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Research Article

Habitat protection and planning for indicator species using the MaxEnt model in Alborz

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Abstract

Predicting and mapping appropriate habitats for endangered and threatened species is crucial for monitoring and restoring their dwindling populations in their natural surroundings. Additionally, it aids in selecting suitable conservation sites and effectively managing their habitats. An ideal approach for habitat suitability modeling involves utilizing MaxEnt machine learning techniques. The MaxEnt model was employed to forecast habitat suitability for key species, including Ursus arctos, Capra aegagrus, Ovis ammon, Lutra lutra, Martes foina, Lynx lynx, and Panthera pardus. Additionally, Linkage Pathways were employed to model ecological corridors connecting core habitats, enhancing our understanding of landscape connectivity for these species. The results showed that it is imperative to safeguard vital northern and southern areas between the prohibited hunting zones and the protected area. These areas provide the best routes for species to move between two habitats. However, settlements and rural areas pose a significant threat that can lead to the reduction or destruction of these communication areas. Therefore, protecting these regions should be a top priority.

Keywords: MaxEnt model, Ecological corridor, Habitat suitability

Introduction

The world is currently witnessing a monumental transformation as cities expand at an unprecedented rate globally. Over recent decades, there has been a significant rural-to-urban migration trend, projected to continue, with an estimated 68% of the global population expected to reside in urban areas by 2050, predominantly in developing regions (Chang et al., 2021; United Nations, 2018). However, this rapid urbanization comes at a considerable environmental cost. Industrialization, land use changes, and land cover alterations have all contributed to adverse effects on ecological environments and landscape integrity (McDonald et al., 2008). Human activities have increasingly fragmented natural habitats and altered landscape patterns, leading to a decline in biodiversity. Habitat destruction has displaced species, reducing their populations. Fragmentation also isolates species, limiting gene transfer and decreasing genetic diversity. Therefore, regulating human activities contributing to habitat fragmentation is critical for preserving natural habitats and regional biodiversity. A key approach to addressing these challenges is habitat suitability assessment, which helps predict optimal conditions for species survival. By identifying suitable habitats, this method plays a crucial role in preventing habitat destruction and mitigating biodiversity degradation.

Predicting species distribution and assessing habitat suitability involve employing various methodologies, with Support Vector Machines (SVMs) and MaxEnt (Maximum Entropy) being prominent. MaxEnt, a machine learning algorithm, excels in capturing complex relationships based on species presence data and habitat suitability, particularly those with non-linear associations. Numerous studies have validated the effectiveness of MaxEnt in habitat suitability modeling (Hoang et al., 2010; Muñoz-Mas et al., 2018; Wei et al., 2018; Hallgren et al., 2019; Jayasinghe et al., 2019; Zhen et al., 2018). The MaxEnt model is favored for its predictive accuracy and usability in defining suitable habitats. It offers fast computation, user-friendly application, high precision, and commendable performance in geographic distribution studies and conservation initiatives (Warren & Seifert, 2011; Phillips et al., 2017). Researchers utilize MaxEnt to simulate various scenarios and identify optimal zones for species protection, considering factors such as environmental conditions, socioeconomic influences, and minimizing human impact (Cudlín et al., 2020; Struebig et al., 2015; Kaky et al., 2020; Schmidt et al., 2020; Singh et al., 2020; Wang et al., 2020).

This research focuses on identifying optimal distribution regions for seven species Aegagrus, Ursus arctos, Panthera pardus, Ovis ammon, Lutra lutra, Lynx lynx, and Martes foina-using the MaxEnt model. It explores the correlation between environmental factors and habitat suitability while evaluating the impact of each parameter on species distribution. Additionally, an ecological corridors model is applied to devise effective conservation strategies. The study aims to pinpoint priority conservation areas within the Alborz province, emphasizing habitat suitability and ecological corridor establishment and proposing specific conservation actions.

Material and methods

Study area

The Alborz province, spanning 5,833 km2, is located in northwestern Iran. Within this province, the Karaj District is one of six districts. It is situated near the Central Alborz Protected Area (Figure 1), covering approximately 640 km2 and renowned for its diverse and abundant biodiversity. The city of Karaj itself covers around 4,000 km2 and lies within the Alborz province. This region supports a variety of large mammal species, including brown bears (Ursus arctos), Eurasian lynx (Lynx lynx), Persian leopards (Panthera pardus), wild goats (Capra aegagrus), wild sheep (*Ovis ammon gmelini*), and gray wolves (Canis lupus), collectively enhancing the biodiversity of the province. As the provincial capital, Karaj is the second most densely populated megacity in Iran after Tehran.

