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Research Article

Habitat suitability modeling of the Caspian Red Deer (*Cervus elaphus maral*) in the central zone of the Hyrcanian region: Identification of priority conservation areas

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Abstract
As human development expands, wildlife managers face increasing challenges related to human-wildlife conflicts and land-use changes. Understanding how wildlife selects optimal landscapes is crucial for resolving these conflicts. This study focuses on analyzing the Caspian red deer's habitat status in the Hyrcanian region's central zone to identify optimal habitats. Five habitat suitability models and one combined model were employed to identify areas with high conservation priority for the Maral species. The Random Forest (RF) model was recognized as the best among the species distribution models. Elevation and land use are the most critical factors affecting the distribution of the Maral species. Based on the combined habitat evaluation model, 26.45% of the suitable habitats for the Maral species are located within areas protected by the Department of Environment of Iran. The findings of this research can be used to strengthen or create more efficient pathways for protecting Caspian red deer habitats and to develop conservation plans for areas with high conflict.
Keywords: Habitat Suitability, Species Distribution Models, Combined Model, Conservation

Introduction
Human beings have always benefited directly or indirectly from biodiversity, securing their survival by utilizing the valuable resources provided by nature. Factors such as habitat

fragmentation, land-use changes in forested areas, encroachment on wildlife habitats, and road accidents pose serious challenges to the survival of wildlife populations, particularly large mammals (Sevigny et al., 2021; Lanman et al., 2022). Among these large mammals, species such as the Caspian red deer (Maral) , Roe deer, Gazelle, Jebeer, Wild goat, and Wild sheep have become the focus of conservation and management programs due to recent population declines (Khosravi et al., 2019). Habitat destruction and overexploitation have been identified as the most common threats to mammals. Overexploitation directly increases mortality, while habitat destruction indirectly impacts living organisms by reducing the environment's carrying capacity (Romero-Muñoz et al., 2021). Consequently, processes that reduce habitat availability are expected to be more harmful to specialized and large-bodied species, which typically have longer life cycles than other species (Keane et al., 2005). The red deer was first described by Linnaeus in 1758, and the Maral subspecies was identified by Gray in 1850. Red deer have a wide but patchy distribution across various parts of the world, particularly in Europe and Asia, and they comprise multiple subspecies in the Northern Hemisphere (Geist, 1998). This species plays a significant role in various regions, including northern Iran, where it contributes to the survival of dependent organisms through grazing, nutrient cycling, and seed dispersal. The removal of this species could inflict irreparable damage on the region's ecosystems (Iravani et al., 2011; Murray et al., 2013).

The red deer is a herbivore with a social lifestyle, feeding on grasses, fungi, lichens, fruits, and the twigs of shrubs and short trees that grow in grasslands on the edges of dense forests (Adam et al., 1992; Weckerly, 2005; Frair et al., 2005; Connor et al., 2023). The average habitat range of red deer is estimated to be about 61.5 ± 1.1 hectares, with males typically having a slightly r range than females (Yang et al., 2019). Specifically, deer tend to prefer more open habitats at dawn and dusk, when predator visibility is low, and select edge and forested habitats during daylight hours (Weckerly, 2005; Hinton et al., 2020; Mohr, 2020).

The Caspian red deer is characterized by long legs and a body, weighing between 130 and 260 kilograms, with short grayish-brown fur (Walker et al., 2002). According to the regulations of the Iranian Department of Environment, the Maral subspecies is classified as a protected species; however, due to habitat destruction and poaching, its population has significantly decreased, with a reduction of up to 70%. Iranian wildlife experts consider this species to be at risk of extinction (Karami et al., 2016; Torbati et al., 2008). The distribution range of the Maral in Iran extends from the eastern border in Golestan National Park to the Azerbaijan border in the northeast, provided that suitable habitats remain (Kiabi et al., 2004). In recent years, the natural habitats of the Maral have become fragmented due to natural and human-made barriers and climate change, resulting in isolated populations surrounded by human land-uses (Wikramanayake et al., 2004).

Barriers and changes in habitats can disrupt the movement, connectivity, survival, and population dynamics of wildlife, particularly large mammals, and have profound ecological impacts on their distribution and abundance (Thompson, 1961; McCorriston, 1994; McInturff et al., 2020; Visscher et al., 2023). Therefore, identifying suitable habitats and their characteristics is crucial for effective conservation efforts. One of the most common methods for describing species distribution and biodiversity is species distribution models (SDMs), which have been widely used in conservation biology, biogeography, and environmental science in recent years (Guisan & Thuiller, 2005). Multivariate models are commonly used for habitat suitability modeling, utilizing spatial data to create species distribution maps and habitat suitability assessments at various scales (Guisan & Zimmermann, 2000; Muñoz-Mas et al., 2014). Other models have also been widely used to identify suitable areas (Hirzel et al., 2006; Hirzel et al., 2008; Mocq et al., 2013; Domisch et al., 2013; Yi et al., 2014; Fukuda et al., 2015; Shearer et al., 2015).

