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Original Articles

Integrated Coastal-Terrestrial Conservation Planning for landscape-scale reserve design in Southeastern Iran

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ABSTRACT

Natural habitats of Southeastern Iran are threatened by both natural and anthropogenic pressures such as long-term drought, dust storms, and land use change. Surveys on habitat suitability of vulnerable species and integration of protected areas have raised alarm over potential species extinction and geographical isolation of populations. Reducing the threats of human activities on sensitive terrestrial and coastal ecosystems requires integrated planning and management of terrestrial and coastal protected areas, however many of these areas have been selected and managed independently. Selecting coastal protected areas network require a systematic conservation planning approach, to reduce the development impacts on sensitive habitats. Therefore, this study aimed to identify an optimized integrative network of terrestrial and coastal protected areas in southeast Iran. An attempt was made to maximize biodiversity conservation, reduce the isolation of populations, and increase the resilience of the region's natural habitats to new development plans by including coastal habitats meeting the requirements of key species. Firstly, suitable habitats for seven key species were simulated by Species Distribution Models (SDMs) performed via Generalized Linear Model (GLM), Generalized Boosted Model (GBM), Random Forest (RF), and Maximum Entropy (MaxEnt) models fitted with 20 ecological and anthropogenic variables. A habitat suitability map was produced by integrating the SDM-derived habitat suitability maps with the suitable extents identified for egg-laying green sea turtle and potential habitat for aquatic and semi-aquatic birds. An attempt was then made for selecting new terrestrial and coastal protected areas using the simulated annealing algorithm under six scenarios. All SDMs exhibited promising performances in predicting the distribution of suitable habitats with AUC values of above 0.8 and the discrimination power of GBM and RF was higher than that of the other SDMs. In total, more than 34 percent of the study area, along the coastline, was categorized as sensitive or extremely sensitive habitat. An east-west habitat corridor presently unprotected playing an important role in connecting habitats needs to be safeguarded to maintain regional biodiversity. Moreover, our study revealed that the majority of suitable habitats with high potential for sensitive species are not currently protected by the existing protected area network.

1. Introduction

Coastal environments are a combination of terrestrial ecosystems and fresh and marine waters and due to the exchange of materials, energy and organisms between them, are viewed as a model of open ecosystems (Reiners and Driese, 2001; Stoms et al., 2005). Protected area networks in land and sea are usually designed independently regardless of their interaction (Beck, 2003; Stoms et al., 2005), however reducing the threats of human activities for sensitive terrestrial and coastal ecosystems requires integrated planning and management of terrestrial and coastal protected areas (Álvarez-Romero et al., 2015).

Biodiversity hotspots are not only characterized by supporting the largest number of species, but may also be prone to high risk of extinction (Myers et al., 2000). The first step to slow down biodiversity loss is to identify species-rich and sensitive areas and assess the interactions among species and their influence on each other's spatial distribution (Margules et al., 2002; Myers et al., 2000). However, many sensitive biodiversity-rich regions remained unknown due to inaccessibility and sampling difficulties (Ficetola et al., 2013). A considerable body of research has shown that the current protected areas often do not properly represent the biodiversity and therefore may not be in line with the global conservation objectives (Maiorano et al.,

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2006).

Species Distribution Models (SDMs) or Habitat Suitability Models (HSMs) are based on the both species' distribution pattern and natural and anthropogenic characteristics of the environment. Further they have notable implications for identifying contributing factors to biodiversity, assessing the effects of human development on wildlife distribution and establishing conservation priorities, even when limited data are available (Guisan et al., 2013). These models are widely utilized to characterize ecological niches such as fundamental (potential), realized (actual) niches (Rotenberry et al., 2006) and climate niches. A species distribution model, when applied to the environmental variable maps, predicts the species potential distribution range (probability of occurrence at a location) and the resulting map has been termed ecological response surfaces (Lenihan, 1993), bio-geographical models of species distribution (Hirzel et al., 2006), spatial prediction of species distribution, prediction maps (Franklin, 2010), occurrence prediction (Rushton et al., 2004) or predictive distribution maps (Rodríguez et al., 2007).

Various techniques have been developed to model the species distribution pattern. However, each of these methods relies on a specific algorithm and, although some of them follow similar methodologies, gives different results in terms of performance and species distribution prediction (Elith et al., 2006; Tsoar et al., 2007). These models have been employed in a variety of fields including multi-species habitat suitability modeling (Fithian et al., 2015), past climate changes by modeling the habitat suitability of fossils (Gavin et al., 2014) and even continental-scale modeling of habitat suitability (Petitpierre et al., 2017). In Iran, habitat suitability modeling has been carried out mostly for big species such as wild goat *Capra aegagrus* (Esfandabad et al., 2010; Sarhangzadeh et al., 2013), leopard *Panthera pardus* (Erfanian et al., 2013; Farhadinia et al., 2015), wild sheep *Ovis orientalis* (Bashari and Hemami, 2013), and gray wolf *Canis lupus* (Ahmadi et al., 2013).

Natural habitats and local fauna, in general, increasingly are under the effects of structural pressures such as poaching, habitat fragmentation (Makki et al., 2013) and noise pollution (Madadi et al., 2014) through new roads and the other developmental activities. But, Arid and semi-arid regions in the southeast of Iran suffer from a lack of knowledge about their biodiversity because of their remoteness and security issues. Southeastern Iran has experienced very low levels of socio-economic development due to a lack of arable lands, fresh water and security issues. Additionally, the strategic geoeconomic situation of the region with significant commercial marine routes has led to largely uncontrolled development of large-scale industries potentially affecting the region's biodiversity and its highly sensitive habitats. Moreover, small populations and the secretive habits of some of the involved species may cause additional problems with monitoring and conservation (Brito et al., 2009).

