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Investigating habitat degradation of *Ursus arctos* using species distribution modelling and remote sensing in Zagros Mountains of Iran

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Abstract

Knowledge on habitat suitability of ecologically important species is central for their conservation management. The occurrence records of brown bear (*Ursus arctos)* in Kurdestan Province of Iran and environmental data were compiled to predict the ecological niche of this bear using Maxent species distribution algorithm. Satellite imagery of Landsat 5 and Landsat 8 for 1990 and 2017 was also employed to investigate human-induced land degradation in the suitable habitats of the species. The images were pre-processed and classified into seven land use and land cover (LULC) classes using support vector machine (SVM) algorithm. According to Maxent model, about 9% of the study area could be regarded as highly suitable habitat, followed by moderately suitable habitat (11.6%) and marginally suitable habitat (29.3%). The integration of Maxent potential habitat map and LULC changes revealed that more than 6997 ha of the suitable habitats of the species have been degraded due to different human activities mainly related to the conversion of natural lands and Daryan Dam construction.

Keywords Brown bear · Habitat degradation · Maximum entropy modelling · Landsat sensors · Kurdistan

Introduction

Forests provide numerous provisioning, regulating, and supporting ecosystem services such as soil and water conservation, biodiversity, and climate regulation (Tayyebi and Jenerette 2016). Increase in human activities and population growth has led to land use/land cover (LULC) change, deforestation, and adverse impact on the ecosystem in the world (Al-sharif and Pradhan 2014). The Zagros forests in western Iran, also known as the western oak forests due to the dominance of oak species (*Quercus* spp.), cover almost six million hectares (ha) which correspond to 3.5% of the country (Ziaie 2010). The overall forest health has recently been influenced by severe drought (Azizi et al.

2013; Arsalani et al. 2015); wildfire (Heydari et al. 2016); soil erosion, pests, climate change induced disturbances, and fungal pathogen attacks, resulting in canopy and stand dieback of the oak forests (Ghadirian et al. 2018; Mirabolfathy et al. 2011; Ghanbari Motlagh et al. 2020); and subsequent impact on environmental issues, conservation of water and soil resources, and socioeconomic status (Jazirehi and Rostaghi 2002). The Zagros forests have also undergone wide deforestation associated with urban population growth (Henareh Khalyani and Mayer 2013) creating loss of habitat for keystone species like the Caucasian (Persian) squirrel (*Sciurus anomalus*; Sadeghi 2014) and the brown bear (*Ursus arctos* Linnaeus, 1758). As keystone hosts, these oak forests foster numerous crucial food sources in the forms of fruit, nuts, leaves, and honey, making them the most suitable LULC for such species (Fernández et al. 2012; Wilson and Ruff 1999). Forests are among the natural ecosystems most endangered by dam construction, and extensive tracts of the Zagros forests have been destroyed as a result of constructed dams (Sadeghi et al. 2017). Any decline in habitat size may lead to extinction risk of individual populations (Ceballos and Ehrlich 2002). Dam building in Iran has accelerated

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desertification and is recognized as responsible for deforestation (Zafarnejad 2009) as well as restricting habitat connectivity and wildlife movement (Kaya Özdemirel et al. 2016; Swenson et al. 2000).

Brown bears are a priority for conservation, as covering the needs of these umbrella species in their vast home ranges and establishing viable populations can potentially protect other mammal species, vertebrates, plants, and insects (Beier et al. 2008). In recent past, west Asian bears were severely threatened due to the impact of human disturbances, yet there is a critical lack of knowledge about their status and requirements for survival, which complicates conservation efforts (Gutleb and Ziaie 1999; Wolf and Ripple 2017). The brown bear, the largest carnivore in Iran, distributed along the Alborz and Zagros mountain ranges in north, northwest, and west of the country, and is an important as keystone and an umbrella species (Yusefi et al. 2019). The brown bear population has had a significant decrease and is officially listed as a vulnerable species (Ziaie 2010). Changes and destruction of habitat and increased accessibility of remaining habitat are among the principle causes of tensions and pressure on this species (Farashi et al. 2016).

Intensive field surveys cannot keep pace with the rate of LULC change over large areas, and new methods are needed for regional-scale mapping (Osborne et al. 2001). Remote sensing has recently shown a great potential for species distribution mapping, LULC changes, and habitat condition assessment (Ivosevic et al. 2021; Moon et al. 2017; Randin et al. 2020) and anticipated to be utilized more in studying combined effects of climate and land use changes (Santos et al. 2017).

An important step in the direction of proactive management methods to reduce conflict and increase the viability of a population of large carnivore is successful forecasting of viable range expansion region (Zarzo-Arias et al. 2019). Species distribution models (SDMs) can be employed to analyze habitat thresholds through calculation of the relative environmental variable contribution rates and plotting of factor response curves (Liu et al. 2019). Species distribution modelling (SDM) is a common approach employing for a long time for predicting species distribution and identifying corridors (Drouilly et al. 2018; Jiménez-Valverde 2014; Littlefield et al. 2019). These models rely on geo-referenced occurrences (i.e., latitude, longitude) to identify relationships between a species' occurrence and its environment. The environmental data can include multiple remote sensing and other spatial layers. Application-specific variables and distribution model inputs such as distance to roads, water, and edge can be calculated in a GIS environment to describe proximity to disturbance or important resources (Osborne et al. 2001). Maxent is a machine learning method developed for modelling the spatial distribution of species; that the resulting habitat suitability map expresses the suitability of each grid cell as a function of the environmental variables at that grid cell (Phillips et al. 2006).

Vast numbers of studies regarding LULC change have been conducted, but more research is needed regarding the impact of LULC change particularly when these changes occur inside the potential habitats of endangered species. To date, there have been no studies that have evaluated the capability of remote sensing change detection and habitat modelling techniques to evaluate brown bear habitat degradation in the region. Therefore, the present study proposes a new approach for investigating LULC changes inside the potential habitats of the species by integrating remote sensing data and SDM. This framework provides valuable information on brown bear habitat and would help the managers to detect changes and implement required conservation recovery plans. This approach can be applied to an extensive range of the species and help the planners to predict potential habitats where should be prioritized for conservation and protected from degradation. The objectives of this paper consist of four main aspects: (1) predicting potential habitats and spatial distribution of brown bear, (2) determining dominant environmental variables influencing species distribution, (3) assessing LULC change from 1990 to 2017 and its impact on brown bear habitat in a part of the Zagros forests in Kurdistan Province, and (4) finally proposing a methodological framework to help planners implement species-specific habitat conservation and restoration programs.

