study was to determine the habitat suitability of brown bear in the present and predicting the distribution of this species in the future under the climate change in order to better planning for conservation of endangered brown bear.

2. Methods and Materials

2.1 Data Collection for Species Occurrence

The occurrence data of species were collected in three ways: 1) direct observation of species by authors, documented and georeferenced observations by personnel of the department of environment (DOE) of Iran and randomly located camera traps, 2) indirect signs of species such as fur, footprints and documented human reports of damages by brown bear and 3) data obtained from literatures [28]. All observations, documents and signs were recorded by GPS. A total of 216 records were used for modelling after removing invalid data with high uncertainty (Figure 1).

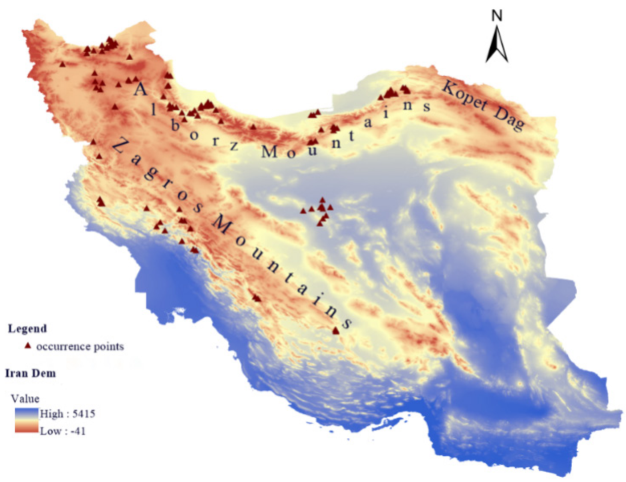


Figure 1. Recorded presence data of brown bears in Iran

2.2 Environmental Data and Effect of Climate Change on Species Distribution

Climatic data layers for HadGEM2-AO model two climate change scenarios: optimistic (2050) and pessimistic (2070) under two future emissions pathways (RCP 2.6 and RCP 8.5) were used to demonstrate the effect of climate change on the distribution of brown bears and predict their future potential distribution [29,30].

The above mentioned emissions pathways (RCP 2.6 and RCP 8.5) are described as levels of radiative forcing in different climate change conditions (between the preindustrial era and 2100) which are the quantity of energy entering the atmosphere and the reflected back [11,31]. To compare current and future conditions, 19 bio-climate variables which were maps with a resolution of 30 second (~1 km^2) and containing world climatic information were taken from the WorldClim database [32]. Then, from the 19 bio-climate maps, Iran's climate maps were extracted in the ArcGIS 10.3 software based on the Dem (Digital

Elevation Model) maps of study area to enhance the accuracy of outputs [33]. A principal component analysis was used in ArcGIS 10.3 to calculate the correlation between layers. In this way, layers with a correlation less than 0.7 were selected to avoid collinearity (auto-correlation) among variables [14,34]. Regarding the habitat and ecological needs of brown bear, finally, 7 climatic layers were selected as bio-climate variables that included annual mean temperature (Bio1), temperature seasonality (Bio4), min temperature of coldest month (Bio6), temperature annual range (Bio7), annual precipitation (Bio12), precipitation of wettest month (Bio13), precipitation of driest month (Bio15).

The total climatically suitable habitats for brown bears in different climate scenarios (present and future) were calculated by ArcGIS 10.3. Finally, in order to show any shift in the distribution of the species under climate change, the suitable range size of species in the present and future conditions were compared.

2.3 Ensemble Distribution Modeling

Species distribution modeling was fitted using SDM package in R [21]. R as an open source environment and high-level programming language widely used for numerous purpose such as graphical visualization, statistical analysis, mathematical computing, spatial analysis and modelling [21,35]. In addition to above mentioned capabilities, developing specialized and new techniques and tools through user-created packages, make R very powerful and distinguishable among other software [21].

SDMTools is a computerized platform in R which is suitable for processing the output of a set of species distribution models [21,35]. SDM includes solving a wide range of ambiguities, imperfections and shortcomings in other methods [21]. Because under different conditions, a method can be chosen as the superior model which is not universally applicable to other species, therefore, one of the possible solutions is the use of Ensemble modeling [21,36] which is suitable for dealing with mistakes and uncertainties between models [37]. In the present study sdm package in R were applied using several algorithms including MAXENT, GLM, MARS, BRT, RF, GAM for Ensemble distribution modeling under different climate scenarios as described by Naimi and Araujo, (2016) [21]and finally, the performance of the models were cross validated.