Identification of sensitive habitats that may face adverse developments in near future may help conservation planning. In the past, the majority of protected areas have been chosen based on traditional methods and without considering ecological planning concepts (Mehri, 2012). New methods include site selection, designation and management of protected areas in such a way that they fully represent the region's biodiversity (Ardron et al., 2008). Optimal and heuristic algorithms are two examples of artificial intelligence-based algorithms which have been widely used to systematically select protected areas. Optimal and heuristic algorithms are designed based on mathematical processes and decision trees, respectively (Mehri et al., 2014). Marxan model (Ball and Possingham, 2000; Watts et al., 2009) has been utilized for systematic conservation in marine ecosystems (Göke et al., 2018; Jumin et al., 2017), fresh water ecosystems (Witt and Hammill, 2018), management of irrigated agricultural lands (Henriques et al., 2017), introduction of new protected areas proportional to the distribution of vulnerable species (Dehaghi et al., 2018), development and implementation of conservation policies (Gibson et al., 2017), and evaluation of the effectiveness of the current protected area network (Momeni Dehaghi et al., 2013).

The main aim of this study is to integrate conservation planning of terrestrial and coastal areas. In order to reach this objective, the following steps are undertaken: 1) habitat suitability modeling and ecological niche mapping for focal species in the study region, 2) identifying sensitive animal specie's habitats, 3) designing conservation scenarios, and 4) selecting optimal protection sites using simulated annealing algorithm under different conservation scenarios.

2. Material and methods

2.1. Study area

The study area of this research encompasses two basins in the southeast of Iran including South of Sistan and Baloochestan province in the east and East of Hormozgan province in the west where is called Mokran region. The region spans over 25° 04′–28° 30′ N longitude and 55° 58′–63° 12′ E latitude with an area of 9,434,040 ha. The region is characterized by vast deserts lying between the Oman Sea in the south and Hirmand highlands (with a maximum elevation of 3600 m above sea level) in the north. From a climatic point of view, this region is heavily influenced by erratic autumn and winter precipitation induced by Monsoon systems from the Indian Ocean. This region is located at the intersection of three biogeographical realms: Palearctic, Ethiopian, and Oriental realms and characterized by varying elevation gradients, providing a diversity of habitats for various wildlife species. Moreover, central deserts have acted as barrier for species between the highlands in the north and the coastal areas in the south. In total, 8% of the area is protected in seven separate areas. Four of these are located along the coast and the remaining three in the in-land (Fig. 1).

2.2. Focal species selection

The sensitive-species approach by focusing on large-sized threatened and vulnerable species across the Mokran region, such as the endangered Persian leopard (*Panther pardus saxicolor*) and the vulnerable Asian black bear (*Ursus thibetanus*), Wild goat (*Capra aegagrus)*, Wild sheep (*Ovis orientalis)*, Chinkar (*Gazella bennettii*), Macqueen's bustard (*Chlamydotis macqueenii*), and Mugger crocodile (*Crocodylus palustris)* was based on extensive contemporary literature review and library research (IUCN, 2018; Karami et al., 2016; Moradi, 2016; Ziaie, 2008) We recorded geographical coordinates of the species' presence points with the help of environmental guards and experts of the Iranian Department of Environment (DoE). Table 1 shows the name of the species and the number of presence points collected during field investigation.

2.3. Environmental variables

Ten variables related to land use/cover (LULC), human presence and topography were selected for habitat suitability mapping. Five LULC classes including agriculture (rainfed and irrigated agricultural lands and fruit tree areas), low-density rangeland (vegetation canopy cover of 2–25%), grassland and shrubland (shrubs with a canopy cover of more than 10%), bare land (desert areas, sand dunes and salinized lands), and stream (un-vegetated river bed areas) were extracted from an updated LULC map of the study area at the scale of 1:50,000 from Iranian Forests, Rangelands and Watershed Organization (FRWO, 2015). Rural density per unit area, distance to cities and road network density were used as the human-presence variables. Two topographical variables, elevation and roughness were also taken into account. The Aster Digital Elevation Model (DEM) map (NASA, 2015) was used as the elevation variable. Roughness (also known as ruggedness), as an indicator of topographical complexity, was produced from DEM layer. Due to the large extent of the study region and for convenient spatial analysis, all data layers were provided at pixel resolution of 2.5 km.

Fig. 1. The layout of the study area, southeast of Iran.

Table 1
Species selected for identification of sensitive animal habitats and habitat suitability mapping.

Name	Scientific name	Conservation Status	Number of presence points
Asian Black Bear	*Ursus thibetanus*	Vulnerable	35
Persian leopard	*Panthera pardus saxicolor*	Endangered	30
Wild Goat	*Capra aegagrus*	Vulnerable	33
Wild Sheep	*Ovis orientalis*	Vulnerable	38
Chinkara	*Gazella bennettii*	Vulnerable	30
Macqueen's bustard	*Chlamydotis macqueenii*	Vulnerable	27
Mugger crocodile	*Crocodylus palustris*	Vulnerable	13

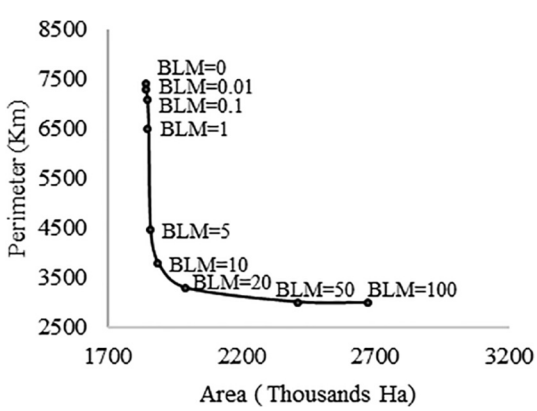

Fig. 2. The perimeter-to-area graph resulted from running the model under different BLM values.

