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**ORIGINAL ARTICLE**

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# Habitat suitability modeling and local community attitudes toward conservation of the Chinese pangolin (Manis pentadactyla) in the Division Forest Office, Rapti, Makawanpur District, Nepal

**Vijay Kumar Yadav[1], Hari Prasad Adhikari[1] and Punit Yadav[2]**

[1]Department of Forestry, Tribhuvan University, Institute of Forestry, Hetauda Campus, Nepal
[2]Faculty of Forestry, Agriculture and Forestry University, Nepal

## ABSTRACT

Pangolins are highly threatened mammals with specialized diets of ants and termites, and the Chinese pangolin (Manis pentadactyla) remains poorly documented in many parts of Nepal. This study assessed habitat suitability for the Chinese pangolin and evaluated local community attitudes toward its conservation in the Division Forest Office, Rapti, Makawanpur District, Nepal. We combined reconnaissance surveys, key informant consultation, field-based burrow surveys, and household questionnaires. A total of 351 pangolin burrows (257 old and 93 new burrows) were recorded, and 108 households were surveyed, including 67 respondents from community forests located in suitable habitat and 41 from the least suitable habitat. Occurrence records were spatially thinned to reduce clustering, and 81 retained records were used for ensemble species distribution modeling in the biomod2 package in R. Ten algorithms were evaluated using the True Skill Statistic (TSS) and the Area Under the Receiver Operating Characteristic Curve (AUC). Models with TSS > 0.60 and AUC > 0.70 were retained and combined using a TSS-weighted ensemble approach. Random Forest (TSS = 0.800, AUC = 0.969), Generalized Boosting Model (TSS = 0.764, AUC = 0.981), and MAXENT (TSS = 0.757, AUC = 0.880) of the 1,109.3 km2 study area as highly suitable and 150.6 km2 (13.6%) moderately suitable habitat. Population density, vegetation type, distance to settlement, and NDVI were the most influential predictors. Community attitudes were generally positive, but ecological knowledge remained limited. Education and habitat suitability class significantly influenced conservation interest, whereas age and gender did not. The results identify spatially explicit priority areas and highlight the need for targeted outreach in community forests and agricultural buffer areas adjoining suitable pangolin habitat.

## KEY WORDS

Chinese pangolin; Habitat suitability; Ensemble modeling; Species distribution modeling; Community perception; Nepal

## ARTICLE HISTORY

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## Introduction

Pangolins are among the most threatened mammals globally because of illegal trade, hunting, habitat loss, and low reproductive rates. Two pangolin species occur in Nepal: The Chinese pangolin (Manis pentadactyla) and the Indian pangolin (Manis crassicaudata). Both are protected in Nepal, and the Chinese pangolin is categorized as Critically Endangered in the IUCN Red List and in the National Red List of Nepal [1-3]. Chinese pangolins occur in the northern Indian subcontinent, parts of Southeast Asia, and southern China, and they occupy a wide range of forested and human-modified habitats, including primary and secondary subtropical forests, mixed broadleaf forests, grasslands, bamboo forests, agricultural edges, and degraded forest mosaics [1-6]. Because pangolins are nocturnal, fossorial, and rarely observed directly, conservation assessments frequently rely on indirect signs such as burrows, feeding signs, and local ecological knowledge [4,7,8].

Habitat suitability modeling is an important tool for identifying priority areas for the conservation of rare and threatened species. Species distribution models (SDMs), also known as ecological niche models, use species occurrence data and environmental predictors to estimate suitable habitat across a landscape [9,10]. SDM outputs have been used to prioritize conservation areas, guide field surveys, identify conservation gaps, and evaluate the likely effects of land-use and environmental change on species distributions [11-13]. For cryptic species such as pangolins, however, SDM performance is influenced by sparse occurrence data, uneven survey effort, spatial clustering around accessible areas, and uncertainty in true absence records. These limitations require careful algorithm selection, spatial thinning of occurrence records, transparent pseudo-absence/background generation, and cautious interpretation of model outputs [14-16].

Several algorithms are available for SDM. Regression-based approaches such as Generalized Linear Models (GLM) and Generalized Additive Models (GAM) estimate species-environment relationships using relatively interpretable statistical functions. Machine-learning approaches such as Random Forest (RF), Generalized Boosting Model (GBM), Classification Tree Analysis (CTA), Artificial Neural Networks (ANN), and Flexible Discriminant Analysis (FDA) can capture complex and nonlinear responses. Multivariate Adaptive Regression Splines (MARS) model piecewise relationships, while Maximum Entropy (MAXENT) and Surface Range Envelope (SRE) are commonly applied to presence-only or presence-background datasets [17-19]. Because these algorithms differ in their assumptions, sensitivity to sample size, ability to handle nonlinear responses, and dependence on pseudo-absence or background data, relying on a single

***Correspondence:** Dr. Vijay Kumar Yadav, Department of Forestry, Tribhuvan University, Institute of Forestry, Hetauda Campus, Nepal
e-mail: vijay.yadav@hc.tu.edu.np

algorithm can produce biased or unstable predictions. Ensemble modeling, which combines predictions from multiple algorithms, is therefore recommended to improve robustness and reduce the influence of individual model bias [16,20-22].

In Nepal, SDM applications for pangolins have increased but remain geographically uneven. Suwal et al. modeled pangolin habitat at the national scale and estimated that approximately 15.2% of Nepal could be potentially suitable habitat [23]. Sharma et al. used MaxEnt to predict potential distribution of Chinese pangolin in Nepal under current and future conditions, while Panta et al. examined habitat preference, distribution, and community attitudes in Gorkha District [4,24]. These studies have provided important national and district-level baselines, but several limitations remain. First, many available studies are either broad-scale, making them less directly actionable for local forest management units, or limited to selected districts. Second, the relationship between habitat suitability and community perception has rarely been evaluated within the same management landscape. Third, the administrative units responsible for forest management, such as Division Forest Offices and Community Forest User Groups (CFUGs), often lack spatially explicit maps that can be directly used for local conservation planning.

Beyond Nepal, habitat modeling and field-based assessments of pangolins in South Asia and China show that pangolin occurrence is shaped by forest cover, elevation, slope, soil/vegetation conditions, water availability, and human disturbance [13,25,26]. Gao et al., for example, used ensemble SDMs in Guangdong, China, and found that climatic, geographic, vegetation, and anthropogenic variables jointly determined Chinese pangolin suitability [13]. Such studies demonstrate the value of multi-algorithm approaches but also emphasize that model performance and variable importance are landscape specific. Therefore, local habitat assessments remain necessary, particularly in human-dominated landscapes where forest patches, agricultural edges, and settlements occur in proximity.