Although machine learning models have been widely utilized, researchers' primary concern is selecting the most efficient model from among the available approaches (Domisch et al., 2013; Fukuda et al., 2015; Visscher et al., 2023; Fukuda et al., 2015; Elith et al., 2008; Lin et al., 2015). There is no consensus on an optimal model that can be applied universally in all relevant situations and be suitable for all species (Segurado & Araujo, 2004). This is because ecological and environmental conditions vary greatly across different regions, making it difficult to design a general and uniform model (Mosebo Fernandes et al., 2020). Additionally, species' behaviors and interactions with their habitats can differ significantly, requiring specific approaches (Amindin et al., 2024). As a result, researchers often need to adapt or develop models tailored to each region's unique characteristics and specific species. Research on machine learning models has shown that errors in the modeling process and errors related to using the value of all pixels are among the weaknesses of these models. Therefore, by combining models with specific strengths, a more appropriate assessment can be achieved, partially addressing the weaknesses of the models (Zhao et al., 2021). Habitat fragmentation, the resulting isolation of wildlife populations, and poaching have placed the Maral species in a vulnerable and endangered situation. To enhance the conservation and management of this species, it is crucial to first identify potential and suitable habitats (Riddle et al., 2003). Effective strategies generally include soil and water conservation, direct species management, monitoring, and comprehensive national, regional, and legislative planning.

Material and Methods

Study Area

Mazandaran Province, located in northern Iran, lies between the Alborz mountain range and the Caspian Sea. Politically, it borders Gilan Province to the east, Golestan Province to the west, and Tehran and Semnan provinces to the north. Geographically, the province spans latitudes from 35°47' to 36°35' N and longitudes from 50°35' to 54°10' E. Covering an area of approximately 23,527 square kilometers, a significant portion consists of forested regions and wildlife habitats (Fig. 1).

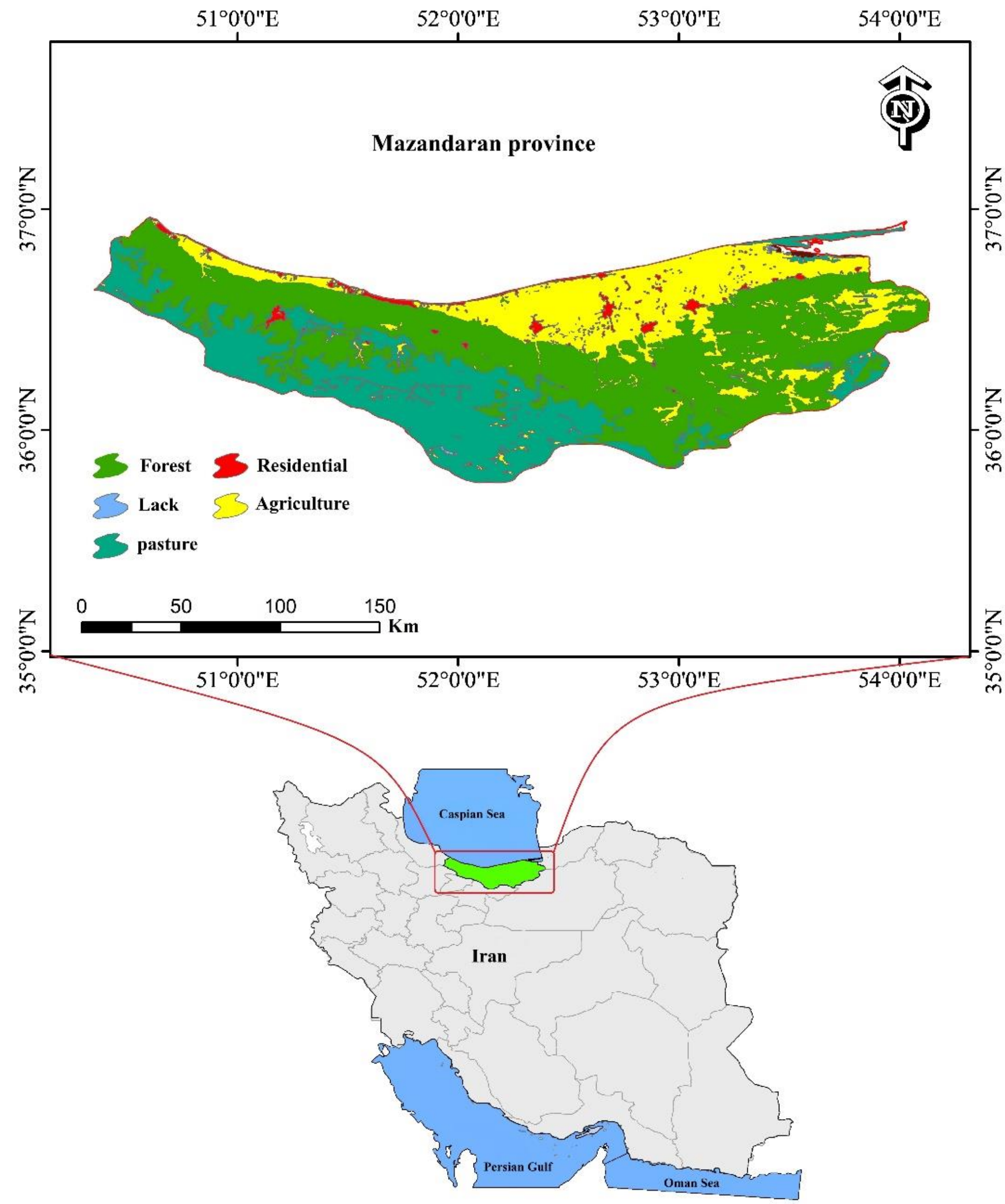

Figure 1. Study Area

Research Methodology

This research aims to model the habitat suitability of the Caspian red deer (*Cervus elaphus maral*) using species distribution models and an ensemble model in Mazandaran Province. Initially, potential habitats for the Caspian red deer were identified. During the rut in 2021 and 2022, 239 presence points were collected from protected areas and natural habitats in Mazandaran Province.

