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MaxEnt-based habitat suitability of the Rinjani scops-owl on Lombok, West Nusa Tenggara, Indonesia

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Abstract. *Hadiprayitno G, Wirajagat GC, Suana IW, Larasati SAN, Asyafiq BA, Nuri TSK, Ilhamdi ML, Kawirian RR, Karyanto P. 2026. MaxEnt-based habitat suitability of the Rinjani scops-owl on Lombok, West Nusa Tenggara, Indonesia. Biodiversitas 27 (5): d270501. https://doi.org/10.13057/biodiv/d270501.* This research models the habitat suitability of the Rinjani scops-owl (*Otus jolandae*) by identifying key environmental factors influencing its distribution on Lombok Island, Indonesia, through Maximum Entropy (MaxEnt). Field surveys conducted between 2020 and 2023 at 135 sites, using point counts aided by vocalization techniques, yielded 298 detections, which were spatially filtered to 29 distinct occurrence points. The spatial distribution was modeled using four non-collinear environmental predictors: elevation, distance to human settlements, Normalized Difference Vegetation Index (NDVI), and slope. The model's performance was assessed using the Area Under the Receiver Operating Characteristic (AUC-ROC) Curve. A thresholding approach based on the 10th percentile of the training presence (P10) was employed to define the binary suitable habitat distribution from the complementary log-log (cloglog) output. The model achieved a mean AUC of 0.794 (±0.078 SD), indicating a reliable distinction between suitable and unsuitable areas. Elevation emerged as the most significant predictor, contributing 53.4% and having a permutation importance of 50.1%. Suitable habitats were primarily located in mid-elevation forests (600-1,000 m asl) with high NDVI and gentle slopes. The total predicted suitable habitat spanned 2,635.09 km², accounting for approximately 57.7% of the island's total area (4,570.66 km²). The model identified 626.116 km² of high suitability and 528.50 km² of very high suitability, covering both protected and non-protected areas. Areas of moderate suitability (724.334 km²) and low suitability (756.141 km²) were more widespread. Conservation efforts should focus on protecting mid-elevation core habitats by maintaining the canopy to support foraging and breeding. In non-protected areas, targeted restoration and forest patch protection are crucial to expanding suitable habitats, reinforcing buffer zones, and enhancing landscape connectivity.

Keywords: Conservation, distribution modelling, Lombok Island, MaxEnt, *Otus jolandae*

INTRODUCTION

The Rinjani scops-owl (*Otus jolandae* Sangster, King, Verbelen, and Trainor 2013) is a recently described species of scops owl bird in the family Strigidae that is considered endemic to Lombok Island, Indonesia. This scops-owl was formally described in 2013 as a cryptic species, distinguished from its congeneric species, the Moluccan scops-owl (*Otus magicus* S.Müller, 1841), by acoustic performance rather than its morphological characteristics (Sangster et al. 2013). This scops-owl species currently faces threats from habitat alteration driven by anthropogenic activities, including agricultural expansion, infrastructure development, and illegal trade (Shepherd et al. 2020). Due to its declining population and limited distribution, this bird was listed as Near Threatened in the IUCN Red List in 2014. In line with the IUCN's conservation status, the Indonesian Ministry of Environment and Forestry has included the Rinjani scops-owl in Ministerial Regulation P.106/MENLHK/SETJEN/KUM.1/12/2018, which establishes the legal foundation for its protection. Despite the Near-Threatened status of the Rinjani scops-owl, developing targeted conservation interventions for this species remains challenging due to its insufficient ecological knowledge. Information on this species stems from only two microhabitat studies conducted by Muttaqin et al. (2020) and Permatasari et al. (2025), which reported a preference for typical microhabitats within the middle canopy layer of dense vegetation. The canopy-dwelling behavior shown by this scops-owl is strongly related to its trophic ecology, since the dense middle canopy provides abundant insect prey, whose availability depends heavily on specific environmental conditions. While these earlier studies offer valuable insights into microhabitat use of Rinjani scops-owl, broader island-wide questions, such as how the species responds to Lombok's specific topographic and ecological gradients, which change significantly from the dry coastal area to the dry forest and the cool middle-elevation vegetation of Mount Rinjani in a relatively short distance, remain unanswered. Indeed, despite this scops-owl's adaptability in its current habitat, its highly canopy-dependent nature makes it highly vulnerable to widespread habitat alteration (Grimmett et al. 2020; Hota et al. 2025). In addition, since Lombok has a varied elevation profile, vegetation and insect abundance may also vary greatly. Indeed, elevation changes can alter the neso and micro climate, which in turn influences the types of structural plants and the distribution of insect prey across the entire island. Consequently, engaging the influence of these ecological gradients on vegetation structure and prey availability is crucial for formulating successful conservation strategies (Jiménez and Soberón 2022).

Distribution modeling of Rinjani scops-owl at both macro- and mesoscales is urgently required to identify the environmental factors that determine the species' habitat selection and address the existing critical information gap. Since we dealt with a rare and elusive species with a restricted distribution across the island, it is difficult to generate large samples of occurrence data due to logistical challenges. Maximum Entropy (MaxEnt) modeling analysis is considered an appropriate machine learning approach for modeling the habitat suitability of the Rinjani scops-owl. In this context, Maximum Entropy (MaxEnt) modeling serves as a highly appropriate analytical tool. Rather than assuming MaxEnt is inherently superior to other spatial modeling algorithms, the use of this approach is justified by its mathematical framework for handling presence-only data, which is common for rare and endemic species (Bald et al. 2023; Jianhui et al. 2023; Steen et al. 2024). When combined with rigorous model tuning and spatial bias mitigation strategies to prevent overfitting, MaxEnt provides a reliable mechanism for projecting habitat suitability across Lombok's heterogeneous terrain using the limited but valuable occurrence records currently available. This study aims at determining the distribution and habitat suitability of the Rinjani owl across various ecosystems in Lombok and to empirically identify the ecological factors that primarily determine its spatial distribution. We propose a hypothesis that habitat suitability would be highest in mid-elevation vegetation, where dense, well-connected tree provides optimal mesohabitat conditions and abundant insect prey. These findings will be important as science-based empirical evidence to support practical conservation planning, design, and prioritization, including identifying highly suitable habitat, targeting survey efforts, and allocating management resources to areas most likely to maintain viable populations under current landscape conditions.

MATERIALS AND METHODS

Study area and data source

To address the research objective, this study investigated the island-scale distribution of the Rinjani scops-owl (Figure 1) through a field data-collection procedures conducted from 2020 to 2023 on Lombok Island, West Nusa Tenggara Province, Indonesia (≈8.565°S, 116.351°E; 4,570.66 km²). This broader scope was needed because previous works focused primarily on protected areas (Mount Rinjani and Kerandangan) and did not capture the species' presence across the island.

We identify 29 initial locations at the administrative level based on preliminary information provided by local informants and occurrence records retrieved from the Global Biodiversity Information Facility (GBIF) website at https://www.gbif.org/occurrence/search?taxon_key=7810820 (Figure 2). From these initial points we conducted broader island-scale survey across 135-night survey points using point-count surveys aided by vocalizations. Each purposive point was divided into four quadrants to localize the scops owl detections. Our field survey spanned a broad elevational gradient from coastal lowlands (e.g., Kerandangan and Nipah) to mid-montane zones (e.g., Sembalun and Senaru), primarily between approximately 25 and 1,700 m asl. Our study area comprises secondary rainforests and community forests within protected areas (e.g., Mount Rinjani National Park and the Nature Recreation Parks at Kerandangan and Suranadi), as well as agroforestry systems, private lands, and urban settlements. We ensure spatial independence to avoid double-counting the same individual by separating each point-count by a minimum distance of 300 meters. We conducted the survey at peak nocturnal activity hours, between 19:00 and 23:00. The surveys (15 minutes at all points) were only performed under optimal weather conditions to enhance detection probability and maintain acoustic standardization. To account for misdetection, each of the 135 stations was revisited on three separate nights throughout the survey period. For spatial modeling, duplicate detections (i.e., instances in which the species was recorded at the same point count station across multiple revisit nights) were strictly filtered out to prevent pseudo-replication in our distribution model. Synchronous surveys at adjacent points were conducted to prevent double-counting. During these surveys, owl vocalizations (spontaneous calls or responses to playback) were helpful and utilized as acoustic cues to identify the bird's general occurrence. Once a call was detected, observers conducted a targeted ground check to visually pinpoint the individual. Point locations were georeferenced using a Garmin 64s, and only visual detection was defined as 'presence' for the SDM.

Our three-years field survey finally gained 298 individuals at these 135 points (Table 1). The actual coordinates of all 135 points were georeferenced to the World Geodetic System 1984 (WGS84) and used as initial raw dataset, following Moudrý et al. (2024). Indeed, in this research, the MaxEnt distribution modelling and species occurrence data were based on 135 observation points as initial raw dataset rather than the 298 actual individual sightings of the Rinjani scops-owl. This approach was deliberately chosen to serve as an inherent spatial thinning mechanism, effectively minimizing spatial autocorrelation and sampling bias. Because multiple individuals were frequently recorded in close proximity within a single observation radius, using their exact locations would lead to spatial clustering.