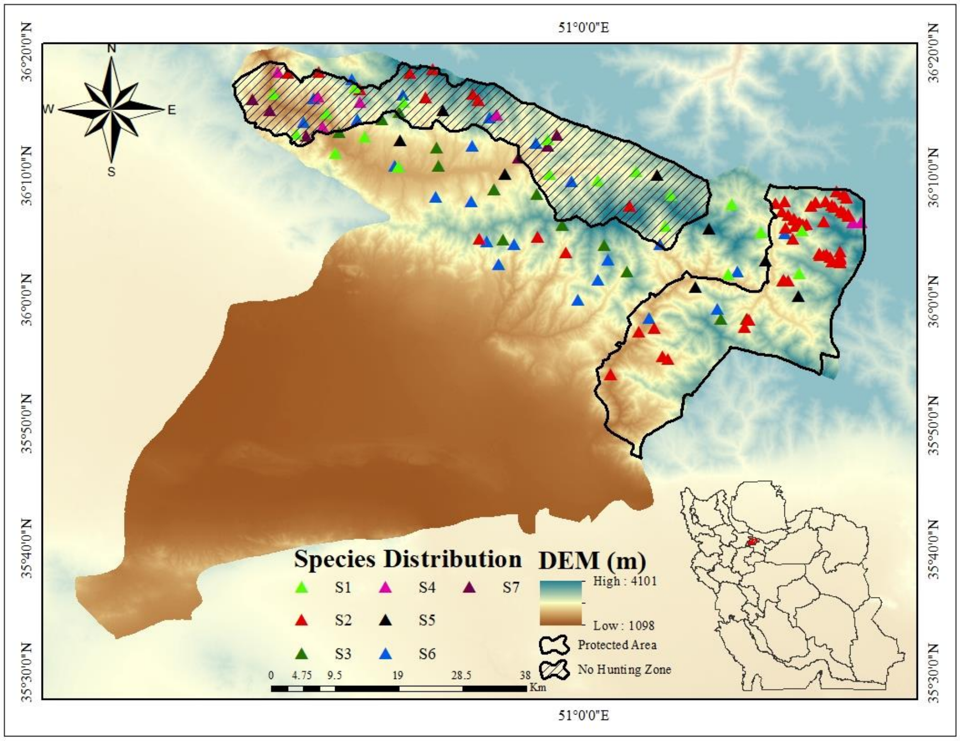

Figure 1. The Alborz province is illustrated with the Digital Elevation Model (DEM) and the distribution of seven species

Maximum entropy (MaxEnt) model construction and evaluation

The modeling technique used in this study assesses the likelihood of species viability by integrating presence data and generating background points to establish a maximum entropy distribution (Sharma et al., 2018; Wei et al., 2018; Abolmaali et al., 2018; Zhang et al., 2019). The MaxEnt model offers several advantages, particularly its ability to adapt to presence-only data, which is beneficial for programs with limited sample sizes or incomplete datasets (Aguilar et al., 2017; Fois et al., 2018; Bosso et al., 2013). It can effectively incorporate categorical and continuous environmental layers, demonstrating reliable performance even when dealing with constrained sample sizes (Yi et al., 2016; Fois et al., 2018).

The Jackknife test was employed to evaluate the significance of conditioning factors. Seventy-five percent of the presence-only data was used for model training, while the remaining 25% was reserved for testing. ENM Tools facilitated the selection of optimal feature parameters with a regularization multiplier set at 0.5. Habitat suitability assessment was performed using the 100-times bootstrap method. Performance evaluation was based on the AUC (area under the curve) metric, ranging from 0.5 to 0.6 indicating inadequate performance, and from 0.9 to 1 indicating outstanding performance (Zhang et al., 2019; Phillips et al., 2006; Jin et al., 2008; Huang et al., 2018; Yu et al., 2020; Lobo et al., 2008; Wang et al., 2007). Occurrence data for this study were collected throughout the year using GPS to document the geographical coordinates of sample sites from spring to winter 2022. The dataset includes 19 points for Ursus arctos (representing 21 populations), 67 points for Capra aegagrus (representing 1,995 populations), 7 points for Lutra lutra, 8 points for Lynx lynx, 14 points for Ovis ammon (representing 135 populations), 14 points for Panthera pardus (representing 15 populations), and 6 points for Martes foina. Following data collection, a thorough review identified and removed points with geocoding errors and duplicate records, ensuring the accuracy and integrity of spatial information.