The Division Forest Office, Rapti, Makawanpur District, includes forest, agricultural, settlement, and Chure hill landscapes where pangolin burrows have been reported, but spatially explicit habitat suitability and community perception data remain limited. This study therefore aimed to (i) map suitable habitat for the Chinese pangolin in the Division Forest Office, Rapti using an ensemble SDM approach; (ii) identify the environmental and anthropogenic variables that most strongly influence predicted habitat suitability; and (iii) assess local community knowledge and attitudes toward pangolin conservation across suitable and unsuitable habitat classes. By linking habitat modeling with community perception, the study provides practical information for spatially targeted conservation planning by the Division Forest Office and CFUGs.

## Materials and Methods

### Study area

The study was conducted in the Division Forest Office (DFO), Rapti, Makawanpur District, Bagmati Province, central Nepal (approximately 27°21′–27°41′ N and 84°41′–85°23′ E). The DFO covers 1,109.3 km$^2$ and extends from low-elevation river valleys to Chure and mid-hill landscapes, with an elevation range of 230–2,584 m above sea level.

The area has a monsoon-dominated climate with warm, wet summers and relatively dry winters. Based on WorldClim 2.1 climatic surfaces, mean annual temperature across the study area ranges approximately from 16 to 25 °C and annual precipitation from about 1,700 to 2,600 mm, with most rainfall occurring during June-September [27]. The ecological gradient supports tropical, subtropical, and warm-temperate vegetation. Major tree species include Shorea robusta, Pinus roxburghii, Pinus wallichiana, Quercus spp., Schima wallichii, Castanopsis indica, and Acacia catechu.

As shown in Figure 1, the DFO boundary was used analytically because it represents the administrative and management unit within which forest permissions, CFUG coordination, habitat protection, awareness campaigns, and anti-poaching interventions are planned and implemented. Although this boundary is administrative rather than strictly ecological, using it makes the results directly relevant to local conservation decision-making. We acknowledge that pangolin habitat extends beyond this boundary and that landscape-scale connectivity should be evaluated in future work.

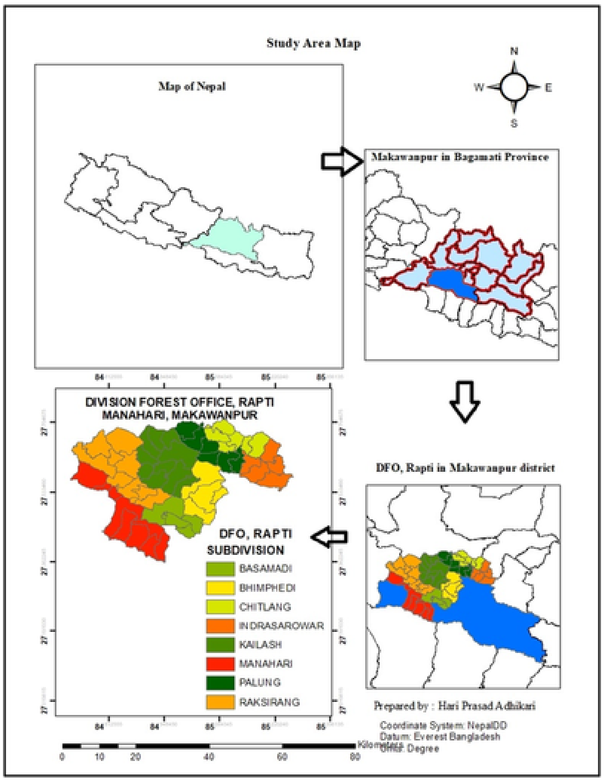


**Figure 1.** Location and elevation context of the Division Forest Office, Rapti, Makawanpur District, Nepal.

### Occurrence data collection

Primary occurrence data were collected through reconnaissance surveys, key informant consultation, and field surveys in community and national forests. Initial consultations were held with DFO staff, CFUG representatives, forest guards, and residents to identify areas where pangolin burrows or sightings had been reported. These consultations guided stratified field searches across forest blocks, agricultural edges, and settlement-adjacent habitats. Field surveys were conducted during the dry and early pre-monsoon season, when burrow entrances and fresh digging signs are easier to detect. Survey routes were placed to cover major habitat



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gradients, including elevation, slope, forest type, and human disturbance. A standardized visual search protocol was followed along walking transects and forest trails, with observers searching both sides of the route for burrows, feeding signs, and associated soil disturbance.

At each burrow, geographic coordinates were recorded using a hand-held GPS. Elevation, slope, aspect, habitat type, land-use context, and signs of recent use were recorded in the field. Burrows were classified as new when they showed fresh excavation, loose soil, clean entrances, recent scratch marks, absence of leaf litter, or evidence of active use. Burrows were classified as old when entrances were partly collapsed, weathered, covered by leaf litter, or overgrown by vegetation. Potential burrows of other animals, such as porcupines or civets, were excluded when diagnostic pangolin features were absent. Species attribution was based on burrow morphology, local ecological knowledge, the known distribution of Chinese pangolin in the mid-hill and Chure landscape, and published descriptions of pangolin burrows [1,4,28,29]. Because the Indian pangolin also occurs in Nepal, species misclassification cannot be fully excluded and is treated as a study limitation. No genetic confirmation was conducted.

A total of 351 burrow locations were recorded. To reduce spatial autocorrelation and sampling bias caused by clustered burrows, occurrence records were spatially thinned using the spThin package in R [15]. A minimum nearest-neighbour distance of 1 km was applied, and 100 thinning replicates were evaluated. The replicate retaining the largest number of spatially independent records was selected, resulting in 81 occurrence points for modeling.

## Environmental predictors and spatial data preparation

The table 1 shows that an initial set of 31 candidate environmental variables representing topography, vegetation, land cover, productivity, water availability, access, and human disturbance was compiled. Highly correlated variables were screened using pairwise correlation analysis and variance inflation factors (VIF). Variables with $|r| >= 0.70$ or VIF > 5 were removed to reduce multicollinearity, leaving ten final predictors: elevation, slope, aspect, vegetation type, land cover, Normalized Difference Vegetation Index (NDVI), population density, distance to water sources, distance to settlements, and distance to roads. Climate variables were used to characterize the study area but were not included in the final model because they were strongly correlated with elevation and provided limited additional information at the DFO scale.