In this study, habitat suitability mapping for Mugger crocodile was carried out using a different set of environmental variables and in a small geographical extent because this species has different habitat and ecological requirements than the other study species (Moradi, 2016) and is exclusively found in Sarbaz River network in Bahookalat Protected Area (southeastern Iran). Environmental variables for Mugger crocodile habitat suitability mapping were: distance to permanent rivers, the river flow accumulation map, surface slope, and rural area density per unit area. The flow accumulation map shows the amount of water that flows into each cell (Erdogan et al., 2007), enabling to identify which part of the river contains the highest volume of water according to surface roughness and upstream water flow. This map was produced by analyzing the DEM layer using Flow Accumulation (Magesh et al., 2012) tool embedded in the Hydrological toolset of ArcGIS 10.3.1.

Most birds of the study area live in coastal or freshwater habitats and are dependent on mangrove forests. Hence, an attempt was also made to identify sensitive bird resources in coastal wetlands, mangrove forests, and other important areas to aquatic and semiaquatic bird species. These species are mostly located around mangrove forests and, in this study, were considered to be within 5-km buffer zones around mangrove forests.

Mokran coastline also provides suitable habitats for sea turtle species, especially Green sea turtle (*Chelonia mydas*). In this research, six sites were identified as the nesting areas for Green sea turtle. In order to recognize sensitive turtle resources, special attention was given to the nest-site fidelity behavior of the egg-laying Green sea turtles (Miller, 1997). In this study, suitable habitats for Green sea turtle were considered to be within the potential fidelity extent of the existing nesting stations (i.e. a mean of 8 km along the coastline and 1 km towards the inner lands).

Strong correlation between variables may lead to statistical biases and incorrect predictions (Franklin, 2010). Hence, collinearity between environmental variables was assessed prior to habitat suitability modeling. Because any pair of variables showed a large correlation (above

Table 2
Different scenarios based on the potential suitable habitat for each species.

Species									
Scenario	Black Bear	MQ bustard	Chinkara	Leopard	Wild Goat	Wild Sheep	Mugger crocodile	Green sea turtle	Mangrove
I	25%	25%	25%	25%	25%	25%	25%	25%	25%
II	30%	20%	20%	30%	20%	20%	30%	30%	30%
III	30%	20%	20%	30%	20%	20%	30%	100%	100%
IV	50%	25%	25%	50%	25%	25%	50%	50%	50%
V	50%	25%	25%	50%	25%	25%	50%	100%	100%
VI	50%	50%	50%	50%	50%	50%	50%	50%	50%

0.6), all of the variables were used for the following analyses. In addition to the field-collected presence points, a large number of pseudo-absence or background points (5000) was generated for each species using Hawth Analysis Tools (Beyer, 2004) in ArcGIS 10.3.1 and used for model development and evaluation.

2.4. Habitat suitability modeling

In this study, one regression-based technique, Generalized Linear Model (GLM), and three machine learning techniques including maximum entropy (MaxEnt), Generalized Boosted Model (GBM or Boosted Regression Models (BRT)) and random forest (RF), embedded in the R package "Biomod"(Thuiller et al., 2009), were utilized to predict the probability of occurrence for the study species. To fit best model in GLM, simple and quadratic terms and stepwise selection procedure based on Akaike Information Criteria (AIC) were used. GBM set to allow up to 2500 trees, and we set the learning rate to 0.001 and the bag fraction to 0.5. For MaxEnt, all feature types (linear, quadratic, product, threshold and hinge) were allowed and a maximum iteration of 200 was used. RF was tuned up to 1000 trees and node size was set to 5.

The area under curve (AUC) of the receiver operating characteristic (ROC), as a threshold-independent measure, was used to evaluate the predictive accuracy of the models. In order to overcome the limitations arising from these models and achieve the most accurate results, the model results were assembled according to their mean weights into an ensemble prediction map (Araújo and New, 2007; Marmion et al., 2009). The weight attributed to each model was based on the results of ROC-AUC. Moreover, the True Skill Statistic (TSS) was utilized for classification accuracy assessment. Because classification accuracy indices are dependent upon defining suitability threshold, the minimum habitat suitability value predicted at the location of presence points was considered as the lowest suitability threshold.