The Environmental Protection Organization recorded these points using GPS from the areas of harem formations and during patrols (Table 1).

Table 1. Presence Points of Caspian Red Deer in Protected Areas and Natural Habitats of Mazandaran Province during 2021 and 2022.

Row	Species name	Habitat type	City	Number of observation
1	*Cervus elaphus maral*	Forest	Noor	13
2	*Cervus elaphus maral*	Forest	Amol	22
3	*Cervus elaphus maral*	Jungle and Ecotone	Babol	3
4	*Cervus elaphus maral*	Mountain Forest	Behshahr	19
5	*Cervus elaphus maral*	Forest	Tonekabon	11
6	*Cervus elaphus maral*	Forest	Chaloos	12
7	*Cervus elaphus maral*	Forest	Lavij	5
8	*Cervus elaphus maral*	Forest	Sari	17
9	*Cervus elaphus maral*	Mountain forest and pasture	Savadkooh	17
10	*Cervus elaphus maral*	Forest	Abbas Abad	10
11	*Cervus elaphus maral*	Forest	Kelardasht	14
12	*Cervus elaphus maral*	Forest and Pasture	Kiasar	55
13	*Cervus elaphus maral*	Steppe forest and Ecotone	Galugah	14
14	*Cervus elaphus maral*	Forest	Naka	10
15	*Cervus elaphus maral*	Forest and Pasture	Nowshahr	17

Key variables influencing Caspian red deer distribution were identified based on existing studies (Staines, 1997; Shirko et al., 2020; Laguna et al., 2021). Maps of these influencing factors were prepared using ArcGIS 10.8 software. The land-use map was categorized into nine classes: urban areas, rocky outcrops, lakes and ponds, irrigated and rain-fed agriculture, poor to medium rangeland, good rangeland, semi-dense forest, and dense forest. Using the species presence points and the prepared maps, suitable habitats across Mazandaran Province were modeled with available R software packages, identifying high-priority conservation areas based on various habitat assessment models and the ensemble model.

Habitat Suitability Assessment Models

Species distribution models (SDMs) are widely employed in habitat modeling (Guisan & Thuiller, 2005; Wood & Augustin, 2002). These models correlate species presence in a habitat with influential environmental or climatic variables to extrapolate spatial data (Guisan & Thuiller, 2005). This approach predicts species presence in areas where it has not been recorded but where the habitat is suitable (Segurado & Araujo, 2004). The Support Vector Machine (SVM) is one such SDM based on statistical learning theory used in environmental studies. This model assumes that more favorable conditions correlate with more species presence points (Shruthi et al., 2014; Rahmati et al., 2019). Generalized Linear Models (GLM) extend classical multiple regression, allowing for the modeling of non-normal response variables (Guisan et al., 2002; Rupprecht et al., 2011). Boosted Regression Trees (BRT), a machine learning method combines multiple simple tree models to optimize predictive performance and is used in ecological and biological studies (De'Ath, 2007; Elith et al., 2008; Soykan et al., 2014). Random Forests (RF), a classification method, creates an optimized set of trees through random combinations and repetitions of numerous decision trees (Breiman, 2001). The only assumption of RF is the adequate representation of sampled data (Liaw & Wiener, 2002). The Maximum entropy (Maxent) model predicts the likelihood of species presence based on environmental variables without requiring absence points, relying solely on species presence points (Elith et al., 2011; Phillips et al., 2021). Due to its high accuracy and performance, Maxent is one of the most commonly used models in environmental studies (Javed et al., 2017).

Ensemble Habitat Suitability Model

Combining models can provide more reliable results for identifying areas with conservation priorities (Amininasab et al., 2023). Ensemble models, which use the weighted average of all species distribution models, provide a flexible and reliable approach (Mohammadi et al., 2022). These models are essential tools in machine learning because they reduce overfitting and improve overall performance, demonstrating greater stability against data variability (Dietterich, 2000; Mohammadi et al., 2022).

Models evaluation

Model validation indicators collectively provide a comprehensive assessment of the model's accuracy and predictive power (Więckowska et al., 2022). Kappa coefficient evaluates the accuracy and quality of classification based on all pixels. Values closer to 1 indicate better agreement between predictions and actual classifications. (Ben-David, 2008). The ROC curve assesses model performance, and the Area Under the Curve (AUC) indicates model accuracy. Values closer to 1 represent higher model accuracy. (Rahmati et al., 2016). The TSS statistic measures the model’s sensitivity and specificity. Values closer to 1 indicate higher sensitivity and specificity of the model. (Allouche et al., 2006). The closer these coefficients are to 1, the better the model's performance Overall, higher values for Kappa, AUC, and TSS indicate better model performance (Devkota et al., 2013; Allouche et al., 2006).

