



Research Article

Identification of potential suitable habitats and high conservation value areas for threatened species in Rajah Sikatuna Protected Landscape, Philippines

Wilbert A. Aureo^{‡,§,||}, Cristino L. Tiburan Jr.[¶], Eduardo C. Calzeta[§], Ireneo L. Lit Jr.[#], Yingwei Yan[□], David Mark Taylor[□], Rico C. Ancog[§]

[‡] College of Forestry and Environmental Science, Bohol Island State University, Bohol, Philippines

[§] School of Environmental Science and Management, University of the Philippines Los Baños, College, Los Baños, Laguna 4031, Philippines

[|] Division of Agriculture and Forestry, National Research Council of the Philippines, 51 General Santos Ave, Taguig, Metro Manila, Philippines

[¶] Institute of Renewable Natural Resources, College of Forestry and Natural Resources, University of the Philippines Los Baños, College, Los Baños, Laguna 4031, Philippines

[#] Institute of Biological Sciences, College of Arts and Sciences, University of the Philippines Los Baños, College, Los Baños, Laguna 4031, Philippines

[□] Department of Geography, National University of Singapore, 1 Arts Link, Kent Ridge, Singapore, Singapore

Corresponding author: Wilbert A. Aureo (wilbert.aureo@bisu.edu.ph)

Academic editor: Artur Gil

Received: 08 Jan 2026 | Accepted: 06 Apr 2026 | Published: 02 Jun 2026

Citation: Aureo WA, Tiburan Jr. CL, Calzeta EC, Lit Jr. IL, Yan Y, Taylor DM, Ancog RC (2026) Identification of potential suitable habitats and high conservation value areas for threatened species in Rajah Sikatuna Protected Landscape, Philippines. One Ecosystem 11: e184595. <https://doi.org/10.3897/oneeco.11.e184595>

Abstract

Identifying suitable habitats and High Conservation Value Areas (HCVAs) for threatened species is critical for informing site-based management in biodiversity-rich, but vulnerable landscapes. In this study, Species Distribution Modelling (SDM) and species richness analysis were applied to identify areas of high conservation value within Rajah Sikatuna Protected Landscape (RSPL). Using the MaxEnt algorithm, we modelled habitat suitability for thirteen threatened species across major taxonomic groups, incorporating topographic and bioclimatic variables. Models showed high performance (mean Area Under Curve (AUC) = 0.905, True Skill Statistic (TSS) = 0.717 and Variance Inflation

Factor (VIF) < 4), with terrain ruggedness, slope, mean annual temperature and annual precipitation identified as primary drivers of model structure. While statistical performance was robust, model outputs were strictly framed as spatial hypotheses to account for the data-limited nature of the focal endemics and the use of bioclimatic layers as proxy gradients. The resulting potential suitability maps revealed heterogeneous, species-specific distributions, ranging from localised and fragmented habitats for *Dipterocarpus grandiflorus*, *Gallicolumba crinigera* and *Shorea guiso*, to broader ranges for *Edolisoma mindanense*, *Platymantis guentheri* and *Voacanga megacarpa*. Stacked binary models produced a species richness map that highlighted northern and north-western RSPL as biodiversity hotspots, while southern areas were relatively depauperate, reflecting probable degradation. Threshold-based analyses to delineate HCVAs showed that the CRFD (Cumulative Richness Frequency Distribution) inflection point (~ 6 species) best balanced spatial extent and ecological sensitivity, capturing 90% of species occurrences. In contrast, conservative thresholds (e.g. 95th percentile, Mean + 1 SD) isolated only a few core hotspots, but excluded moderately rich areas that may serve as corridors or buffer zones. This integrated modelling approach offers valuable insights, enabling the prioritisation of potential critical habitats and identification of targets for ecological restoration.

Keywords

species distribution modelling, MaxEnt, species richness, conservation planning, habitat suitability, Central Visayas

Introduction

Global biodiversity is experiencing unprecedented declines due to habitat loss, fragmentation and climate change, with tropical regions like the Philippines being especially vulnerable (IPBES 2019; Maxwell et al. 2020). Protected areas (PAs) are cornerstones of global conservation strategies, designed to safeguard habitats and threatened species (Watson et al. 2014). However, many PAs, particularly in biodiversity hotspots like the Philippines, suffer from inadequate management, spatial mismatch between protected boundaries and species' actual habitats and increasing anthropogenic pressures (Kark et al. 2009; Pulhin JM et al. 2016; Brooks et al. 2019). Consequently, identifying areas of high conservation value within PAs that truly support threatened species is paramount for effective biodiversity protection.

The RSPL in the Philippines is a recognised biodiversity hotspot due to its unique karst formations and endemic species assemblages (Department of Environment and Natural Resources 2019). Despite its protected status, RSPL faces persistent threats, such as illegal logging, agricultural expansion, and infrastructure development, which fragment habitats and jeopardise species survival (Pulhin JM et al. 2016; Alviola PA et al. 2020). Moreover, conservation efforts have been hampered by limited spatially explicit

information on species distributions and habitat suitability, which are crucial for prioritising management actions (Aureo et al. 2020; Ocampo FA et al. 2022).

Species Distribution Models (SDMs) are powerful tools that predict species' potential geographic distributions by linking occurrence records with environmental variables, enabling the estimation of habitat suitability across landscapes (Elith and Leathwick 2009 ; Zhang et al. 2024). Widely applied in biodiversity-rich and data-deficient regions, SDMs effectively provide information for conservation planning by identifying suitable habitats for threatened species and facilitating spatial prioritisation of High Conservation Value Areas (HCVAs) essential for species persistence and management (De Alban JDT et al. 2015; Guisan et al. 2017; Mancera KF and Lapuz 2021; Bakx et al. 2023). Various methodologies using SDM outputs — such as thresholding habitat suitability, aggregating multi-species richness or weighting by species conservation status — are employed globally to delineate HCVAs tailored to local conservation needs. Despite these advances, SDMs remain underutilised in many Philippines protected landscapes, limiting data-driven conservation efforts and hindering the identification of critical HCVAs necessary to safeguard species survival and ecosystem integrity (De Alban JDT et al. 2015; Mancera KF and Lapuz 2021).

