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Spatial modelling of Sloth Bear *Melursus ursinus* (Shaw, 1791) (Mammalia Ursidae) habitat in Bamni Forested Watershed of Central India

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ABSTRACT Habitat suitability modelling is crucial for evidence-based wildlife conservation, especially for vulnerable species like the sloth bears *Melursus ursinus* (Shaw, 1791) (Mammalia Ursidae). This study assessed the habitat suitability of sloth bears in the Bamni forested watershed of Central India, a region recognized as a stronghold for the species, using Maximum Entropy (MaxEnt) algorithm. The sloth bear occurrence data for this research was collected between November 2023 and May 2025, with 12 uncorrelated environmental variables, including bioclimatic, topographic, land cover, and anthropogenic factors. The model achieved a robust average Area under the Curve (AUC) of 0.870, indicating a fair level of accuracy in distinguishing suitable habitats. The Human Influence Index (HII) was the most significant predictor, contributing 24.1% to the model, highlighting the substantial negative impact of anthropogenic pressures on sloth bear distribution. Land Use Land Cover (LULC) was the second most important variable at 19.5%, underscoring the species' reliance on undisturbed forested landscapes. Topographic variables such as aspect (12.9%), elevation (9.7%), and slope (7.3%) also played significant roles, influencing microhabitats for foraging and denning. Distance to roads (6.4%) and water bodies (6.0%) moderately influenced habitat suitability. Although bioclimatic variables had lower individual contributions. The Jackknife test revealed elevation as the most informative variable when used in isolation. The results provide spatially explicit insights to guide site-specific conservation and landscape-level planning, prioritizing the reduction of human disturbance, maintenance of forest connectivity, and protection of water resources.

KEY WORDS Sloth Bear; habitat suitability; MaxEnt; Central India; Forested Watershed.

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INTRODUCTION

Habitat suitability assessment forms the foundation of evidence-based wildlife conservation, particularly for wide-ranging, habitat-sensitive species like the sloth bear *Melursus ursinus* (Shaw, 1791) (Mammalia Ursidae), which is listed as Vulnerable by the IUCN (Dharaiya et al., 2017; Sharma et al., 2023; Rai et al., 2022). In India, which harbors the largest global population of sloth bears, the species inhabits diverse ecological zones, yet increasingly faces pressure from habitat degradation and fragmentation (Bargali et al., 2012; Dutta et al., 2015). Central India, recognized as a stronghold for sloth bears, comprises extensive forested watershed regions that function as biodiversity reservoirs, providing key habitat features such as food availability, water sources, shelter, and movement corridors (Singh et al., 2018; Sinha et al., 2017).

Forested watersheds not only provide essential ecosystem services but also sustain both terrestrial and aquatic biodiversity across interconnected habitats. Forested watersheds represent ecologically dynamic landscapes that combine forest cover, topographic heterogeneity, and perennial water availability, which are conditions particularly favourable for supporting diverse wildlife, including the sloth bear (Akhtar et al., 2009). These watersheds act as critical ecological corridors and habitat refugia, sustaining a variety of floral and faunal communities across seasons. Given the sloth bear's tendency to utilize rugged terrains, forest edges, and riparian zones, forested watersheds in Central India provide an ideal ecological matrix that supports their movement, foraging, denning, and reproduction (Jangid et al., 2023). However, increasing anthropogenic pressures such as habitat fragmentation, land use change, and linear infrastructure development have threatened habitat connectivity and quality in sloth bear habitats (Dutta et al., 2015; Thatte et al., 2020). Therefore, it becomes imperative to assess and predict habitat suitability for sloth bears within the watershed ecosystems of Central India to guide site-specific management and conservation actions.

Habitat suitability models (HSMs) are increasingly used to assess and map suitable areas for species, drawing on environmental predictors and occurrence data (Guisan & Zimmerman, 2017; Hirzel & Lay, 2008; Stuart et al., 2021). Among various modeling approaches, Maximum Entropy Modeling (MaxEnt) has emerged as a powerful and widely used algorithm, especially suited for species with limited occurrence data (Philips et al., 2006; Elith et al., 2011., Merow et al., 2013; Papes et al., 2016). MaxEnt estimates the distribution of a species by finding the probability distribution of maximum entropy, constrained by the known environmental conditions at occurrence locations. Its strengths include high predictive performance, ease of implementation, and ability to handle complex interactions between variables (Ahmadi et al., 2023; Prestele et al., 2021). The present study employs Maximum Entropy Model (MaxEnt) to model the habitat suitability of sloth bears in the forested watersheds of Central India, using a combination of bioclimatic, topographic, land cover, and anthropogenic variables.