Results

Large mammals are more sensitive to natural and man-made barriers due to their reduced ability to adapt to changing habitats (Connor et al., 2023). Given the specific habitats these species have adapted to throughout evolution, they require protection. One key reason for using species distribution models within an ecosystem is to represent biodiversity and habitats (Pereira et al., 2013; Grenié et al., 2020).

In this study, to identify high-priority conservation areas in Mazandaran Province, 239 presence points of Caspian red deer in Hyrcanian habitats during the rutting season of 2021 and 2022 were recorded in cooperation with the Department of Environmental Protection of Mazandaran Province and used in habitat suitability modeling (Table 1). Based on the red deer's ecology and previous studies, key variables influencing this species' distribution in natural habitats were identified (Staines, 1997; Shirko et al., 2020; Laguna et al., 2021). Among these variables, the Normalized Difference Vegetation Index (NDVI), land-use, distance from major roads (Road-dis), Digital Elevation Model (DEM), distance from rivers (River-dis), slope, and distance from residential areas (Residential-dis) were selected due to their importance in creating suitable living conditions for this species. The factors affecting the distribution of red deer were mapped and organized using ArcGIS 10.8 software, with a cell size of 30 meters (Fig. 2).

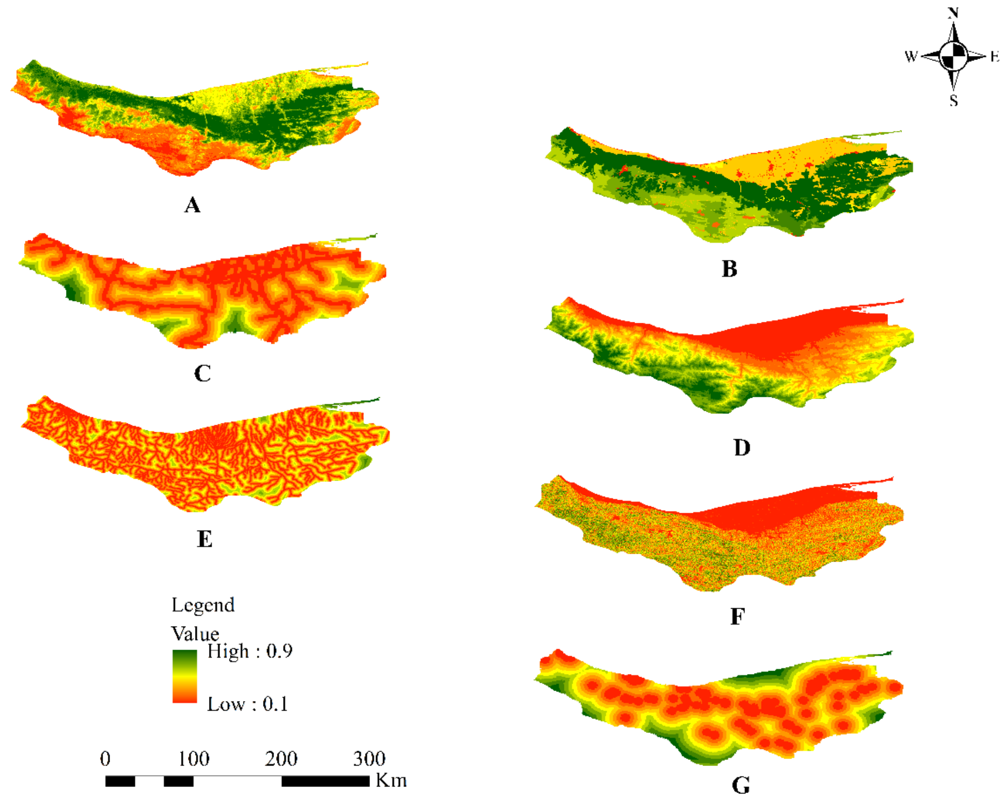

Figure 2. Layers used (A= NDVI, B= Land-use, C= Road-dis, D= DEM, E= River-dis, F= Slope, and G= Residential-dis).

One of the important initial steps in the species distribution modeling (SDM) process for a region is determining the correlation between independent factors (Long et al., 2018; Vu et al., 2015). Therefore, the correlation of these variables was examined using the Pearson method (Figure 3).