**Table 1.** Environmental predictors used for Chinese pangolin habitat suitability modeling.

| Predictor | Type | Source/derivation | Resolution used | Model treatment |
|---|---|---|---|---|
| Elevation | Continuous | SRTM DEM from USGS/NASA [30] | 30 m | Continuous |
| Slope | Continuous | Derived from SRTM DEM | 30 m | Continuous |
| Aspect | Categorical | Derived from SRTM DEM and grouped into east, west, north, and south | 30 m | Categorical dummy variables |
| Vegetation type | Categorical | DFO/CFUG forest-type information and field verification | 30 m | Categorical dummy variables |
| Land cover | Categorical | ESA WorldCover 2021, reclassified for local habitat classes [31] | 30 m | Categorical dummy variables |
| NDVI | Continuous | Dry-season Sentinel-2 Level-2A cloud-free composite | 30 m | Continuous |
| Population density | Continuous | WorldPop 2020 gridded population dataset [32] | 100 m resampled to 30 m | Continuous |
| Distance to water | Continuous | Euclidean distance to rivers/streams derived from OpenStreetMap and DFO layers | 30 m | Continuous |
| Distance to settlement | Continuous | Euclidean distance to settlement polygons/points from OpenStreetMap and local GIS layers | 30 m | Continuous |
| Distance to road | Continuous | Euclidean distance to road network from OpenStreetMap and local GIS layers | 30 m | Continuous |

All raster layers were projected to a common coordinate reference system, clipped to the DFO boundary, resampled to 30 m spatial resolution, and aligned to the same grid before modeling as shown in Table 1. Euclidean distance rasters were generated for water sources, settlements, and roads. Categorical variables were represented as dummy/indicator layers in the modeling workflow.

## Species distribution modeling

Habitat suitability was modeled using an ensemble approach in the biomod2 package in R [33]. Ten algorithms were evaluated: ANN, CTA, FDA, GAM, GBM, GLM, MARS, MAXENT, RF, and SRE. These algorithms were selected because they represent regression-based, tree-based, machine-learning, envelope, and presence-background approaches commonly used in SDM.

Because true absence data were unavailable, pseudo-absence points were generated within the DFO boundary. For each run, 1,000 pseudo-absence/background points were randomly sampled from areas excluding occupied grid cells and their immediate neighboring cells. This approach provided contrast between observed occurrence locations and available environmental conditions across the study area. Presence and pseudo-absence data were split into 70% training and 30% testing subsets, with ten replicate runs per algorithm. Unless otherwise stated, biomod2 default settings were used; RF was run with 500 trees, and MAXENT used default feature classes and regularization settings.

Model performance was evaluated using True Skill Statistic (TSS) and the Area Under the Receiver Operating Characteristic Curve (AUC). TSS is less affected by prevalence



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than some alternative measures and ranges from -1 to +1, with values closer to +1 indicating stronger discrimination [34]. AUC provides a threshold-independent measure of the ability to discriminate suitable from unsuitable conditions; values above 0.70 are commonly considered acceptable for ecological applications, although interpretation should consider data quality and species detectability. Models with TSS > 0.60 and AUC > 0.70 were retained for ensemble modeling. The final ensemble was constructed as a TSS-weighted mean of retained model predictions, giving greater influence to better-performing algorithms. Continuous suitability values were reclassified into least suitable (0.00-0.30), moderately suitable (0.31-0.60), and highly suitable (>0.60) classes for interpretation and conservation planning.

### Community perception survey and statistical analysis

A household questionnaire survey was conducted to assess community knowledge and attitudes toward pangolin conservation. After generating the habitat suitability map, six CFUGs were selected: three located in highly suitable habitat and three in least suitable habitat. Ten percent of households or CFUG members were randomly selected from each CFUG list, yielding 108 respondents. Of these, 67 respondents were from suitable habitat (SH) and 41 from unsuitable habitat (UH). The questionnaire included questions on awareness of pangolins, ability to distinguish Chinese and Indian pangolins, observation history, knowledge of pangolin ecology, perceived population status, perceived threats, awareness of legal protection, support for public awareness, and interest in conservation.

Responses were summarized using frequencies and percentages. Chi-square tests were used to examine whether conservation attitudes differed by age group, gender, education level, and habitat suitability class. Education was collapsed into illiterate and literate categories for chi-square tests because several cells in the full five-category education table had low expected frequencies. Gender-related p-values were recalculated from the underlying contingency tables to verify the originally reported high p-values. Statistical significance was assessed at alpha = 0.05.

## Results

### Occurrence data summary

A total of 351 Chinese pangolin burrows were recorded, including 257 old burrows (72.7%) and 93 new burrows (27.2%). Burrows occurred across an elevation range of 235-2,400 m and on slopes ranging from 1° to 40°. In Table 2 it is shown that the most burrows were recorded between 500 and 1,000 m elevation (49.5%) and on slopes of 10°-20° (41.6%). South-facing slopes contained the highest proportion of burrows (40.7%), followed by north-facing (26.5%), east-facing (18.5%), and west-facing slopes (14.2%). Chi-square goodness-of-fit tests indicated non-uniform distribution across elevation classes ($\chi 2 = 217.76$, df = 4, $p < 0.001$), slope classes ($\chi 2 = 83.66$, df = 3, $p < 0.001$), and aspect classes ($\chi 2 = 57.24$, df = 3, $p < 0.001$). These tests compare observed counts across classes and should be interpreted as descriptive rather than habitat-selection tests because available habitat proportions were not used as the expected distribution.

**Table 2.** Terrain characteristics of recorded Chinese pangolin burrows.

| Variable | Class | Frequency | Percentage (%) |
|---|---|---|---|
| Altitude (m) | <500 | 47 | 13.4 |
| | 500-1000 | 174 | 49.5 |
| | 1000-1500 | 65 | 18.5 |
| | 1500-2000 | 56 | 16 |
| | >2000 | 9 | 2.5 |
| Slope (degrees) | <10 | 70 | 19.9 |
| | Oct-20 | 146 | 41.6 |
| | 20-30 | 105 | 29.9 |
| | >30 | 30 | 8.5 |
| Aspect | East | 65 | 18.5 |
| | West | 50 | 14.2 |
| | North | 93 | 26.5 |
| | South | 143 | 40.7 |

The Figure 2 shows the burrow distribution also varied among localities. The highest numbers were recorded in Basamadi (117), Bhimphedi (99), and Kailash (58), whereas fewer burrows were recorded in Manahari (21), Indrasarowar (15), and Raksirang (5). This locality-level pattern represents the distribution of field records and survey effort rather than an independent model output as shown in the table 3.