MATERIAL AND METHODS

Study area

The Bamni River , a significant tributary of the Hasdeo River, ultimately feeds into the Mahanadi River system and originates in the ecologically rich Amarkantak hills. Its forested watershed, which plays a critical role in sustaining local biodiversity and hydrological balance, lies geographically between latitudes 22°47′N to 23°08′N and longitudes 82°07′E to 82°34′E, covering a substantial area of 1,567.09 square kilometres (Bhadbhade, 2017).

This watershed is predominantly characterized by dry deciduous forest. Among the dominant tree species in this region are Sal, Teak, Tendu, Mahua, and Chironji. The watershed also supports a variety of wildlife species, making it an important zone for biodiversity conservation. Notable mammalian fauna inhabiting this area include the Sloth Bear, Golden Jackal, and Spotted Deer etc.

Species occurrence

Occurrence data for the Sloth Bear in the Bamni forested watershed were systematically collected over a period extending from November 2023 to May 2025. The presence of the species within the study area was verified using a combination of sign surveys and georeferenced coordinates. Given the rugged and challenging terrain, a systematic transect-based approach was not feasible. Instead, an opportunistic field survey method was employed, wherein the survey team explored accessible regions throughout the watershed to identify evidence of sloth bear presence. The occurrence records were based on both direct and indirect signs of the species. Direct evidence included visual sightings, while indirect signs encompassed scat, digging marks, scrapes, and footprints all of which are considered reliable indicators of sloth bear activity. A total of 526 sign occurrences were documented, contributing valuable data for subsequent habitat suitability modelling.

Environmental variables

A total of 19 bioclimatic variables (Table 1) were obtained from the WorldClim version 2 database, available at http://www.worldclim.org/. The WorldClim version 2 dataset provides global climate data layers, with the current climate layers derived from the interpolation of historical average monthly climate data recorded between 1970 and 2000. Digital Elevation Model (DEM) data with a spatial resolution of 30 meters were obtained from the Shuttle Radar Topography Mission (SRTM) via the United States Geological Survey's Earth Explorer platform (https://earthexplorer.usgs.gov/). Using the 30m DEM, two important topographic derivatives slope and aspect were generated in ArcGIS. The distance to water was calculated using the Euclidean Distance. For this purpose, hydrographic data were obtained from the HydroSHEDS database (https://www.hydrosheds.org), which provides high-resolution, GIS-ready hydrological data derived from elevation information. The distance to road was also calculated using the Euclidean Distance tool in ArcGIS. Road network data were extracted from OpenStreetMap (OSM) (https://www.openstreetmap.org), a widely used open-source platform that provides up-to-date and detailed geographic data.

The Human Impact data used in this study were obtained from Global Human Influence Index (HII) Dataset, developed jointly by the Wildlife Conservation Society (WCS) and the Centre for International Earth Science Information Network (CIESIN) at Columbia University. The dataset, published by the Socioeconomic Data and Applications Center (SEDAC), Columbia University, was released on December 31, 2005, and is available in raster format for use in GIS-based spatial analysis. The Land Use and Land Cover (LULC) data were obtained from