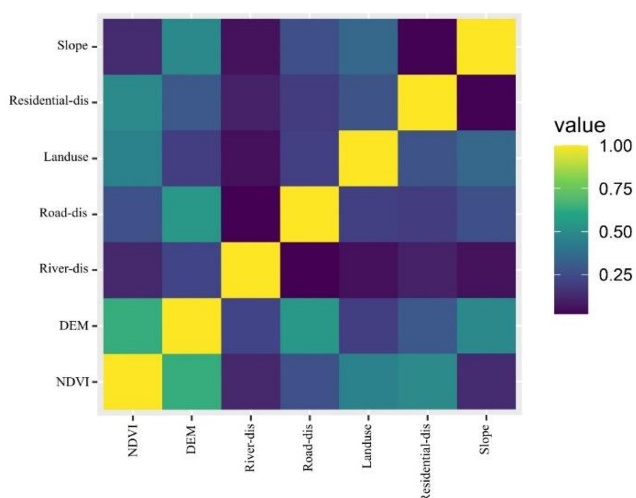

Figure 3. Correlation of Layers

Subsequently, using the presence points of Caspian red deer and the prepared maps, suitable habitats across Mazandaran Province were modeled using the sdm software package in the R environment, leading to the identification of high-priority conservation areas (Figure 4).

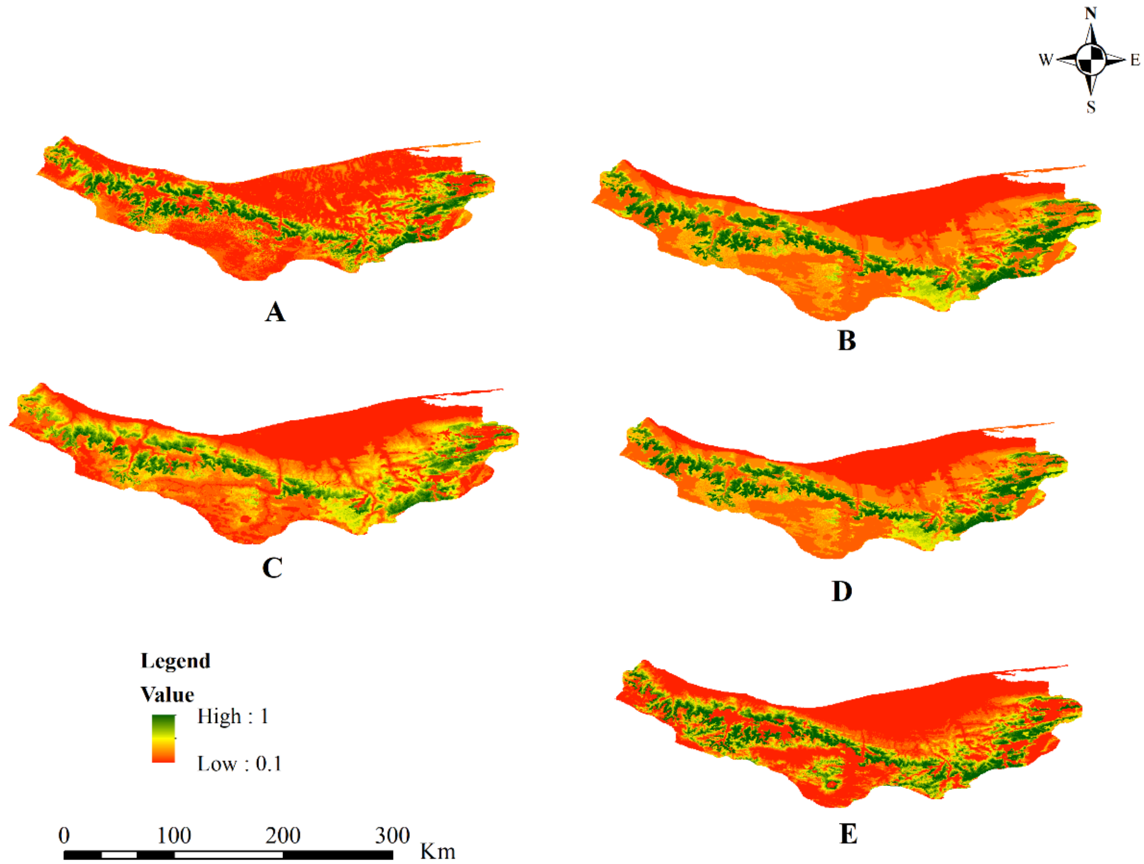

Figure 4. Output of Habitat Suitability Assessment Models (A= SVM, B= RF, C= Maxent, D= BRT, and E= GLM)

According to these models, the most suitable habitats for Caspian red deer are located in the forested areas of Mazandaran Province at elevations above 1,500 meters and at suitable distances from major roads and residential areas. Habitat suitability modeling was performed using five models. According to studies, a more suitable model is one with higher AUC, TSS, and Kappa values (closer to one) (Fielding and Bell, 1997; Rossi and Reichenbach, 2016; Somodi et al., 2017). Based on this criterion, the best models were identified as Random Forest (RF), Support Vector Machine (SVM), Maximum Entropy (Maxent), Boosted Regression Trees (BRT), and Generalized Linear Model (GLM), in that order, based on the highest validation index values (Table 2).