Materials and methods

Study area and species data

The study area includes oak-dominated Zagros forests in the north west of Iran's Kurdistan Province (Fig. 1) located along the border with Iraq (latitude 34° 44′ to 36° 30′ N, longitude 45° 31′ to 44° 16′ E), occupying about 6320 km^2 of the province. Average precipitation of Kurdistan Province accounts for 517 mm with maximum precipitation of 990 mm in the west of the province and average temperature varies from 7 to 14 °C (Hanafi and Hatammi 2013). The altitude varies from 740 to 3161 m (Sharifi et al. 2009). The main watercourse is the Sirwan River that runs through Shaho-Kosalan protected habitat and impound by the Daryan Dam in the south of the study area. This embankment dam was constructed in 2018 with a vast catchment area of about 3135 km^2 and storage capacity of 316 million cubic meters for irrigation and hydropower generation (Chomani and Bijnens 2016; Muhammad Faraj and Zaidan 2020). The Zagros forests in this region have been degrading in the result of population growth, urbanization, agricultural activities, underdevelopment, and the locals' dependence on forests (Henareh Khalyani and Mayer 2013; Taghimollaei
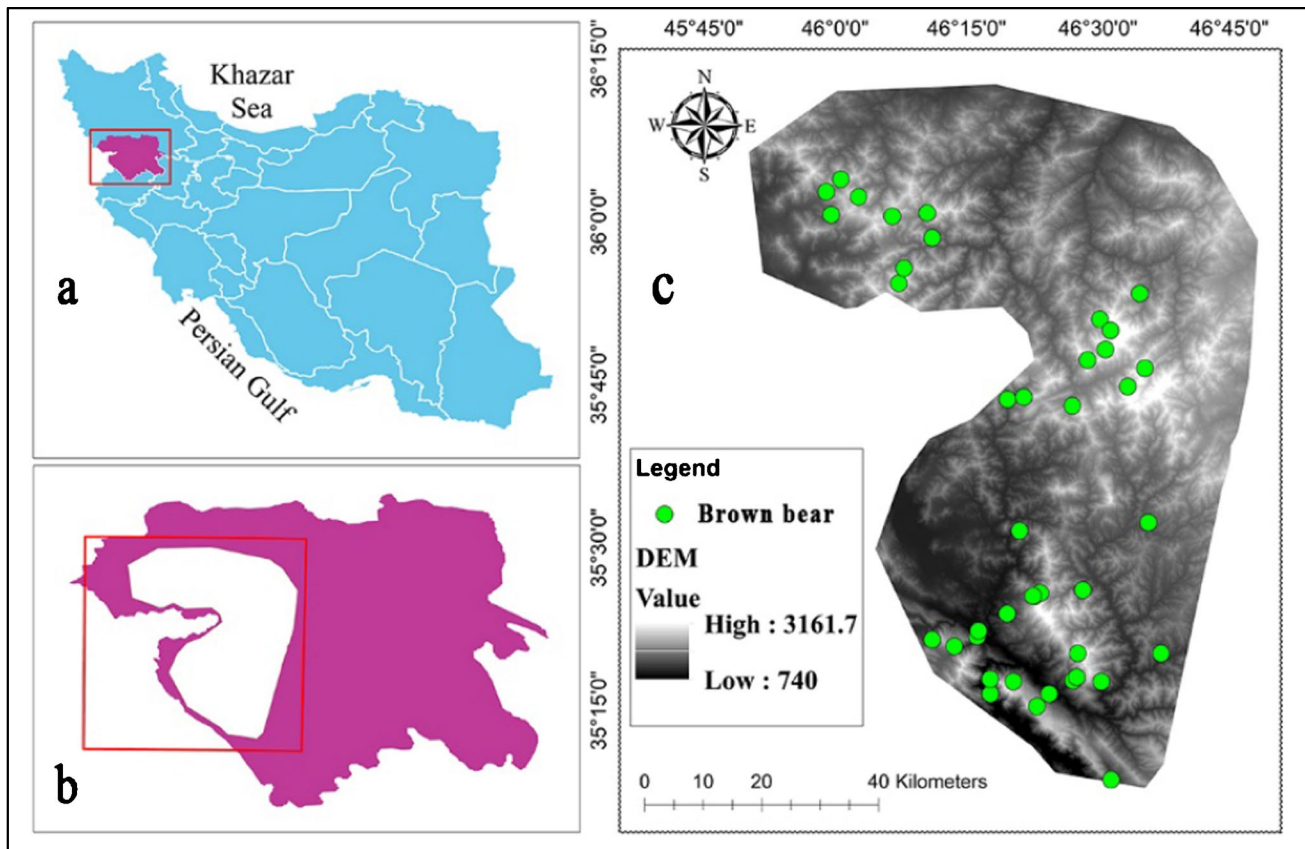
Fig. 1 Location of the study area: (**a**) Iran, (**b**) Kurdistan Province, and (**c**) study area. Occurrence records of brown bear are shown on the map of the study area with green circles

2019). During 1972–2009, approximately 353, 000 ha (69%) of the Zagros forests were converted, mainly through deforestation, into agricultural lands due to increased demand for agricultural products (Henareh Khalyani et al. 2013).

Brown bears are an opportunistic omnivores, and food resources especially plant seeds availability have a vital role in their distribution (Hwang et al. 2010) and gaining required fat for hibernation (Garcia-Rodriguez et al. 2021). Brown bears are an important disperser of seeds because they can consume large quantities of different plant and fruit species and often range over considerable distances, distributing seeds in their scat far from the source. Moreover, seed passage through brown bear digestive tracts and the composition of their scat are known to affect germination rates to some degree (Garcia-Rodriguez et al. 2021; Karimi et al. 2018). Plant dispersal is crucial to maintaining plant community dynamics, especially in the current context of rapid environmental changes such as LULC change and landscape fragmentation (Lalleroni et al. 2017).

A database of 40 independent records of brown bear occurrences (with minimum separation distance of 1 km) within the study area that consists of direct observations and damage records to livestock, beehives, and crops caused by the brown bear was used. These occurrences were based on official reports of Iranian Department of Environment (DoE) which include direct observation, signs, damages to properties, and reports received from local villagers (i.e., 18 records over the years 1990 to 2017). As per Zeller et al. (2011), valuable local community information about regional wildlife was obtained by interviewing villagers and local non-governmental organization (NGO) representatives, and eight more records were obtained, mainly including damage to properties. From this local information, areas with higher probability of brown bear occurrence were selected, and eleven more occurrence records were gathered using signs of the species presence (paw print and scat). An additional three records were collected from existing scientific literature and researchers (Almasieh et al. 2019).