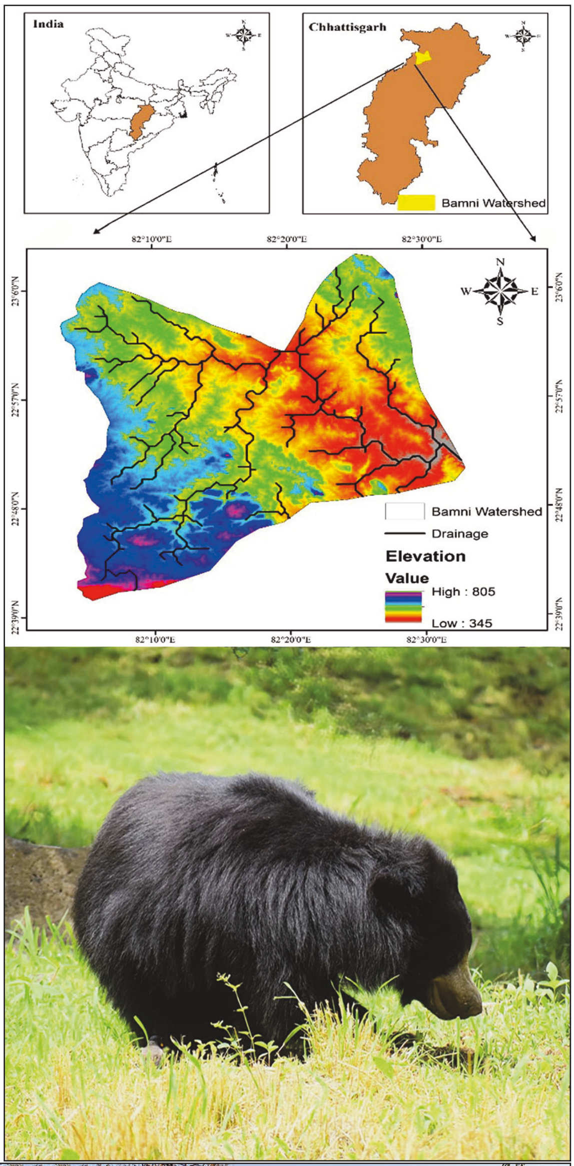


Figure 1. Map of the study area (above) with sloth bear *Melursus ursinus* in Bamni Forested Watershed (Central India) and its natural habitat.

the readily available ESRI Sentinel-2 Land Cover dataset, which provides high-resolution (10-meter) global land cover classification. All spatial datasets including topographic variables (elevation, slope, aspect), distance layers (distance to water and roads), human impact index, and land use/land cover data were resampled to match the native spatial resolution of the bioclimatic variables, which is approximately 1 km × 1 km (30 arc-seconds). Following the resampling, each raster layer was converted into ASCII format for compatibility with species distribution modeling tools such as MaxEnt.

To reduce multicollinearity among the environmental predictors, a correlation matrix was generated in R (R Core Team, 2023) using the Pearson correlation coefficient. This analysis helped identify and eliminate highly correlated variables that could bias the results of the species distribution modeling. A threshold value of |r| > 0.75 was used to determine high collinearity (Fig. 2). Variables with correlation coefficients exceeding this threshold were considered highly correlated and therefore unsuitable for inclusion together in the model.

From the initial set of 19 bioclimatic and additional environmental variables, those exceeding the correlation threshold were systematically removed, retaining only one variable from each highly correlated pair based on ecological relevance and model interpretability. This variable selection process resulted in a final set of 12 uncorrelated environmental variables (Figs. 3–14), which were subsequently used as input for MaxEnt modeling.

Maximum Entropy model parameter settings

Species distribution modeling for *Melursus ursinus* was carried out using the Maximum Entropy algorithm implemented in MaxEnt version 3.4.3