Given these challenges, there is an urgent need to apply spatially explicit and scientifically grounded approaches to conservation planning within RSPL. This study addresses this gap by employing multi-species SDMs to delineate potential suitable habitats for threatened taxa and to identify HCVAs, based on habitat suitability thresholds and species richness patterns. By integrating ecological data with spatial prioritisation techniques, the study aims to support evidence-based decision-making and guide conservation zoning, habitat restoration and resource allocation within RSPL. This approach contributes to strengthening protected area management and enhancing the long-term resilience of threatened species in one of the Philippines' most important biodiversity landscapes.

Methods

Description of the study area

The RSPL, situated in Bohol Province within the Central Visayas Region of the Philippines, spans approximately 10,453 hectares and represents the largest remaining contiguous natural habitat on the island (Fig. 1). The site is characterised by a heterogeneous landscape of forested limestone hills, open grasslands and karst formations, with land cover dominated by open forests and interspersed with brush, cultivated areas and patches of built-up land (Birding2Asia 2014; Aureo et al. 2020). Elevation within the RSPL ranges from 0 to 870 metres above sea level, with higher altitudes concentrated in the central and eastern sections, corresponding to steeper and more rugged terrain (Aureo and Decena 2023). These upland areas form part of Bohol's critical recharge zones, supplying water to numerous springs and rivers. The region experiences a Type IV climate, based on the Modified Coronas Classification (MCC)

system, with rainfall relatively evenly distributed year-round and an annual precipitation average of around 3,756 mm (Lantican 2001; BirdLife International 2014). The predominant soil type is the Batuan–Faraon complex, which, while suitable for agriculture in flatter areas, is subject to fertility constraints and erosion risks on steeper slopes. Approximately 62% of the terrain consists of slopes between 0–18%, allowing for various land uses, whereas steeper zones require targeted management to maintain ecological stability and water quality. The RSPL thus plays a central role in sustaining both biodiversity and ecosystem services within Bohol's complex topography.

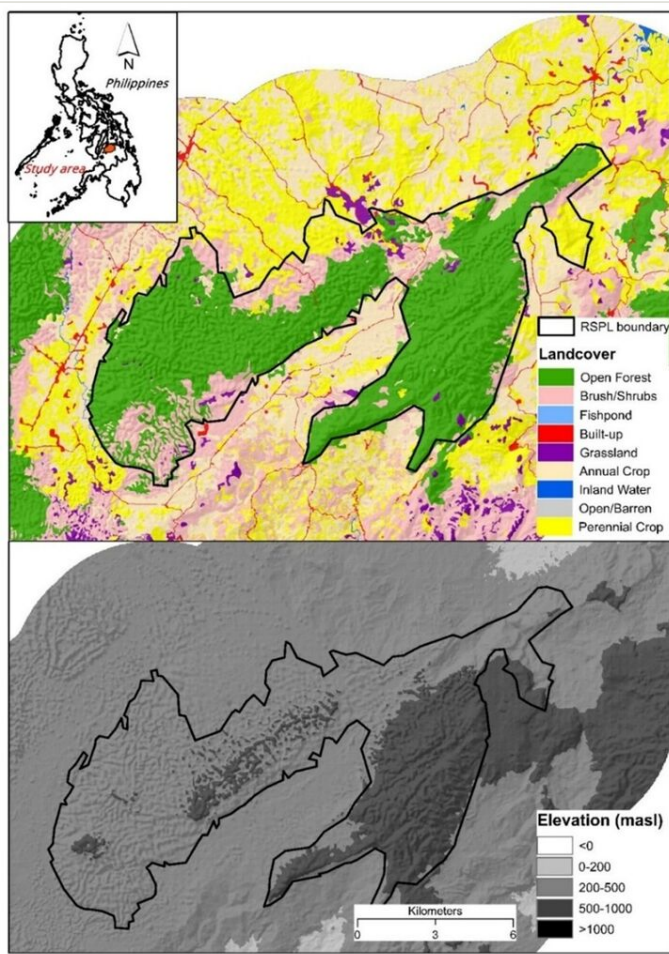


Figure 1.

Location and biophysical features of the RSPL, Bohol, Philippines. *Top panel:* Land-cover classification within and around RSPL, showing dominant open forest areas interspersed with grasslands, cultivated areas and built-up zones. *Bottom panel:* Elevation gradient (in metres above sea level) across RSPL, illustrating topographic variation from lowland areas (0–244 m) to high elevation zones (581–870 m). The black polygon delineates the official RSPL boundary. Inset map shows the location of the study area within the Philippines.

Methodological framework

The study implemented an integrative spatial modelling framework to identify suitable habitats and HCVAs for threatened species in RSPL (Fig. 2). The methodology followed a structured pipeline consisting of four stages: data input, analytical processing, output generation and area identification. Environmental preparation involved standardising bioclimatic and topographic data layers, with climatic variables interpolated and terrain variables, such as the Terrain Ruggedness Index, derived from a DEM. Species occurrence records underwent spatial thinning to mitigate sampling bias before habitat suitability was modelled using MaxEnt. Model performance and data integrity were rigorously assessed using the VIF, Jackknife test, AUC and TSS and sensitivity analysis (MTP vs. maxSSS). Through composite richness mapping and threshold sensitivity analysis, individual habitat suitability maps were converted into binary layers and aggregated to produce a species richness map. Finally, HCVAs were delineated by applying statistical thresholds to the richness distribution, providing a repeatable, quantitative basis for supporting site-based conservation decisions.