Selective criteria for assessing species habitat

Environmental factors significantly impact species distribution, and predicting suitable habitats requires carefully selecting relevant variables. To model species distribution and habitat suitability, we aim to estimate environmental conditions suitable for the target species. Key variables chosen for this study include topographic factors (Digital Elevation Model, slope, distance to rivers, forests, agricultural lands, residential areas, and roads), climatic factors (annual rainfall, average annual temperature), and vegetation density.

Digital Elevation Model (DEM) and Slope

The SRTM DEM data became available for non-U.S. countries, and in 2015, the Southeast Asia dataset of SRTM DEM was released with a higher resolution of 30 meters (Table 1). The DEM with a pixel size of 30 meters was obtained from the USGS website, and specific information regarding the Alborz province was extracted from it. For land use/land cover, road, and river layers, Landsat 8 imagery (accessed on February 10, 2024, from https://earthexplorer.usgs.gov/) was utilized. The imagery underwent preprocessing to enhance its quality, which included atmospheric correction, pan-sharpening techniques, and radiometric calibration. After pre-analysis and manual inspection, land-use classification employed the Maximum Likelihood approach, identifying eight primary classes. Validation through field visits at 86 random points per class yielded a land-use map with a precision rate of 86% and a kappa coefficient of 0.82, indicating high reliability for further analysis. Road and river layers were sourced from the National Cartographic Center (accessed on April 3, 2024, from https://gndb.ncc.gov.ir/) at a resolution 1:250,000, with specific information extracted for the Alborz province.

Normalized Difference Vegetation Index (NDVI) values range from -1 to 1, where lower values indicate vegetation experiencing moisture stress and higher values denote denser green vegetation (Wardlow et al., 2007; Javadnia et al., 2009). This study generated the NDVI map using Landsat imagery downloaded from the USGS website.

Corridor Mapping

Corridors are elongated habitats that typically have a length greater than their width, connecting separate habitat patches. These corridors vary in shape, size, and composition but primarily facilitate species and individual movement. By maintaining connectivity between local populations, corridors promote genetic diversity and reduce species extinction risk. This connectivity is crucial in fragmented landscapes affected by human activities such as urban development, agriculture, roads, and deforestation. Corridors enable plants and animals to disperse and migrate, supporting vital movement patterns essential for species' survival. Today, protected areas often face fragmentation due to human activities, restricting species from freely moving between habitats. In such fragmented environments, species encounter heightened risks such as increased predator encounters, limited resources, and reduced shelter. In this study, identifying optimal corridors for the species under investigation involves using two data sets. First, core habitat areas where the species migrates seasonally or non-seasonally are identified. Second, an environmental resistance layer against species movement is considered. The Central Alborz Protected Area and the Talaghan No-Hunting Zone are recognized as key habitats for the studied species, emphasizing their importance as core areas. Most species observations occur in these regions, highlighting the critical need for favorable connections between these habitats.

To calculate environmental resistance to species movement, the following relationship was utilized (Atwood et al., 2011):

$$\text{Travel cost; cell resistance} = 1 - \text{pixel suitability}$$

Here, "pixel suitability" refers to the final suitability value of each pixel derived from habitat suitability calculations. The delineation of corridors for each species using the least-cost method involves employing the Corridor Designer add-on within the ArcGIS 10.4 software framework. This method begins from the origin and proceeds pixel by pixel toward the destination, selecting the path with the least associated cost for species movement.

Results

Land use and Land cover, and NDVI

As shown in Figure 2, the predominant land cover in the area is grasslands, occupying nearly 70% of the total area. These grasslands are concentrated primarily in the northern and southwestern regions. Following grasslands, fallow land covers 9.52% of the area, while residential areas account for 9%, predominantly situated in the central part of the region. Water bodies, gardens, and agriculture cover 0.93%, 3.4%, and 3% of the area, respectively. Additionally, the highest density of roads is found in the central and northern parts of the Alborz province.