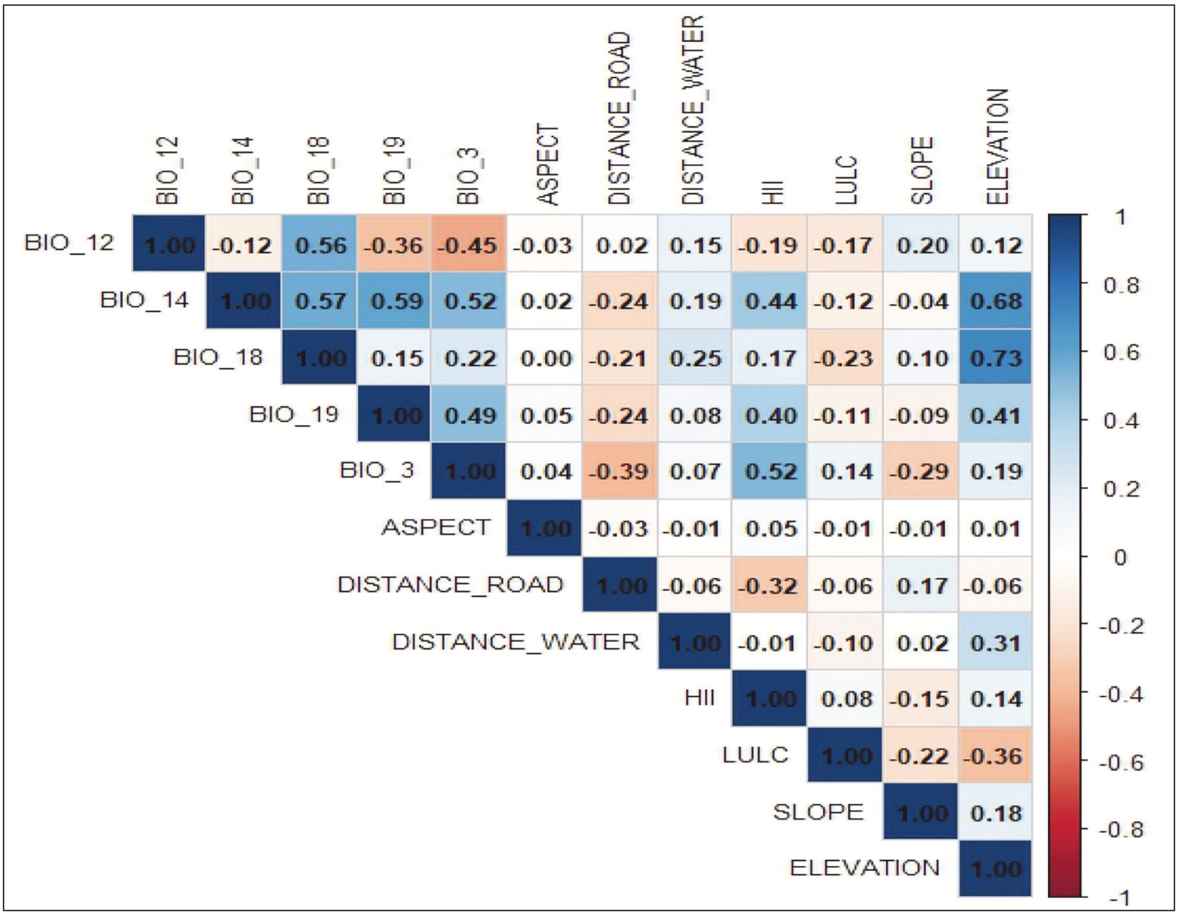
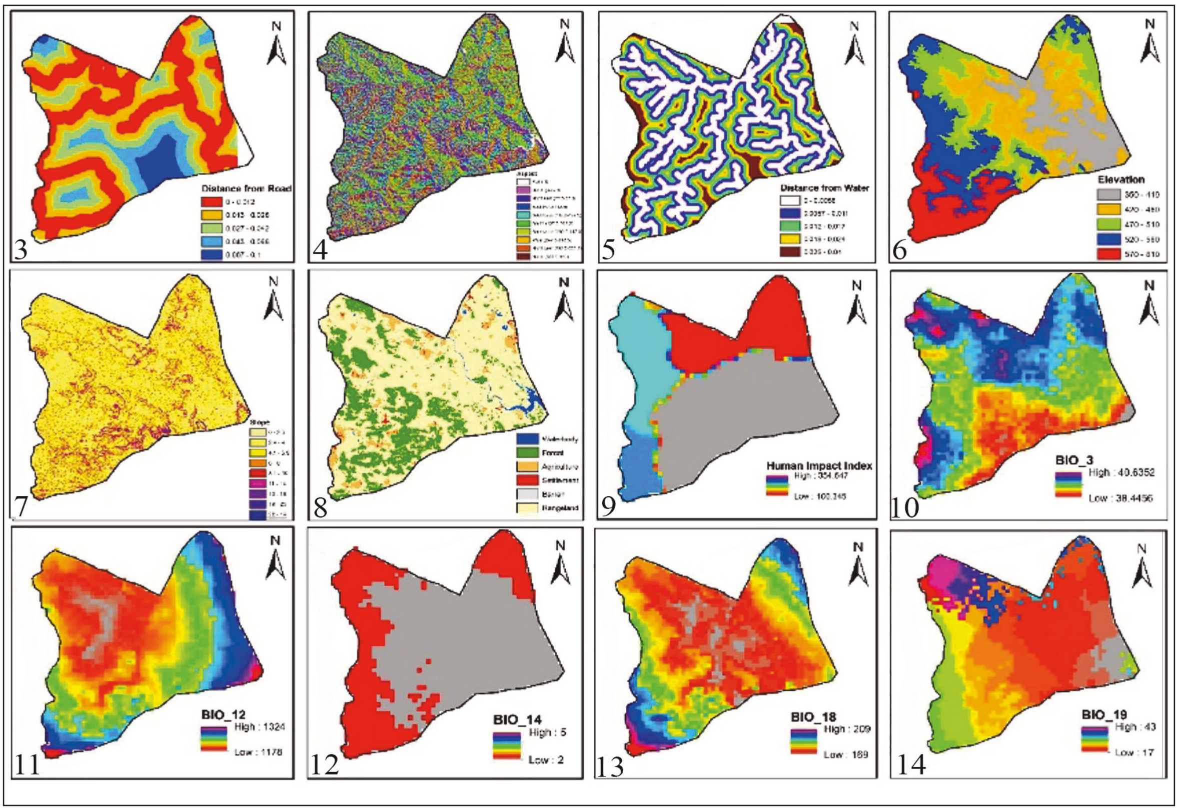