Environmental data

Environmental layers were divided into four sections including bioclimatic variables, normalized difference vegetation index (NDVI), physiographic variables, and anthropogenic factors. Bioclimatic variables, including eleven temperature and eight precipitation factors, were acquired from the

WorldClim database (Version2, http://www.worldclim.org/bioclim.html). This database consists of 19 global gridded climatic variables interpolated based on data derived from climatic stations across the world. This dataset created from average monthly temperature and precipitation measurement and include annual trends, seasonal trends, and extreme or limiting environmental factors at 30 arcsec spatial resolution (Hijmans et al. 2005) (Table 1).

NDVI was another variable that was exploited to full advantage in the modelling and obtained from USGS products (Eq. 1):

$$NDVI = (NIR - R)/(NIR + R) \tag{1}$$

where *NIR* is the near infrared band reflectance and *R* is the red band reflectance. NDVI values range from − 1.0 to +1.0 indicating amount of vegetation on the land surface and help to distinguish green vegetation from bare soils and are commonly used in SDM (Feilhauer et al. 2012; Peterson et al. 2011). As a continuous variable, NDVI is more informative compared to categorical variables (Peterson et al. 2011), and in different studies, this variable is reported as a determining factor in distribution of brown bear (Farashi et al. 2016; Falahati et al. 2020; Kouchali et al. 2019).

Physiographic data encompass elevation, slope, and distance to nearest river and anthropogenic factors including distance to nearest village and to nearest road. The digital elevation model (DEM) data was extracted from advanced spaceborne thermal emission and reflection radiometer (ASTER) and used to generate slope and elevation. The 1.25000 topography map of the study area was also employed to calculate distance to nearest village, road, and river. The layers were finally resampled to 1 km resolution to be utilized in the modelling process.

Table 1 Environmental variables used in Maxent model for mapping suitable habitats of brown bear

Type of variables	Environmental variable	Source/Reference
Bioclimatic	Bio1 = annual mean temperature	WorldClim
	Bio2 = mean diurnal range (mean of monthly (max temp - min temp))	WorldClim
	Bio3 = isothermality (Bio2/Bio7)	WorldClim
	Bio4 = temperature seasonality (standard deviation ×100)	WorldClim
	Bio5 = max temperature of warmest month	WorldClim
	Bio6 = min temperature of coldest month	WorldClim
	Bio7 = temperature annual range (Bio5-Bio6)	WorldClim
	Bio8 = mean temperature of wettest quarter	WorldClim
	Bio9 = mean temperature of driest quarter	WorldClim
	Bio10 = mean temperature of warmest quarter	WorldClim
	Bio11 = mean temperature of coldest quarter	WorldClim
	Bio12 = annual precipitation	WorldClim
	Bio13 = precipitation of wettest month	WorldClim
	Bio14 = precipitation of driest month	WorldClim
	Bio15 = Precipitation Seasonality (coefficient of variation)	WorldClim
	Bio16 = precipitation of wettest quarter	WorldClim
	Bio17 = precipitation of driest quarter	WorldClim
	Bio18 = precipitation of warmest quarter	WorldClim
	Bio19 = precipitation of coldest quarter	WorldClim
Physiographic	Elevation (m)	Advanced spaceborne thermal emission and reflection radiometer (ASTER) DEM data
	Slope	Advanced spaceborne thermal emission and reflection radiometer (ASTER) DEM data
	Distance to river (m)	1/25000 topographic map
NDVI	*NDVI*	US Geological Survey (USGS)
Anthropogenic	Distance to road (m)	1/25000 topographic map
	Distance to village (m)	1/25000 topographic map

Variables employed in the final model are *highlighted*

Landsat imagery with its moderate spatial resolution (30 m) is a source of satellite data that has been used extensively for long-term monitoring purposes (Jafari 2007). For our study, cloud free Landsat 5 (TM) and Landsat 8 (OLI) imagery (US Geological Survey), were employed for detecting changes from 1990 to 2017, respectively.

Image analysis

For preparation of required data for mapping LULC change and for distribution modelling of brown bear, the following procedures were performed: Image to image registration was used for geometric calibration in which the 2017 OLI image was used as the reference image and the 1990 TM Landsat image as the raw image. This procedure was done by using 30 control points distributed evenly in the images and with a root mean square error of 0.026. Atmospheric corrections were applied to the images using the FLAASH (fast line-of-sight atmospheric analysis of hypercubes) modelling tool. According to the metadata, clear condition was set for visibility value (weather condition) of the images. Considering that the study area is a mountainous region, topographic correction was applied to the images with the help of ATCORE software.

The objective of image classification is to create cluster classes from multispectral satellite imagery. Using field data, aerial images, false color composite (FCC), and Google Earth, training areas were selected, and images were classified using the support vector machine (SVM) algorithm (Cortes and Vapnik 1995). After the classification process finished, a 3×3 majority filter was applied to the classified images for reducing salt and pepper effects.

The process of classification accuracy test was implemented by a stratified random sampling method as follows: (1) 350 samples distributing into seven land use classes (water, urban, agriculture, forest, range, rocky, and bareland) for each of the satellite images were collected from field surveys and a published land use map by department of environment (DoE); (2) after selecting samples, geographically corresponding sites were checked in the two-time classification images according to geographical coordinates; (3) correctly classified pixels were picked and counted; and (4) finally, the number of correctly classified pixels was compared with that of samples in each LULC. Overall accuracy (Dellepiane and Smith 1999) and Kappa coefficient (Foody 1992) were used to assess the accuracy of the classification. Overall accuracy and Kappa coefficient were computed as Eqs. 2 and 3, respectively.

$$OA = 1/N \left(\sum Pii \right) \tag{2}$$

where N is number of the training pixels and *Pii* is number of the correctly classified pixels.

$$K = (OA - 1/q)(1 - 1/q) \tag{3}$$

where *OA* is overall accuracy and q is number of the incorrectly classified pixels.

Change detection and mapping require classified images from at least two time periods and are possible only if changes in the surface phenomena of interest result in detectable differences in image radiance or emittance (Lunetta et al. 2002). To obtain the information of LULC conversion, post-classification was carried out using the classification image of 1990 which was defined as the "initial state" image and 2017 which was defined as the "final state" image. Through this procedure, matrix of LULC, and new change image classification which indicated the changes "from" and "to" that took place were acquired.

Maximum entropy model

In this study, Maxent algorithm was used because, first, only occurrence records of the species are required (Elith et al. 2010); second, it is widely used in applied ecological studies by government agencies and research organizations; third, it has been shown to perform well in comparison to several other models when there are few presence records available (Elith and Leathwick 2009); and finally, the resulting probability distributions are easy to analyze.

In Maxent, over fitting can be avoided by using regularization, and it is very robust at detailed scales (Phillips et al. 2006). The performance of the model was assessed using the area under the curve (AUC) metric of the receiving operator characteristic (ROC) curve (Phillips et al. 2006) which is available within Maxent software. An AUC value of 0.5 or less indicates model predictions that are not better or worse than random; values between 0.5 and 0.70 indicate poor performance; and values increasing from 0.70 to 1.0 indicate progressively higher performance (West et al. 2016).