For the modelling extent, a rectangular bounding box was defined encompassing the entire island, covering a total area of 10,622.77 km². In the current modelling approach, water bodies and offshore islets were not explicitly masked from this background extent to ensure that all coastal transition zones and edge habitats were fully evaluated, avoiding arbitrary exclusions caused by spatial resolution mismatches. While the inclusion of non-habitat in the background can influence absolute evaluation metrics, our environmental predictors can clearly delineate the land-water boundary, allowing the Maxent algorithm to constrain habitat suitability estimates to the terrestrial landscape inherently. Therefore, the relative ranking of terrestrial habitat suitability, which is the primary focus of our analysis, still remains robust and controlled by this inclusion.

Selection of environmental predictors against multicollinearity

Environmental predictors were selected based on the ecological and environmental significance to the Rinjani scops-owl habitat selection. Given the limited studies on this species, the researchers examined related references to identify environmental predictors and assess the correlation between predictors and the scops-owl distribution. We selected seven environmental predictor variables to model habitat suitability for the species, covering climatic, topographic, and landscape factors. Climatic conditions were characterized using Isothermality (Bio3) and Annual Precipitation (Bio12). Topographic influence was represented using elevation and slope. To examine the effects of vegetation density, we included the Normalized Difference Vegetation Index (NDVI). In addition, we generated Distance to Water Bodies to represent hydrological affects, and Distance to Human Settlements, to represent a proxy for anthropogenic disturbance using GIS analysis.

Figure 1. The endemic Rinjani scops-owl (*Otus jolandae*). The name 'jolandae' honours Dr. Jolanda A. Luksenburg of George Mason University, Virginia, US, who first discovered it in 2003. Photograph by Puguh Karyanto

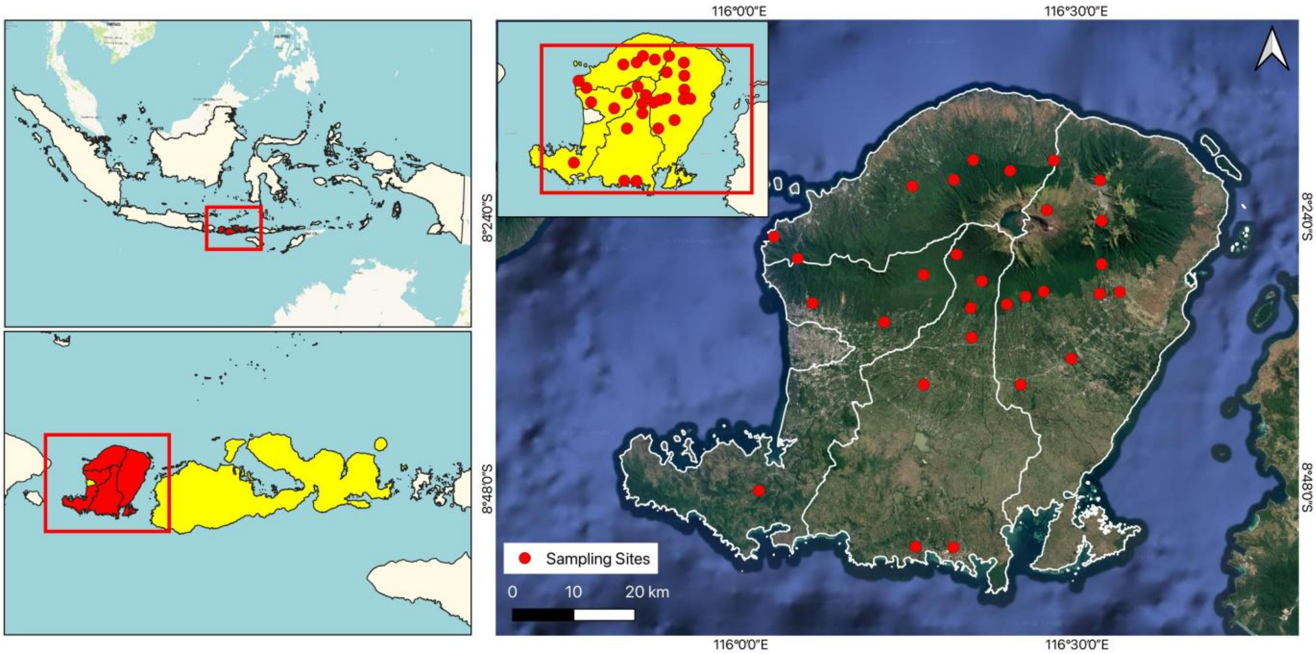

Figure 2. All 29 initial locations in Lombok Island, West Nusa Tenggara Province, Indonesia, were obtained from informants and the GBIF website. These 29 sites were used to locate at the administrative level, not as input for the MaxEnt model training

Table 1. Detection record of the Rinjani scops-owl during the point count survey at Lombok Island, West Nusa Tenggara, Indonesia

District	Site name	Individual	Coordinates	
			Latitude	Longitude
West Lombok	Suranadi	2	-8.451764	116.324508
		2	-8.453649	116.324955
	Kerandangan	4	-8.477944	116.0547
		2	-8.477043	116.055775
		4	-8.479179	116.052962
	Bukit Tembere	4	-8.524219	116.108576
	Lingsar	2	-8.552741	116.214237
	Sesaot	2	-8.487364	116.272397
		3	-8.489869	116.271131
		4	-8.484574	116.270298
	Telagawaru	2	-8.648676	116.272724
	Sekotong	2	-8.80362	116.028073
		2	-8.813359	116.027222
		2	-8.79421	116.036371
		2	-8.796398	116.026129
		2	-8.803087	116.01472
Central Lombok	Aik Bual	2	-8.545593	116.373928
	Aik Bukak	4	-8.576878	116.344567
	Aik Berik	1	-8.49473616	116.3626643
	Setiling	4	-8.546405	116.365912
		4	-8.543778	116.368448
		2	-8.548823	116.367849
		1	-8.487876027	116.365148
		1	-8.49885021	116.3613278
		2	-8.497722436	116.3615833
	Benang Stokel	2	-8.5328717	116.34095
		2	-8.535556	116.341757
	Mandalika	3	-8.886608	116.2589585
		4	-8.886685	116.261346
		5	-8.890653	116.292369
		2	-8.902304	116.297799
		2	-8.900249	116.301634
		4	-8.890637	116.292361
		1	-8.877089	116.302351
		2	-8.889056	116.304242
		2	-8.886253	116.304861
		2	-8.881674	116.307757
		1	-8.880421	116.324526
		2	-8.889123	116.326705
		2	-8.890574	116.331887
		1	-8.886081	116.337063
		2	-8.88962	116.338871
East Lombok	Lemor	4	-8.513599	116.56482
		6	-8.511143	116.5665
		4	-8.511381	116.562323
	Suradadi	2	-8.646827	116.413778
	Kembang Kuning	6	-8.51432	116.425568
		6	-8.517005	116.424574
		4	-8.515411	116.427798
		1	-8.513919964	116.42239
		1	-8.515740016	116.4226
		1	-8.52291747	116.4249654
		1	-8.523070041	116.42526
		1	-8.522999963	116.42564
	Rempung	2	-8.608112	116.493726
	Sembalun	2	-8.406454	116.538002
		2	-8.408638	116.537695
	Beriri Jarak	2	-8.513802	116.534342
	Pergasingan	3	-8.344645	116.535402
	Tete Batu	2	-8.53233	116.415871
		2	-8.531196	116.415369
		4	-8.511348766	116.4018449
	Pesugulan	2	-8.471157	116.539094
		2	-8.469497	116.538878
		2	-8.469121	116.537651
	Timbanuh	2	-8.528678	116.462279
		4	-8.528536	116.461632