Figure 2. Correlation coefficients among various environmental variables.



Figures 3–14. Maps showing the spatial patterns of environmental predictors used in the habitat suitability modeling, including anthropogenic. Fig. 3: Distance from Road. Fig. 4: Aspect. Fig. 5: Distance from Water. Fig. 6: Elevation. Fig. 7: Slope, land cover. Fig. 8: LULC, and selected bioclimatic variables. Fig. 9: Human Impact Index. Fig. 10: BIO_3 – Isothermality. Fig. 11: BIO_12 – Annual Precipitation. Fig. 12: BIO_14 – Precipitation of Driest Month. Fig. 13: BIO_18 – Precipitation of Warmest Quarter. Fig. 14: BIO_19 – Precipitation of Coldest Quarter).

(Philips et al., 2004, 2006; Mardaraj et al., 2023). The modeling process utilized a replicated subsample approach, generating a total of 10 replicate models to ensure robustness and reliability. For each replicate, 70% of the occurrence records were randomly selected for model training, while the remaining 30% were used for testing. The modelling was executed with key parameters such as logistic output format, a maximum of 1000 iterations, and 1000 background points. To avoid artificial inflation of model predictions, extrapolation and clamping were disabled. The receiver operating characteristic curve (ROC) method was used to test the model's accuracy. The ROC curve is based on the model accuracy of non-threshold-independent evaluation, that is, each value of the predicted result is used as a possible judgment threshold, and the corresponding sensitivity and specificity are calculated from this. The AUC value is the ROC curve and the abscissa range. The area under the ROC curve can be used to describe the accuracy of the model simulation value. The ideal situation is that the predicted distribution area of the model completely matches the actual distribution area of the species, and the AUC value is 1 at this time. The AUC (area under the receiver operating characteristic curve) values vary from 0 to 1; values < 0.5 indicate that the model performance is worse than random, 0.5 indicates performance that is not better than random, 0.5–0.7 indicates poor performance, 0.7–0.9 indicates reasonable or moderate performance, and >0.9 indicates high performance (Jiang et al., 2018).

RESULTS

Area under ROC Curve (AUC)

The model achieved an average AUC value of 0.870, reflecting a fair level of accuracy in differ-