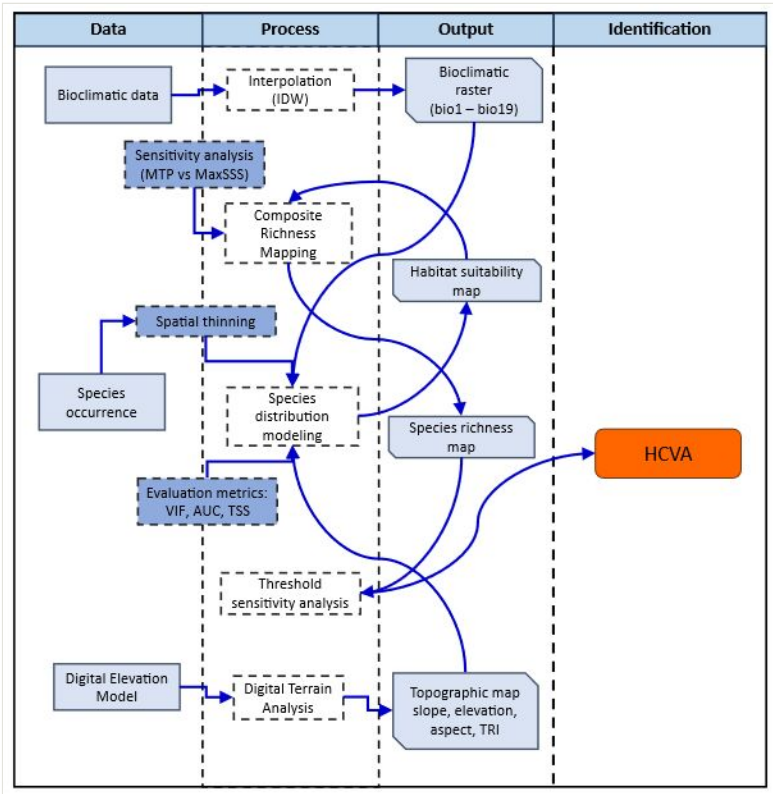


Figure 2. Methodological framework used to identify potential suitable habitats and HCVAs for threatened species in RSPL.

Data acquisition

Environmental and species occurrence data were sourced from authoritative local, national and international repositories to support the spatial analyses conducted in this study (Suppl. material 1). Climatic variables, including temperature and precipitation data (Suppl. material 2), were obtained from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (<https://www.pagasa.dost.gov.ph>), which provides long-term climate data and derived bioclimatic layers for the Philippines (Department of Science and Technology - Philippine Atmospheric, Geophysical and Astronomical Services Administration 2023). Species occurrence records were compiled from the Global Biodiversity Information Facility (GBIF 2023) available at <https://www.gbif.org/>, supplemented by local data from the Biodiversity Assessment and Monitoring System (BAMS) reports of the Department of Environment and Natural Resources (Department of Environment and Natural Resources 2019), as well as field survey data collected by the Central Visayas Agriculture, Aquatic and Natural Resources Research and Development Consortium (CVAARRDEC). These species observations were vetted for coordinate accuracy and taxonomic consistency prior to inclusion in the analyses. In addition, topographic variables, such as elevation, slope, aspect and terrain ruggedness (Suppl. material 3), were derived from the ALOS Digital Elevation Model (<https://www.eorc.jaxa.jp/ALOS/>), which provides a 12.5-metre resolution terrain dataset ideal for fine-scale ecological and spatial analyses (JAXA 2019). Moreover, the RSPL boundary shapefile was obtained from World Database on Protected Areas available at <https://www.protectedplanet.net/en> and was verified using spatial data from the DENR. Together, these multi-source datasets (Suppl. material 4) enabled a robust assessment of species richness, habitat distribution and topographic variability across the protected area.

Interpolation of microclimatic variables

In this study, spatial interpolation of 19 bioclimatic variables was performed using IDW to generate continuous proxy environmental gradients aligned with the spatial resolution and extent of the reference DEM. The input data consisted of point-based climatic observations (e.g. Bio_1–Bio_19) stored in CSV format, each containing geographic coordinates and associated climate values. The IDW method was implemented using the gstat package in R (Pebesma 2004), with a power parameter of $p = 2$, based on the following formula:

$$Z(x_0) = [\sum(Z(x_i)/d(x_0, x_i)^p)] / [\sum(1/d(x_0, x_i)^p)],$$

where $Z(x_0)$ is the estimated value at an unsampled location x_0 , $Z(x_i)$ is the observed value at location x_i , $d(x_0, x_i)$ is the Euclidean distance between x_0 and x_i and p is the inverse distance weighting exponent.

A value of $p = 2$ was selected as it is a common choice that ensures closer points have a stronger influence on the interpolated value. Since only three sampling points were available, the interpolation was constrained to the three nearest neighbours ($n_{\max} = 3$),

minimising extrapolation artefacts and overfitting. The resulting raster was then projected and resampled to match the spatial resolution, extent and coordinate reference system (CRS) of the DEM. IDW was selected over geostatistical methods such as kriging due to the extremely limited number of input points, which are insufficient to reliably fit a semi-variogram model (Li and Heap 2014). IDW is a deterministic method that performs robustly under data-sparse conditions and does not assume statistical properties of spatial autocorrelation, making it a practical and reproducible approach for interpolating environmental surfaces in data-limited contexts.

Derivation of topographic variables

To derive key topographic variables for SDM, a digital elevation model was processed using terrain analysis methods implemented in the *terra* package in R. The variables generated included elevation, slope, aspect and the topographic ruggedness index (TRI), all of which can shape microclimates and species distribution patterns (Wilson et al. 2007). These topographic predictors capture terrain complexity and environmental gradients, which are critical for explaining species distributions, especially in mountainous or heterogeneous landscapes (Körner 2007; Elith and Leathwick 2009). Elevation was extracted directly from the DEM and represents the height above sea level in metres. Slope was calculated as the maximum rate of elevation change between a cell and its neighbours and is expressed in degrees. The slope (S) is calculated as:

$$S = \text{atan}(\sqrt{(dz/dx)^2 + (dz/dy)^2}),$$

where dz/dx and dz/dy are the partial derivatives of elevation in the x and y directions, respectively.

Aspect, representing the compass direction that a slope faces, is calculated as:

$$A = \text{atan}^2(dz/dy, -dz/dx).$$

The Topographic Ruggedness Index (TRI) is calculated as:

$$\text{TRI} = (1/n) \sum |z_0 - z_i|,$$

where z_0 is the elevation of the central cell, z_i are the elevations of surrounding cells and n is the number of surrounding cells.

Species distribution modelling

A MaxEnt modelling approach (version 3.4.4) was employed to predict the potential habitat suitability of the target species using presence-only occurrence data and a suite of environmental predictors (Phillips et al. 2006a; Phillips et al. 2006b; Phillips et al. 2009). Occurrence records were initially cleaned by removing duplicate entries and erroneous coordinates. To mitigate the effects of spatial autocorrelation and sampling bias, we applied spatial thinning and "bias file", resulting in a final dataset of 83 spatially independent occurrence records (Pearson et al. 2006).

To ensure reproducibility and address the complexities of species-environment relationships, the model was parameterised using Linear, Quadratic, Product, Threshold and Hinge (LQPTH) features (Suppl. material 5). We utilised the logistic output format and enabled clamping and extrapolation to account for environmental values outside the training range. Model performance and variable importance were evaluated using response curves and jackknife tests, respectively. To improve calibration, presence samples were added to the background and all output grids were generated in .asc format.