**Table 3.** Summary of selected environmental conditions at recorded burrow locations.

| Environmental variable | Class | Burrows (n) | Percentage (%) |
|---|---|---|---|
| Population density (people/km2) | <250 | 214 | 61 |
| | 250-500 | 91 | 25.9 |
| | 500-1000 | 38 | 10.8 |
| | >1000 | 8 | 2.3 |



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|---|---|---|---|
| NDVI | <0.20 | 31 | 8.8 |
| | 0.20-0.40 | 126 | 35.9 |
| | 0.40-0.60 | 151 | 43 |
| | >0.60 | 43 | 12.3 |
| Distance to water (m) | <500 | 198 | 56.4 |
| | 500-1000 | 104 | 29.6 |
| | >1000 | 49 | 14 |
| Distance to settlement (m) | <500 | 90 | 25.6 |
| | 500-1000 | 112 | 31.9 |
| | >1000 | 149 | 42.5 |
| Dominant land cover | Tree cover/forest | 228 | 65 |
| | Cropland/agricultural edge | 61 | 17.4 |
| | Shrubland/grassland | 46 | 13.1 |
| | Built-up/open/bare areas | 16 | 4.5 |

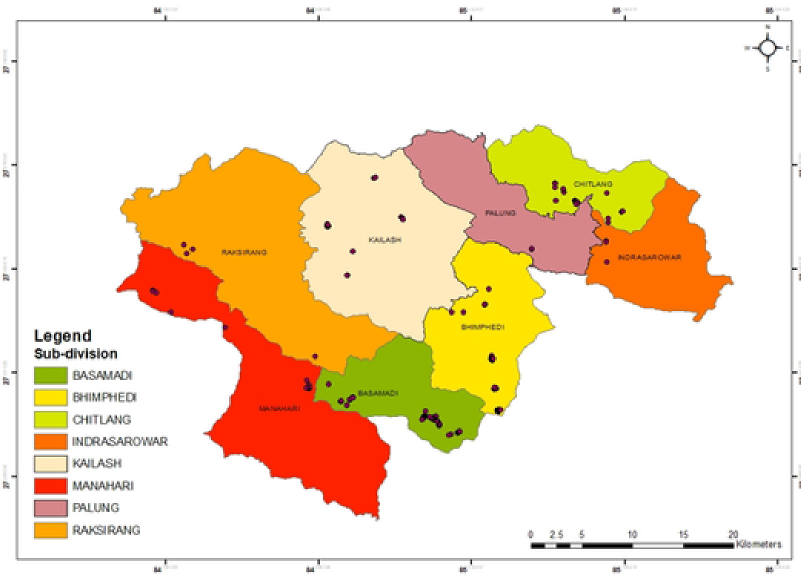


Figure 2. Recorded Chinese pangolin burrow locations in the Division Forest Office, Rapti.

## Model performance

Table 4 shows model performance varied among algorithms. All ten algorithms produced AUC values greater than 0.70, but TSS ranged from 0.446 to 0.800 as seen in Figure 3. Four algorithms, SRE (TSS = 0.446), GAM (TSS = 0.525), FDA (TSS = 0.545), and ANN (TSS = 0.571), did not meet the TSS > 0.60 retention criterion and were excluded from the final ensemble. RF, GBM, and MAXENT were the strongest-performing models. Tree-based and machine-learning algorithms generally performed better than the envelope-based SRE model, indicating that flexible algorithms captured nonlinear habitat relationships more effectively in this dataset.

**Table 4.** Performance of individual habitat suitability models. AUC refers to the Area Under the Receiver Operating Characteristic Curve.

| Algorithm | Full name | TSS | SD | AUC | SD | Retained? |
|---|---|---|---|---|---|---|
| RF | Random Forest | 0.8 | 0.037 | 0.969 | 0.011 | Yes |
| GBM | Generalized Boosting Model | 0.764 | 0.111 | 0.981 | 0.049 | Yes |
| MAXENT | Maximum Entropy | 0.757 | 0.048 | 0.88 | 0.027 | Yes |
| CTA | Classification Tree Analysis | 0.744 | 0.149 | 0.894 | 0.075 | Yes |
| MARS | Multivariate Adaptive Regression Splines | 0.734 | 0.068 | 0.92 | 0.023 | Yes |
| GLM | Generalized Linear Model | 0.624 | 0.06 | 0.879 | 0.026 | Yes |
| ANN | Artificial Neural Network | 0.571 | 0.078 | 0.85 | 0.046 | No |
| FDA | Flexible Discriminant Analysis | 0.545 | 0.069 | 0.833 | 0.033 | No |



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| | | | | | | |
|---|---|---|---|---|---|---|
| GAM | Generalized Additive Model | 0.525 | 0.059 | 0.833 | 0.027 | No |
| SRE | Surface Range Envelope | 0.446 | 0.062 | 0.723 | 0.031 | No |

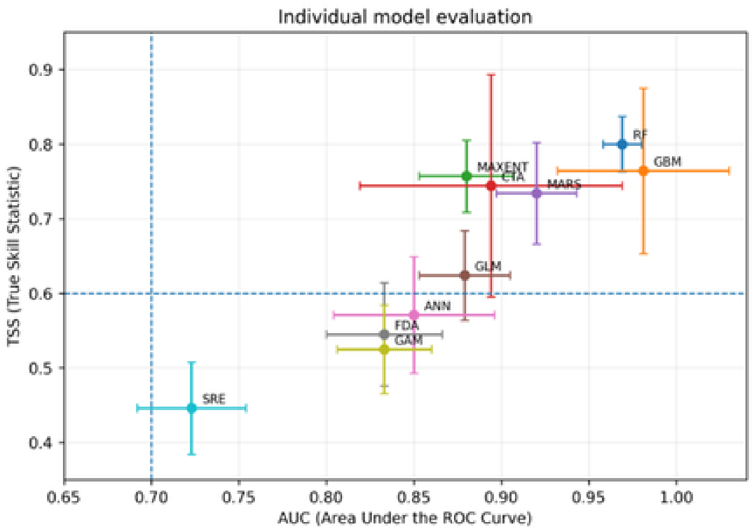


**Figure 3.** Evaluation of individual algorithms using AUC and TSS.

### Habitat suitability

The TSS-weighted ensemble model classified 26.3 km$^2$ (2.4%) of the DFO area as highly suitable habitat, 150.6 km$^2$(13.6%) as moderately suitable habitat, and 932.4 km $^2$(84.0%) as least suitable habitat for the Chinese pangolin as seen in table 5. Highly suitable habitat was concentrated mainly in forested Chure hill areas and adjoining community forests, whereas moderately suitable habitat occurred in fragmented forest-agricultural mosaics around Indrasarowar, Chitlang, and adjacent mid-hill landscapes. The recalculated percentages are based on the reported total DFO area of 1,109.3 km2 as shown in Figure 4.