Category	Variables	Abbreviation	Unit	Source
Bioclimatic Variables	Annual Mean Temperature	Bio1	°C × 10	WorldClim v2 (1970–2000)
	Mean Diurnal Range (Mean of monthly (max temp - min temp)	Bio2	°C × 10	
	Isothermality (Bio2/Bio7) (* 100)	Bio3	%	
	Temperature Seasonality (standard deviation ×100)	Bio4	%	
	Max Temperature of Warmest Month	Bio5	°C × 10	
	Min Temperature of Coldest Month	Bio6	°C × 10	
	Temperature Annual Range (Bio5–Bio6)	Bio7	°C × 10	
	Mean Temperature of Wettest Quarter	Bio8	°C × 10	
	Mean Temperature of Driest Quarter	Bio9	°C × 10	
	Mean Temperature of Warmest Quarter	Bio10	°C × 10	
	Mean Temperature of Coldest Quarter	Bio11	°C × 10	
	Annual Precipitation	Bio12	mm	
	Precipitation of Wettest Month	Bio13	mm	
	Precipitation of Driest Month	Bio14	mm	
	Precipitation Seasonality (Coefficient of Variation)	Bio15	%	
	Precipitation of Wettest Quarter	Bio16	mm	
	Precipitation of Driest Quarter	Bio17	mm	
	Precipitation of Warmest Quarter	Bio18	mm	
	Precipitation of Coldest Quarter	Bio19	mm	
Topographic	Elevation	Elevation	meters	USGS-SRTM
	Aspect	Aspect	degrees	Derived from DEM
	Slope	Slope	degrees	Derived from DEM
	Distance to Water	Distance_Water	meters	Hydrosheds
Anthropogenic	Human Impact Index	HII	Index (unitless)	Global Human Influence Dataset, SEDAC, NASA
	Distance to Road	Distance_Road	meters	OpenStreetMap
Land Cover	Land Use Land Cover	LULC	Class	ESRI Sentinel-2

Table 1. Maximum entropy modeling of environmental factors, listing the bioclimatic variables used in the study along with other environmental factors.

entiating between suitable and unsuitable habitats for *Melursus ursinus*. The Receiver Operating Characteristic (ROC) curve (Fig. 15) demonstrates the trade-off between sensitivity (true positive rate) and 1-specificity (false positive rate), with the model's performance significantly exceeding that of a random prediction (AUC = 0.5). This relatively high AUC value indicates that the selected environmental variables effectively represent the ecological requirements of the species.

The omission and predicted area plot for *Melursus ursinus* (Fig. 16) illustrates the model's reliability in predicting species presence across different cumulative thresholds. The predicted omission rate (black line) closely follows the observed omission rate on test data (green line), with narrow confidence intervals represented by the yellow bands (± one standard deviation). This close alignment indicates that the model's predictions are statistically consistent and not overfitted. Additionally, the mean predicted area (red line) and its variation (blue band) remain stable across thresholds, reinforcing the model's robustness.

Contributions of Environment variables

The Jackknife test of variable importance, based on the Area Under the Curve (AUC), was used to assess the individual contribution of each environmental variable to the MaxEnt model (Figs. 17, 18). The results indicate that elevation had the highest individual predictive power when used in isolation, suggesting it contains the most useful information for modeling sloth bear distribution. Additionally, elevation also caused the greatest decrease in AUC when omitted, implying that it provides unique information not captured by other variables.

DISCUSSION

The model achieved a high average AUC value of 0.870, indicating strong predictive accuracy. This suggests that the environmental variables selected effectively capture the ecological requirements of the species, reinforcing the utility of MaxEnt as a reliable tool for species distribution modeling (Phillips et al., 2006; Elith et al., 2011).

Similar studies conducted in India and abroad have yielded comparable AUC values when modeling species with similar ecological characteristics. For instance, Jena & Nandi (2017) achieved model accuracy (AUC = 0.732) in the Similipal biosphere reserve of Odisha. The current model's results shows the significant role of anthropogenic disturbances in shaping the distribution of sloth bear. The Human Influence Index (HII) emerged as the most influential variable (24.1%), emphasizing how human settlements, infrastructure, and land use changes negatively impact sloth bear habitats. This finding aligns with studies by Dutta, 2015, who documented the adverse effects of increasing human encroachment on wildlife corridors and habitat quality in Central India. Land Use Land Cover (LULC) was the second-most important predictor (19.5%), reflecting the sloth bear's reliance on forested landscapes with minimal fragmentation. This supports earlier observations by Garshelis (1999) and Bargali (2012), which noted that sloth bears prefer undisturbed forests, often avoiding open agricultural lands or areas near human

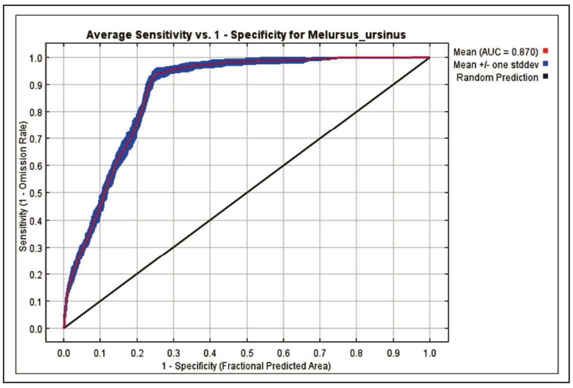


Figure 15. Receiver Operating Characteristic (ROC) Curve for *Melursus ursinus*.