		1	-8.513640496	116.4521458
		2	-8.513685964	116.4523183
		4	-8.511795361	116.4521666
		1	-8.511793708	116.4509945
		1	-8.507332232	116.4493473
		3	-8.512640496	116.4485674
		3	-8.510821981	116.4482247
		4	-8.508460591	116.4477557
		1	-8.506858662	116.4470674
		2	-8.513091594	116.4541636
		2	-8.513320289	116.4559986
		1	-8.511554342	116.4544384
		1	-8.510059813	116.4529322
	Joben	1	-8.533809993	116.398227
		1	-8.533839982	116.39826
		1	-8.531830016	116.39807
		1	-8.529980011	116.39797
		1	-8.528319961	116.39782
		1	-8.52638004	116.39748
		1	-8.499888984	116.398194
		4	-8.533840253	116.39826
	Hutan Jeruk Manis	5	-8.523072036	116.425263
		4	-8.519351043	116.42409
		6	-8.52139504	116.424602
		5	-8.515743994	116.422599
		2	-8.513916978	116.422389
	Lenek	1	-8.512777994	116.4746667
	Jenggik	1	-8.536666877	116.3808333
	Sapit	1	-8.442162026	116.53085
North Lombok	Pemenang	2	-8.456332	116.116733
	Pusuk	2	-8.471642	116.108402
	Gangga	4	-8.355081	116.257999
	Senaru	4	-8.3305663	116.401245
		4	-8.331648	116.402457
		4	-8.328422	116.402303
		1	-8.31979	116.4023
		4	-8.319246338	116.4021452
		1	-8.336583379	116.4025556
	Torean	2	-8.326715	116.446057
		2	-8.327265	116.446682
	Sajang	6	-8.312571	116.484362
	Gumantar	2	-8.295215	116.314648
	Nipah	2	-8.429681	116.050366
		1	-8.429101	116.050883
		1	-8.428902	116.051162
	Jebak Gawah	1	-8.326674962	116.446534
		1	-8.326843992	116.446584
		1	-8.327030589	116.4466478
		1	-8.327222181	116.4467261
		1	-8.3273972	116.4467252
		1	-8.326676156	116.4465473
		1	-8.326858296	116.4465931
		1	-8.327038925	116.4466584
		1	-8.327225003	116.4467395
		1	-8.327225003	116.4467395
	Pal Besi	1	-8.339444014	116.323056
		1	-8.344444405	116.3138889
		1	-8.34166664	116.3163889
	Anyar	1	-8.34323787	116.3959071
		1	-8.324680088	116.4097832
		1	-8.308611078	116.3597222
		1	-8.308275552	116.3581736
		1	-8.308889027	116.359722
		1	-8.309166699	116.36
		1	-8.309239972	116.360231
		1	-8.309449602	116.3603247
	Gunung Rinjani	2	-8.361771	116.475567
		2	-8.365122	116.46588
Total		298 Individuals		

We retrieved the Digital Elevation Model (DEM) from the Ina-Geoportal site at https://tanahair.indonesia.go.id/portal-web to acquire the elevation and slope raster data. We used these two topographic predictors to represent fundamental abiotic determinants affecting the distribution of Rinjani scops-owl since this two are strongly linked to vegetation zonation and microclimatic gradients on Lombok. Elevation was involved as a proxy for temperature-moisture conditions and forest belt transitions, while slope was included to catch terrain steepness that can influence forest structure, accessibility, and habitat continuity. The selection on these two abiotic factors were supported by previous studies indicating that scops-owls are most frequently associated with low to mid-elevations and relatively gentle terrain (Ševčík et al. 2021; Theux et al. 2022). The DEM-based layers were clipped to Lombok Island, projected to a standard coordinate system, and resampled to match the spatial resolution and extent of the other environmental predictors before being used in the MaxEnt model. Since the Rinjani scops-owl forages and roosts primarily within vegetated forest strata, vegetation cover and greenness were represented using the Normalized Difference Vegetation Index (NDVI). NDVI was selected as a quantitative, spatially continuous proxy for vegetation density, as well as canopy condition, which are closely linked to the availability of invertebrate prey and suitable mid-canopy microhabitats used by small scops-owls (Najmi-Hanis et al. 2016). Given the Rinjani scops-owl's significant reliance on the vegetation layer, NDVI was incorporated in the initial model prediction. The NDVI data for 2024 were obtained from the Earth Explorer website at https://earthexplorer.usgs.gov/. Although the field surveys were conducted between 2020 and 2023, the 2024 NDVI is highly representative of the survey period because the study area consists of stable vegetation cover with no significant land-use or land-cover changes documented during this timeframe. The NDVI layer for 2024 was selected as a proxy for vegetation productivity. Our analysis showed high temporal stability in NDVI values across Lombok from 2020 to 2024 (Pearson's $r>0.88$), suggesting no significant large-scale changes in vegetation cover during the survey period. This justifies the use of the 2024 dataset as a representative predictor for the Rinjani scops-owl's current habitat suitability. The stability of the vegetation cover is further supported by the fact that the species' primary range is situated within the protected boundaries of Mount Rinjani National Park, where large-scale land-use changes are restricted.

Although scops-owl distributions are not directly related to water bodies, distance to water bodies in this study was included because areas near streams often support higher humidity, denser understory, and greater invertebrate biomass than surrounding uplands, which can increase prey availability for insectivorous scops-owls. Proximity to water can also indicate structurally complex vegetation that provides roosting and calling sites, making it a plausible driver of Rinjani scops-owl's habitat selection (Silva et al. 2023). The researchers, therefore, considered distance to water bodies as a predicting variable for the Rinjani scops-owl's distribution. According to Ševčík et al. (2021), the scops-owl species commonly inhabits areas near human settlements for the availability of invertebrate prey. The variable distance to human settlement was therefore included as a predictor.

We retrieved two bioclimatic variables: Bio3 for isothermality and Bio12 (for annual rainfall) from WorldClim at https://www.worldclim.org/data/bioclim.html. We used WorldClim version 2.1 with a spatial resolution of 30 arc seconds (~1 km²). These two climatic variables have been recognized to influence habitat selection by the scops-owl through their effects on prey availability and foraging effectiveness (Romano et al. 2018). Isothermality was included to represent landscape-scale thermal stability, which influences insect prey activity patterns and thus shapes habitat suitability beyond vegetation and topography. Annual rainfall was chosen because of its effects on vegetation productivity, canopy structure, and humidity, which, in turn, indirectly affect invertebrate prey availability, making it a reasonable climatic determinant of the Rinjani scops-owl's habitat selection. All data sources and preliminary predictors are summarized in Table 2. Since all predictor data are raster data, the coordinates were transformed from WGS 1984 to WGS 1984 UTM50S using ArcGIS Pro 3.5.0, and the environment data were converted to ASCII format. The research workflow is summarized in Figure 3.

To prevent model overfitting and reduce bias, we assessed multicollinearity among the preliminary environmental variables before modeling. We calculated pairwise Pearson correlation coefficients using the Band Statistics tool in ArcGIS Pro 3.5. Variables exhibiting high collinearity (Pearson's $r>0.70$) were scrutinized (Karyanto et al. 2023). To avoid circular logic from preliminary model runs, we made a priori ecological decisions to retain the variable with the most direct biological relevance to the Rinjani scops-owl. Consequently, Elevation (DEM) was retained over Annual Precipitation and Isothermality, as it captures a broader range of microclimatic and structural forest gradients. Distance to human settlements was retained over distance to water bodies, as settlement edges present more direct limiting factors (e.g., artificial lighting, fragmented foraging openings) (Sevčík et al. 2021). NDVI and Slope were automatically retained because they showed no strong correlation with other variables ($r<0.70$). Therefore, elevation (DEM), NDVI, slope, and Euclidean distance to human settlements were the final four covariates retained for analysis using MaxEnt (Table 3).

While the Pearson correlation screening effectively addressed pairwise collinearity, we acknowledge that this linear assessment may not fully capture more complex spatial redundancies between terrain-derived variables, such as elevation and slope. Consequently, post-modeling metrics like permutation importance were utilized to further scrutinize the unique contribution of each predictor, ensuring a more coherent and methodologically transparent interpretation of shared topographical information.

Selection of environmental predictors against multicollinearity

We used the spatial harmonization workflow in ArcGIS Pro 3.5.0 to standardize all environmental predictors and ensure data consistency before modeling. We aligned all datasets to a common coordinate reference system using WGS 1984 UTM Zone 50S. We adjusted the final spatial resolution for all layers to 30 arc-seconds (about 1 km²) to match the native resolution of the WorldClim bioclimatic variables. The Elevation (DEM) layer was selected as the Snap Raster in the ArcGIS environment settings to maintain pixel-to-pixel alignment and a shared raster origin, ensuring that every grid cell is completely aligned with all predictors.

We selected resampling methods based on the data type. For continuous variables such as elevation, slope, NDVI, and bioclimatic data, Bilinear Interpolation was used to maintain smooth environmental gradients. The Euclidean Distance algorithm was used to generate distance-based raster's of human settlements and bodies of water by calculating the straight-line distance from the center of each pixel to the closest vector feature yielded from the Ina-Geoportal database. All processed layers were subsequently clipped to the extent of Lombok Island and converted into ASCII (.asc) format for input into the MaxEnt v3.4.4.