**Table 5.** Predicted habitat suitability classes for Chinese pangolin in the Division Forest Office, Rapti.

| Suitability class | Suitability threshold | Area (km$^2$) | Percentage of study area (%) |
|---|---|---|---|
| Least suitable | 0.00-0.30 | 932.4 | 84 |
| Moderately suitable | 0.31-0.60 | 150.6 | 13.6 |
| Highly suitable | >0.60 | 26.3 | 2.4 |
| Total | | 1,109.30 | 100 |

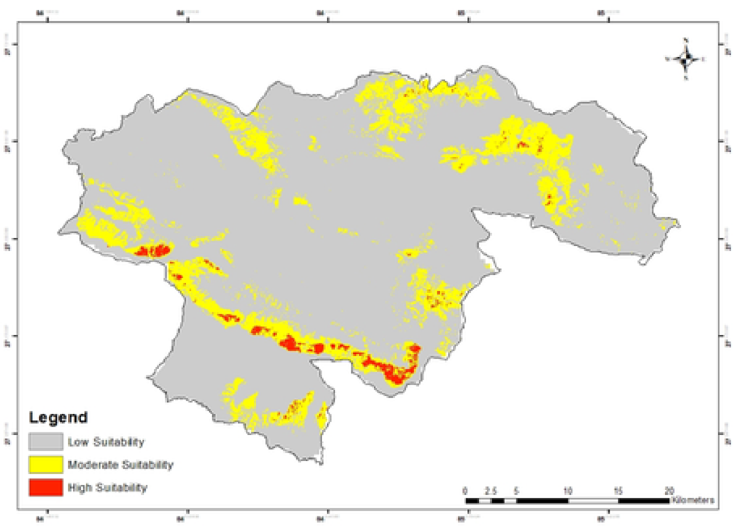


**Figure 4.** Ensemble habitat suitability map for Chinese pangolin in the Division Forest Office, Rapti.



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**Variable importance and response curves**

Population density was the most influential predictor in the ensemble model (28.343%), followed by vegetation type (20.597%), distance to settlement (13.368%), NDVI (12.628%), and distance to water source (10.876%) as shown in table 6. Together, these five variables accounted for 85.8% of total model contribution. Variables with lower contributions included land cover, slope, elevation, distance to road, and aspect. The high contribution of population density and distance to settlement indicates that anthropogenic pressure strongly influenced predicted suitability in this landscape.

**Table 6.** Percentage contribution of environmental variables to the ensemble habitat suitability model.

| Rank | Environmental variable | Contribution (%) |
|---|---|---|
| 1 | Population density | 28.343 |
| 2 | Vegetation type | 20.597 |
| 3 | Distance to settlement | 13.368 |
| 4 | NDVI | 12.628 |
| 5 | Distance to water source | 10.876 |
| 6 | Land cover | 3.918 |
| 7 | Slope | 3.729 |
| 8 | Elevation | 3.079 |
| 9 | Distance to road | 2.356 |
| 10 | Aspect | 1.108 |
| | Total | 100 |

**Table 7.** Variable contributions (%) across individual algorithms.

| Variable | ANN | CTA | FDA | GAM | GBM | GLM | MARS | MAXENT | RF | SRE |
|---|---|---|---|---|---|---|---|---|---|---|
| Population density | 32.55 | 34.99 | 54.21 | 12.88 | 26.34 | 11.44 | 12 | 25.64 | 44.54 | 9.42 |
| Vegetation type | 15.47 | 19.05 | 13.43 | 36.92 | 16.24 | 24.73 | 19.8 | 17.34 | 14.03 | 11.09 |
| Distance to settlement | 0 | 14.22 | 10.79 | 10.12 | 16.11 | 16.09 | 14.78 | 10.41 | 14.97 | 3.57 |
| NDVI | 0 | 11.94 | 7.81 | 13.4 | 15.91 | 11.98 | 13.74 | 8.38 | 4.63 | 11.11 |
| Distance to water | 17.82 | 0.72 | 3.37 | 1.72 | 6.98 | 6.58 | 6.08 | 7.12 | 4.76 | 14.79 |
| Land cover | 6.97 | 3.46 | 3.56 | 8.58 | 1.47 | 6.35 | 5.81 | 5.99 | 2.12 | 9.82 |
| Slope | 0 | 2.15 | 2.45 | 5.32 | 4.36 | 7.52 | 4.68 | 9.18 | 2.4 | 13.25 |
| Elevation | 18.58 | 8.6 | 1.28 | 1.76 | 4.33 | 7.81 | 16.28 | 5.73 | 7.85 | 10.23 |
| Distance to road | 7.81 | 3.26 | 0.98 | 6.28 | 4.98 | 4.54 | 3.45 | 5.5 | 2.04 | 10.65 |
| Aspect | 0.8 | 1.6 | 2.12 | 3.01 | 3.28 | 2.95 | 3.39 | 4.71 | 2.68 | 6.07 |

Variable importance differed among algorithms. Population density ranked highest in most algorithms, but vegetation type was the dominant predictor in GAM and GLM. Elevation had low contribution in the ensemble despite its common importance in other pangolin habitat studies, suggesting that within the DFO boundary, elevation effects were partly captured by correlated vegetation and human-disturbance variables. Response curves indicated higher suitability at intermediate elevations near 1,500 m, NDVI values of 0.20-0.60, lower to moderate population densities, areas closer to water sources, slopes around 20°, and forested vegetation types, as seen in Table 7 and Figures 5-7, respectively.