2.4 Data Analysis

Background data (e.g. pseudo-absence points) are required for all of the used models, hence a randomly drawn sample of 10,000 background points from Iran (extent of study area) was generated excepting occurrence point [14,38] by dismo package in R environment (v. 3.4.3). All available data were randomly divided into two different categories before modeling: 75% of occurrence points as training data and the remaining 25% of data set as test data were used to model cross-validation [39]. One of the most important methods in the sdm package which used for analysis in this study is weight method. The weight method makes an optimal modeling by averaging the quantitative models used to predict the distribution of species. Weighting was based on the area under the curve (AUC) and true skills statistic (TSS). AUC (a threshold-independent measure) and TSS statistics were used for estimate accuracy in the models performance. The AUC curve obtained from the Receiving Operator Characteristic (ROC) curve which is an effective indicator of threshold and prevalence for model performance evaluation [5,14,36,40]. In a model that lacks the ability to detect and predict, the AUC is 0.5 and a very high predictive and detectable model will have an AUC equal or close to 1 [5,41]. Also the TSS statistic is a good measure to predict accuracy of presence-only models which avoids reliance on prevalence or size of validation set [42]. A range from 0 to 1 is considered for TSS. In this way the performance of model was considered good in which values were higher than 0.6 [42].

3. Results

3.1 SDMs for Brown Bear

A total of 200 presence points of brown bears were obtained in this study. Based on the results the highland areas of Zagros and Alborz mountains were the most suitable habitats for brown bears (Figure 1).

The success rates of all algorithms used in the modeling were 100%. So the results are fully acceptable. Accuracy estimates of models using TSS and AUC statistics are given in Table 1. The TSS in all models was higher than the threshold level (i.e. 0.5), indicating high accuracy of modeling. Given the results the values of the AUC were higher than 0.7 which states the high accuracy of modeling.

Table 1. TSS and AUC statistics obtained for accuracy of modeling in different algorithms.

methods	Current	RCP 2.6(2050)	RCP 2.6(2070)	RCP 8.5(2050)	RCP 8.5(2070)
	AUC / TSS	AUC / TSS	AUC / TSS	AUC / TSS	AUC / TSS
GLM	0.84 / 0.58	0.85 / 0.56	0.85 / 0.59	0.86 / 0.6	0.87 / 0.63

methods	Current	RCP 2.6(2050)	RCP 2.6(2070)	RCP 8.5(2050)	RCP 8.5(2070)
	AUC / TSS	AUC / TSS	AUC / TSS	AUC / TSS	AUC / TSS
RF	0.89 / 0.65	0.92 / 0.75	0.92 / 0.72	0.91 / 0.7	0.93 / 0.75
BRT	0.84 /0.61	0.85 / 0.62	0.85 / 0.59	0.85 / 0.62	0.85 / 0.6
MARS	0.79 / 0.59	0.81 / 0.56	0.82 / 0.56	0.84 / 0.57	0.82 / 0.56
MAXENT	0.84 / 0.54	0.88 / 0.64	0.87 / 0.6	0.86 / 0.58	0.89 / 0.66
GAM	0.84 / 0.57	0.88 / 0.63	0.86 / 0.61	0.84 / 0.6	0.87 / 0.63

3.2 Variable Importance

CV testing suggested that the RF model performed reasonably well, with average AUC scores of 0.91 and TSS scores of 0.7. Brown bear species in current climate condition and under the optimistic scenario (2050) will primarily affect by temperature variables more than other variables. Annual mean temperature and temperature seasonality were two main variables affecting the distribution of this species under RCP 2.6 in 2050. Other climatic factors affecting the distribution of brown bear in the current climate condition was annual precipitation. Under the optimistic scenario for the year 2070, the most important factors affecting the distribution of brown bear were annual precipitation and precipitation of the driest month, besides the annual mean temperature. In addition, for the years 2050 and 2070, under the pessimistic scenario, annual precipitation and also precipitation of driest month and annual mean temperature were identified as the main factors affecting the distribution of brown bear. In contrast, the min temperature of coldest month had the least effect on the distribution of this species in Iran (Figure 2).