MaxEnt modelling, validation, and post processing

Since occurrence data can be geographically biased, spatial filtering was conducted to reduce bias and standardize spatial resolution. To ensure each retained record represented an ecologically independent locality and to structurally eliminate spatial autocorrelation (SAC) and sampling bias, we applied a strict spatial filter of ~8-9 km (Vasconcelos et al. 2024). This specific distance was selected to account for dispersal capacity, ensure ecological independence between populations, and mitigate sampling bias while retaining sufficient data for model calibration (Najmi-Hanis et al. 2016; Manzoor et al. 2021). Applying this spatial filter inherently removed 106 redundant, highly clustered records. Consequently, only 29 of the initial 135 raw occurrence points were retained as independent inputs for MaxEnt modelling. Figure 4 illustrates these points and confirms the absence of highly clustered sites based on our spatial analysis. Given our small sample size (n: 29), we utilized a conservative parameterization strategy to prevent overfitting.

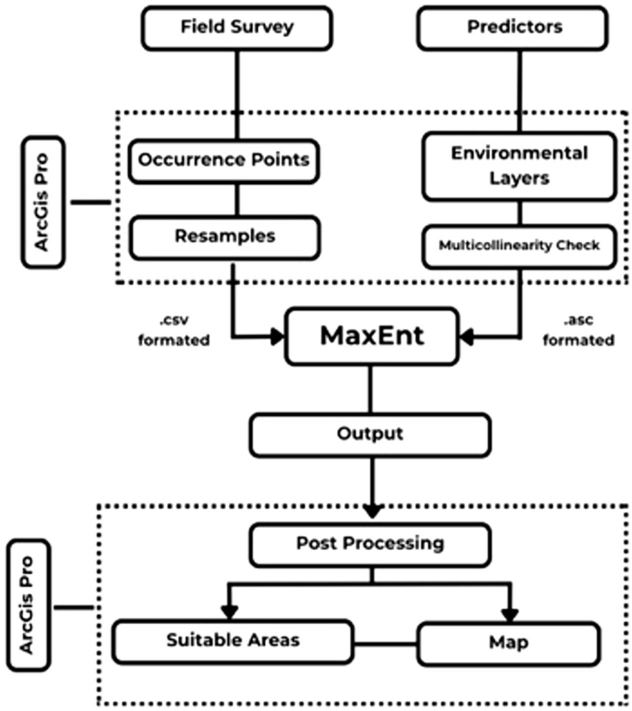

Figure 3. Workflow for research on habitat suitability for Rinjani scops-owl on Lombok Island. The process is divided into three main stages: pre-processing, modelling, and post-processing. The habitat model was generated using the MaxEnt algorithm with occurrence points (.csv) and environmental layers (.asc) as inputs

Table 2. Preliminary predictors and measurement units used to model the distribution of *Otus jolandae*

Variables	Unit	Source
Isothermality (Bio3)	%	WorldClim
Annual precipitation (Bio12)	mm	WorldClim
Occurrences	coordinate in decimal degree	Survey
Distance to human settlements	m	GIS analysis
Distance to water body	m	GIS analysis
Normalized Difference Vegetation Index (NDVI)	no measurement unit	USGS earth Explorer
Elevation from the digital Elevation Model (DEM) data	m	Ina-geoportal
Slope	degree	Ina-geoportal

Table 3. Pearson correlation coefficients for candidate environmental variables. Values in bold indicate high multicollinearity (|r|>0.7). Asterisks (*) indicate the four final predictors retained for the Rinjani scops-owl distribution model: Elevation (DEM), Slope, NDVI, and Distance to human settlements. These variables were selected to minimize multicollinearity (Pearson's |r|<0.70) while prioritizing the most ecologically significant factors for this species

Layer	1	2	3	4	5	6	7
DEM*	1.00000	-0.01194	-0.31777	0.39586	0.61784	0.61986	**0.70651**
Distance to human* settlements	-0.01194	1.00000	**0.91380**	-0.43502	-0.17455	0.17483	0.23068
Distance to water body	-0.31777	0.91380*	1.00000	-0.52959	-0.37899	-0.03419	-0.01116
NDVI*	0.39586	-0.43502	-0.52959	1.00000	0.59239	0.05220	0.02781
Slope*	0.61784	-0.17455	-0.37899	0.59239	1.00000	0.38247	0.34512
Annual precipitation	0.61986	0.17483	-0.03419	0.05220	0.38247	1.00000	0.70911*
Isothermality	**0.70651**	0.23068	-0.01116	0.02781	0.34512	0.70911*	1.00000

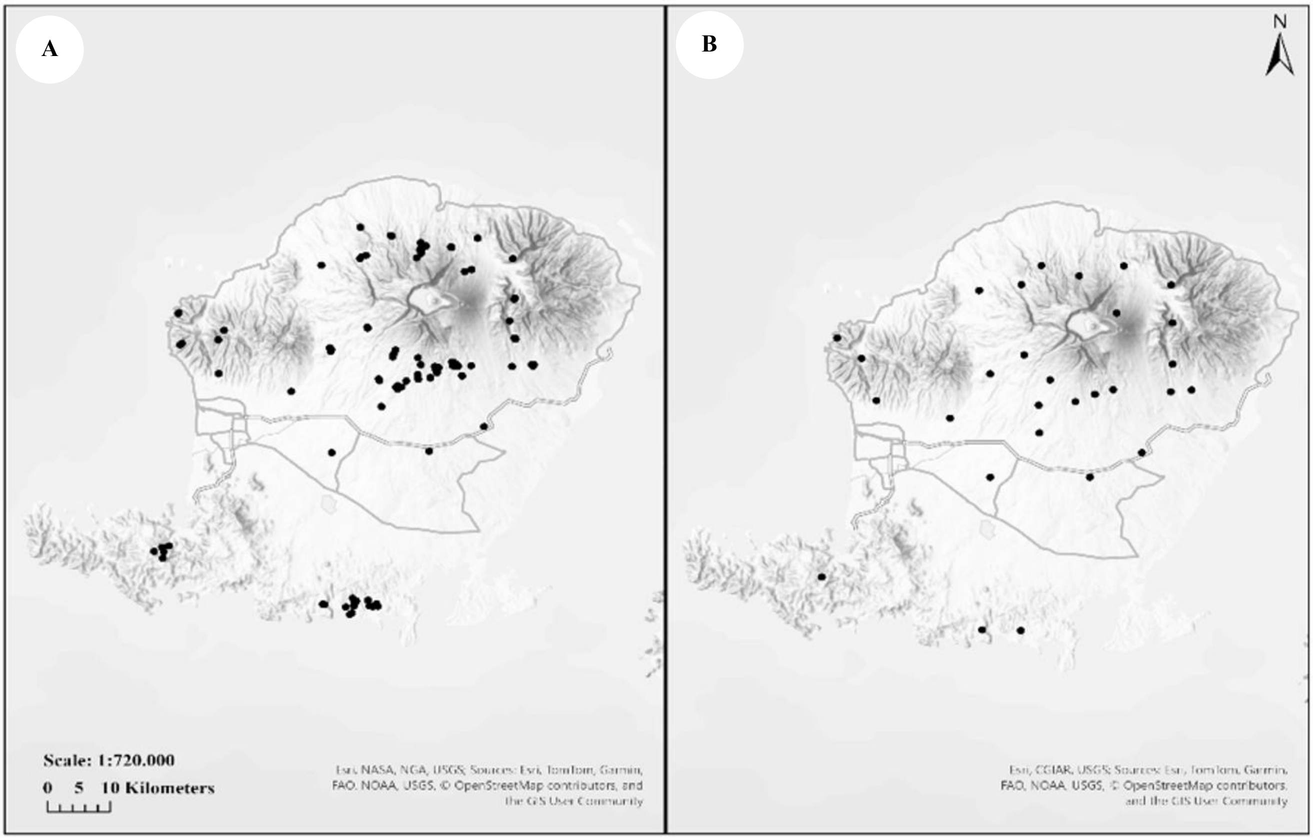

Figure 4. Resampling of *Otus jolandae* occurrence points on Lombok Island, Indonesia. The maps compare the distribution data before and after processing. A. The initial dataset containing 135 innitial raw datasets, B. The final 29 points retained after resampling was conducted using ArcGIS Pro 3.5.0

We employed MaxEnt v3.4.4 to model the distribution of the Rinjani scops-owl at an island-scale. Given our limited dataset of only 29 final occurrence points, it was essential to manage model complexity to prevent overfitting. We approach this via a priori, conservative parameterization instead of post-hoc adjustment. We employed the default 'auto features' configuration; for sample sizes of n<80, this setting inherently constrains model complexity by turning off product and threshold features, thus restricting the algorithm to simpler linear, quadratic, and hinge feature classes (Phillips and Dudık 2008). To further smooth response curves and penalize localized overfitting to our small sample, we manually applied a Regularization Multiplier (RM) of 2 (Liu et al. 2025), a convergence threshold of 1×10^{-5}, a maximum of 5,000 iterations, and 10,000 background points (Singh et al. 2021). Such adjustment enables robust value to generate broader, more conservative spatial predictions without the need for exhaustive grid searches, which can sometimes over-tune models to limited background data. Indeed, our choice was a priori to achieve a smoother, more generalized response curve. This setting can also generate more conservative spatial predictions that are suitable for endemic species with limited occurrence data, since this adjustment can ensure that the resulting habitat suitability maps reflect broad ecological requirements rather than sampling artifacts. The 10,000 background points were sampled across a rectangular bounding box encompassing the entirety of Lombok Island and its immediate surrounding waters. While the theoretically accessible area ('M' in the BAM framework) for this highly mobile avian species is the island itself (4,570.66 km²), we retained the full bounding box without explicit coastal masking to capture all potential coastal transition zones. We assume that the species' absence in lowland and offshore areas is primarily driven by environmental filtering (e.g., unsuitability of temperature, land cover, and aquatic environments) rather than physical dispersal barriers. Because our environmental predictors strongly delineate the land-water boundary, the algorithm inherently constrains habitat suitability to the terrestrial landscape. Variable importance was assessed using jackknife tests and response curves (Ahmadi et al. 2023). We realize that using random cross-validation rather than spatially structured partitioning may yield optimistic performance estimates due to spatial autocorrelation. In addition, since explicit bias correction was not implemented, we interpret these suitability maps as conservative estimates of potential habitat.