To minimise model over-fitting and improve the interpretability of environmental responses, we implemented a variable reduction process to refine the initial set of 23 bioclimatic and landscape predictors. We subjected the initial variables to a VIF analysis, iteratively excluding those with a VIF > 5 to eliminate extreme redundancy (Dormann et al. 2012). This screening ensured that the final models were calibrated using a robust subset of five independent predictors — Annual Mean Temperature, Annual Precipitation, Elevation, Slope and Terrain Ruggedness Index (TRI) — all of which maintained VIF values < 4.0, well below the conservative threshold of 5.0 (Naimi et al. 2013). The relative influence of these predictors was further evaluated using Percent Contribution and Jackknife tests of variable importance, where a variable was considered a "primary driver" if it yielded the highest regularised training gain in isolation or if its omission resulted in the most substantial decrease in gain.

To represent the available environment, 10,000 background points were randomly generated across the RSPL. Model performance was evaluated using a dual-metric approach: the Area Under the Receiver Operating Characteristic Curve (AUC) to assess general discrimination and the True Skill Statistic (TSS) to evaluate accuracy independently of prevalence. To ensure reliability across varying sample sizes, we utilised an adaptive validation framework: 5-fold cross-validation for species with $n < 10$ and a Jackknife (Leave-One-Out) procedure for data-limited taxa ($n < 10$).

Final models were trained using the fully thinned dataset to produce continuous habitat suitability maps. To transform continuous probability surfaces into binary presence-absence maps, we applied the maxSSS threshold. While MTP was initially considered to minimise omission, a sensitivity analysis revealed that MTP inflated predicted presence by up to 74% in certain taxa by encoding spatial noise into the binary maps (Suppl. material 6). The maxSSS threshold was selected as it optimises the trade-off between sensitivity and specificity and is widely recognised as one of the most robust thresholds for conservation planning (Liu et al. 2013). All modelling procedures were conducted using the *dismo*, *terra*, *raster* and *usdm* packages (Naimi et al. 2013; Hijmans et al. 2017; Hijmans 2020; R Core Team 2023).

Species richness and threshold analysis

The species richness data were analysed and visualised to assess the distribution and determine appropriate conservation thresholds (Table 1). We aggregated taxa to identify 'multi-taxa hotspots' that represent high-integrity ecosystems beneficial to the broader

community, rather than managing for a single flagship species. The species richness values for each grid cell were compiled into a numeric vector and used to generate both the cumulative distribution and the frequency distribution graphs. The cumulative distribution was created using the `ecdf()` function, which calculates the empirical cumulative distribution of species richness across the landscape. Vertical lines were added to mark the statistical thresholds (Mean $\pm$ 1 SD, CRFD inflection point, 80th, 90th and 95th percentiles) using the `abline()` function in the `ggplot2` package, with distinct line styles and colours for clarity. The frequency distribution was generated as a histogram using `hist()` and complemented with a density plot overlay (`lines(density(...))`) to highlight the distribution's shape and modality. The thresholds were similarly annotated with vertical lines.

Table 1.

Summary of threshold methods used to identify HCVAs, based on species richness distributions within the RSPL.

Threshold	Description	References
CRFD Inflection Point	Point of sharp change in the cumulative richness curve	Bartolino V et al. (2010); Fitzpatrick et al. (2015)
80 th Percentile	Top 20% of species-rich cells	O'Donnel and Ignizio (2012); Liu et al. (2013) Dullinger et al. (2016); Lu et al. (2018)
90 th Percentile	Top 10% of species-rich cells	Myers et al. (2000); Xu et al. (2017)
95 th Percentile	Top 5% of species-rich cells	O'Donnel and Ignizio (2012); Liu et al. (2013) Dullinger et al. (2016); Lu et al. (2018)
Mean + 1 SD	Cells with richness above one standard deviation from mean	Santora and Veit (2013); Zipkin et al. (2015)

Identification of HCVAs

To identify HCVAs, five statistical thresholds were assessed: the Mean $\pm$ 1 SD, the inflection point of the Cumulative Richness Frequency Distribution (CRFD), the 80th, 90th and the 95th percentiles. These thresholds were selected to capture a range of richness intensities across the landscape, from common areas (Mean $\pm$ 1 SD) to rare hotspots (90th and 95th percentiles). The CRFD inflection point was computed to locate the richness value at which the trend shifts from common to rare (Kukkala and Moilanen 2012). In selecting an appropriate threshold, both statistical rigour and ecological relevance were considered, especially within the context of an existing protected area (Hansen et al. 2020). Each HCVA map was treated as a binary surface (1 = HCVA, 0 = Non-HCVA) and species occurrences were extracted to assess whether they fell within HCVA areas. The sensitivity of each HCVA map, defined as the proportion of observed species occurrences correctly identified within HCVA areas (True Positive Rate), was calculated using the formula:

Sensitivity = Number of occurrences within HCVA / Total occurrences x 100.

To estimate the uncertainty of these sensitivity values, 95% confidence intervals were calculated using the normal approximation for binomial proportions (Agresti and Coull 1998), an approach well established for assessing spatial prediction performance (Fielding and Bell 2002). This approach provides a robust and interpretable measure of map effectiveness for conservation planning, aligning with best practices in species distribution modelling (Fawcett 2006). Recent studies also emphasise the use of threshold-based metrics, such as sensitivity, specificity and AUC, in selecting spatial prediction maps for conservation prioritisation (Buckland ST et al. 2022; Bracken FSA et al. 2022; Thomas et al. 2024). By focusing on sensitivity and its associated uncertainty, this method allows for a direct and transparent assessment of how well HCVA thresholds capture actual species occurrences, making it a valuable tool for guiding site-level conservation and management.

Results

Model performance and environmental predictors

The MaxEnt models for the 13 species yielded high predictive scores, with a mean AUC of 0.905 and a mean TSS of 0.717 (Table 2). Performance remained statistically robust across the ensemble, with AUC values ranging from 0.860 (*E. mindanense*) to 0.950 (*G. crinigera*). The high TSS values (mean 0.717) further confirm that the models maintained high accuracy independent of prevalence, effectively distinguishing suitable habitats across the RSPL. However, the robust statistical performance of the models must be interpreted through the lens of the data constraints inherent to high-diversity, data-poor tropical landscapes. A primary limitation is the reliance on bioclimatic variables interpolated from only three local sampling points. These layers should be viewed as proxy gradients reflecting broad landscape transitions rather than high-fidelity climate surfaces.