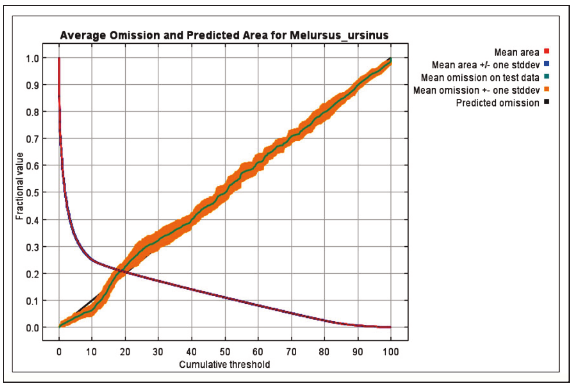


Figure 16. Average Omission Rate and Predicted Area for *Melursus ursinus*.

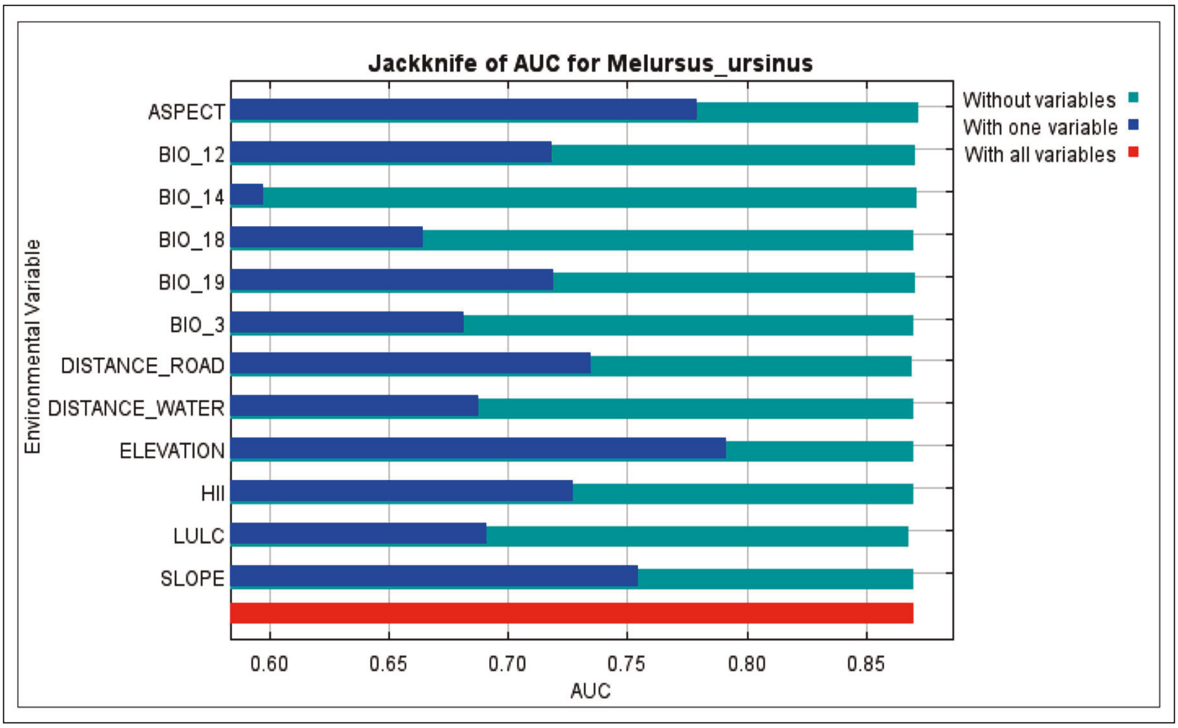


Figure 17. Jackknife area under the curve (AUC) of different environmental variables.