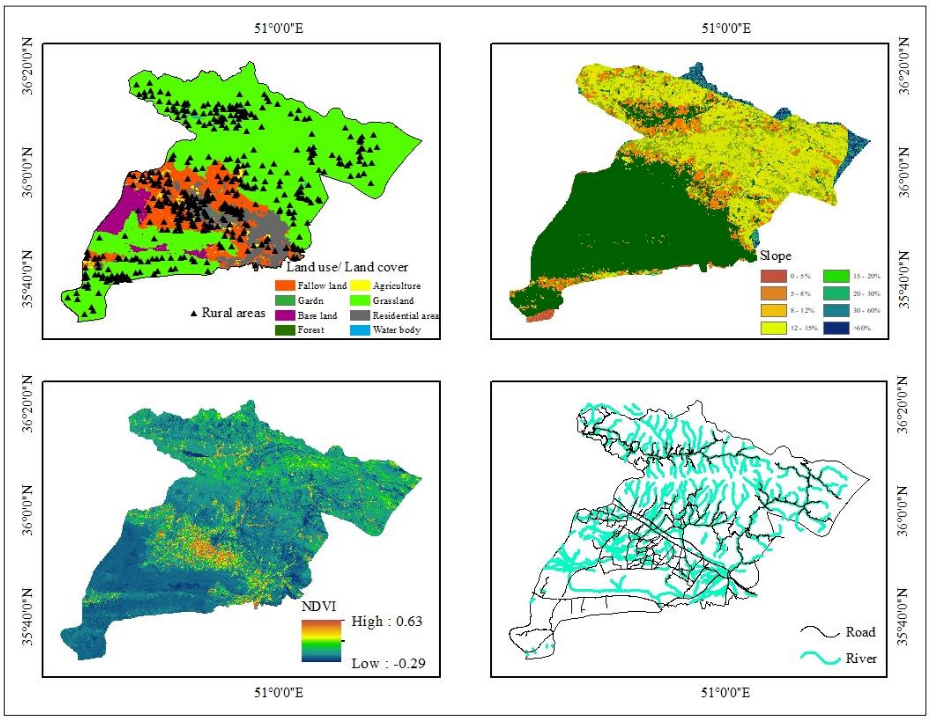

Figure 2. The land use/land cover map is shown with River, and Road and NDVI in 2022

Model Accuracy

Based on the assessment outcomes of the Receiver Operating Characteristic (ROC) curve, the average Area Under the Curve (AUC) values are as follows: 0.953 for Ursus arctos, 0.886 for Capra aegagrus, 0.867 for Ovis ammon, 0.988 for Lutra lutra, 0.925 for Martes foina, 0.873 for Lynx lynx, and 0.856 for Panthera pardus. These results indicate that the model demonstrated superb predictive accuracy and reliability. Therefore, it is a dependable tool for evaluating habitat suitability for each species.

Identified Environmental criteria

According to Table 1, the environmental criteria influencing habitat suitability for each species are as follows:

- For Ursus arctos: distance to the forest (35.4%) > distance to the river (29.2%) > NDVI (23.8%).
- For Capra aegagrus and *Ovis ammon*: DEM (Digital Elevation Model) is the main factor, accounting for almost 55%.
- For Lutra lutra: distance to the river is the most important factor, contributing 55.7%.
- For Martes foina, Lynx lynx, and *Panthera pardus*, distance to the forest is the primary factor, with percentages of 50.3%, 78.6%, and 62.8%, respectively.

These percentages indicate the relative importance of each environmental criterion in influencing habitat suitability for the respective species.

Table 1. Percent contribution of environmental parameters

Species	**Percent contribution**							
	Forest	River	NDVI	Slope	Road	Cultivation	DEM	Residents
Ursus arctos	35.4	29.2	23.8	6.4	3.4	1.2	0.6	-
Capra aegagrus	1.4	38.4	0.4	3.9	-	-	55.8	-
Ovis ammon	-	0.4	-	0.2	40.9	0.2	55.4	3
Lutra lutra	21	55.7	9.2	11.3	2.8	-	-	-
Martes foina	50.3	43.8	0.2	-	0.4	-	3.4	2
Lynx lynx	78.6	-	1.3	19.2	0.5	-	0.4	-
Panthera pardus	62.8	3.3	-	21.3	9.5	3	-	-

Prediction of suitable habitat

The results of the suitability habitat have been presented in Figure 3.