Response curves of the species to environmental variables were also generated by Maxent. These response curves represent how the probability of predicted presence of the species changes as each environmental variable varies, while all other variables are set to their average value. Besides, Maxent estimates the environmental variables' contributions to the SDM by "percent contribution".

For running Maxent, it is necessary to prepare the ecological relevant data as input. Projections, grid cell size, and spatial extent were manipulated to ensure consistency across all layers. All maps were projected to Lambert conformal conic (WGS84 datum) with a grid cell size of one kilometer. Variable selection is one of the important parts of SDMs such as Maxent due to its substantial influence on the model outputs (Amiri et al. 2020). Three scenarios, that represent the three common approaches to variable selection, were ran for the species using different sets of predictor variables to

obtain important variables and a potential distribution map with the highest accuracy. In the first scenario only bioclimatic variables, in the second scenario physiographic, NDVI and anthropogenic variables, and in the third scenario all the variables were considered. Initially, complete (full) model with all variables in each scenario was ran, and variables with more than 5% contribution to the preliminary models were selected. Then, correlation analysis was implemented among the selected variables to exclude the highly correlated ones. The second (reduced) model was ran with these effective uncorrelated variables (Chunco et al. 2013).

The predicted suitability map was classified into four probability classes to interpret easily as follows: class 0–0.25, 0.25–0.5, 0.5–0.75, and 0.75–1 representing unsuitable, marginally suitable, moderately suitable, and highly suitable habitats, respectively. Habitats with maximum suitability of 0.75–1 were converted to a vector file and then to shapefile for further analysis. Finally, LULC change inside the shapefile was assessed as brown bear habitat degradation.

Results

LULC mapping

The LULC classes and their spatial distribution derived from the analysis of Landsat imagery of 1990 and 2017 for the study area are shown in Fig. 2, and the area of each LULC in hectare is given in Table 2. Figure 2 and Table 2 illustrate that in 2017 land occupied predominantly by range LULC with 483, 604 ha following by forest, agriculture, bareland, water,

Table 2 Area of the classes in the classified images of 1990 and 2017 in hectare (ha)

LULC	Area (ha) 1990	Area (ha) 2017
Water	2077	3607
Urban	811	2521
Agriculture	44134	41759
Forest	98335	94939
Range	484064	483604
Rocky	471	471
Bareland	1965	4953

urban, and rocky. New water bodies on the 2017 image represent constructed dams during the timeframe due to increasing demands of drinking water and electricity. Moreover, the development of cities is noticeable and implies population growth. Rocky is the class with the lowest area of 471 ha and remained constant during the studied period (Table 2).

The overall accuracy of the Landsat-derived LULC maps by SVM algorithm for TM 1990 was 83.71% and that of 2017 was 86%, and the Kappa coefficients were 0.81 and 0.83, respectively. Accuracy of the classification is categorized as perfect based on scale of Landis and Koch (1977). Kappa coefficients represent the difference between actual agreement and the agreement that is contributed by chance. In the present study, Kappa coefficient of 0.81 and 0.83 implied 81% and 83% more accurate classification than random assignment of classes, respectively.

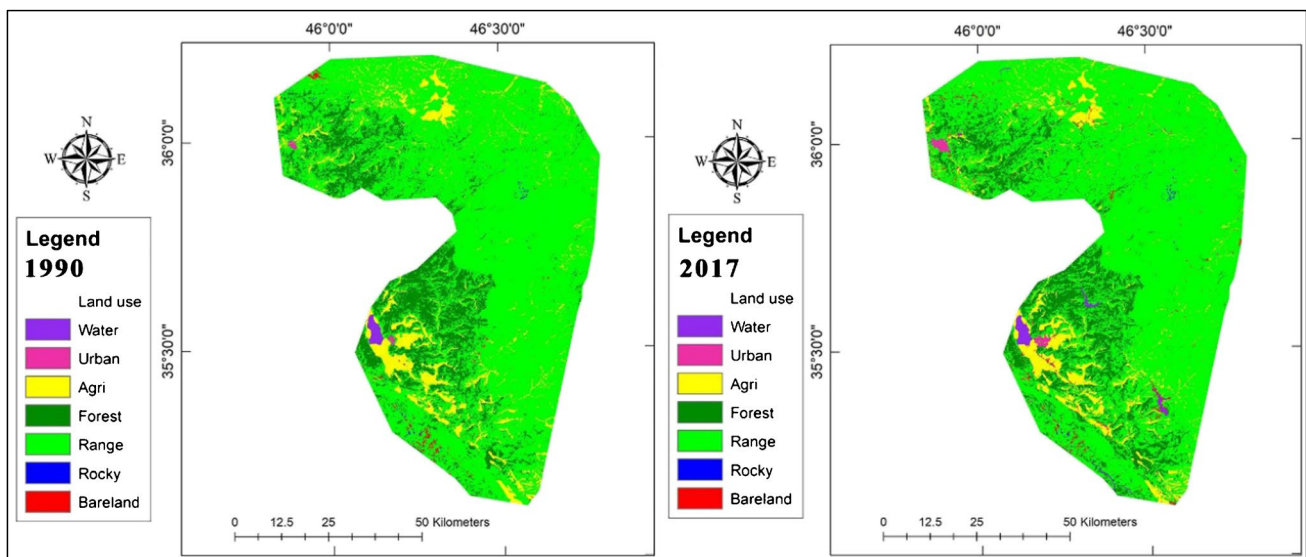Table 3 summarizes losses and gains for each LULC classes as a change detection matrix. This matrix lists

Fig. 2 (Left) LULC map derived from 1990 Landsat TM image. (Right) LULC map derived from 2017 Landsat OLI image classified by SVM classification algorithm

LULC of 1990 image in the columns and LULC of 2017 image in the rows. Unchanged pixels are along the major diagonal of the matrix. According to this change detection matrix in 2017, the area of water surfaces had an increase of about 1531 ha, mainly resulting from construction of three dams (Azad, Daryan, and Garan) in the study area. As it is clearly visible from the classified maps, a significant change occurred in the residential and urban area which increased 1710 ha that could be because of the development and urbanization in cities. At the same time, agricultural lands significantly reduced for 2376 ha changing to barelands, residential area, and sink below the constructed dams. Area under forest conversion to other LULC accounts for 3395 ha.

Rows and columns represent the categories for 2017 and 1990, respectively. Unchanged pixels are along the major diagonal of the matrix. Negative and positive values indicate decrease and increase in area of LULC over studied time, respectively

Figure 3 is a post-classification map representing change (color) and without change (black) in LULC in the study area from 1990 to 2017. As it could be found from the map, the majority of the changes happened along the forests in the Zagros Mountain Range in the west of the study area that could be attributed to higher population concentration in comparison with the eastern and northeastern parts of the study area.