2.5. Vulnerability assessment

The presence probability values estimated for each species (i.e. the values of the species habitat suitability maps) were first transformed with a fuzzy model using a favorability function proposed by Real et al. (2006). Favorability has two important advantages respect to suitability. Firstly, favorability is independent of prevalence while habitat suitability models may use species presence points in sink habitats, where environmental conditions are unfavorable, and accordingly may identify some unfavorable areas as suitable. Secondly, this function provides the same threshold of favorability for all species, allowing direct comparison and integration of the species' distribution maps. Eq. (1) shows the fuzzy favorability function (Real et al., 2006):

$$F = \frac{\frac{p}{(1-p)}}{\frac{n_1}{n_0} + \frac{p}{(1-p)}} \tag{1}$$

In this equation, F is favorability of species presence, p is the probability of species presence derived from the ensemble prediction, n_1 and n_0 are the numbers of the species presence and absence points, respectively. The final vulnerability map was produced by integrating the fuzzified favorability maps with the threatened level of the species through Eq. (2) (Estrada et al., 2008)

$$FVul_j = \sum_{i=1}^{n} (V_i \times F_{ij}) \tag{2}$$

where $FVul_j$ is the fuzzified vulnerability at point (pixel) j, V_i is the weight or threatened level of the species i and F_{ij} is the favorability value measured for the species i at point (pixel) j. According to the species status in the IUCN's list of threatened species and their national importance, a V_i value of 8 was assigned to leopard, black bear and Mugger crocodile and a value of 4 was attributed to vulnerable species including Wild goat, Wild sheep, Chinkara and MQ bustard. The most important biodiversity regions of the study area were finally delineated by integrating the fuzzified suitable terrestrial and coastal habitats (5-km buffer zones around mangrove habitats and 8-km buffer zones around the Green sea turtle's egg-laying stations). The fuzzified map of sensitive terrestrial habitats was classified into four classes: low sensitive (sensitivity values from 0 to 0.5), moderately sensitive (sensitivity values from 0.5 to 2), highly sensitive (sensitivity values from 2 to 8) and extremely sensitive (sensitivity values above 8). The threshold of the low sensitivity class (0.5) was assigned based on the mean minimum of the predicted suitability values at the location of species presence points.

2.6. Selection of new protected areas

The Marxan model was utilized to prioritize and select protected areasto generate alternative configurations of protected patches that achieved our objectives for conservation while minimizing the costs.

Various techniques are embedded in Marxan, among which the simulated annealing (SA) has been widely adopted due to its higher computational speed and performance in solving complex problems and simultaneous assessment of multiple objectives and costs than other exploratory techniques (Mehri et al., 2014; Pressey, 2002). Hence, with respect to the large extent of the study area and the large number of the study species, this technique was used in this study to identify new protected areas. This technique requires a planning unit layer and the species' distribution layers in Boolean format (1 = species presence and 0 = species absence). Due to the arid nature of the study area and the homogeneity of the vegetation cover, a hexagonal map with the hex length of 4 km was selected as the planning unit layer (Game and Grantham, 2008). Moreover, an optional cost layer was also introduced to the algorithm to ignore hexagons containing urban and industrial areas and large-scale piers during the process of selecting protected area and also make a random selection between the remaining units.

The Boundary Length Modifier (BLM) is one of the most important parameters of this model which controls the level of compactness and fragmentation of the proposed protected area network (Mehri et al., 2014). Higher BLM values minimize the finial boundary length of the proposed protected area network. In order to assign an optimal BLM value, the model was performed by changing the BLM values and