3.3 Comparison of Different Models

The results of comparison the distribution modeling of brown bear under different climate change scenarios are presented in Figure 3. Based on the results of six modeling methods, it is obvious that some models showed a wider suitable area than the other models. As an instant, in all scenarios most and least suitable habitat of brown bear were observed in prediction maps made by maxent and MRS models, respectively.

3.4 Ensemble modeling and prediction of climate change on the distribution of brown bear

Ensemble modeling was implemented to achieve a more precise model (Figure 4). Based on the results, three categories of habitats are determined for brown bear: habitats without any changes in suitability (areas that are suitable both in the current and in the future), habitats which lost their suitability (areas that are suitable in the current but will lose their suitability in the future) and habitats which will be suitable (areas that are not suitable in the present but will be suitable in the future).

Area shifts of the species distribution under different

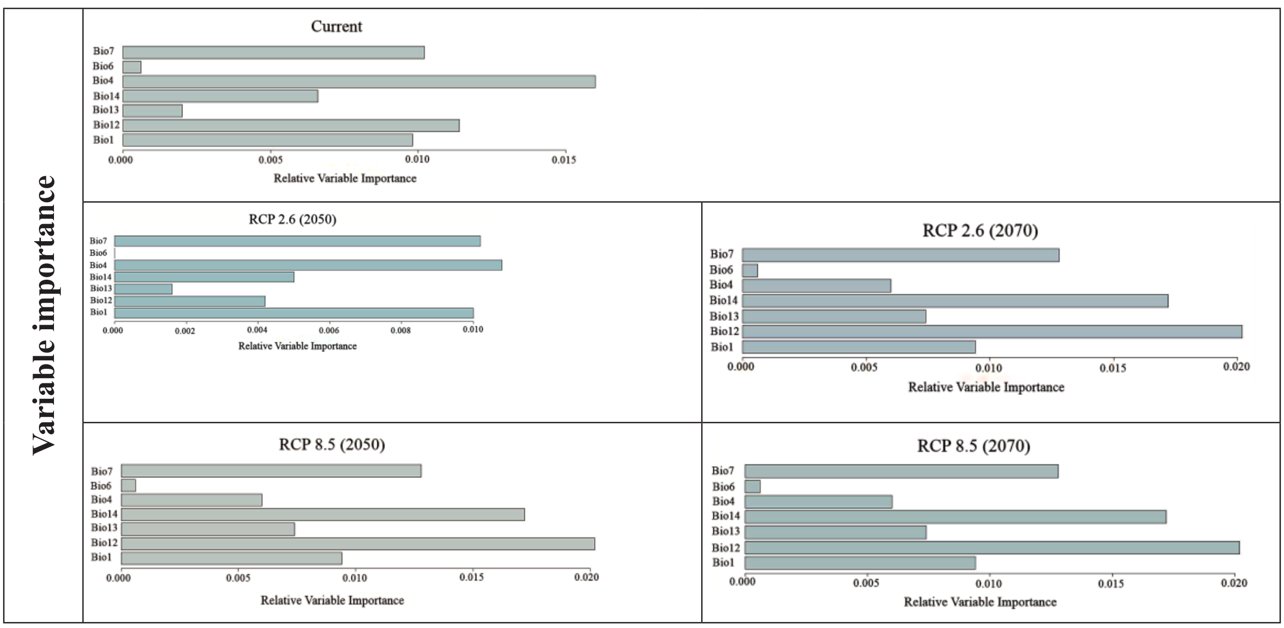
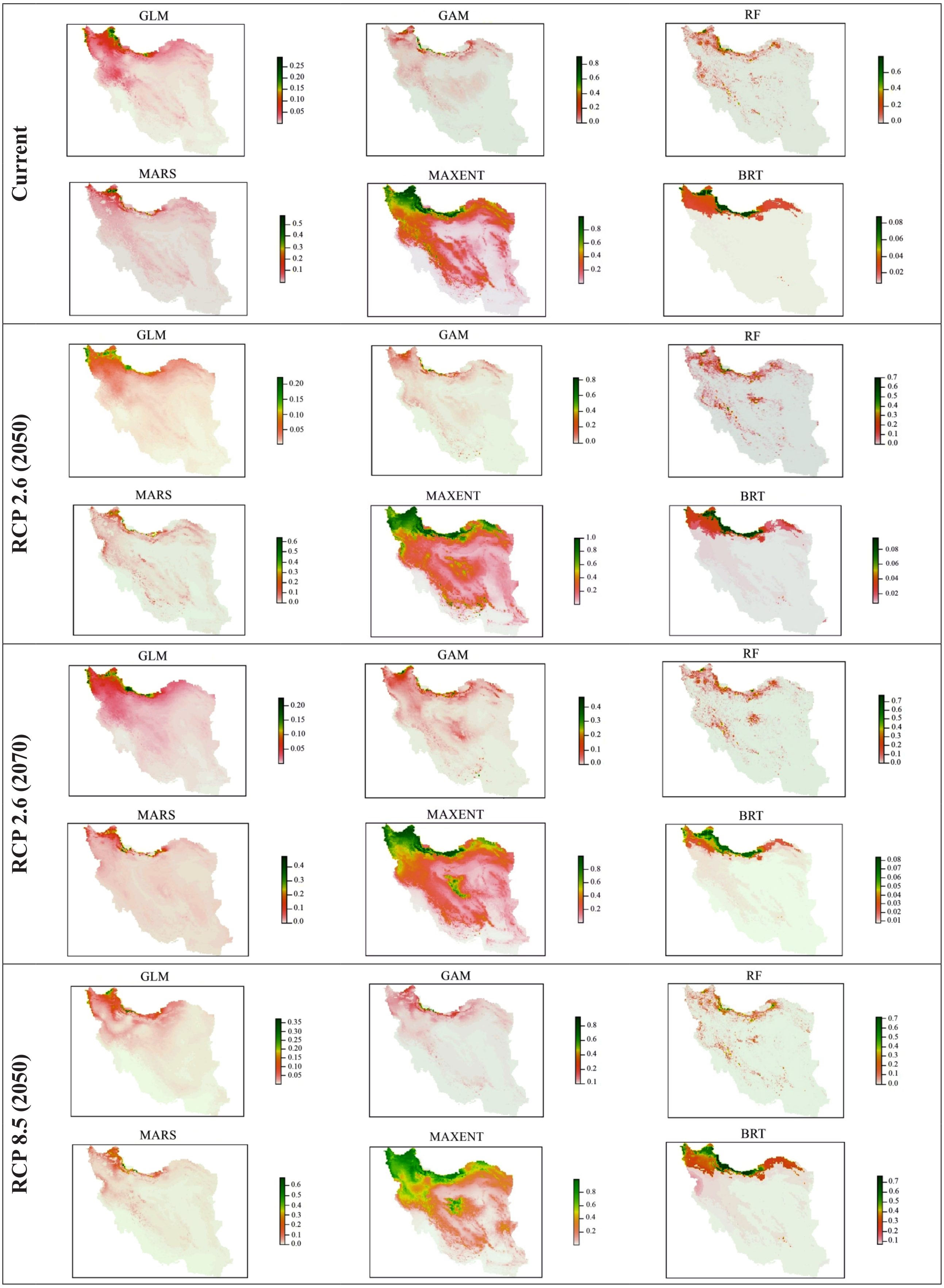