Table 3 Summary of LULC changes from 1990 to 2017

1990								
	Class	Water	Urban	Agriculture	Forest	Range	Rocky	Bareland
2017	Water	**2053**	0	269	207.7	1074.6	0	2.7
	Urban	0.1	**741**	927	209.6	626	0	17.2
	Agriculture	21.8	16	**30979**	168.5	9029.7	0	30.1
	Forest	0	0	1284	**69725**	23818.7	0	111.3
	Range	0.5	33	10050	25606	**446838.7**	0	1073.4
	Rocky	0	0	0	0	0	**471.2**	0
	Bareland	1.1	20.6	621	904.5	2675	0	**731**
	Overall changes	+ 1531	+ 1710	− 2376	− 3395	− 460	0	+2988

Example: Water changes = (2017) − (1990) = (269 + 207.7 +1 074.6 + 2.7) − (0.1 + 21.8 + 0.5 + 1.1) ≅ + 1531

Fig. 3 Change detection map among different LULC from 1990 to 2017 obtained by post-classification method. Areas experiencing no change is represented in black and other LULC changes are indicated in other colors
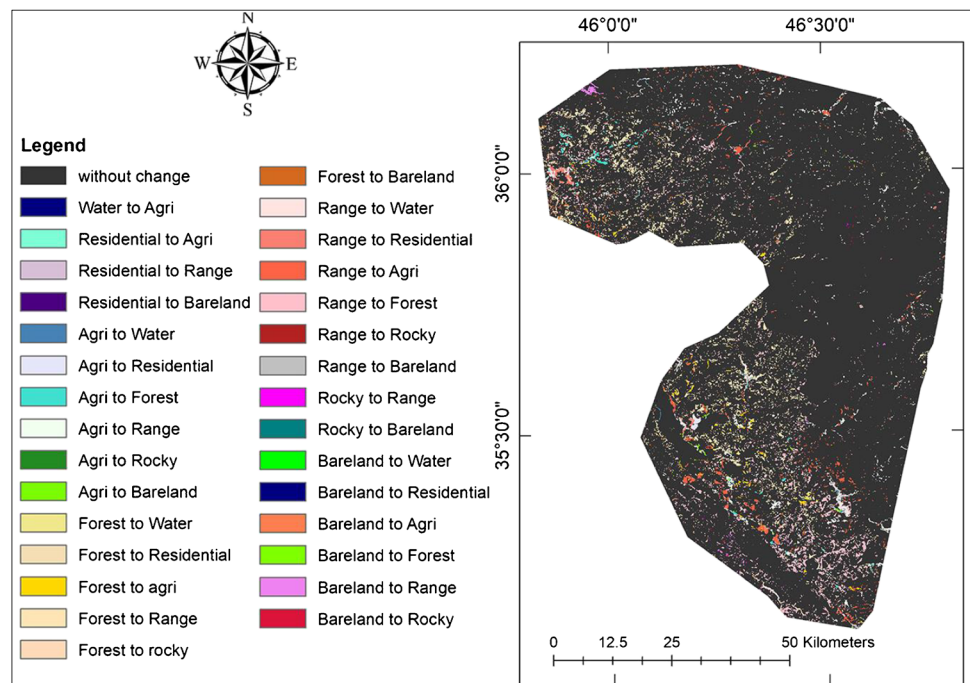
Potential habitat distribution of brown bear

Results of the potential habitat modelling of the species under three different scenarios are discussed below. Under scenario I, full model of the species distribution using all bioclimatic variables was ran, and variables of Bio2, Bio16, Bio8, and Bio7 showed contribution percentage larger than 5% (Appendix Table 8). A significant correlation was observed between the variables Bio2 and Bio7 (Appendix Table 10), and considering the lower contribution of Bio7, this variable was removed, and reduced model was ran using Bio2, Bio16, and Bio8. Under scenario II, full distribution modelling of the species using physiographic, anthropogenic variables and NDVI was implemented. Elevation, slope, distance to nearest villages, and NDVI had more than 5% contribution rate (Appendix Table 9). Based on statistical analysis, there was no significant correlation among these variables (Appendix Table 11), and reduced modelling was ran using these four variables. Under scenario III, complete distribution modelling of the species was executed using geo-environmental (physiographic, anthropogenic, and NDVI) variables in addition to bioclimatic variables. Six variables including Bio2, Bio16, slope, NDVI, and Bio7, and distance to nearest villages considering higher contribution rate of the prediction were selected as the most influential variables (Table 4). There was a meaningful correlation between Bio2 and Bio7 (Appendix Table 12). Due to lower contribution rate of Bio7, this variable was eliminated and reduced model with rest of the five uncorrelated variables was implemented.

Scenario I in which only bioclimatic variables were employed had a higher predictive ability in proportion to the modelling under the scenario II. Acceptable prediction accuracy implies effectiveness of bioclimatic variables in brown bear habitat distribution. AUC value of the reduced model under scenario II is more significant than the random forecast of 0.5 (training AUC = 0.78) but lower than the AUC values obtained from running other scenarios. As we expected modelling, the potential distribution of the species using all the environmental variables under the scenario III showed the highest accuracy of 0.84 and reflected the effectiveness of using geo-environmental variables used in addition to bioclimatic variables only in the modelling. Despite reliable predictive power indicated by all the scenarios modelling, the potential distribution of the species and further analysis are performed under scenario III. Table 5 represents the most important variables in determining the species habitat suitability as well as AUC values obtained in each scenario. Maxent modelling had a good performance in identification of favorable habitats and important factors influencing habitat of the species.

Response curves showed the quantitative relationship between the probability of the species occurrence and environmental variables. Response curves of the species to variables contributing most to the model prediction under scenario III are analyzed and are indicated in Fig. 4. Bioclimatic variables had highest contribution rate of the prediction model under this scenario. It can be understood from response curves analysis that (1) the most suitable habitats are regions with mean diurnal range of fewer than 11.5 °C; (2) maximum and minimum probability of occurrence is at precipitation of 390 mm and below 220 mm, respectively, during the wettest quarter that could be explained by the optimum vegetation coverage; (3) NDVI has a positive impact on occurrence of the species and level of the probability of presence increases in higher NDVI that may be because of food availability; (4) brown bear individuals are more likely to be observed around the villages where adequate food resources could be found; and (5) a significant increment in suitability of brown bear habitat is observed when slope increased and suitability reached the maximum value in 30 degree and stabilized in the greater slopes.