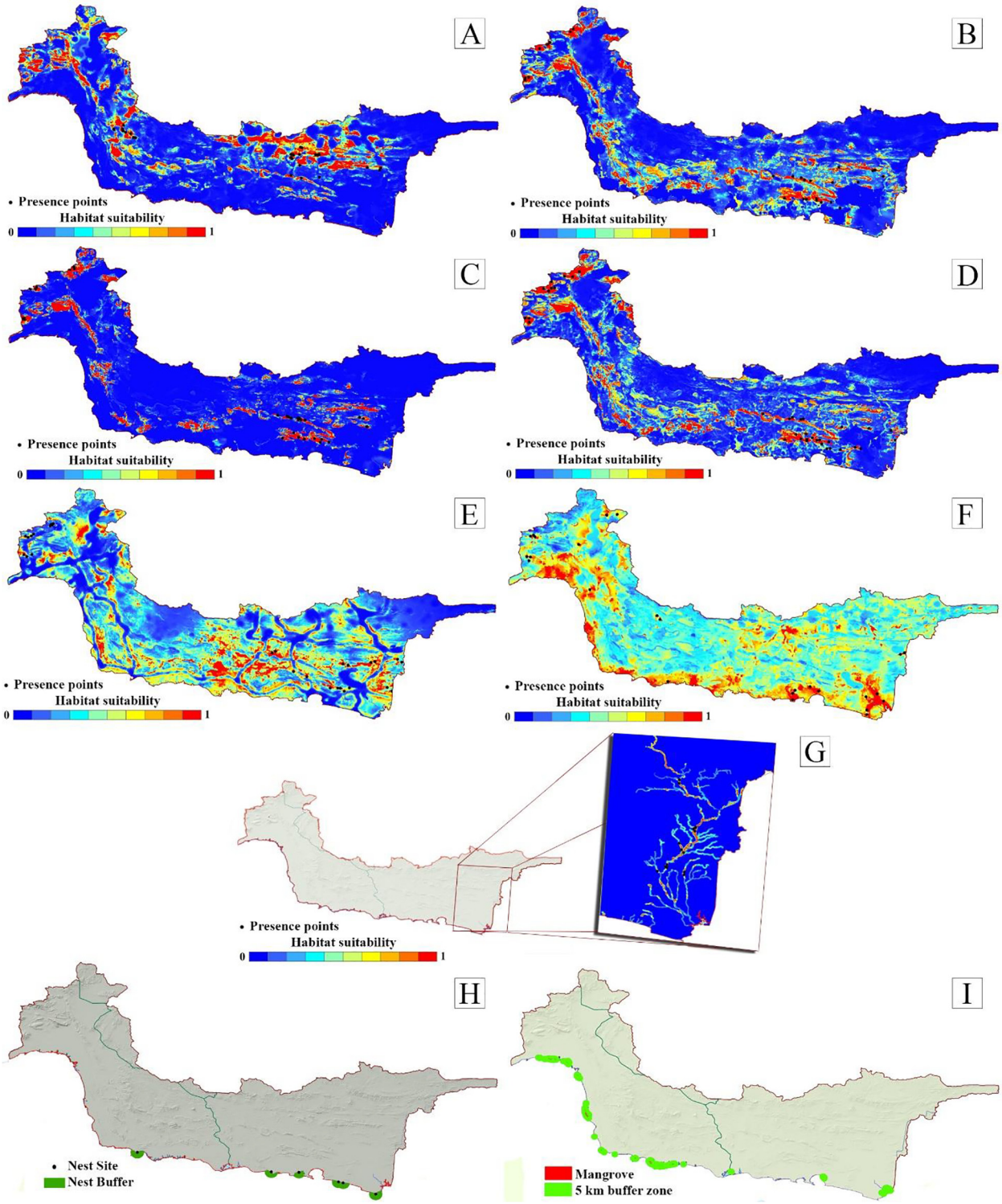

Fig. 3. The habitat suitability maps for Asian Black Bear (A), Persian leopard (B), Wild goat (C), Wild sheep (D), Chinkara (E), Macqueen's bustard (F) and Mugger crocodile (G) as well as the suitable habitat areas identified for egg-laying turtle (H) and aquatic and semi-aquatic birds (I).

holding the other variables as constant. The resulting perimeter-to-area ratios were then graphed (Fig. 2) and its turning-point value (BLM of 10) was used through modeling processes.

The study species were divided into three categories due to their national conservation importance. MQ bustard, Chinkara, Wild goat and Wild sheep fell into one category due to their vulnerable status (Table 1). The second category contained leopard, as an Endangered species, and black bear and Mugger crocodile, due to their limited habitats only in this part of Iran. Sea turtle and other mangrove-dependent species were included in the third category. The third group of species received the highest level of conservation importance due to their restricted distribution range in some parts of coastline areas. According to this classification scheme, six scenarios were designed to prioritize the selected protected areas in which each scenario differs in terms of the protection percentage of various habitats ranging from 20 to 100%. These scenarios are presented in Table 2.

Table 3
Predictive performance of the habitat suitability models in predicting sensitive habitat area in Mokran region.

Species	Model	AUC	TSS
Asian Black Bear	GLM	0.94	0.763
	GBM	0.989	0.961
	RF	0.980	1
	MaxEnt	0.95	0.753
Persian leopard	GLM	0.934	0.735
	GBM	0.995	0.982
	RF	1	1
	MaxEnt	0.956	0.798
Wild Goat	GLM	0.979	0.921
	GBM	0.995	0.982
	RF	0.996	1
	MaxEnt	0.951	0.842
Wild Sheep	GLM	0.917	0.752
	GBM	0.989	0.98
	RF	1	0.985
	MaxEnt	0.939	0.752
Chinkara	GLM	0.81	0.62
	GBM	0.99	0.974
	RF	1	1
	MaxEnt	0.878	0.673
MQ bustard	GLM	0.71	0.612
	GBM	0.92	0.98
	RF	0.962	1
	MaxEnt	0.881	0.688
Mugger crocodile	GLM	0.988	0.982
	GBM	0.995	0.982
	RF	1	0.997
	MaxEnt	0.981	0.935

Table 4
The mean importance of environmental and anthropogenic variables over 10 replications and four SDMs used for habitat suitability modeling of each species.

Variables						
Species	Asian Asian Black Bear	Persian leopard	Wild Goat	Wild Sheep	Chinkara	MQ bustard
Agriculture	0.013	0.015	0.015	0.015	0.016	0.051
DEM	0.210	0.221	0.221	0.221	0.222	0.244
Stream	0.003	0.071	0.071	0.071	0.071	0.251
Rangeland	0.098	0.080	0.355	0.305	0.355	0.182
Road network density	0.058	0.205	0.205	0.205	0.204	0.126
Roughness	0.532	0.554	0.554	0.554	0.553	0.213
Bare land	0.016	0.018	0.018	0.018	0.018	0.200
Distance to city	0.289	0.365	0.365	0.365	0.363	0.295
Rural density	0.232	0.211	0.211	0.211	0.212	0.263
Grassland and shrubland	0.038	0.030	0.030	0.030	0.030	0.046

Table 5
The mean importance of variables over 10 replications and four SDMs used for habitat suitability modeling of Mugger crocodile.

Variables				
Species	Water flow accumulation	Slop	Distance to rivers	Rural density
Mugger crocodile	0.341	0.365	0.419	0.13

The scenarios show that the protection percentage is generally increasing from scenario I to VI. Scenarios I and VI were set to 25 and 50%, respectively, to all species. Setting percentage of protection equal to all species in these two scenarios, allowed us to ensure that protected patches are placed on the most suitable land and with optimum landscape configuration.