Table 2. Summary of species-specific sample sizes, predictive performance and environmental variable contributions.						
Scientific name	Raw N	Thinned N	AUC	TSS	Primary predictor	Max VIF
<i>Pitta steerii</i>	18	12	0.92	0.74	Elevation	3.35
<i>Macaca fascicularis</i>	9	8	0.91	0.72	TRI	1.57
<i>Miniopterus schreibersii</i>	9	7	0.90	0.69	Slope	1.55
<i>Dipterocarpus grandiflorus</i>	13	7	0.93	0.76	Elevation	1.16
<i>Hydrosaurus pustulatus</i>	7	6	0.88	0.69	Annual temperature	3.16
<i>Hopea acuminata</i>	8	6	0.90	0.71	Slope	1.55
<i>Platymantis guentheri</i>	7	6	0.94	0.81	Annual precipitation	3.35

Scientific name	Raw N	Thinned N	AUC	TSS	Primary predictor	Max VIF
<i>Vatica mangachapoi</i>	13	5	0.88	0.67	Elevation	1.16
<i>Gallicolumba crinigera</i>	10	5	0.95	0.82	Annual temperature	3.16
<i>Edolisoma mindanense</i>	15	5	0.86	0.57	TRI	1.57
<i>Shorea guiso</i>	6	4	0.87	0.65	Elevation	1.27
<i>Todiramphus winchelli</i>	7	5	0.87	0.61	Annual temperature	3.12
<i>Voacanga megacarpa</i>	13	7	0.89	0.61	Annual temperature	2.07
Total/Mean	135	83	0.91	0.72	--	Max < 4

The multi-collinearity screening successfully reduced the environmental suite to five independent predictors, all maintaining VIF values < 4.0 (Table 2). Across the 13 species, Annual Mean Temperature (29.2%) and Elevation (28.2%) emerged as the most frequent primary drivers of habitat suitability (Fig. 3). However, the percentage contribution values revealed high niche specificity amongst taxonomic groups. For instance, temperature was the dominant constraint for restricted endemics, contributing 62.3% to the model for *G. crinigera*. Annual Precipitation was the critical driver for the amphibian *P. guentheri* (60.2%), reflecting the physiological dependency of karst-dwelling amphibians on moisture regimes. Elevation was the primary predictor for dipterocarp trees, notably *P. steerii* (54.9%) and *D. grandiflorus* (45.2%). Furthermore, terrain complexity — represented by TRI and Slope — contributed significantly to the models for *M. fascicularis* (33.1%) and *M. schreibersii* (35.6%), respectively.

Spatial patterns of habitat suitability

Species distribution models (SDMs) for thirteen threatened species (Fig. 4) revealed distinct spatial patterns of habitat suitability across the RSPL. Each species exhibited a unique spatial signature, reflecting ecological specificity and differential responses to environmental gradients within the landscape. Highly restricted and fragmented suitability patterns were identified for *Gallicolumba crinigera*, *Dipterocarpus grandiflorus* and *Shorea guiso*. These species are primarily concentrated in the western and northern sectors of the RSPL, where suitable habitat is confined to intact forest interiors. Similarly, localised hotspots of high suitability were identified for *Hydrosaurus pustulatus*, *Macaca fascicularis* and *Todiramphus winchelli*, suggesting a heightened vulnerability to site-specific disturbances within their narrow ranges. Meanwhile, intermediate spatial patterns were observed for *Pitta steerii*, *Hopea acuminata* and *Miniopterus schreibersii*, with habitat suitability concentrated primarily in the southern and central corridors of the protected area. In contrast, a broader and more continuous suitability gradient was predicted for *Platymantis guentheri*, *Edolisoma mindanense* and *Voacanga megacarpa*. The expansive distributions of these three species across the central and western portions of the landscape indicate higher ecological plasticity compared to the more restricted endemics. These results highlight a stark spatial heterogeneity across the RSPL, where specialised "suitability islands" for forest-dependent birds and dipterocarps

contrast with the broader landscape-level suitability predicted for certain herpetofauna and flora.

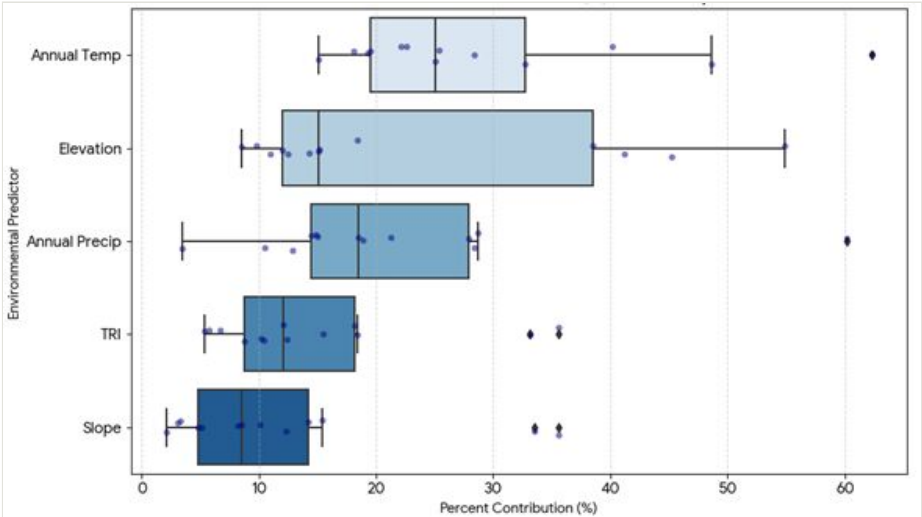


Figure 3.
Jackknife test of variable importance and mean percentage contribution.

Table 3.
List of threatened species assessed within the RSPL, including taxonomic class, species codes and IUCN Red List status. A total of thirteen species (indicated in **bold**) were selected for species distribution modelling (SDM), based on data availability, occurrence record quality and model performance criteria. VU – Vulnerable; EN – Endangered; CR - Critically Endangered.