Table 2. Specifications of the Models Used

Models	Model validation indices			Weight of validation indicators in the combined model			
	AUC	TSS	kappa	AUC	TSS	kappa	cumulative weight
RF	0.96	0.85	0.83	0.203	0.219	0.212	0.634
significant	0.93	0.93	0.95				
SVM	0.95	0.82	0.80	0.201	0.211	0.205	0.617
significant	0.9	0.9	0.92				
Maxent	0.94	0.76	0.77	0.199	0.195	0.197	0.591
significant	0.87	0.88	0.88				
BRT	0.94	0.74	0.77	0.199	0.190	0.197	0.586
significant	0.8	0.81	0.82				
GLM	0.92	0.71	0.73	0.195	0.182	0.187	0.564
significant	0.8	0.8	0.82				

The accuracy and capability of the RF model for Caspian red deer, as indicated by the model validation indices (AUC = 0.96, TSS = 0.85, and Kappa = 0.83), were higher, demonstrating excellent predictive ability compared to the other models. The other models also performed well in depicting suitable habitats and can be used to evaluate habitat suitability in the Hyrcanian forests. The ensemble habitat suitability model provides a weighted average of all models, giving greater importance to those with higher validation index values (Table 2). This model effectively depicted the suitable habitats for Caspian red deer and confirmed and complemented the results of the other models. Given the accuracy and reliability of the ensemble model, it can be used to assess the compatibility of Mazandaran Province's four protected areas with the suitable habitats for Caspian red deer.

In the RF model and all species distribution models, two factors—elevation and land-use—have a greater impact on the presence of Caspian red deer in Mazandaran Province (Figure 5).

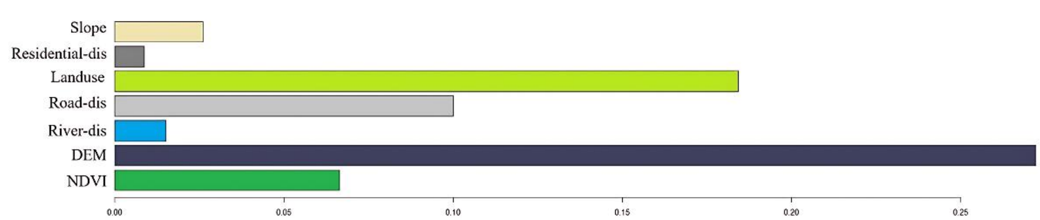

Figure 5. Most Important Variables in Caspian Red Deer Habitat Suitability in the RF Model

An elevation of 1,500 meters is optimal for Caspian red deer, with an elevation range of 1,300 to 2,300 meters indicating the lower and upper limits for this species (Fig. 6).

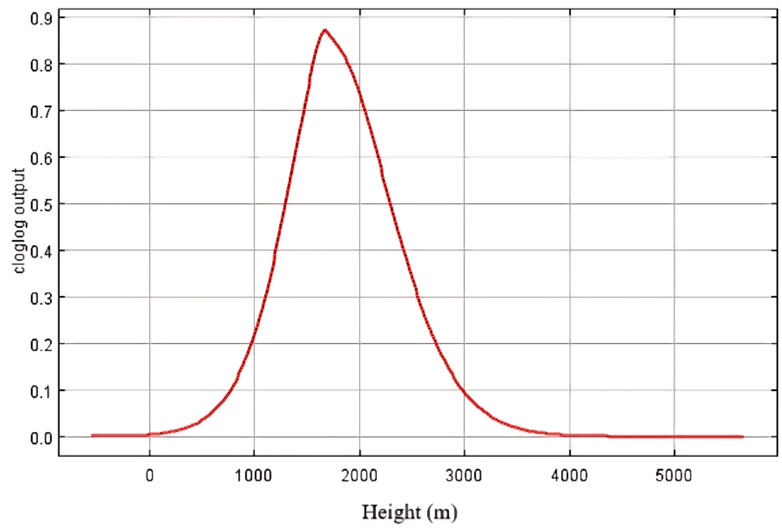

Figure 6. Caspian Red Deer's Response to Elevation Changes

In Mazandaran Province, Caspian red deer prefer dense forest cover, semi-dense cover, and high-quality pastures compared to other variables (Fig. 7).