In scenarios II and IV, the higher protection percentage are given to large-sized endangered and vulnerable species (Persian leopard, Asian black bear, Mugger crocodile), Green turtle nesting habitats, and mangrove forests. In scenarios III and V, 100% protection is given to the small habitat patches (Green turtles nesting habitats, and mangrove forests). The maps of spatial solutions across scenarios and the total area allocated to protection per scenario were compared. Finally, a set of class-level landscape metrics including coverage of total study area (%), Area (ha), Total Edge (m), Total Core Area, Total Core Area Index, Mean Core Area, Mean Nearest Neighbor Distance, Edge Density, Mean Patch Size and Number of Patches was used to investigate the spatial pattern of the new protected areas such as their composition (non-spatial characteristics of the selected patches) and spatial configuration (spatial agreement of the selected patches).

3. Results

The habitat suitability maps of threatened and vulnerable animal species and the suitable areas identified for egg-laying green sea turtle and aquatic and semi-aquatic birds are represented in Fig. 3. The largest area of suitable habitat was found for MQ's bustard (Fig. 3F) and for Chinkara (Fig. 3E), respectively, and Mugger crocodile was found to have the smallest suitable habitat area limited to the river bed areas (Fig. 3G). The mean AUC and TSS values of 10 replicates of each model are represented in Table 3. All models showed promising performances in predicting the distribution of suitable habitats with mean AUC values of above 0.8 (except for the GLM, with a mean AUC of 0.71 in predicting the habitat suitability of Macqueen's bustard) and TSS values of above 0.6.

In general, the results showed that the discrimination power of the decision tree-based machine learning techniques (GBM and RF) in separating presence points from background points is higher than that of the other techniques. The higher discrimination power or AUC values obtained by these models led to the identification of highly suitable small habitat areas which are significantly different from other parts of the region.

The importance of every variable with less than 10 replications of each model was calculated using BIOMOD. The mean importance of each variable for each model is shown in Table 4. Distance from cities and rural area density were the most important variables for MQ bustard while the importance of roughness was highest for the other species studied. In general, distance to cities was the second most important variable after roughness. The importance of each variable to Mugger crocodile is shown in Table 5. Due to high dependency of this species to rivers, distance to river was to be most important. Slope and water flow accumulation were the next most important variables, respectively, to Mugger crocodile. The results of integrating all habitat suitability maps into an overall vulnerability map showed that the most important sensitive biodiversity areas are distributed in rugged areas of the south of Sistan and Baloochestan Province, parallel to the coastline (Fig. 4). Moreover, in the western parts of the study area within the boundary of Hormzgan Province, some interconnected suitable habitat patches were identified as having the potential of providing high-quality habitat for the region's species in terms of both area and connectivity, especially east-west habitat corridor that ran parallel to the coastline (Fig. 4). The results of the classified vulnerability map showed that 34.28 percent (32,887 km^2) of the study area falls into the high sensitive and extremely sensitive habitat classes (Table 6). In general, the largest portion of the region (34.67%) has a moderate sensitivity followed by low sensitivity areas with a coverage of 33.14% of the total

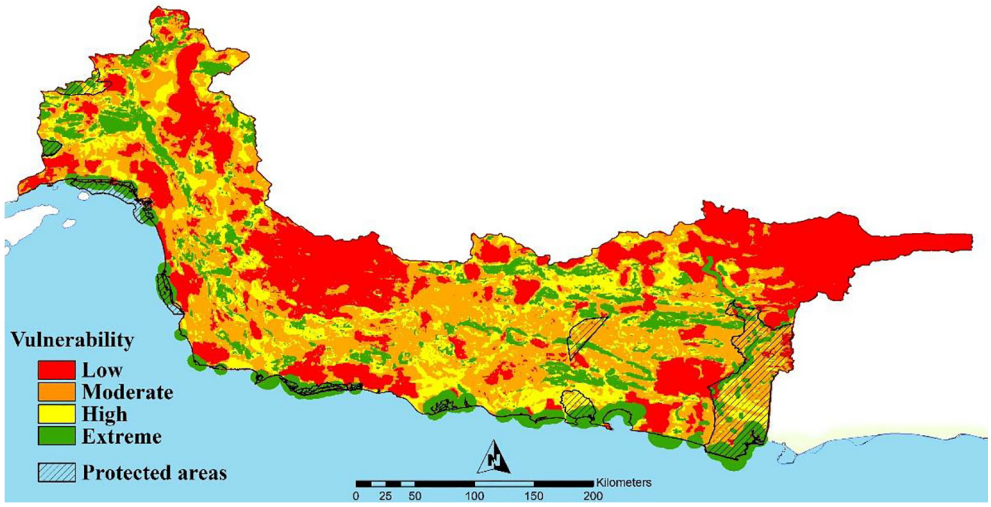

Fig. 4. The distribution pattern of sensitive animal habitats and the current protected area network of the Mokran region.

Table 6
Area and percentage of habitat sensitivity classes.

Vulnerability	Area (Km^2)	Coverage of total study area (%)
Low	31795.75	33.14
Moderate	33257.75	34.67
High	18429.64	19.21
Extreme	14457.37	15.07

area of the region.

Marxan produces two maps for each scenario (12 maps for 6 scenarios); one of them shows the number of times in which a planning unit is selected through 100 replicates and the other map represents the areas proposed by the scenario. According to the results of Marxan (Table 7 and Fig. 5), from Scenario I to VI, the area of the protected patches increased. The largest area and the smallest boundary length were yielded under the scenario VI, while scenario V showed the maximum boundary length. Scenarios with equal percentage protection for all species (scenario VI and I) had relatively lower boundary length. Similar results were noticed for the distance to the nearest patches, in which the highest mean distance between patches was observed for scenario VI and the lowest was observed for scenario IV and V.