Scientific name	Class	Species code	IUCN Red List
<i>Adonidia merrillii</i>	Liliopsida	am	VU
<i>Agathis dammara</i>	Pinopsida	ad	VU
<i>Cacatua haematuropygia</i>	Aves	ch	CR
<i>Ceyx melanurus</i>	Aves	cm	VU
<i>Chloropsis flavipennis</i>	Aves	cf	VU
<i>Edolisoma mindanense</i>	Aves	em	VU
<i>Egretta eulophotes</i>	Aves	ee	VU
<i>Gallinolumba crinigera</i>	Aves	gc	VU
<i>Nisaetus pinskeri</i>	Aves	np	EN
<i>Pitta steerii</i>	Aves	ps	VU
<i>Sarcophanops samarensis</i>	Aves	ss	VU
<i>Sarcophanops steerii</i>	Aves	sa	VU
<i>Todiramphus winchelli</i>	Aves	tw	VU

<i>Coffea arabica</i>	Magnoliopsida	ca	EN
<i>Celtis luzonica</i>	Magnoliopsida	cl	VU
<i>Dipterocarpus grandiflorus</i>	Magnoliopsida	dg	EN
<i>Dipterocarpus hasseltii</i>	Magnoliopsida	dh	EN
<i>Ficus inaequifolia</i>	Magnoliopsida	fi	VU
<i>Gossypium hirsutum</i>	Magnoliopsida	gh	VU
<i>Hopea acuminata</i>	Magnoliopsida	ha	VU
<i>Hopea plagata</i>	Magnoliopsida	ho	CR
<i>Psychotria quisumbingiana</i>	Magnoliopsida	pq	CR
<i>Pseuduvaria luzoniensis</i>	Magnoliopsida	pl	EN
<i>Shorea guiso</i>	Magnoliopsida	sg	VU
<i>Vatica mangachapoi</i>	Magnoliopsida	vm	VU
<i>Voacanga megacarpa</i>	Magnoliopsida	vo	VU
<i>Macaca fascicularis philippensis</i>	Mammalia	mf	EN
<i>Miniopterus schreibersii</i>	Mammalia	ms	VU
<i>Platymantis guentheri</i>	Amphibia	pg	VU
<i>Hydrosaurus pustulatus</i>	Reptilia	hp	VU

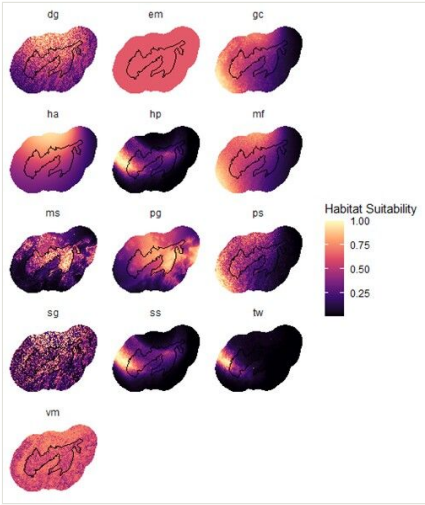


Figure 4. Habitat suitability maps for 13 threatened species in the RRSPL generated using MaxEnt species distribution models. Each panel (labelled by species code) displays the predicted suitability of habitat across the landscape, ranging from low suitability (dark purple) to high suitability (yellow-white). The maps reflect variation in environmental preferences amongst species and highlight potential areas for conservation focus. All maps are scaled consistently from 0 (unsuitable) to 1 (highly suitable) to allow comparative interpretation. Black line is the RSPL boundary. See Table 3 for the complete list of threatened species.

Species richness and conservation zoning

The species richness underscores the spatial heterogeneity of habitats within the RSPL, highlighting areas of high ecological significance (Fig. 5). The northern and north-western sections of RSPL, which register the highest richness classes (10–12 species), align with findings from other tropical forest ecosystems that identify intact, mature forest areas as hotspots of species diversity (Myers et al. 2000; Jarnevich et al. 2015). In contrast, southern and eastern portions of RSPL, classified within lower richness classes (0–3 species), likely reflect degraded or fragmented habitats that offer fewer niches and lower resource availability for threatened species.

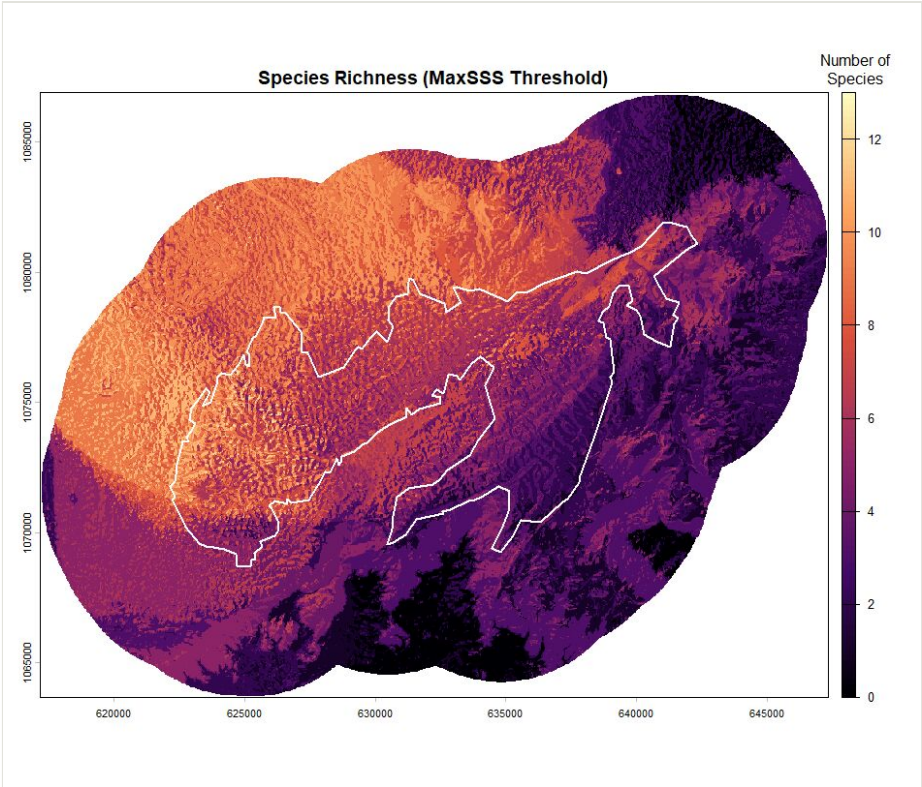
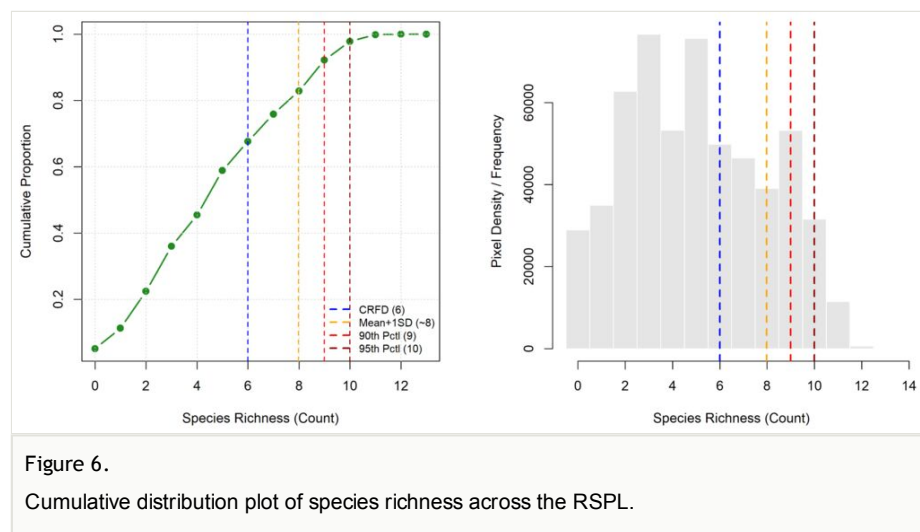