Potential habitats of the species modelled in scenario III are classified and indicated graphically in Fig. 5. The suitability of the habitats ranges from 0 (minimum suitability) represented in blue to 1 (maximum suitability) represented in purple. Favorable habitats are mainly distributed along the lands with vegetation cover, especially oak forests and high-quality rangelands. In eastern and northeastern parts

Table 4 Percent contribution of each environmental variable in the bear distribution modelling under scenario III

Variable	Percent contribution	Variable	Percent contribution
Bio2	**37.2**	Bio4	1.5
Bio6	**16.1**	River-dis	1.4
Slope	**11.1**	Bio3	1
NDVI	**7.9**	Bio17	0.8
Bio7	**7.4**	Bio12	0.7
Village-dis	**5.4**	Bio15	0.6
Bio8	3.8	Bio14	0.6
Road-dis	2.3	Bio11	0.3
DEM	2	Bio5/Bio6/Bio19/Bio18/ Bio13/Bio10/Bio9/Bio1	0

Variables with more than 5% contribution are highlighted

Table 5 Environmental variables used as input in the reduced modelling and AUC values obtained under each scenario

Scenario	Environmental variables	AUC
I	Bio2, Bio16, Bio8	0.80
II	Elevation, slope, distance to villages, NDVI	0.78
III	Bio2, Bio16, NDVI, distance to villages, slope	0.84

Fig. 4 Response curves of the probability of presence to important variables (Bio2, Bio16, NDVI, distance to nearest village, slope) under the scenario III. *Y* axis represents the species occurrence probability, and *X* axis represents the value of environmental variable
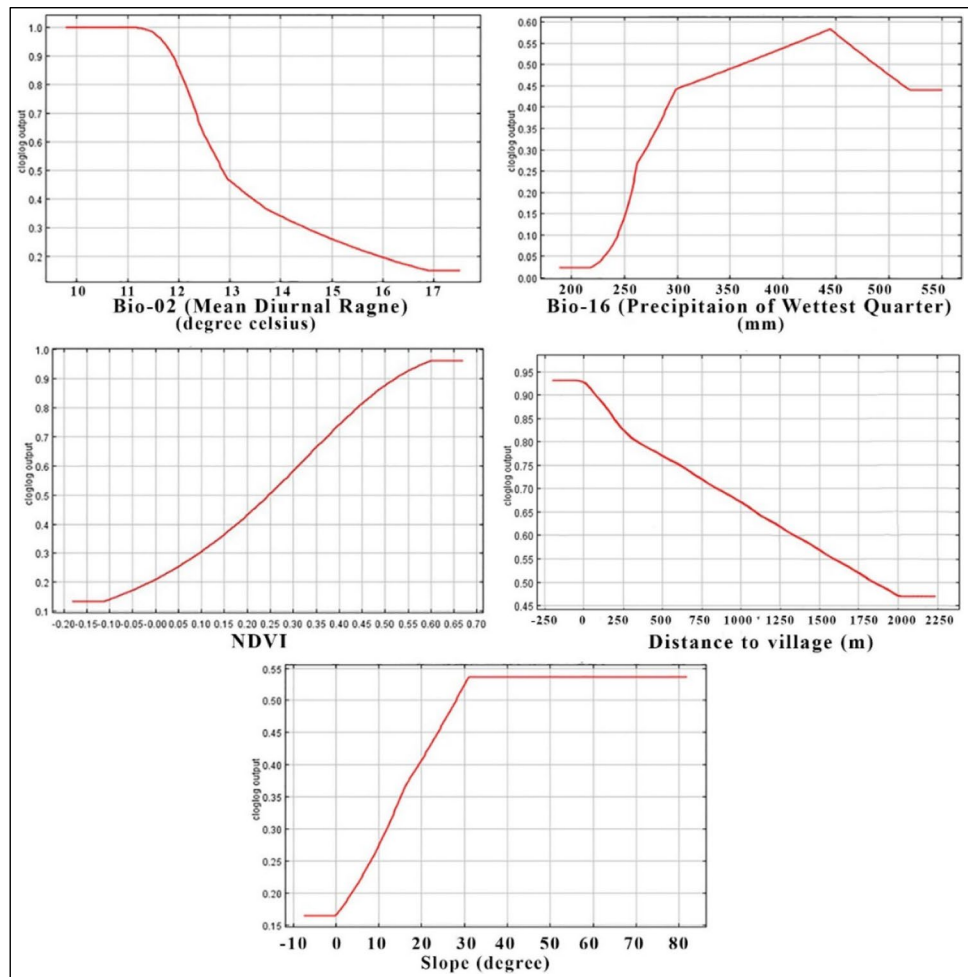
of the study area, suitability of the habitat decreases due to land flatness and poor vegetation cover.

The area and percentage of each suitability class are measured and are given in Table 6. As seen in the Fig. 5 and Table 6, only 9.1% of the study area could be considered as highly suitable habitat, followed by moderately suitable habitat (11.6%) and marginally suitable habitat (29.3%). The greatest percentage of approximately 50% of the study area was classified as unsuitable habitat.

LULC change within the potential habitats of brown bear

Highly suitable habitats covered an area of 57, 949 ha out of 631, 844 ha. Integrating the species distribution map with the LULC change map led us to a LULC change map within the potential habitats of the species and loss of suitable habitat map (Fig. 6). It highlighted the LULC change that occurred to the detriment of potential habitats of the species.

According to analyses of the matrix of LULC within potential habitats (Table 7), it could be found that (1) an increase of 123 ha in the area of water surfaces is the result

of the lake of Daryan Dam where construction has taken place at the expense of irreversible losses of 4.32 ha and 89.82 ha of the forest and rangelands, respectively; (2) the largest LULC trajectory was seen in the conversion from forest to rangeland, so that 3774 ha of forest is transformed to range resulting in deforestation; (3) residential area indicated an expansion of more than 10 ha and because of population growth and LULC change from range, agricultural, and forest; (4) bareland surfaces had a rise of 46 ha in the year 2017 which could be explained by agricultural lands abandonment and range and forest degradation; (5) area of 3.5 and 55.9 ha of the forest land cover has altered to urban and agricultural lands, respectively; and (6) significant area of 1586 ha of forests within the potential habitat were changed to other LULC.