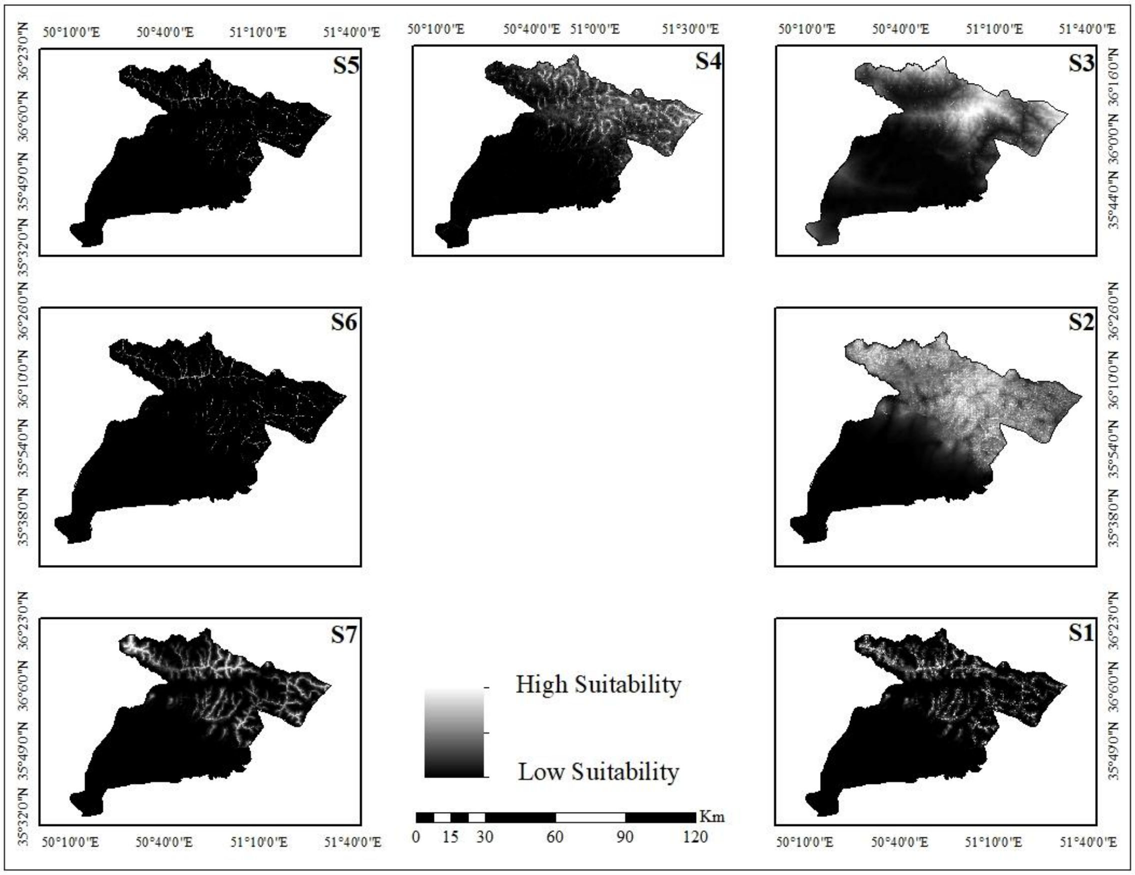

Figure 3. Habitat suitability for seven species in Alborz province as modeled. Light and Dark areas represent the greatest habitat suitability.

The "10 percentile training presence" method was employed to convert Figure 3 into a binary map distinguishing desirable and undesirable habitats for the seven species. The outcomes of this conversion are illustrated in Figure 4.