Scenario VI and V obtained the largest Total Core Area and Total Core Area Index values, respectively. The Mean Core Area Index under scenario VI obtained a significantly larger value than that obtained under the other scenarios. Scenario VI showed the minimum Edge Density and Number of Patch values, while the largest values were obtained for scenario II, under which the SA algorithm was forced to select smaller patches with a lower freedom than under the other scenarios such as scenario I and VI.

The protected areas identified in this study were also prioritized using Marxan model. As shown in Fig. 5, the main west-east corridor in the study area was frequently prioritized across multiple model replicates, however due to its lower suitability values than other patches, the fact that 10 percent of the region is currently under protection and the tendency of model to locate new patches around the existing protected areas, this corridor was not recognized as an optimum protection area. However, with the increase in the percentage protection level from scenario I to VI, the east-west corridor was more visibly displayed among the selected patches. Under scenario IV, a relatively large and distinct area was selected in the central north part of the study area. The size of this his patch shrunk under scenario V and becoming smallest under scenario II. This patch was selected due to higher weights of leopard and black bear in these scenarios, but had completely disappeared under scenarios with similar weights.

4. Discussion

The results showed that in the current protected area network on the final habitat suitability map, it was seen that only a small portion of high and very high sensitive regions are now being protected by the current protected area network which are mostly distributed along the coastline. Nonetheless, the majority of highly suitable regions have been missed from protection by conservation plans.

The limited number of presence points due to inaccessibility and thus insufficient data was one of the main challenges for this study. However, these points were distributed across the whole region for all the species studied. The results showed an acceptable accuracy by being calibrated with few sample points. In this line, studies as Hernandez et al showed that such models are capable of producing reliable results

Table 7
The results of landscape metric quantification under different scenarios of protected area selection.

Scenario	I	II	III	IV	V	VI
Coverage of total study area (%)	14.58223	14.68097	14.91429	18.65692	19.32533	20.20191
Area (ha)	1,358,400	1,367,325	1,389,025	1,737,825	1,800,875	1,887,475
Total Edge (m)	3,870,000	4,022,000	3,947,000	4,548,000	4,701,000	3,778,000
Total Core Area	1,224,300	1,227,600	1,252,800	1,578,350	1,636,275	1,755,375
Total Core Area Index	90.13	89.78	90.19	90.82	90.86	93
Mean Core Area	24,486	23162.26	25,056	37579.76	37188.07	58512.5
Mean Nearest Neighbor Distance	9841.96	9569.4	9809.5	7966.74	7043.97	9886.99
Edge Density	2.85	2.94	2.84	2.62	2.61	2
Mean Patch Size	27722.45	26294.71	27780.5	42385.98	41880.81	65085.34
Number of Patches	49	52	50	41	43	29