Discussion

The Zagros forests in the study area are home to a rich biodiversity including brown bear. Recently, these forests have been subjected to intense human influence, and

Fig. 5 Percentage probability of occurrence for brown bear modelled under scenario III pooled in four classes and expressed in different colors shown in the legend
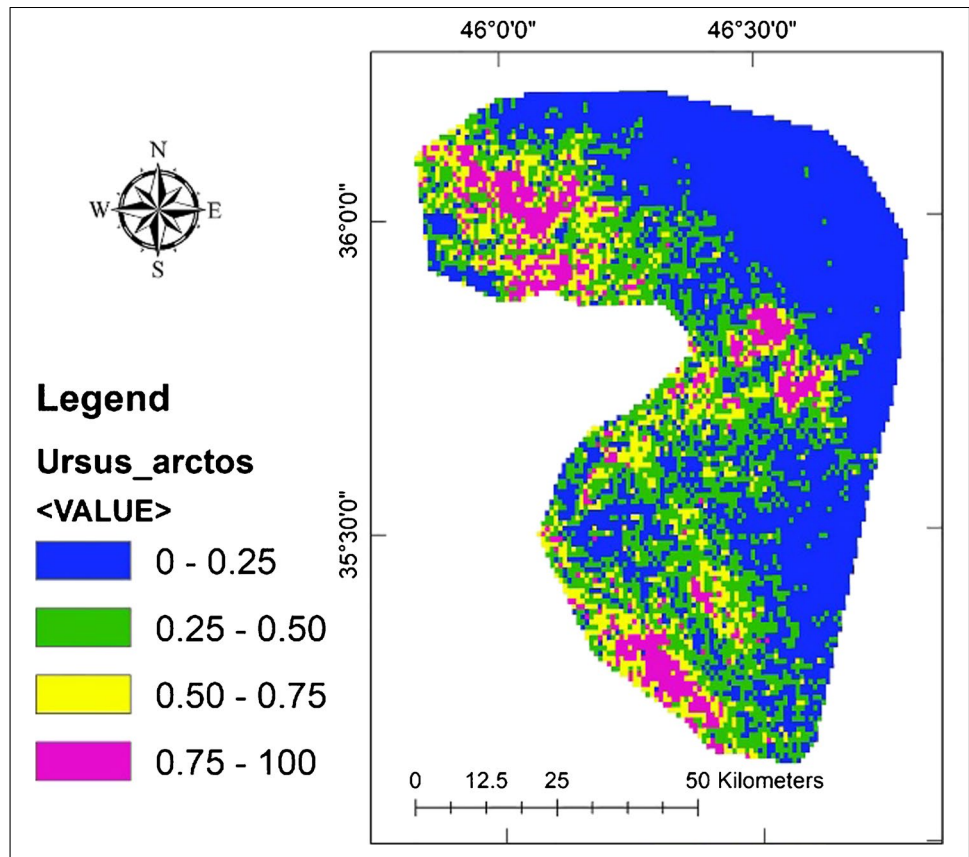

Table 6 Extent of different habitat suitability classes for brown bear and area of each class based on hectare (ha) and percentage

Class	Area (ha)	percentage	Suitability
0–0.25	315, 251	49.9%	Unsuitable
0.25–0.5	185, 129	29.3%	Marginally suitable
0.5–0.75	73, 515	11.6%	Moderately suitable
0.75–1	57, 949	9.1%	Highly suitable

consequently, their species are affected. In this study and in order to highlight the habitat condition of brown bear, SDM and remote sensing were employed to investigate the effect of LULC change on brown bear habitat. LULC change assessment during 1990 to 2017 within the potential habitat revealed a remarkable decline in forest land use which is in line with previous results of Rahimi (2013) and Sadeghi et al. (2017). Population growth and resulting expansion in anthropogenic activities are the driving factors that have led to deforestation and losses of vital ecosystem goods and services. Over the study period, three dams were constructed in

Fig. 6 Suitable habitats (left) integrated with LULC change from 1990 to 2017 (middle) = LULC change within potential habitats of brown bear from 1990 to 2017 (right)
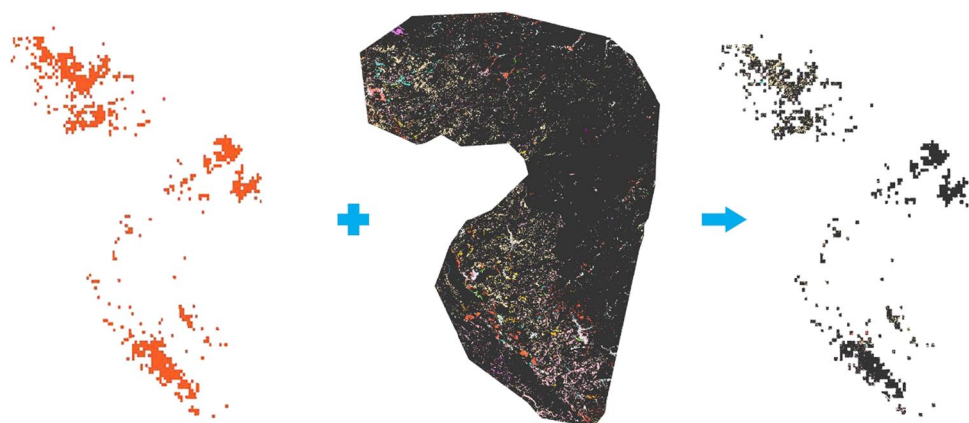
Table 7 LULC change matrix within potential habitats from 1990 to 2017 (in ha)

	1990							
	Class	Water	Urban	Agriculture	Forest	Range	Rocky	Bareland
2017	Water	-	0	29.25	4.32	89.82	0	0
	Urban	0	-	3.6	3.51	7.11	0	0.72
	Agriculture	0	4.41	-	55.98	44.55	0	0
	Forest	0	0	354.6	-	1963.98	0	11.7
	Range	0	0	266.58	3774.69	-	0	161.91
	Rocky	0	0	0	0	0	-	0
	Bareland	0	0	27.99	76.05	115.29	0	-
	Overall changes	+ 123.39	10.53+	− 577.08	− 1586.43	+ 2008.71	0	+ 46.67

Rows and columns represent the categories for 2017 and 1990, respectively. Negative and positive values indicate decrease and increase in area of LULC within potential habitats over the timeframe, respectively

which one of them (Daryan Dam) was built inside the potential habitat of the species. This dam has been one of the most controversial plans that has met with numerous protests from environmentalists mainly because of relocations of local communities and ecological impacts (Chomani and Bijnens 2016; Hassaniyan 2020). Furthermore, the lake of Daryan Dam not only submerged tens of hectares of range and forest and food resources inside, but cut the corridor of one of the habitats (Shaho-Kosalan) in the study area and fragmented it into smaller patches. Suitable habitat fragmentation for bear that has a large area requirement is more destructive than habitat loss (Swenson et al. 2000). During the dam construction, many hundreds of years old trees were cut down (Amini 2020), and several villages were also submerged, and local villagers who lost housing land were displaced and resettled to new settlements built on higher lands which in turn leads to further destruction (Chomani and Bijnens 2016; Farzi 2018). LULC change induced habitat fragmentation may adversely influence dispersal ability of the large mammals and hinders them to shift their ranges in response to climate change (Robillard et al. 2015). Decline in brown bear dispersal ability caused by habitat fragmentation can translate into adverse effects on plant seed dispersal. Karimi et al. (2018) stated that any degradation in brown bear habitat or decline in the population of this species may translate into problems in natural regeneration of the plants.