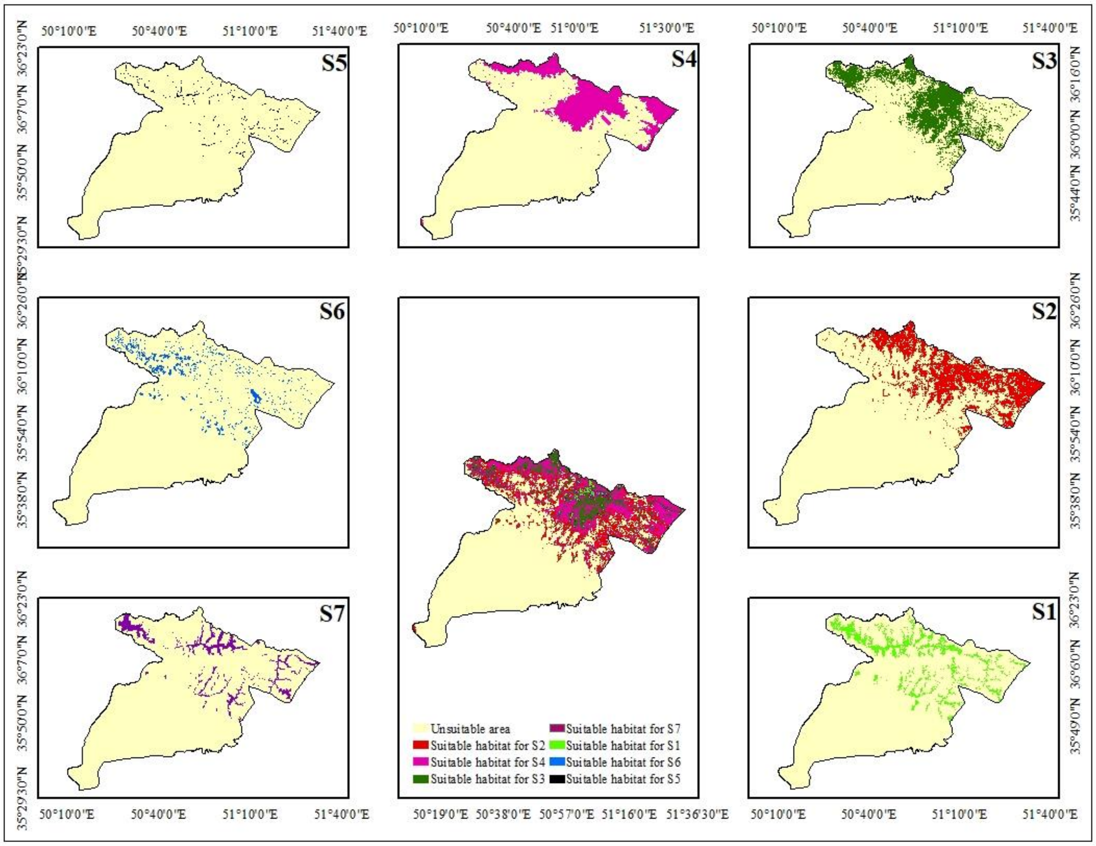

Figure 4. Suitable habitat for seven species

More than 50% of the desirable habitat for Ursus arctos (27,385 hectares), Lutra lutra (6,331 hectares), and Martes foina (43,222 hectares) are located outside of protected areas. Additionally, 41.8% of the desirable habitat for Capra aegagrus (44,020 hectares) and 45% of that for Ovis ammon (40,862 hectares) are situated outside of protected areas (Table 2).

Table 2. The area of desirable-, and protected area

Species	**Area (ha)**			%
	Desirable habitats	Protected habitats	Habitats outside protected areas	Habitats outside protected areas
Ursus arctos	47206	19821	27385	58
Capra aegagrus	105248	61228	44020	41.8
Ovis ammon	90823	49961	40862	45
Lutra lutra	10908	4577	6331	58
Martes foina	66905	23683	43222	64.6
Lynx lynx	34175	17204	16971	49.6
Panthera pardus	86876	53456	33420	38.4

Corridor Maps

Figure 5 illustrates the modeling of the optimal route based on land use types within the study area, considering both the least distance and cost between two habitats for the species under investigation. The ecological corridor designated for Capra aegagrus (S2) is located in the northern part of the region. In contrast, the most favorable route for Ursus arctos (S1), Panthera pardus (S3), Ovis ammon (S4), Lutra lutra (S5), Lynx lynx (S6), and Martes foina (S7) is situated in the southern part of the region.