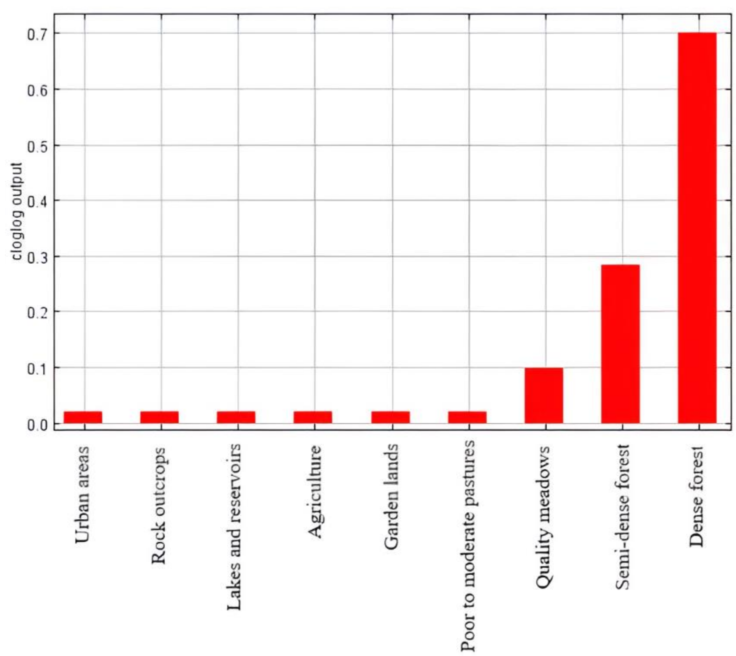

Figure 7. Caspian Red Deer's Response to Land-use

The results related to other variables in the distribution of Caspian red deer indicate that their positive response is greatest in areas with vegetation density ranging from 0.5 to 0.9, distances of 4,000 to 15,000 meters from residential areas, distances of less than 6,000 meters from main rivers, distances of 4,000 to 20,000 meters from main roads, and slopes ranging from 5% to 70%. Analysis of the area covered by the habitat suitability models for Caspian red deer shows that approximately 12.5% of Mazandaran Province consists of highly suitable habitats. The st suitable area for Caspian red deer is associated with the RF model, covering 4,001 square kilometers, while the smallest area is associated with the Maxent model, covering 3,183 square kilometers. Habitats with low, medium, high, and very high suitability levels occupy the most significant portions of the province (Table 3).

Table 3. Proportions of Habitat Suitability Classes Predicted by Different Models

Models	Areas of different classes (km^2)			
	Average	**Average**	**High**	**Very high**
RF	10402	6191	2932	4001
SVM	14723	3195	2250	3358
Maxent	12090	5359	2895	3183
BRT	10955	6313	2430	3829
GLM	14463	3075	2419	3569
Ensemble	13152	4229	2567	3579

Analysis of the ensemble model output revealed that the Department of Environment protects 662 square kilometers of habitats with high suitability and 964 square kilometers of habitats with very high suitability for Caspian red deer (Fig. 8).

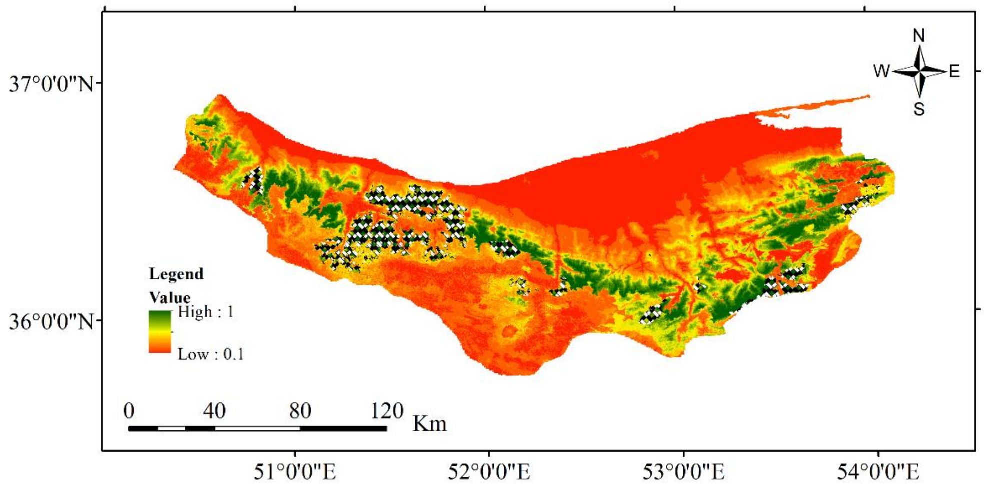

Figure 8. Protected Areas in Highly Suitable Habitats based on ensemble model (Black and white stripes)

Discussion

In recent years, human activities, such as land-use changes and habitat fragmentation, have significantly diminished effective habitat areas and disrupted connectivity between habitats, posing serious threats to biodiversity globally (Fahrig, 2002; Sala et al., 2000; Araújo & New, 2007). A critical response to mitigate harm to living organisms is the protection of their habitats. Consequently, habitat suitability modeling techniques have been developed to prioritize conservation areas and represent regional biodiversity from various perspectives (Komori et al., 2020; Labarrere et al., 2011; Mazel et al., 2014). Key approaches in species distribution modeling (SDM) include identifying sensitive and non-sensitive points within ecosystems, aiding habitat management, assessing regional biodiversity, and predicting ecosystem performance (Cardinale et al., 2012; Scherrer et al., 2018). Typically, SDM employs various independent parameters to model the habitats of different species (Schmitt et al., 2017). This study utilizes various species distribution models and an ensemble model to depict suitable habitats for Caspian red deer in Mazandaran Province. The ensemble habitat assessment model indicates that approximately 12.5% of Mazandaran's total geographical area is highly suitable (3,579 square kilometers), while about 11% (2,567 square kilometers) is classified as having high suitability for Caspian red deer. The extensive suitable areas in Mazandaran can be attributed to the province's abundant forests and pastures compared to other land-uses, which provide favorable conditions for the survival of Casoian red deer. The proximity of these habitats to the Caspian Sea and the adjacent Alborz mountain range contributes to high atmospheric humidity, supporting the growth of herbaceous plants and branches that serve as food for Caspian red deer. Additionally, dense forest cover offers camouflage and escape routes, creating a secure environment for populations of Caspian red deer. The presence of various elevation classes in these habitats, along with limited human access for poaching and effective protection of four designated protected areas, further enhance the living conditions for Caspian red deer, as confirmed by all habitat suitability assessment models utilized in this study. Those with the most significant impact on habitat suitability for Caspian red deer were identified among the various factors analyzed.