Figure 2. Importance of bioclimatic variables on the spatial distribution of brown bears in current climate condition and different climate change scenarios


Current
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GAM
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RCP 2.6 (2050)
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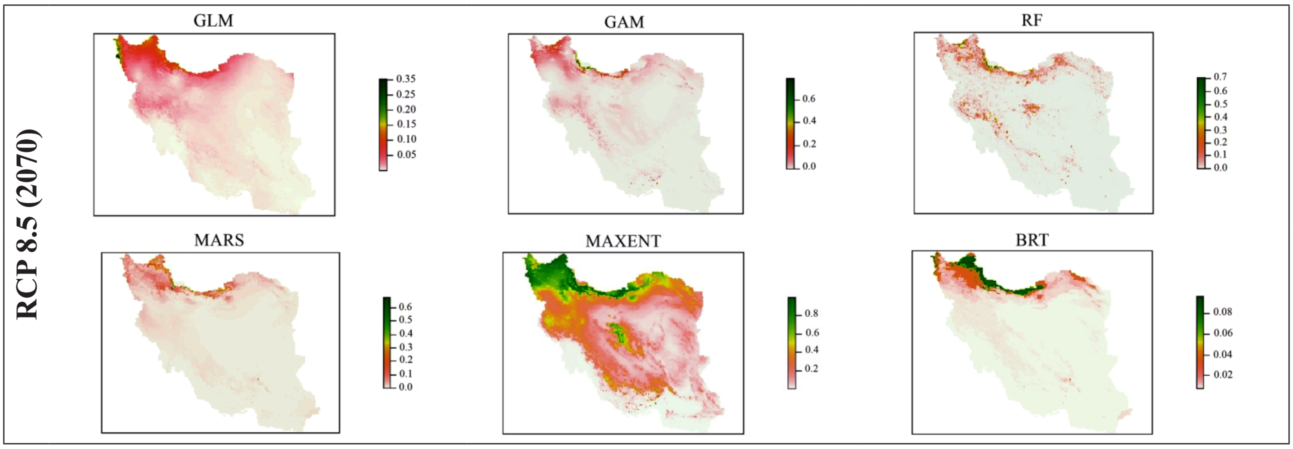

Figure 3. Comparison of predicted species distribution models in different climatic scenarios, using different algorithms