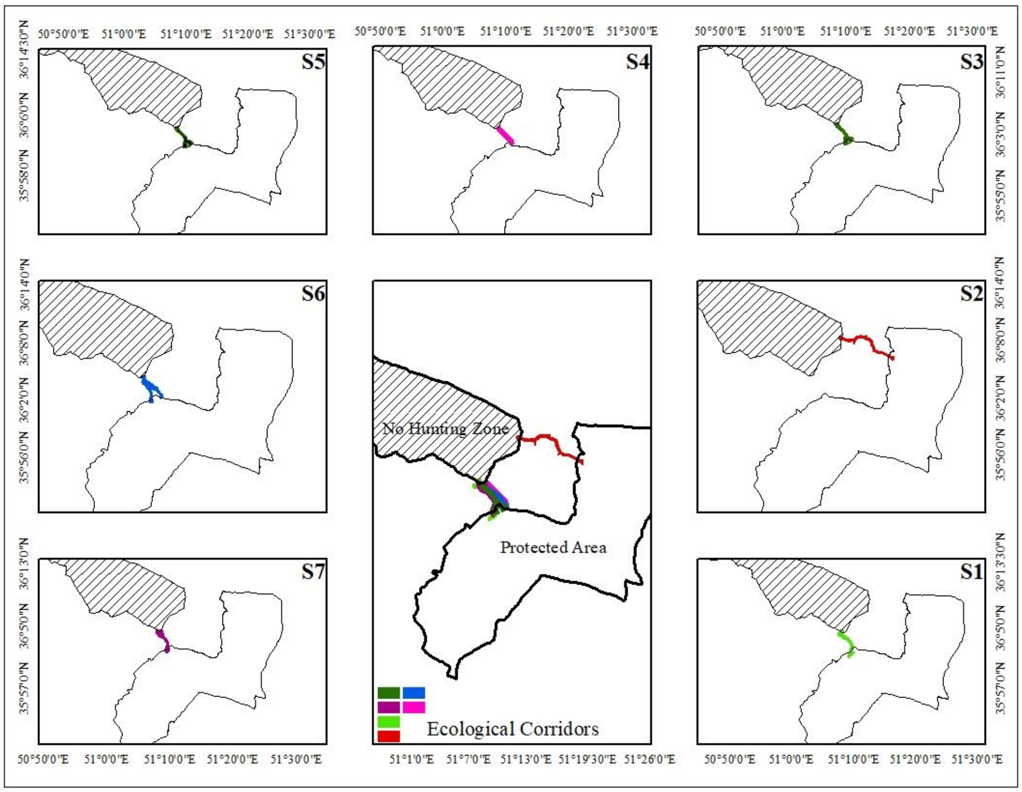

Figure 5. Ecological corridors for seven species

Conclusion

The MaxEnt model effectively predicted suitable distribution regions for all seven species *Ursus arctos*, *Capra aegagrus*, *Ovis ammon*, *Lutra lutra*, *Martes foina*, *Lynx lynx*, and *Panthera pardus* in the Alborz province. Among these species, distance from forests emerged as the most critical factor influencing habitat suitability and distribution probability for Martes foina, Lynx lynx, Panthera pardus, and Ursus arctos. Elevation, contributing almost 60%, was also identified as a significant determinant of Capra aegagrus and Ovis ammon distribution patterns. Distance from roads and rivers also played crucial roles in determining habitat suitability for some species. In contrast, NDVI (Normalized Difference Vegetation Index), distance from cultivated areas, and residential areas did not significantly affect habitat suitability compared to other factors. A significant outcome of the study was the identification of crucial connectivity zones for the seven indicator species within the study area. These vital areas are located in the northern and southern parts, between the two prohibited hunting zones and the protected area, providing essential routes for species movement between habitats. However, rural areas and the high density of roads and rivers pose significant threats that could reduce or destroy these vital connectivity areas. Therefore, safeguarding these regions should be a top conservation priority.

The study also highlighted that road density is a significant threat to wildlife movement and species presence, particularly in the northern section of the region where ecological corridors already exist. Road construction exacerbates threats such as habitat fragmentation and destruction, impacting the movement and survival of wildlife, especially carnivores with large home ranges. To mitigate these negative impacts, measures such as reducing road width, traffic volume, and vehicle speed and constructing wildlife overpasses and underpasses can be implemented. These efforts can contribute to restoring biodiversity and landscape integrity to some extent. Conservation biology theory emphasizes the importance of wildlife crossing structures in enhancing connectivity between isolated habitat patches, maintaining gene flow, and ensuring population viability. Therefore, integrating wildlife crossings into road construction projects is essential for the region's conservation strategy. Even existing infrastructure not specifically designed for wildlife can still play a crucial role in this regard (Sanderson et al., 2006; Shi et al., 2018; Seiler et al., 2003; Huijser et al., 2016).

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