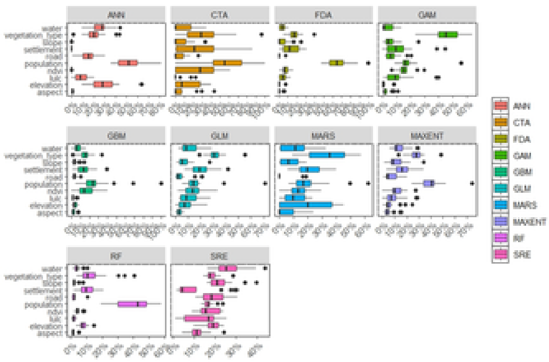


Figure 5. Variable importance of environmental predictors across the ten habitat suitability algorithms.



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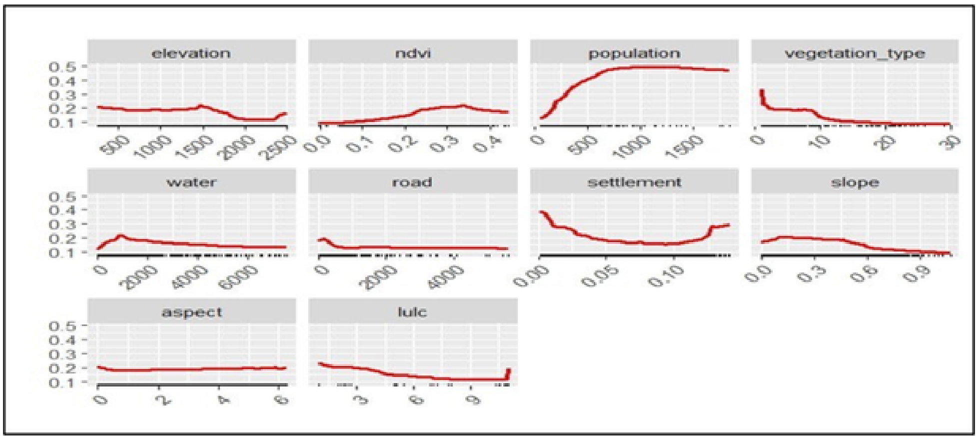


**Figure 6.** Ensemble response curves showing relationships between environmental predictors and Chinese pangolin habitat suitability.

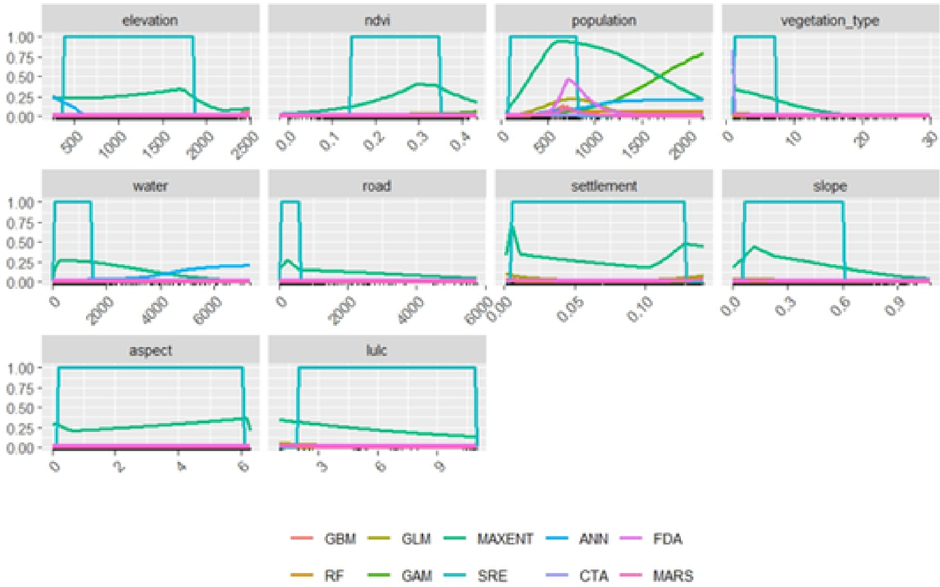


**Figure 7.** Response curves from individual algorithms used in the habitat suitability analysis.

### Community knowledge and attitudes toward pangolin conservation

In table 8 it is shown that a total of 108 respondents participated in the household survey: 67 from suitable habitat (SH) and 41 from unsuitable habitat (UH). Overall, 67 respondents were male (62.0%) and 41 were female (38.0%). Most respondents were 40-60 years old (41.7%), engaged in agriculture (57.4%), and belonged to Janajati ethnic groups (50.0%). Educational attainment was generally low: 26.9% were illiterate, and only 5.6% had a bachelor's degree. Demographic composition did not differ significantly between SH and UH respondents for gender, age, occupation, ethnicity, or education (all $p > 0.05$), suggesting that attitude differences by suitability class were unlikely to be driven solely by major demographic imbalance.

**Table 8.** Demographic characteristics of respondents overall and by habitat suitability class. SH = suitable habitat; UH = unsuitable habitat.

| Demographic variable | Category | Overall n (%) | SH n (%) | UH n (%) |
|---|---|---|---|---|
| Gender | Male | 67 (62.0) | 42 (62.7) | 25 (61.0) |
| | Female | 41 (38.0) | 25 (37.3) | 16 (39.0) |
| Age | <20 | 1 (0.9) | 1 (1.5) | 0 (0.0) |
| | 20-40 | 37 (34.3) | 23 (34.3) | 14 (34.1) |
| | 40-60 | 45 (41.7) | 29 (43.3) | 16 (39.0) |
| | >60 | 25 (23.1) | 14 (20.9) | 11 (26.8) |



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| | | | | |
|---|---|---|---|---|
| Occupation | Agriculture | 62 (57.4) | 39 (58.2) | 23 (56.1) |
| | Business | 25 (23.1) | 16 (23.9) | 9 (22.0) |
| | Private job | 8 (7.4) | 5 (7.5) | 3 (7.3) |
| | Student | 3 (2.8) | 2 (3.0) | 1 (2.4) |
| | Others | 10 (9.3) | 5 (7.5) | 5 (12.2) |
| Ethnicity | Brahmin | 39 (36.1) | 24 (35.8) | 15 (36.6) |
| | Chhetri | 11 (10.2) | 7 (10.4) | 4 (9.8) |
| | Janajati | 54 (50.0) | 34 (50.7) | 20 (48.8) |
| | Dalit | 4 (3.7) | 2 (3.0) | 2 (4.9) |
| Education | Illiterate | 29 (26.9) | 16 (23.9) | 13 (31.7) |
| | Primary | 31 (28.7) | 18 (26.9) | 13 (31.7) |
| | Secondary | 29 (26.9) | 20 (29.9) | 9 (22.0) |
| | Higher secondary | 13 (12.0) | 9 (13.4) | 4 (9.8) |
| | Bachelor's degree | 6 (5.6) | 4 (6.0) | 2 (4.9) |

Most respondents (92.6%) had heard of pangolins, but only 10.2% reported that they could distinguish between Chinese and Indian pangolins. Most respondents had never observed a pangolin in the wild (80.0%). Knowledge of pangolin ecology was generally limited: 57.4% reported no ecological knowledge and no respondent demonstrated good ecological knowledge. However, 78.0% of respondents were aware that pangolin hunting and poaching are illegal, and 39.0% identified hunting and poaching as the main threat to pangolins shown in Figures 8-12 respectively.