Results of the modelling illustrated that geo-environmental variable utilization in the model enhanced mean accuracy statistics as pointed out also by Elith and Leathwick (2009) and Zimmermann et al. (2007). The results also showed that protected and no-hunting regions in the study area such as Shaho-Kosalan and Chehel Cheshmeh regions are highly suitable for the species. Analysis of LULC change within the potential habitats (combining species distribution map and LULC change map) proved that protected and no-hunting regions have been adversely affected by humans over the timeframe.

Weather, and in particular high temperature, likely has a strong effect on activity levels and daily activity patterns of mammals (Speakman and Król 2010; Schwartz et al. 2010; Vieira et al. 2010). Based on response curves, our results indicated that there is an increase in population of the species when exposed to the mean diurnal range of fewer than 11.5 °C. Kamaei (2013) observed that the most favorable monthly mean temperature for brown bear is 12 °C and less. We also found that as precipitation of the wettest quarter increases, ecological suitability rises for the species that corroborates results of Su et al. (2018). Brown bear shows a strong preference for vegetated lands, and there is a strong positive relationship between brown bear probability of presence and NDVI. Kouchali et al. (2019) and Falahati et al. (2020) modelled spatial distribution of brown bear in the Alborz and Zagros forests, respectively, and pointed out that the species prefers regions with higher NDVI that would be related to omnivorous nature of brown bear. The response curve of brown bear to distance to nearest villages showed that maximum presence of the species is observed in the vicinity of the villages. Kouchali et al. (2019) study showed a similar result; however, the study conducted by Almasieh et al. (2019) in the Zagros forest along the Iran-Iraq border indicated a direct relationship between brown bear habitat suitability and distance to nearest villages which is against present study results. This could be explained by employing the occurrence records in or around the villages in the present study. Habitat loss triggered by forest degradation and land cover change leads to natural bear food sources become insufficient and makes bears search for human foods like garbage, fruit trees, livestock, and bee yards (Yousefi 2016). Attraction to anthropogenic food brings brown bears into more frequent contact with people, leading to a higher probability of human-bear conflicts. Brown bear is considered dangerous to humans and their livestock, and any contact with human could result in attacks on humans, damage to human belongings and agricultural products,

and preying on livestock and domestic animals (Can et al. 2014). According to Karami et al. (2015), brown bear poaching occurs in Iran mostly in response to human-bear conflict.

In the study area, the maximum habitat suitability observed at slopes greater than 30 degree. In the words of Almasieh et al. (2019) and Kouchali et al. (2019), brown bear prefers steep slopes for its safety and better nesting. Other variables such as annual precipitation and annual mean temperature had low percentage contribution and were insignificant in modelling, possibly because of their low variation over the study area. In general, we found that potential habitats of brown bear have been affected by population growth and LULC changes and that the combination of modelling and remote sensing techniques is a practical tool for assessing habitat loss and degradation and can be used for other species, too.

Conclusions

This study demonstrated that integrating Maxent species distribution model and remote sensing image classification is a practical approach in predicting habitat suitability of brown bear and assessing habitat changes and degradation over time. Conservation of the Zagros forests is highly important as they have a critical importance for wildlife and human and encompass slow-growing trees that need years to become mature. Anthropogenic interventions and most importantly the conversion of natural lands and dam construction were the main reasons behind species habitat loss and isolation. There should be more study of dam site selection by considering possible degradation to endangered species potential habitats. Brown bear and oak trees have mutualistic relationships, in which brown bear is provided with ecological requirements like food sources and shelter and in exchange brown bear contributes in dispersal of plant seeds and forests' regeneration. This relationship becomes more vital when both forests and brown bear are threatened by LULC change and deforestation. These characteristics make brown bear an ecologically important agent of dispersing fertilized seeds in degraded oak forests and finally an essential part of reforestation efforts. So considering the indispensable role of brown bear in the Zagros ecosystem, especially in the regions experiencing rapid environmental changes, it is very important to plan conservation programs and implement conservation treatment for this species. Overall, the approach presented here provides a clear methodological pathway to better understanding of how LULC changes influence species suitable habitat during a specified timeframe. This approach can be simply used for assessing habitat condition of a large variety of species, helping conservation and restoration programs.

Appendix

Table 8 Percent contribution of variables under scenario I

Variables	Percent contribution
Bio2	**55.1**
Bio16	**24.1**
Bio8	**5.9**
Bio7	**5.2**
Bio4	2.7
Bio11	2.1
Bio13	0.9
Bio3	0.8
Bio10	0.7
Bio15	0.6
Bio14	0.5
Bio12	0.5
Bio17	0.5
Bio5	0.3
Bio9	0.1
Bio19	0
Bio18	0
Bio6	0
Bio1	0

Variables included in the reduced model are **highlighted**

Table 9 Percent contribution of variables under scenario II

Variables	Percent contribution
DEM	**45.4**
Slope	**25.9**
NDVI	**18.7**
Village-dis	**5.3**
Road-dis	3.1
River-dis	2

Variables included in the reduced model are **highlighted**

Table 10 Variables correlation matrix under scenario I

	Bio2	Bio16	Bio8	**Bio7**
Bio2	1	0.18	0.12	**0.94**
Bio16	0.18	1	− 0.17	0.18
Bio8	0.12	− 0.17	1	0.07
Bio7	**0.94**	0.18	0.07	1

Highly correlated variables are **highlighted**

Table 11 Variables correlation matrix under scenario II

	DEM	Village-dis	NDVI	Slope
DEM	1	0.54	− 0.01	0.23
Village-dis	0.54	1	0.01	0.13
NDVI	− 0.01	0.01	1	− 0.007
Slope	0.23	0.13	− 0.007	1

Highly correlated variables are **highlighted**

Table 12 Variables correlation matrix under scenario III

	Bio2	NDVI	Slope	Bio16	**Bio7**	Village-dis
Bio2	1	− 0.14	− 0.23	0.18	**0.94**	− 0.45
NDVI	− 0.14	1	0	0.24	− 0.13	0.01
Slope	− 0.23	0	1	− 0.08	− 0.22	0.13
Bio16	0.18	0.24	− 0.08	1	0.18	− 0.26
Bio7	**0.94**	− 0.13	− 0.22	0.18	1	− 0.49
Village-dis	− 0.45	0.01	0.13	− 0.26	− 0.49	1

Highly correlated variables are **highlighted**

Declarations

Conflict of interest The authors declare no competing interests.

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