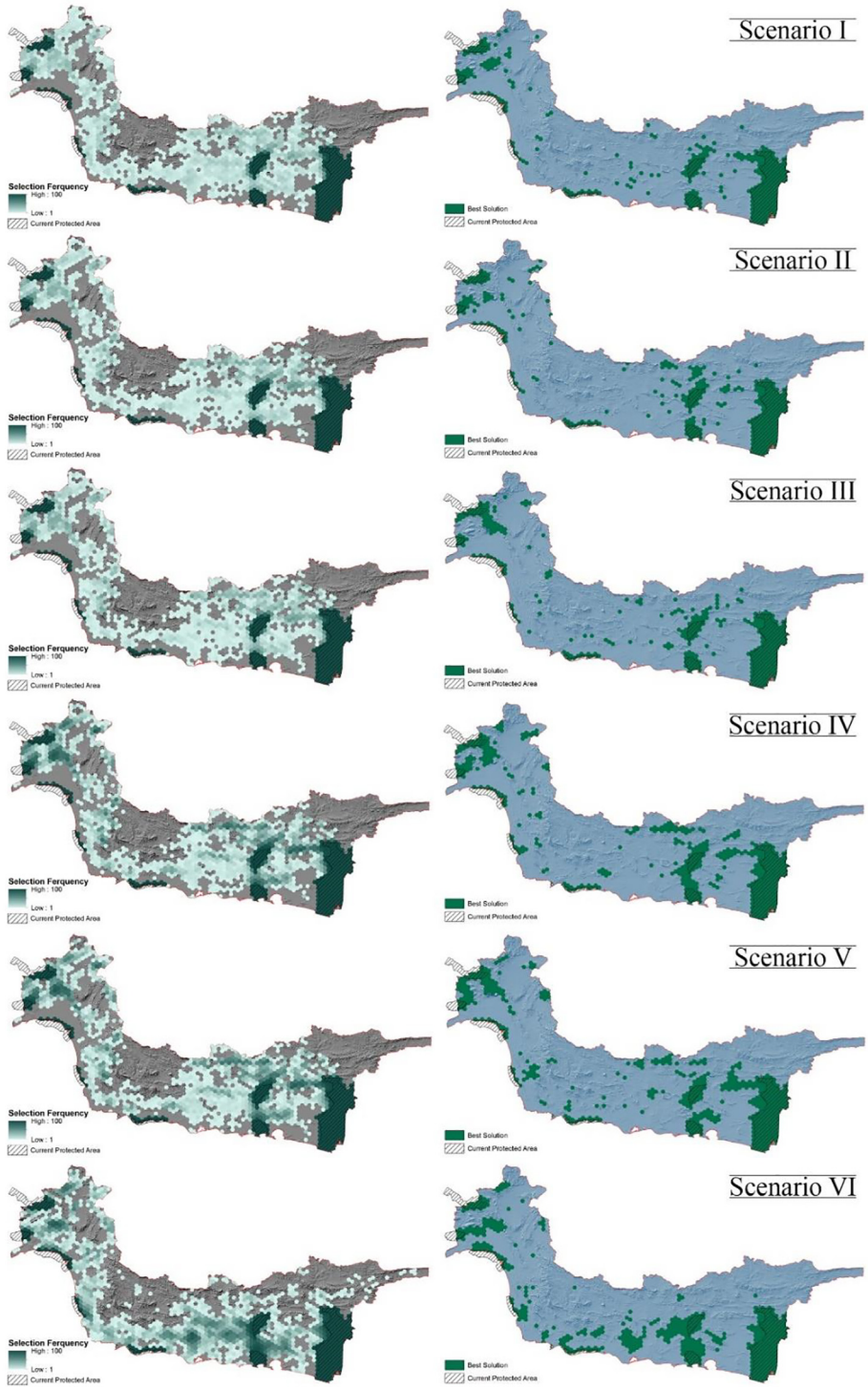

Fig. 5. The resulting maps from 6 scenarios; the selection frequency of a unit (left) and best-selected regions (right).

even by utilizing limited numbers of sample points (Hernandez et al., 2006). In line with these studies, our results showed that the majority of suitable habitats with high conservation priorities, such as movement corridors, are not currently protected by the existing protected area network. These protected areas conserve species living at the coast and mangrove forests and have failed to account for terrestrial habitats. Furthermore, the proximity of residential areas to some sensitive habitat and ongoing development of human infrastructure along the coastline are potential threats to biodiversity in the southeast of Iran.

The majority of presently unprotected patches of suitable habitat may act as corridors or stepping stone areas and play an important role in connecting habitats (Morato et al., 2014; Rabinowitz and Zeller, 2010). In this case, maintaining the west-east corridor found in this study is of utmost importance, and thus increasing conservation efforts and management in these areas are highly necessary. Di Minin et al. (2013) also argued that the creation of larger protected areas well-connected and thus acting as a network as well as increasing level of protection in these areas are essential for mitigating threats to African leopard and other large carnivores and promoting their long-term survival.

Large-scale studies showed that the protection level needed for most species and habitats has not been well fulfilled under the current

protected area networks (Bergl et al., 2007; Maiorano et al., 2006). Rising the awareness about the habitat requirements of large animal species and the natural and anthropogenic factors affecting their distribution may allow, on the one hand outlining effective protection strategies in areas which, provide suitable conditions for their long-term survival. On the other hand, the results of habitat suitability modelling (Di Minin et al., 2013; Morato et al., 2014; Rabinowitz and Zeller, 2010) showed that the current protected areas are not consistent with the distribution extents and requirements of these species. The results of the present study showed that only a small portion of the entire sensitive animal habitats lie within the current protected area network. Accordingly, establishing new protected areas and improving the protection level of the current protected area network will not only help the target species but due to the umbrella function of charismatic species such as black bear and leopard, also foster less-preferred and potentially threatened sympatric species.

The results of this study showed that the tendency to select areas near the coastline is significantly increased by assigning the highest weight (100%) to the Green sea turtle's habitat and mangrove forests. This could be seen by comparing the maps under scenario III and V with those under scenario II and IV. In general, however, with the increasing area of suitable patches under scenario VI, the highest tendency was observed towards selecting coastal habitats.

Quantifying landscape metrics in analysis, showed that with increasing protection percentages from scenario I to VI, there was increasing in Mean Patch Size and Mean Core Area, while the total Number of Patches decreased in study area. The Mean Nearest Neighbor Distance was minimum in scenario IV and V, while it was increased again in scenario VI due to elimination of some smaller protected patches and selection of more integrated larger areas.

These approaches by including landscape structure and connectivity analysis in spatial planning of protected area network could be greatly useful for reserve design related to ecologically relevant conservation objective.

In addition to systematically planning for protected areas, this approach can be used as a tool to evaluate the efficiency of the current protected area network. This can play a leading role both in determining conservation strategies and implementation of biodiversity conservation plans. Hence, modeling by Marxan may provide a systematic planning framework for evaluating the advantages and threats of various options in selecting areas for conservation (Watts et al., 2009). The distribution of suitable habitats across the arid and semi-arid region along with increasing level of development have raised the vulnerability of the region's natural habitats (Moradi, 2016).

5. Conclusion

The protection of sensitive flagship species such as large carnivores may help to attract monetary resources from economic and political sources and thus play a major role in protection of the entire biodiversity (Sergio et al., 2006). Nevertheless, it is necessary to carry out protection efforts based on accurate and reliable information about the focal species' spatial distribution. Modeling the distribution of critical species in Mokran region based on data collected through a long-term field investigation enabled accurate and reliable prediction of the species' distribution. The R package "Biomod" allowing the production of multi-model ensemble maps provided the opportunity to use benefit from each model for integrated planning.

This study is an attempt which utilized multi-species habitat suitability modeling together with landscape ecology concepts for planning of protected area network. Due to the fragile nature of coastal and arid ecosystems in Southeastern Iran and insufficient data along with the government's plans to establish large-scale industrial centers in the region, application of integrated techniques and multifold models and determination of suitable habitats for several focal species will provide a sound scientific basis for maintaining regional biodiversity and minimizing negative impacts of planned developments on natural habitats.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2019.03.006.

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