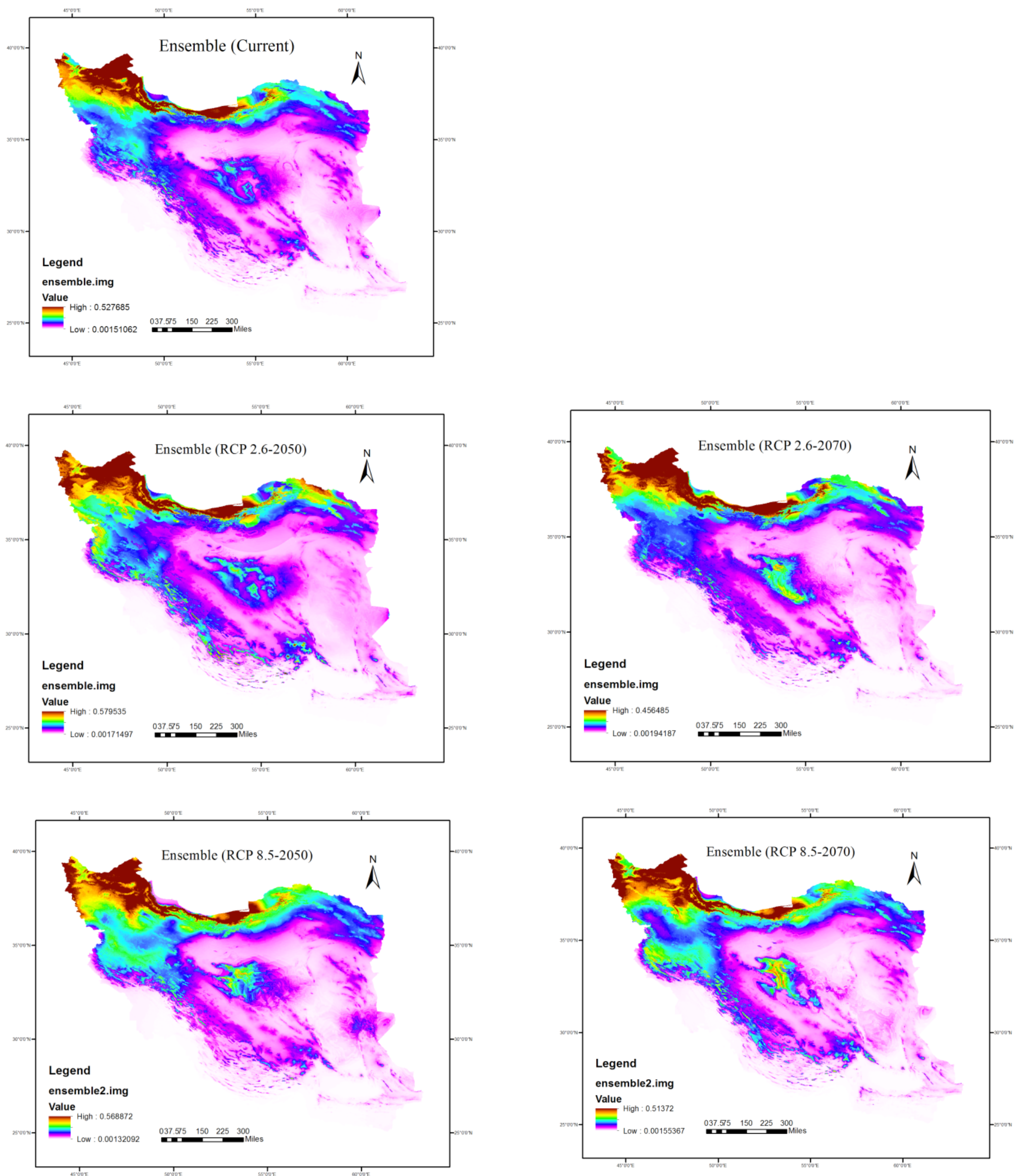

Figure 4. Ensemble modeling of brown bear under different climate change scenarios

climate changes scenarios are given in Table 2. The results demonstrated that under the optimistic scenarios for the 2050 and 2070, the distribution of this species in areas with moderate climatic suitability will be increased 24709 and 7661 km^2, respectively. However in 2050 and 2070, around 22,745 km^2 and 27,661 km^2, will be added to unsuitable areas of brown bear distribution respectively. Under the pessimistic scenario for the 2050 and 2070 the distribution of species in both moderate and suitable climates will be decreased especially in the southwestern part of the country. So that approximately 24305 km^2 and 30322 km^2 will be added to unsuitable areas in 2050 and 2070 respectively.

Prediction maps of brown bear distribution showed that in an optimistic scenario in 2050, suitable habitats of brown bear in Zagros Mountains will lose their suitability compared to current distribution. Consequently, they will have little habitat suitability for brown bear, and this trend is on the rise by 2070 so that only in the northern part of Iran as well as Alborz and Caucasus Mountains will have suitable climates.

According to the prediction maps, reduction in habitat suitability of brown bear were mostly related to western parts of Iran which are the main habitats of brown bear in the Zagros Mountains as well as in central parts of Iran. On the other hand, the climatic suitability of brown bear were increased under both optimistic and pessimistic scenarios in some of northwestern parts of Iran including northern part of West-Azarbaijan, East-Azarbaijan and Ardebil, and northern parts of the Zanjan province, and also northern parts of Iran including Gilan, Mazandaran provinces, and some parts of Golestan and North-Khorasan province, which indicated that the habitat of brown bear affected by climate change will be shifted towards the northern parts of the country.

Table 2. Comparison of distribution area of the species under different scenarios.

	suitable areas / KM^2	Moderate suitable areas / KM^2	Unsuitable areas / KM^2
Current	1478946	623108	144040
RCP 2.6 - 2050	1390156	647817	208121
RCP 2.6 - 2070	1449828	630769	165497
RCP 8.5 - 2050	1506291	571458	168345
RCP 8.5 - 2070	1472959	598773	174362