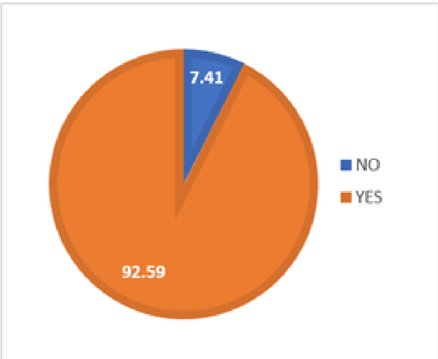


**Figure 8.** Percentage of respondents who had heard of pangolins.

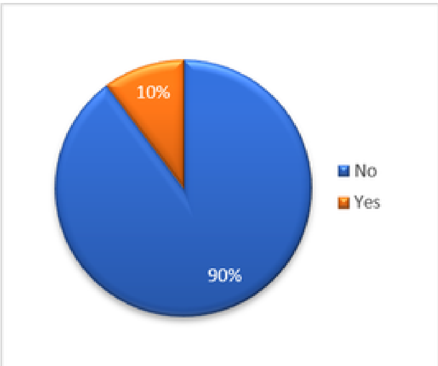


**Figure 9.** Percentage of respondents who could distinguish between Chinese and Indian pangolins.

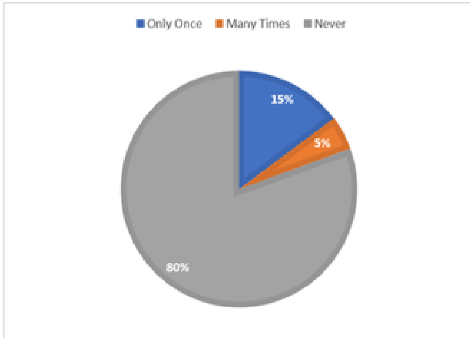


**Figure 10.** Frequency of pangolin encounters reported by respondents.


**Figure 11.** Respondents' self-reported knowledge of pangolin ecology.

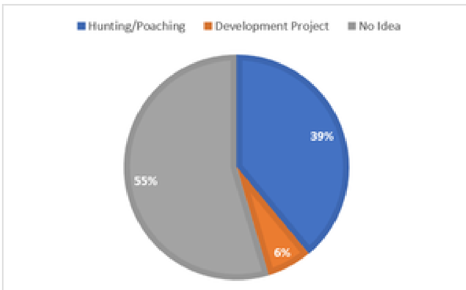


**Figure 12.** Major threats to pangolins identified by respondents.



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Tables 9 and 10 shows the Chi-square tests which showed that education significantly influenced the belief that public awareness helps conserve pangolin habitat ($\chi2$ = 17.334, df = 2, p = 0.0001). Literate respondents were more likely to agree with this statement than illiterate respondents. Education also significantly influenced respondents' interest in pangolin conservation ($\chi2$ = 16.29, df = 2, p = 0.0002), and respondents from suitable habitat showed higher conservation interest than respondents from unsuitable habitat ($\chi2$ = 13.354, df = 2, p = 0.0012) as seen in figure 10. In contrast, age and gender were not significantly associated with conservation attitude variables. The high p-values for gender (p = 0.89 and p = 0.90) were retained after recalculation because male and female response distributions were nearly identical.

**Table 9.** Respondents' responses to the statement "Public awareness helps conserve pangolin habitat." * indicates p < 0.05.

| Variable | Category | Agree (%) | Neutral (%) | Disagree (%) | df | χ2 | p-value |
|---|---|---|---|---|---|---|---|
| Age | Young | 92 | 4 | 4 | 4 | 6.6 | 0.15 |
| | Adult | 74 | 5 | 21 | | | |
| | Old | 67 | 13 | 20 | | | |
| Gender | Male | 72 | 13 | 15 | 2 | 0.22 | 0.89 |
| | Female | 76 | 12 | 12 | | | |
| Education | Illiterate | 45 | 31 | 24 | 2 | 17.334 | 0.0001* |
| | Literate | 83 | 6 | 10 | | | |
| Habitat class | SH | 76 | 10 | 14 | 2 | 1.101 | 0.57 |
| | UH | 68 | 15 | 17 | | | |

**Table 10.** Interest level of respondents toward pangolin conservation. * indicates p < 0.05.

| Variable | Category | A lot (%) | Little (%) | None (%) | df | χ2 | p-value |
|---|---|---|---|---|---|---|---|
| Age | Young | 48 | 32 | 20 | 4 | 3.21 | 0.52 |
| | Adult | 42 | 44 | 14 | | | |
| | Old | 30 | 47 | 23 | | | |
| Gender | Male | 42 | 43 | 15 | 2 | 0.19 | 0.9 |
| | Female | 41 | 46 | 13 | | | |
| Education | Illiterate | 21 | 45 | 34 | 2 | 16.29 | 0.0002* |
| | Literate | 49 | 44 | 7 | | | |
| Habitat class | SH | 55 | 34 | 11 | 2 | 13.354 | 0.0012* |
| | UH | 20 | 61 | 19 | | | |

## Discussion

### Distribution and habitat characteristics of Chinese pangolin

Chinese pangolin burrows were recorded between 235 and 2,400 m elevation, with the highest proportion between 500 and 1,000 m. This range is broadly consistent with previous studies in Nepal and the wider Himalayan foothill region, where Chinese pangolins have been reported mainly in mid-elevation forests, community forests, and forest-agricultural mosaics [1,4,23,29]. The concentration of burrows on slopes of 10°-30° is also consistent with studies that report pangolin burrows on moderately sloping terrain, which may provide suitable drainage, soil stability, and protection from disturbance [25]. South-facing slopes contained the largest proportion of burrows in this study, but aspect preferences vary among studies and may depend on local microclimate, soil moisture, vegetation, and survey effort.