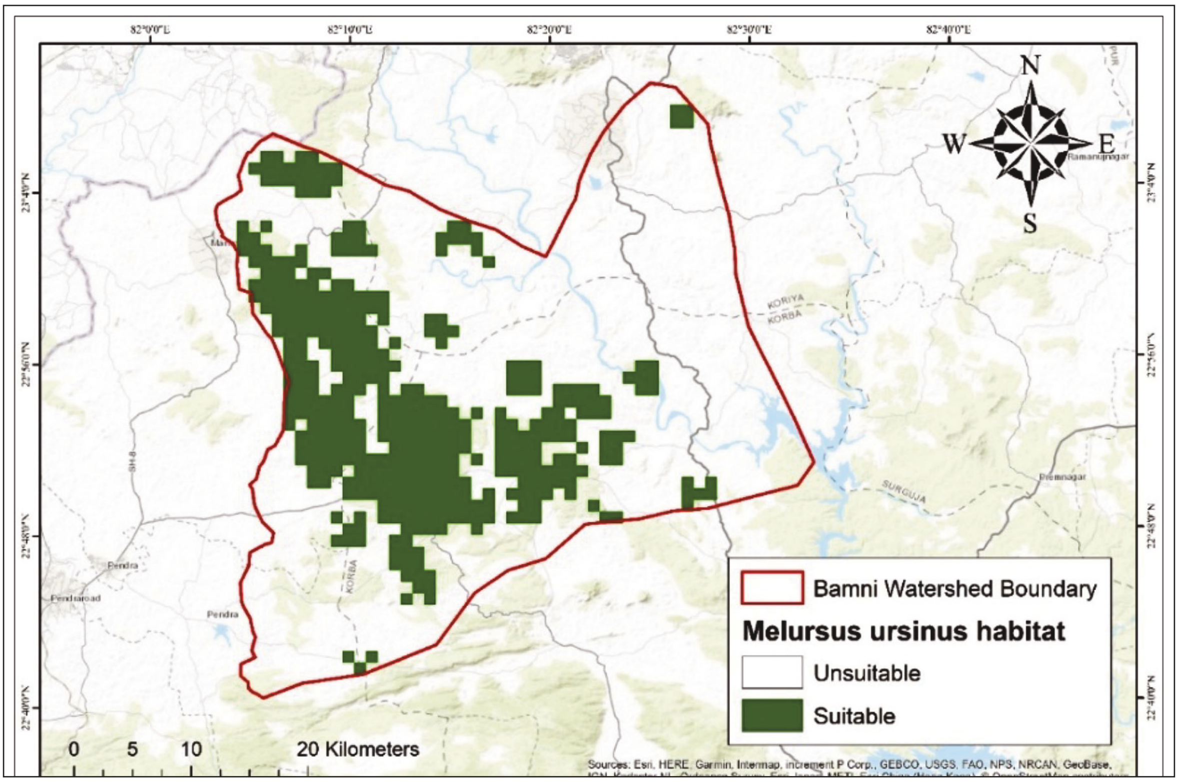


Figure 18. Spatial distribution of suitable habitat for *Melursus ursinus*.

settlements. Among topographic variables, aspect (12.9%), elevation (9.7%), and slope (7.3%) played significant roles, likely because these features influence the distribution of microhabitats suitable for foraging, denning, and thermoregulation. Studies in the Eastern Ghats (Palei et al., 2014) reported that sloth bears frequently use hill slopes and rugged terrains, which provide both cover and access to insect prey like termites. Distance to linear features, such as roads (6.4%) and water bodies (6.0%), also influenced habitat suitability. The Jackknife test of variable importance confirmed elevation as the most informative variable when used in isolation, indicating its central role in determining habitat preference. Variables like aspect, distance to water, and slope also showed considerable standalone predictive strength. In contrast, variables such as BIO_19 (Precipitation of Coldest Quarter) showed low individual AUC values, implying limited andalone significance but possible synergistic effects when combined with other variables.

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Variable	Percent contribution
HII	24.1
LULC	19.5
ASPECT	12.9
ELEVATION	9.7
SLOPE	7.3
DISTANCE_ROAD	6.4
DISTANCE_WATER	6
BIO_12	5.1
BIO_14	4.1
BIO_3	3
BIO_18	1.8
BIO_19	0.1

Table 2. Contribution of environmental variables in the MaxEnt model.

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