4. Discussion

Understanding the factors affecting the wildlife activities (for example climate change) plays an important role in the conservation of endangered species [43]. The results of six prediction models showed that despite the high accuracy of models used in the present study, the results obtained from six prediction models were comparable. So that the suitable habitat predicted in maxent models were wider than other models. In consistent with our results Kafash et al., (2019) [8] observed approximately different results in predictions made by four modeling methods. They suggested that results of GLM and Maxent were most liberal and conservative, respectively. So we agree with Naimi and Araujo, (2016) [21] who suggested that ensemble distribution modeling used in this study can eliminate these ambiguities, imperfections and shortcomings in other methods.

Results of the present study showed that temperature and precipitation were two main factors affecting the distribution of brown bear in Iran; on the other hand, the min temperature of coldest month had the least effect on the distribution of brown bear in Iran. These results were similar to the results of Farashi *et al.,* (2018) [44] who suggested that changes in temperature and precipitation are the most important factors which threaten mammals as other studies demonstrated [45,46]. According to the results suitable habitat of brown bear will be decreased under the climate changes which are in line with the results of Segan *et al.,* (2016) [47] who suggested that increasing the average temperature and reducing precipitation will be major factors in the habitat loss and fragmentation in the future. Also the results are consistent with the findings of Ye *et al.,* (2018) [42] and Dar et al., 2021 [48] who showed that the threatened mammals will be affected by future climate changes and will lose much of their suitable habitats. This seems to be the same trend for many mountainous species as climate change and global warming are predicted to have a more prominent effect on mountainous species [49] which stimulate species to migrate to higher altitudes of the mountains and to become isolated [49] and consequently would have promoted species extinctions through direct effects on key life-history traits of animals [31,19] and/or decrease in resource availability [52].