Model discriminatory performance was evaluated using the Area Under the ROC Curve (AUC) in a presence-background framework and the omission rate (Bowers and Zhou 2019). AUC from an omission analysis was used to assess the model's ability to differentiate between positive and negative cases, enabling model comparison and optimal threshold determination. AUC evaluates model performance across all thresholds to assess its predictive accuracy and ability to distinguish suitable occurrence areas. According to Swets' classifications, an AUC value greater than 0.7 is considered satisfactory for predictive performance.

We initially calculated the True Skill Statistic (TSS) using 10,000 background points as pseudo-absences, we recognized that estimating specificity using background data is problematic in presence-only models (Allouche et al. 2006). We therefore prioritized omission rate as a more direct evaluation of true presences incorrectly classified as unsuitable. We used an ecological conservatism-based threshold selection approach to convert continuous MaxEnt cloglog data into decision-ready binary maps. We chose the 10th percentile training presence (P10) criterion because it is known to filter out marginal or 'sink' habitats and conservatively estimate the core distributional extent for species with minimal occurrence data. The model's performance was assessed by comparing the observed test omission rate to the expected 0.10 value after the threshold application. Despite a test omission rate significantly higher than expected, indicating model overfitting, the P10 threshold was maintained to ensure that the habitat suitability maps were ecologically strict and focused on the Rinjani scops-owl's most reliable core habitats.

To evaluate the individual influence of each environmental predictor on the model, we calculated Percent Contribution (PC) and Permutation Importance (PI) metrics. The Jackknife test was subsequently employed to clarify each variable's unique contribution and its power in isolation by systematically omitting each predictor and measuring the resulting changes in model performance (Gueye et al. 2025).

RESULTS AND DISCUSSION

Results

Our Maxent model produced an average AUC value of 0.794 (±0.078 SD). The corresponding ROC curve is illustrated in Figure 5. Binary habitat maps that were generated using a clog-log threshold of 0.4113 (±0.05) produced the test omission rate of 0.267 (±0.19), exceeding the expected theoretical value of 0.10 based on the 10th percentile training presence rule. The model shows a True Skill Statistic (TSS) of 0.3806 (±0.29).

The MaxEnt model for the Rinjani scops-owl has been successfully generated and is presented in Figure 6. The model predicts the probability distribution based on four selected environmental predictors (DEM, NDVI, Distance to human settlements, and Slope) as covariates. The resulting output delineates habitat suitability across the study area, extending predictions to unsampled regions of Lombok. Following the application of a binary presence/absence threshold at 0.4113 (10th percentile training presence), the resulting suitability map was reclassified into four distinct intervals: Low (0.411-0.532), Moderate (0.532-0.661), High (0.661-0.798), and Very High (0.798-0.991). The total predicted suitable habitat covers 2,635.09 km², representing approximately 57.7% of the island's total area (4,570.66 km²). The Low suitability class covers 756.141 km², while the 'Moderate' (724.334 km²), 'High' (626.116 km²), and 'Very High' (528.50 km²) categories collectively cover 1,878.95 km² (41.1% of the island). The details of all suitability classes are given in Table 4. The modeled extent was defined as the total geographical area of Lombok Island predicted as suitable (above the 0.4113 threshold), excluding small offshore islets and aquatic bodies.

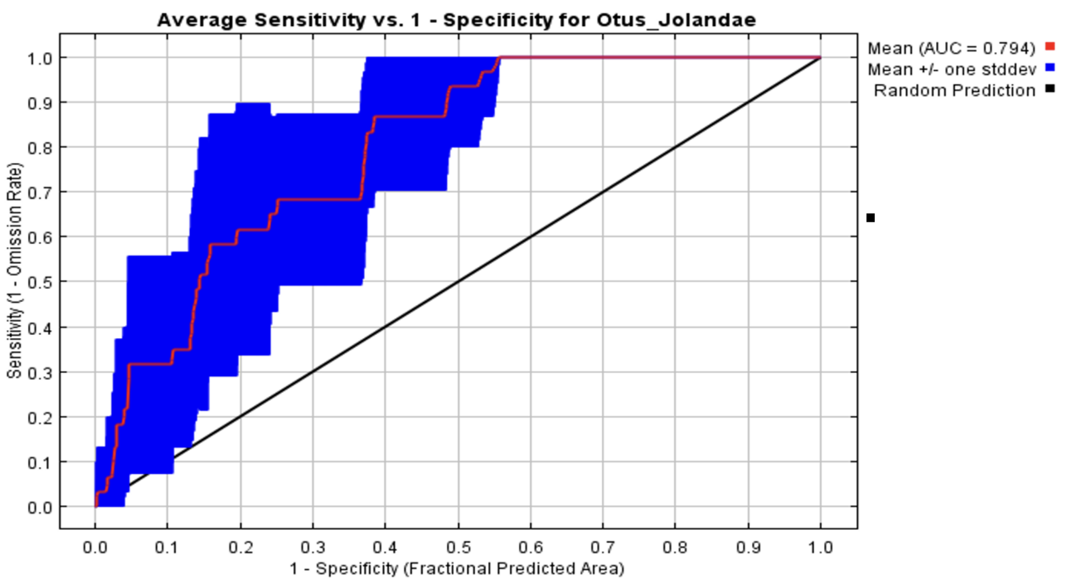

Figure 5. The AUC profile of the spatial modelling result of Rinjani scops-owl. The mean AUC (greater than 0.7) indicates an accurate prediction of the distribution model