Figure 5. Species richness map of the RSPL showing spatial variation in predicted species co-occurrence, based on stacked binary habitat suitability models. Richness values are classified into five intervals, with darker shades representing areas of higher species richness.

The distribution of species richness across the study area is characterised by a multimodal frequency pattern, with a notable concentration of lower richness values (Fig. 6, left). The cumulative distribution indicates that the landscape is predominantly composed of areas supporting 2–5 species, after which the cumulative proportion increases more gradually. A critical inflection point is observed at the CFRD threshold of

six species, representing approximately the 70th percentile of the landscape. Beyond this point, the availability of high-richness areas decreases significantly, confirming that locations with high species counts are spatially restricted and relatively rare. The frequency distribution (Fig. 6, right) highlights a primary peak in pixel density at a richness count of 3, followed by a secondary peak at 5, suggesting a landscape dominated by moderate biodiversity. However, the distribution exhibits a sharp decline following the 90th percentile (~ 9 species) and 95th percentile (10 species) thresholds. These statistical markers delineate the most ecologically significant hotspots, which represent less than 10% of the total study area.



Threshold selection for HCVAs

While the 90th and 95th percentiles effectively pinpoint rare hotspots, these thresholds capture only the very top fraction of species-rich areas, making them suitable for highly-targeted conservation priorities (Fig. 7). However, in a context where the area already has a formal protected status, it is vital to consider thresholds that balance ecological significance with spatial coverage, ensuring the protection of both rare hotspots and areas of moderate richness that may serve as vital habitats or corridors (Hansen et al. 2020). The CRFD threshold yielded the highest sensitivity (90%), followed by standard deviation and top 20% (both 83%). The top 5% threshold performed the least effectively (29%), highlighting the trade-off between spatial precision and ecological inclusivity (Fig. 8). The CRFD inflection point (~ 6 species) emerges as an ideal threshold for this purpose, as it marks the point at which species richness transitions from common to rare within the landscape. Similar inflection points analyses have been used to justify thresholds for identifying HCVAs, as they capture ecologically meaningful richness patterns, while still representing a more inclusive range of habitats (Kukkala and Moilanen 2012). Thus, using the CRFD inflection point allows for a balanced approach — one that captures significant hotspots without excluding moderately rich habitats, aligning

well with conservation best practices and ensuring long-term resilience of biodiversity within the protected area.

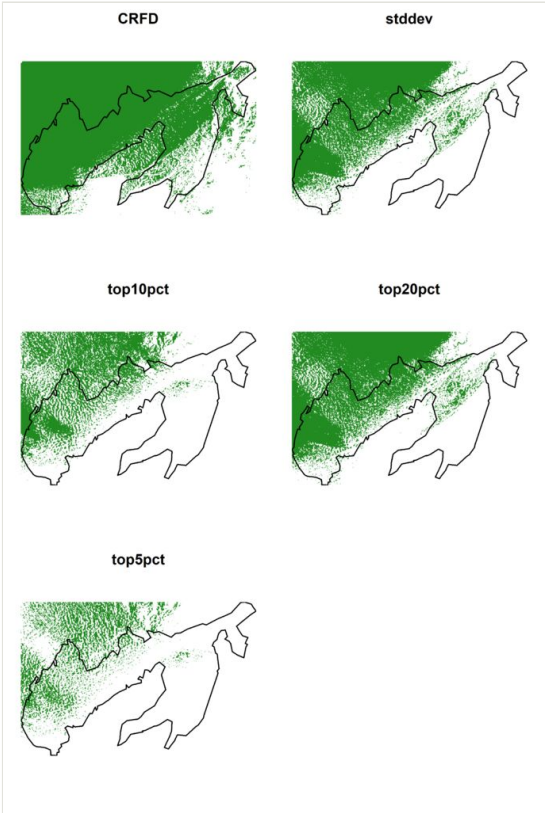


Figure 7. Spatial distribution of HCVA in the RSPL under five thresholding methods: CRFD inflection point, Mean + 1 Standard Deviation (stddev), top 10%, top 20% and top 5% of species richness values. Red pixels represent areas classified as HCVA.