### Predicted habitat suitability and conservation relevance

The ensemble model predicted that only 2.4% of the DFO area was highly suitable and 13.6% was moderately suitable for Chinese pangolin. This indicates that potentially important habitat is spatially restricted and concentrated mainly in forested Chure hill landscapes and adjoining community forests. Compared with the national assessment of Suwal et al., which estimated 15.2% of Nepal as potential pangolin habitat, the present study identified a smaller proportion of highly suitable habitat at the DFO scale [35]. This difference is expected because local models capture finer-scale constraints imposed by settlements, roads, agriculture, forest fragmentation, and local vegetation composition.

Highly suitable areas should be treated as priority zones for targeted conservation. These zones can support focused anti-poaching patrols, burrow monitoring, habitat protection, and awareness programs. Moderately suitable areas are also important because they often occur at the interface between forest and agricultural land, where pangolin occurrence and human activity overlap. Conservation in these areas should emphasize farmer engagement, reduce burrow disturbance, and reporting of hunting or trade. Least suitable areas should not be ignored entirely, but conservation investment should be prioritized toward high- and moderate-suitability zones where management actions are more likely to produce measurable benefits.



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### Model performance and methodological implications

RF, GBM, and MAXENT were the strongest-performing algorithms, while SRE, GAM, FDA, and ANN performed comparatively poorly based on TSS. The higher performance of RF and GBM likely reflects their ability to capture complex, nonlinear relationships among predictors, while MAXENT is well suited to presence-background datasets such as those commonly available for cryptic species [17,18,36]. The weaker performance of SRE suggests that simple environmental envelope models may be inadequate where occurrence records are clustered and suitable habitat is shaped by interacting ecological and anthropogenic variables. These differences justify the ensemble modeling approach used here, because the final prediction integrates across algorithms while giving greater weight to better-performing models.

The use of pseudo-absence/background points was necessary because true absence data were unavailable. This is common in pangolin studies because the species is difficult to detect, and failure to observe a burrow does not necessarily indicate absence. However, pseudo-absence selection can influence SDM outputs, especially in landscapes where survey effort is uneven. Spatial thinning reduced clustering bias, but it cannot fully remove all sampling bias. Future modeling should consider bias files, target-group background sampling, occupancy modeling, camera-trap confirmation, or repeated surveys to better account for imperfect detection.

### Variable importance and ecological interpretation

Population density was the most important predictor, followed by vegetation type, distance to settlement, NDVI, and distance to water. This pattern suggests that habitat suitability for Chinese pangolin in the Rapti landscape is shaped by both ecological conditions and human disturbance. The high importance of population density and settlement distance is consistent with evidence that pangolins are sensitive to human pressure, hunting, and habitat disturbance [13,37]. The importance of vegetation type and NDVI indicates that forest cover and vegetation productivity are likely to influence prey availability, burrow-site suitability, and shelter.

Elevation contributed relatively little to the ensemble model, despite being important in previous pangolin habitat studies [23,24]. This difference may reflect the local scale and environmental structure of the present study area. Within the DFO, elevation is correlated with vegetation type, settlement distribution, and population density, and these variables may have captured much of the ecological information otherwise associated with elevation. Thus, elevation should not be interpreted as unimportant to pangolins generally; rather, within this specific management landscape, direct measures of vegetation and human disturbance were more informative predictors.

### Community perception and conservation outreach

Community awareness of pangolins was high, but ecological knowledge was limited. This pattern suggests that many respondents recognize pangolins but lack detailed understanding of their ecological role, burrow use, legal protection, and conservation needs. Similar knowledge gaps have been reported in other pangolin studies in Nepal [4,38,39]. Education significantly influenced conservation attitudes, and respondents as reported by Bhattarai et al. [40]. These findings indicate that outreach should be spatially targeted and tailored to literacy level. Awareness activities should move beyond general messages and provide practical guidance on identifying pangolin burrows, avoiding disturbance, reporting poaching, and protecting agricultural-edge habitats.

The lack of significant gender differences suggests that conservation messages can be designed for whole households and CFUG communities rather than targeting only one gender group. However, women, farmers, forest guards, and CFUG committee members may play distinct roles in detecting burrows, reporting threats, and implementing local conservation activities. Participatory monitoring involving CFUGs could therefore help convert positive attitudes into practical conservation behavior.

## Limitations and Future Research

Several limitations should be considered. First, occurrence records were based on burrows rather than genetic confirmation or direct observation. Although burrow morphology and local expertise were used to identify pangolin signs, species misclassification cannot be completely excluded. Second, the survey design relied partly on local reports and accessible forests, which may have introduced sampling bias. Third, pseudo-absence generation and model thresholds influence predicted suitability. Fourth, the study boundary was administrative rather than ecological, so habitat connectivity beyond the DFO boundary was not fully evaluated. Fifth, model uncertainty was assessed through replicate performance metrics but not mapped spatially. Future studies should incorporate camera traps, environmental DNA or genetic confirmation, repeated burrow monitoring, bias-corrected background sampling, spatial uncertainty maps, and landscape-scale connectivity analysis.

## Conclusion

This study provides a spatially explicit assessment of Chinese pangolin habitat suitability and community attitudes in the Division Forest Office, Rapti, Makawanpur District, Nepal. Ensemble modeling identified 26.3 km²(2.4%) of the study area as highly suitable and 150.6 km² (13.6%) as moderately suitable habitat. RF, GBM, and MAXENT were the best-performing models, and population density, vegetation type, distance to settlement, NDVI, and distance to water were the most important predictors. These results show that pangolin habitat suitability in the Rapti landscape is driven not only by terrain and vegetation but also by human disturbance.

The study also shows that local attitudes toward pangolin conservation are generally positive, although ecological knowledge remains limited. Education and residence in suitable habitat significantly influenced conservation interest. We recommend that conservation planning prioritize highly suitable forest areas in the Chure hills, maintain connectivity among suitable and moderately suitable forest patches, engage farmers in agricultural-edge habitats, strengthen anti-poaching surveillance, and develop targeted ecological-literacy programs through CFUGs and the Division Forest Office. Future research should verify burrow-based occurrence records using camera traps or genetic methods, expand modeling beyond the DFO boundary to evaluate connectivity, and monitor whether awareness programs lead to measurable reductions in pangolin disturbance and illegal hunting.



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## Disclosure Statement

No potential conflict of interest was reported by the author.

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