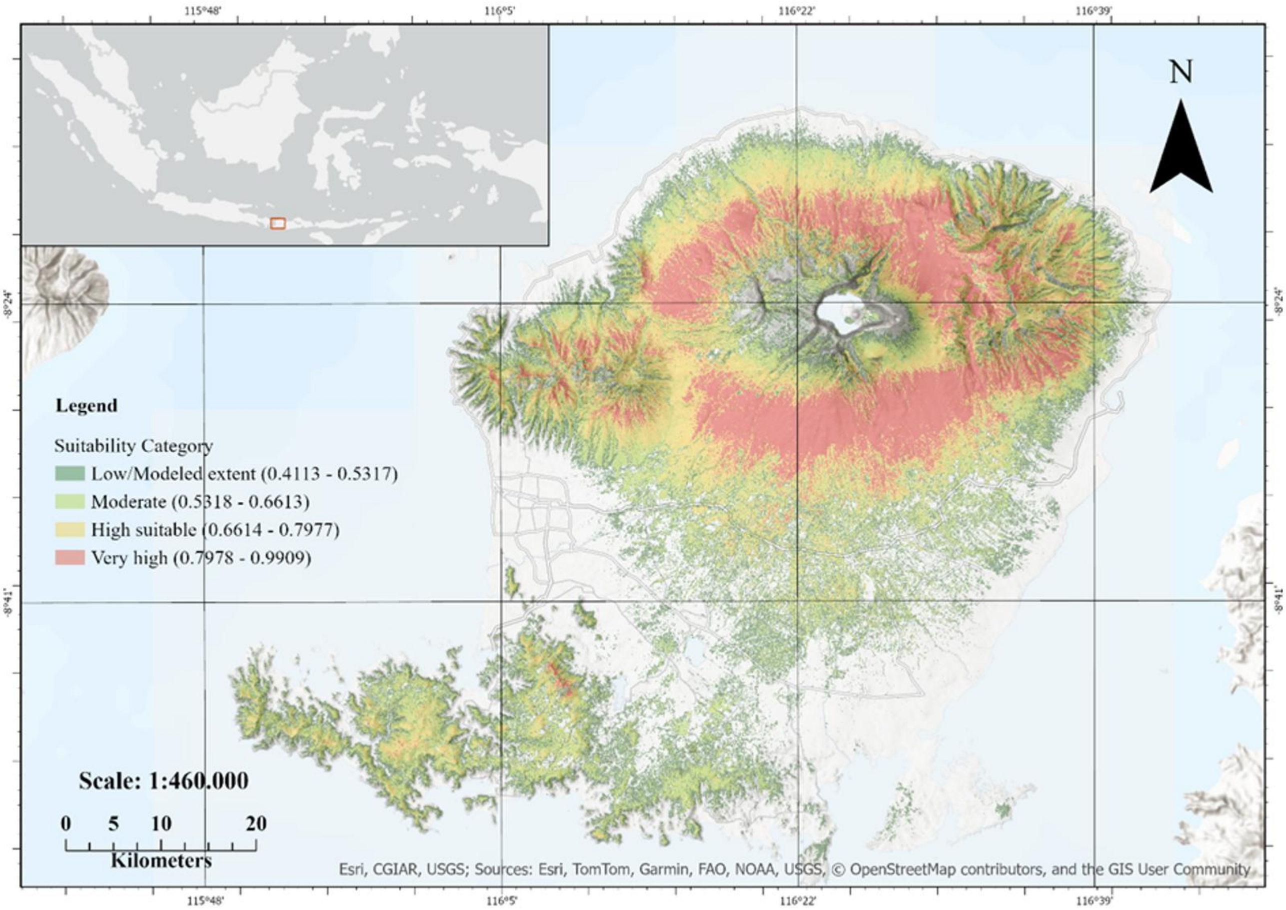

Figure 6. Species' distribution and suitability map of Rinjani scops-owl on Lombok Island, Indonesia

Jackknife of regularized training gain showing each predictor's contribution and unique information in the MaxEnt model for Rinjani scops-owl is given in Figure 7. Elevation (DEM) emerged as the strongest standalone predictor, resulting in the largest loss in model performance when omitted. Table 5 further details these variable importance estimates. Elevation ranked first in both metrics (Percent Contribution [PC]: 53.4%; Permutation Importance [PI]: 50.1%). Slope exhibited a high PC (35.8%) but a low PI (7.3%), whereas NDVI showed the opposite, with a low PC (8.8%) and a higher PI (30.1%). Distance to human settlement contributed minimally to initial model fitting (PC: 1.9%) but retained moderate permutation importance (PI: 12.3%).

To evaluate the specific influence of these variables, Figure 8 illustrates the response curves of all predictors regarding the distributional pattern of the Rinjani scops-owl. To account for model uncertainty, these curves depict the average response of ten replicate MaxEnt runs, accompanied by the mean±standard deviation (represented by the blue shaded regions). The response curve for elevation (Figure 8.A) exhibits a logistic growth pattern, showing optimal suitability between approximately 500 m and 1,500 m, with confidence intervals widening above 1,700 m. While the univariate response curve indicates a broad elevational tolerance (500-1,500 m asl), the spatial projection of the multi-variable model reveals that the highest quality habitat is more geographically restricted.

The distance to human settlement (Figure 8.B) shows a general negative relationship; the predicted probability of occurrence is highest (>0.7) near settlements and approaches zero beyond 15,000 m. For slope (Figure 8.C), suitability rapidly increases to peak at approximately 5 degrees and declines slowly as steepness increases, with uncertainty widening at slopes greater than 20 degrees. Lastly, the NDVI response curve (Figure 8.D) shows a positive sigmoidal relationship, remaining near zero for values below 0.1 and reaching peak suitability (>0.9) at values above 0.55.

Discussion

Species distribution modeling and habitat suitability analysis

The model showed good predictive performance with an AUC value of 0.794 (±0.078 SD), indicating that the selected environmental predictors provide a statistically significant explanation in determining the spatial distribution of the Rinjani scops-owl across Lombok Island. This value of AUC is highly consistent with MaxEnt studies on related owl species; for example, study of the European scops-owl (*O. scops*) conducted by Treggiari et al. (2013) reported a comparable AUC value of 0.773±0.034. Studies on the Sokoke scops-owl (*O. ireneae*) carried out by Habel et al. (2021). yielded AUCs ranging from 0.77 to 0.87. This comparability in model performance is likely driven by shared ecological constraints; similar to the European and Sokoke scops-owls, the distribution of the Rinjani scops-owl is heavily constrained by strict macro-habitat boundaries, particularly topography and vegetation quality. This consistency across different biogeographical regions also suggests a degree of phylogenetic niche common pattern within the genus *Otus*, where related species exhibit similar levels of environmental predictability and specialization. In this research however, due to our small sample size (n: 29) after spatial rarefaction, the model exhibited elevated test omission rates and signs of overfitting at the chosen threshold. With such low data density, the algorithm lacks the capacity to fully generalize the species' environmental plasticity, instead defaulting to the specific environmental constraints of the observed locations. However, the model can still be valuable to characterize the realized niche of *O. jolandae* rather than its broader fundamental niche. This trade-off between sample size and model generality is a well-documented limitation in species distribution modeling for rare taxa. Therefore, rather than invalidating the results, this constraint inherently produces a strictly conservative, high-confidence estimate of the species' core habitat.

The jackknife evaluations and importance measurements indicate that elevation is the primary determinant for the Rinjani scops-owl habitat suitability, ranking first in both percent contribution (PC: 53.4%) and permutation importance (PI: 50.1%). This variable strongly predicts species distribution, causing the largest decrease in predictive performance when omitted. Slope exhibited a high PC (35.8%) but a low PI (7.3%). This discrepancy, high contribution to model fitting but low unique information, typically indicates collinearity, suggesting that slope and elevation share information derived from the same DEM. Thus, while slope helped optimize the model during training, permuting its values had little effect on the final predictions. Conversely, NDVI displayed the opposite pattern: low PC (8.8%) and higher PI (30.1%). This value suggests that while NDVI was less dominant during initial model fitting, it contains unique information essential for refining suitability predictions, likely by capturing vegetation quality in the mid-elevation zone that topography alone cannot explain. Finally, distance to human settlement contributed minimally to model fitting (PC: 1.9%) with moderately important (PI: 12.3%), indicating that anthropogenic proximity alters habitat suitability and that the owl may be sensitive to disturbance gradients associated with settlements.

Figure 7. Jackknife of regularized training gain showing each predictor's contribution and unique information in the MaxEnt model for Rinjani scops-owl

Table 4. Habitat suitability classes of Rinjani scops-owl and its range of suitable elevation

Category	Areas (sq. km)	Habitat description
Low suitability	756.141	A marginal habitat representing a highly modified habitat (for example, for settlements, intensive agriculture, sparse tree cover), with high disturbance and limited dense and continuous vegetation cover
Moderate suitability	724.334	A suitable habitat with a mosaic of landscapes around vegetated margins (secondary vegetation, mixed smallholder gardens/agroforestry, shrub-tree patches, moderate canopy cover) with moderate disturbances
High suitability	626.116	A core suitable habitat with a more continuous natural/semi-natural vegetated areas (such as evergreen/secondary forest with a closed canopy and a complex understory) and anthropogenic vegetation coverage experiencing lower disturbance
Very high suitability	528.496	A core suitable habitat that is least disturbed with a closed and dense vegetated canopy, higher structural complexity (multi-layer vegetation), and minimal fragmentation
Total	2,635.087	

Driven by these four environmental predictors, our MaxEnt models estimate habitat suitability across the entire study area and extend predictions into unsampled areas of Lombok. By estimating a maximum entropy probability distribution, the model can identify areas that meet species requirements, even when surveys do not cover all areas (Wang et al. 2025). Furthermore, by defining the entire island as the calibration area (M), the model effectively contrasts the highly suitable montane forests against the inherently unsuitable lowlands, accurately reflecting the species' island-wide restrictions. The stratification of the suitability map into four intervals enhances the interpretability of these spatial outputs (Karuppaiah et al. 2024).

Ecologically, the 'Low' suitability class represents marginal habitats situated at the periphery of the species' niche, whereas the 'Moderate', 'High', and 'Very High' categories constitute the core suitable habitat. This defined extent ultimately represents the primary accessible area for this island-endemic species. Although this conservative model may miss some marginal areas where the physiological tolerance of Rinjani scops-owl extends beyond the training data's envelope, it successfully minimizes omission errors within the crucial montane belt. The areas identified as highly suitable should be interpreted as the species' core habitat, providing a reliable and actionable baseline for prioritizing protection efforts. Furthermore, these findings point to the necessity of targeted ground-truthing in marginal zones. Future surveys should prioritize areas that the model classified as 'unsuitable' but which lie close to the suitability threshold. Verifying whether the species is truly absent from these elevational limits, or if the model simply failed to detect its full environmental plasticity, is crucial for refining future iterations of this habitat suitability map.