Bojarska and Selva, (2012) [53] suggested that climate conditions especially temperature and snow conditions can affect the feeding ecology of brown bears. It is determined that plants are considered as the most portion of brown bear diet [53]. Since climate change can alter the plant distribution and phenology so it may lead to changes in food availability and foraging behavior of brown bear and will cause competition [31,54,55]. It is noticeable that plants can shift their geographic ranges as a response to climatic change [56]. So new patterns of plant occupancy/abundance can affect on animals which rely on plant availability for both food and shelter [31,36,57-59]. However it cannot be ignored that it is possible for brown bears to cope with this food challenge due to climate change as they have a wide food niche [60].

Since brown bear is a hibernator species and adapted to seasonal climates, so climate change can also affect breeding of brown bear [50]. During the hibernation period, female brown bears give birth [61], as a consequence they face a trade-off between reproductions and overwinter survival [62]. According to the Humphries *et al.,* (2002) [50] during warm winters in which energetic costs of torpor is increasing it can be expected that energy demands of hibernating mammals increase. As a result, these animals will face to lake of suitable amount of energy for reproduction [62]. So brown bears must increase energy uptake during the growing season especially by feeding plant food to increase body fat before den entry and subsequently to compensate for loss of reproductive potential [61]. Therefore, winter temperature and net primary productivity can directly affect the reproductive rate of brown bear and consequently the population dynamics of the species during the warming period as suggested by Albrecht *et al.,* (2017) [62].

The results showed that in both optimistic and pessimistic conditions suitable habitats of brown bear in the Zagros Mountain as well as central parts of Iran will almost lose their climate suitability for brown bear. On the other hand, the level of climate suitability of the brown bear habitat will increase in both optimistic and pessimistic scenarios in northern parts of Iran such as several parts of the Alborz, Caucasus as well as Kopet Dagh Mountains. So a migration will be expected for brown bear toward the mentioned climatically suitable habitat. Similarly, Chen *et al.,* (2011) [62] found that one of the factors affecting the species range shift is temperature and with increasing level of warming the rates of latitudinal and elevational shifts will increase. In response to rapid climate changes, however, some mammals will be unable to move their ranges quick enough to track shifts in habitats with suitable climates and most of them may not be able to keep pace with climate change [63].

In a study on effects of climate change on predictable food resource and shelter alterations of endangered brown bear, Penteriani *et al.,* (2019) [31] suggested that an increase in human-bear conflicts and bear mortality rates can be expected during range shifts of brown bear individuals from mountainous areas towards more humanized ones. Moreover, we agree with Penteriani *et al.,* (2019) [31] who pointed out more negative effects on brown bear including a) reduction of food resources leads to limited fat storage before hibernation; b) increasing conflicts with cattle farmers by an increase in tendency to a more carnivorous diet; c) increasing road kill during larger displacements between seasons to find main food resources; and d) increasing intraspecific competition with other species which have similar diet. So an appropriate management measures are quite vital to successful mitigation of such conflicts and avoid local extinction of species in the future decades.

5. Conclusions

The present study was the first step in predicting the brown bear distribution under future climate change in Iran. The results showed that temperature and precipitation reduction as the most effective factors in 2050 and 2070 would decrease the distribution range of brown bear and a shift toward higher latitudes will be expected. Hence, it is expected that the effectiveness of current existed protected areas for conservation of brown bear and their feeding resources/habitats will be reduced to protect this species in the future. Therefore, in this condition it is vital to communicate and train target groups for conservation measures including politicians, decision makers, general public, local communities, protected area officials and conservation officers and upgrade the extent of protected areas along with constant monitoring of endangered species, affected by climate change as suggested by Velásquez-Tibatá et al., (2013) [64]. It is recommended that protecting brown bear habitats along with protecting their food resources, minimizing stressor human activities and creating reserve protected areas can be much more effective to their conservation.

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