The study combined models with different algorithms to enhance output accuracy in identifying suitable areas. Numerous studies have shown favorable results using the Random Forest (RF) model to compare factors affecting the distribution of target species (Srinet et al., 2019; Li et al., 2020). The RF model demonstrated high accuracy for Caspian red deer, based on validation indices (AUC = 0.96, TSS = 0.85, and Kappa = 0.83), indicating excellent predictive power compared to other models. The RF algorithm was preferred for its superior accuracy in determining the most effective factors influencing Caspian red deer distribution (Table 2). This model combines decision trees in random states, yielding the most accurate decision tree that establishes the relationship between variables and species presence points. This is particularly crucial for large mammals, which rely on a set of favorable factors that must be readily available. Thus, this model effectively identifies suitable areas by integrating various environmental factors through multi-modal combinations of decision trees.

Some researchers have reported satisfactory outcomes from the Boosted Regression Tree (BRT) model, considering it superior to Generalized Linear Models (GLM) and RF models (Catry et al., 2009; Vilar et al., 2010). In studies related to natural hazards, the BRT model has produced more accurate results than the RF model (Elith et al., 2008). However, similar to this research, other studies have found that the RF model has higher accuracy in classifying suitable habitats (Oliveira et al., 2012; Vorpahl et al., 2012). This research employed seven environmental variables as independent factors to create a habitat suitability map. Wu et al. (2016) utilized the MaxEnt method to model habitat suitability for red deer and roe deer, estimating habitat overlap in northern China. Their findings indicated that distance from agricultural lands, elevation, and proximity to population centers were the most influential factors for habitat suitability. The present study revealed that DEM and land-use were the most critical factors for Caspian red deer distribution. The significant influence of these factors may be due to the extensive areas in

Mazandaran Province that provide favorable conditions for Caspian red deer, allowing them to seek refuge in habitats distant from human land-uses while accessing necessary food sources. The results indicate that Caspian red deer habitats positively correlate with the average elevation of forested areas, where lower human pressure is prevalent. Communities of oak-hornbeam, chestnut, and eastern beech trees offer suitable habitats, providing herbaceous cover for feeding and shelter for Caspian red deer (Akhani et al., 2010). Increased rainfall in forest areas significantly influences the distribution and establishment of herbaceous vegetation (Hou et al., 2020), primarily found at elevations above 1,300 meters (Ondier et al., 2019). Thus, Caspian red deer's preference for higher elevation habitats is justified. Other variables affecting Caspian red deer distribution showed positive responses to vegetation cover densities between 0.5 and 0.9, distances of 4,000 to 15,000 meters from residential areas, distances of less than 6,000 meters from main rivers, distances of 4,000 to 20,000 meters from main roads, and slopes ranging from 5 to 70 percent. The findings align with a study by Madadi et al. (2019) in Golestan National Park, indicating that suitable habitats for Caspian red deer are characterized by moderate terrain ruggedness, low slope, and diverse topographic conditions (Harper, 2023). Based on habitat suitability evaluation models, the best areas for Caspian red deer habitation are found in densely forested regions. In areas with higher protective performance, Caspian red deer are also observed in high-quality pastures, which provide suitable habitats. These areas encompass most factors influencing Caspian red deer distribution and can be designated as conservation hotspots if human land-use is minimized. The combined habitat evaluation model, like other models used in this study, identified the habitats within protected areas of Mazandaran Province as priorities for conservation and suitable habitats for Caspian red deer. Additionally, the model highlighted potential migration corridors for Caspian red deer in the western parts of Mazandaran Province, specifically in the forests of Nowshahr, Chalous, Tonekabon, and Ramsar, which were less apparent in other models. A study on red deer habitat modeling in northern China confirmed similar distribution patterns, underscoring the influence of geographical factors and suitable vegetation cover on species presence (Zhang et al., 2013). In conclusion, this study's results, which depict a map of priority and suitable habitats across Mazandaran Province, demonstrate that extensive areas provide favorable conditions for Caspian red deer survival. Parts of these habitats can serve as alternative and migratory habitats even amidst human interference. These findings can inform scale management decisions, emphasizing the need to prioritize conservation efforts in forest areas at 1,300 meters and above elevations.

Conclusion

Achieving a habitat suitability map and identifying optimal habitat areas as core conservation zones for the Caspian red deer can significantly assist protected area managers in effectively conserving the Hyrcanian forests. Recent research indicates that this species faces habitat challenges in many regions of Iran, potentially leading to habitat degradation and loss. A precise and comprehensive evaluation of habitat suitability is essential for the conservation of species like the Caspian red deer. This article uses modern evaluation methods to assess the habitat suitability of Caspian red deer in Mazandaran Province and highlights the most important variables influencing the species distribution. With this information and a spatial map of high-quality habitats, environmental managers in Mazandaran Province can develop a comprehensive conservation plan for this valuable species. The results of this study can greatly aid in preserving the remaining populations and preventing the extinction of Caspian red deer in their natural habitats.

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