Table 5. Variable importance estimates for the Rinjani scops-owl MaxEnt model. Values represent the Percent Contribution (PC) and permutation importance (PI) for each environmental predictor

Predictor	Percent contribution	Permutation importance
DEM	53.4	50.1
Slope	35.8	7.3
NDVI	8.8	30.1
Distances to human settlement	1.9	12.3

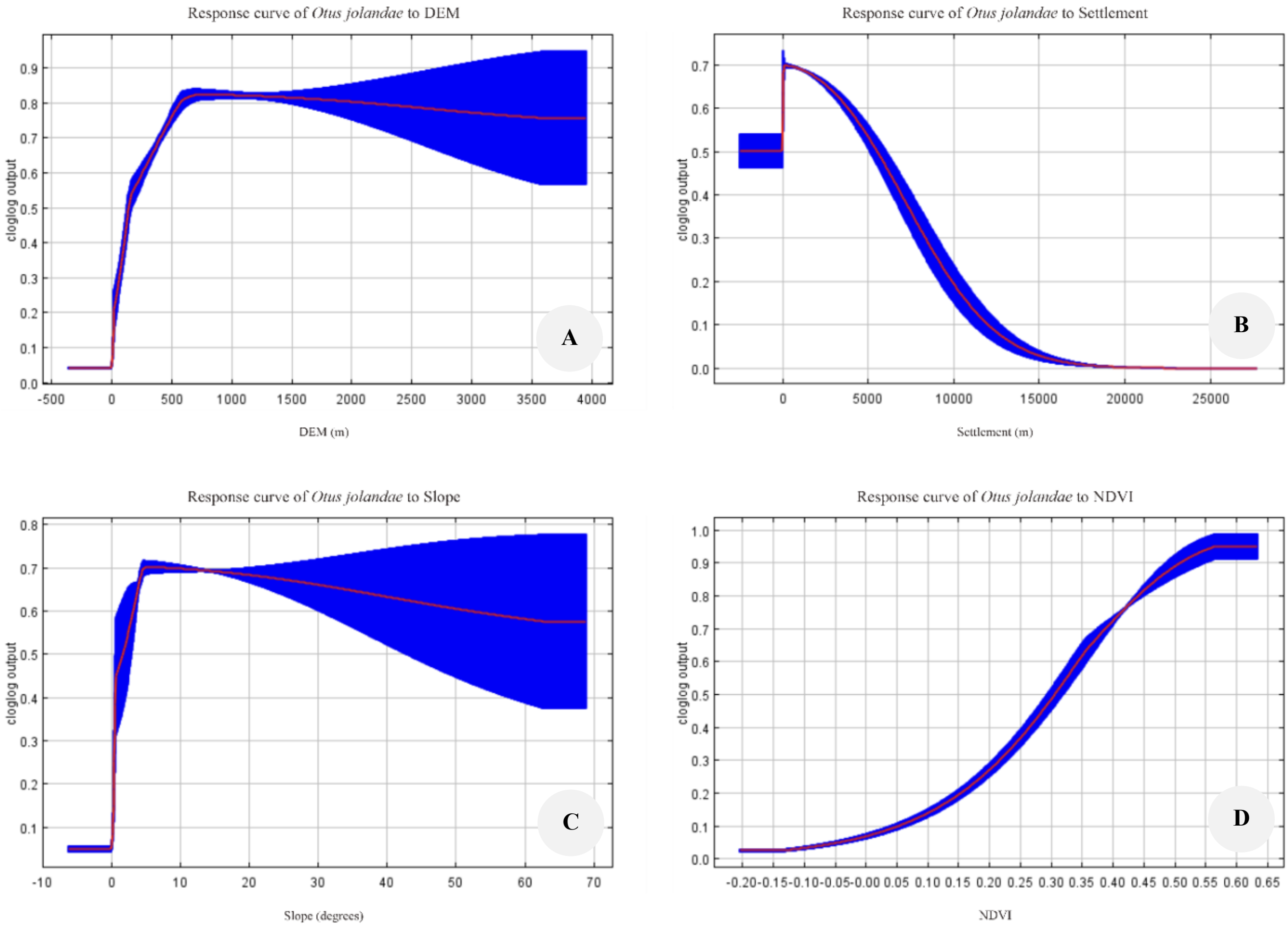

Figure 8. MaxEnt response curves for Rinjani scops-owl: A. DEM (elevation), B. Distance to human settlements, C. Slope, D. NDVI. For the MaxEnt response curve for DEM, note that occurrence data used for model training was limited to 25-1,700 m. Predictions above 1,700 m represent model extrapolation and are characterized by high uncertainty (wide blue bands)

Habitat selection and suitability of Rinjani scops-owl

Our suitability model shows that the Rinjani scops-owl's distribution is mainly determined by elevation (53.4% contribution), with a plateau in suitability between 600 and 1,000 m. This elevation preference aligns with the concepts of physiological and ecological tolerance limits, where the scops-owl select where to live in suitable environments that optimize their reproductive success and survival (Bridle and Hoffmann 2022; Northrup et al. 2022). A similar elevational preference is also observed in other small Strigidae. The Sooty owl (*Tyto tenebricosa* Gould, 1845) selects mid-elevations to balance moderate temperatures with humidity requirements (Westaway et al. 2025), while the little owl (*Athene noctua* Scopoli, 1769) avoids the thermal stress of high altitudes (Ševčík et al. 2021). In the case of the Rinjani scops-owl, this mid-elevation selection is likely functionally linked to prey availability. Like other scops-owls, Rinjani scops-owls are strongly insectivorous, feeding primarily on invertebrates and occasionally small vertebrates (Latková et al. 2012; Mori et al. 2016; Kassinis et al. 2024). Insect abundance typically peaks at mid-elevations, as higher altitudes impose cooler microclimates that depress insect reproduction and community structure. Consequently, the owl's high occupancy at 600-1,000 m zone reflects a phenomenon of the predator-prey interaction, optimizing access to abundant food resources within a physiologically tolerable ecological amplitude.

This research shows that Rinjani scops-owl selects habitats that are considered gently inclined slopes. A study on habitat selection of the congeneric scops owl (*Otus scops* Linnaeus, 1758) conducted by Treggiari et al. (2013), showed similar findings: the owls preferred intermediate slopes (from 0 to 15%). The study argued that slope correlates with land-use and vegetation structure in our research localities. Slope also influences local microclimate and local vegetation structure where insects are most available to eat. In addition, gentle to moderately sloped terrain likely supports deeper soil strata (Brosens et al. 2020) and enhances a more stratified forest (Jia et al. 2024). The abundance of a diversified canopy layer in the study site can enhance prey availability, causing a higher occurrence of the Rinjani scops-owl than in the steeper landscape. As for elevation, habitat selection by this species is strongly linked to slope as a function of the predator-prey interaction between the scops-owl and its prey.

In the MaxEnt model, NDVI and Distance to Settlements contributed less than 10% to the overall model gain, indicating that their influence on the predicted distribution of Rinjani scops-owl was relatively minor compared to elevation and Slope. The low contribution of these two variables does not necessarily imply ecological insignificance but reflects their relative explanatory power within the set of environmental predictors included in the model. Variables with low percent contribution should be interpreted as having a limited influence on broad-scale distribution patterns but potentially significant effects on fine-scale habitat use (Vorstenbosch et al. 2024). NDVI is an appropriate proxy to indicate the goodness of vegetation cover that potentially provides prey-rich environments and habitat heterogeneity used by Rinjani scops-owl for foraging and nesting. An analogue study on the congeneric bird, Eurasian scops-owl (*O. scops*), showed that vegetation enhances the prey availability and serves as a more important predictor than climatic factors at local scales (Theux et al. 2022).

Distance to settlement contributed less to predicting the spatial distribution model of the Rinjani scops-owl. Despite having a low percent contribution, this predictor should be considered in the discussion on a fine scale due to its unique factor affecting the overall model. Unlike its congeneric owl, the Principe scops-owl (*Otus bikegila* Melo, Freitas, Verbelen, da Costa, Pereira, Fuchs, Sangster, Correia, de Lima & Crottini, 2022) highly depends on a dense native forest and is sensitive to noise, light, and fragmentation (Freitas et al. 2023). Rinjani scops-owl is likely to tolerate habitats close to human settlements. Indeed, a positive trend shows that suitability increases as this scops-owl has a closer distance to settlement. The evidence was recorded as the photo of a wild Rinjani scops-owl presented in Figure 1, which was taken very close to the settlement. Despite its predominantly montane forest association, Rinjani scops-owl may benefit from proximity to settlements for several reasons. First, artificial light at night can aggregate nocturnal insects, creating prey 'hotspots' around villages and roads (Adams et al. 2021; Owens et al. 2024). Second, garden-agroforestry mosaics and forest edges near settlements can elevate arthropod activity and availability, potentially improving foraging patch relative to closed-canopy interiors (Greyvenstein et al. 2021). Third, mature fruit trees, bamboo clumps, and occasional buildings provide cavities and sheltered roosts for the scops-owl. The abundance of prey and perching/nesting structures could make near-settlement habitats attractive to the scops-owl, even though it contributes less to the model. Although that the model outputs suggest suitability closer to human settlements, careful interpretation should be performed. Rather than an explicit ecological attraction to human-dominated landscapes, this pattern likely reflects the species' tolerance to modified environments found near rural settlements. Furthermore, as acknowledged, this variable is highly susceptible to accessibility bias, where survey efforts are disproportionately concentrated near accessible roads and villages. Therefore, while *O. jolandae* demonstrates adaptability to fragmented forest edges, further systematic surveys with unbiased distance-sampling are required to definitively untangle true ecological preference from observer bias.

The spatial patterns revealed by our model can be interpreted through the Ideal Free Distribution (IFD) theory (Fretwell and Lucas 1969). The theory predicts that individual scops-owl will preferentially occupy high-suitability habitats until density-dependent factors reduce resource quality, forcing spillover into marginal areas. Therefore, the "Very High" suitability zones identified in our model likely represent the species' core realized niche (Matthiopoulos 2022), where population densities are expected to be highest. The species' ability to recognize and colonize these specific environmental gradients, defined by elevation, slope, and vegetation structure, demonstrates the efficacy of intrinsic traits and learned behaviors shaped by natural selection (Shirani and Miller 2025).

Several limitations should temper the interpretation of these results. Our model assumes that current occurrences reflect a near-equilibrium with present environments and does not explicitly represent fine-scale habitat features (e.g., nesting sites, prey dynamics), biotic interactions, or dispersal limits; therefore, predicted 'high suitability' may not translate to occupancy everywhere. Additionally, because our final model is primarily based on static topographic and vegetation variables, it represents a baseline hypothesis for current suitability. It does not account for future hydro-climatic shifts. Future work should aim to integrate high-resolution, non-collinear climatic variables to project suitability under multiple climate change scenarios, which will be essential for evaluating the long-term persistence of these montane refugia.

The MaxEnt suitability model generated here serves as a proxy for the species' Grinnellian niche, based on broad-scale abiotic constraints, rather than a direct map of realized occupancy (Wang et al. 2025). While the model effectively delineates fundamental environmental requirements, these results must be interpreted strictly as a baseline of current habitat suitability. This static approach assumes near-equilibrium with present environments. It does not account for dynamic biological factors, such as dispersal limitations, biotic interactions (e.g., competition), or fine-scale habitat features, such as the availability of specific nesting cavities (Krebs 2001). Consequently, areas identified as "high suitability" indicate potential habitat availability rather than confirmed occupancy.

Furthermore, a critical distinction must be drawn between this current baseline and future persistence. By design, our predictor selection focused on establishing the species' present-day environmental condition and did not incorporate future climate scenarios. This exclusion limits the model's temporal applicability; as global temperatures rise, the specific montane conditions preferred by the Rinjani scops-owl (600-1,000 m) may shift upslope, potentially contracting the climatic refugia identified in this study. Therefore, we caution against using these maps to predict long-term viability without further analysis. Future research should build upon this baseline by integrating downscaled Global Climate Models (GCMs) under multiple Shared Socioeconomic Pathways (SSPs). Such projections are necessary to evaluate the stability of these refugia and to distinguish between areas that are suitable now versus those likely to remain suitable under future warming and altered precipitation regimes.

Implications for the conservation of Rinjani scops-owl

The output from MaxEnt modeling has been widely used for long-term predictions to inform future conservation efforts (Smith et al. 2020). Despite Maxent's capabilities, we chose to prioritize analysis based on the principle of model parsimony over temporal transferability by eliminating bioclimatic predictors due to their high collinearity with topographic covariates. Consequently, the resulting map can only model the habitat suitability of the Rinjani scops-owl for current conditions while still providing robust proximal predictors such as elevation, slope, and vegetation. This limitation limits the model's applicability for long-term climate adaptation planning, as it does not account for potential future climate conditions. To address the gap between current conditions and future projections, further research is recommended using more appropriate models. Furthermore, expanding the occurrence dataset will be crucial to reducing overfitting, enabling future models to robustly predict the sustainability of the Rinjani scops-owl population under dynamic climatic conditions.

Given that the Rinjani scops-owl inhabits both protected areas (national and nature parks) and privately managed lands, conservation initiatives must extend beyond formally protected zones. Because land tenure influences management possibilities, distinct strategies are required. In protected areas with high suitability mandated for public use (e.g., Suranadi Nature Recreation Park), management should focus on preserving forest complexity. This management involves strictly regulating in-forest activities to prevent canopy opening and maintain the vegetation structure required by the species. In areas of very high suitability (e.g., Sembalun and Senaru at Mount Rinjani National Park), stricter measures are necessary. These areas should be designated as "non-negotiable" core habitat zones where forest disturbance is prohibited entirely. These cores require routine enforcement and a long-term monitoring program to detect early signs of degradation or population decline. Finally, where high-suitability zones occur outside protected areas, conservation relies on establishing buffer zones and negotiating agreements with private landholders to retain tree cover, reduce edge effects, and prevent further fragmentation. In addition, targeted restoration should also focus on moderately suitable areas adjacent to high-suitability cores, using assisted natural regeneration and native-enrichment planting to expand habitat and strengthen connectivity among suitability patches. The remaining low suitability lies between moderate-core patches of high to very high suitable habitat. This zone should not be dismissed as marginal habitat for the species; instead, it should be managed as the supporting landscape that sustains the moderate and core areas. The low- to moderate-altitude areas under conservation authorities (within the optimum altitudinal range of suitability) may serve as the restoration zone, where assisted natural regeneration, enrichment planting, and canopy-structure recovery can increase NDVI and promote sites toward higher suitability over time. The residual low-suitability landscape in non-conservation areas is designated as a sustainable use zone, where agriculture, plantations, and settlements may continue, provided they retain an appropriate canopy structure and do not create barriers to movement (for example, vast, clear areas without proper management). Indeed, agriculture, plantations, and human settlement do not erode suitability at the species' habitat periphery.

Our island-scale MaxEnt model explicitly identifies high vegetation density (NDVI) as a critical requirement for the Rinjani scops-owl habitat suitability. To translate this broad-scale raster output into practical, site-level management, we draw upon local field observations and prior studies. These localized studies indicate that the structural complexity and dense canopy required by the species are frequently provided by specific mid-canopy and shade trees, such as *Dalbergia latifolia* Roxb., *Samanea saman* (Jacq.) Merr. (Muttaqin et al. 2020), *Gmelina arborea* Roxb. ex Sm., and *Nauclea orientalis* (L.) L. (Permatasari et al. 2025). Therefore, while our macro-scale model does not predict the distribution of these individual plant species, preserving and restoring these specific locally-observed trees is a highly effective, practical strategy to maintain the high-NDVI conditions and vertical heterogeneity that our model confirms are essential for the owl's persistence.

Based on our suitability model, we suggest several practical conservations plans for the Rinjani scops-owl. First, we recommend protection actions focusing on the scops-owl's best mid-elevation range (approximately 600-1,000 m) within current conservation areas, ensuring suitable habitat is conserved in the long run. This action should be carried out in concert with habitat protection in nearby non-conservation buffer zones at both lower and higher elevations. Second, although the species frequently utilizes several specific mid-canopy trees, such as *D. latifolia*, maintaining high tree diversity in the habitat should be prioritized to spread risk across varying plant phenology and drought responses, reduce vulnerability to tree-specific pests, and maintain the vertical heterogeneity required for roosting and foraging. Third, the socioeconomic dimension of bio-conservation (for example, citizen science ships) must be involved to protect these mid-elevation habitats, raise awareness, and foster local support. Ultimately, our baseline suitability map can be used in regional spatial planning, encouraging authorities to explicitly delineate non-negotiable core zones and sustainable-use buffers across mainly protected lands, and can be referred to for privately managed land. Furthermore, our suitability delineation provides baseline data for future climatic scenarios, enabling conservationists to anticipate range shifts and proactively design climate-resilient survival strategies for Lombok's endemic species.

In addition, although our results provide a baseline for actionable and landscape-level policies, protecting Rinjani scops-owl requires an appropriate translation of our spatial models into an adaptive management framework. These findings should be carefully interpreted in the context of our methodological constraints, notably the limited post-resample size (n: 29) and the inherent accessibility bias, which can create ambiguity and limit the model's ability to draw the realized niche rather than the fundamental niche. Taking these limitations into account, the most reasonable conservation suggestion is to use this baseline suitability map to set priorities rather than as a blueprint for fixed zoning. Indeed, a strict adoption using our outputs model to prescribe fixed, non-negotiable zoning regulations should be avoided. Our baseline suitability map should be used as a preliminary tool for flexible conservation prioritization, to be referred to underscore a preliminary conservation plan, such as targeted habitat protection and sustainable agroforestry programs, as more empirical field data becomes available.

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