Discussion

The SDMs for the 13 species demonstrated high discriminatory power (Hosmer et al. 2013), characterised by a mean AUC of 0.905 and a mean TSS of 0.717. However, in accordance with a disciplined interpretation of spatial ecology, these robust statistical metrics must be calibrated against the study's inherent data constraints. Primarily, our bioclimatic layers were interpolated from three local sampling points; consequently, these layers should be treated as proxy gradients reflecting broad landscape-scale transitions rather than high-fidelity surfaces. Identified climatic "drivers" — such as the 62.3% contribution of Annual Temperature for *G. crinigera* — likely represent correlations with altitudinal or longitudinal transitions across the RSPL rather than mechanistic biological

limits. Despite these environmental proxy constraints, the statistical stability of the models remains high. The narrow range of fold-specific AUCs (0.859–0.905) and a TSS exceeding the 0.60 benchmark for substantial performance (Allouche et al. 2006) indicate that the models effectively balanced sensitivity and specificity. This balance is critical when modelling endemics, as it minimises both omission and commission errors that could otherwise lead to "paper parks" or overlooked critical habitats. Our results align with or exceed performance values reported for threatened species across Southeast Asia (Wisz et al. 2008a; Wisz et al. 2008b; Mallari et al. 2013; Ramos et al. 2021). Furthermore, the use of a cross-validation framework mitigated the biases often associated with small, spatially autocorrelated datasets in tropical forest ecology (Zhang et al. 2020; Valavi et al. 2021). By explicitly acknowledging the sensitivity of these models to individual occurrence points ($n < 5$), we frame our outputs not as immutable boundaries for legal zoning, but as exploratory decision-support tools. The high statistical agreement across both threshold-independent (AUC) and threshold-dependent (TSS) metrics reinforces the reliability of these spatial hypotheses. They serve as a rigorous evidence base to prioritise future ground-truthing, guide denser sensor deployment and identify HCVAs within the complex karst landscape of the RSPL.

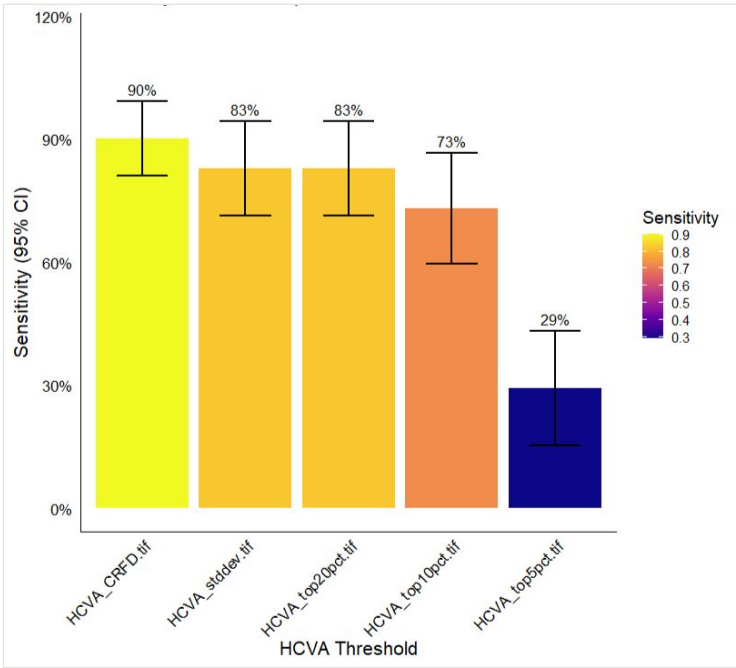


Figure 8. Sensitivity analysis of HCVA thresholds, based on species occurrence data. Bars indicate the proportion of species records located within each HCVA surface, with 95% confidence intervals. Colour gradient indicates sensitivity values for visual comparison.

The environmental response curves and Jackknife importance values demonstrate that habitat suitability in the RSPL is governed by a synergy of climatic proxies and

topographic filters. The primary influence of Elevation (28.2%) and Annual Mean Temperature (29.2%) is consistent with ecological theory, where fine-scale topographic variation and bioclimatic gradients exert strong filtering effects in karst landscapes (Elith and Leathwick 2009a; Elith and Leathwick 2009b; Elith et al. 2011; Merow et al. 2013). To ensure the structural integrity of these relationships, a rigorous multi-collinearity diagnostic was employed. By retaining only five non-collinear covariates with a Maximum VIF of 3.35, we ensured that the predictive power of each variable was independent and not inflated by statistical redundancy (Zuur et al. 2009; Dormann et al. 2012). This parsimonious approach was a strategic decision to prevent bioclimatic drivers from being overshadowed by secondary thermal indices, ensuring that identified suitability patterns represent distinct environmental signals rather than mathematical artifacts (Naimi et al. 2013).

The multi-species SDM uncovered a mosaic of species-specific habitat signatures, reflecting the ecological complexity of the RSPL. Highly restricted suitability patterns were identified for *Gallicolumba crinigera*, *Dipterocarpus grandiflorus* and *Shorea guiso*, which appear as concentrated "islands" in the western and northern sectors. This spatial restriction suggests that these species are strictly tethered to undisturbed forest interiors, making them highly vulnerable to site-specific disturbances (Elith et al. 2006; Jarnevich et al. 2015; Ramos et al. 2021 Aureo et al. 2021). In contrast, more widespread species, such as *Edolisoma mindanense*, *Platymantis guentheri* and *Voacanga megacarpa*, exhibited broader suitability, suggesting higher ecological plasticity and potential resilience to moderate landscape-level disturbances (Gardner et al. 2009; Guisan et al. 2017; La Marca et al. 2019). The richness clusters (10–12 species) were confined to the northern and north-western sectors, areas known for relatively intact forest cover and topographic complexity — key factors driving richness in other tropical systems (Myers et al. 2000; Hughes et al. 2011). Conversely, the species-poor zones in the south and east likely mirror global patterns where biodiversity is concentrated in limited, often shrinking native core areas due to anthropogenic pressure (Newbold et al. 2015; Brooks et al. 2019). The contrast between the hyper-localised hotspots for forest-dependent birds and the expansive suitability for certain herpetofauna indicates that a "one-size-fits-all" management plan may fail; while widely distributed taxa may benefit from broad landscape protection, restricted endemics require strict preservation of their specific refugia (Valavi et al. 2021).

The species richness analysis further complements the SDM outputs, revealing a stark spatial contrast in biodiversity distribution. The highest richness clusters (10–12 species) were confined to the northern and north-western sectors, areas known for their relatively intact forest cover and topographic complexity — key factors driving richness in other tropical systems (Myers et al. 2000; Hughes et al. 2011). Conversely, the species-poor zones in the south and east are likely symptomatic of ongoing anthropogenic pressure, such as agriculture, encroachment and forest fragmentation. This uneven distribution mirrors global patterns where tropical biodiversity is concentrated in limited, often shrinking native core areas (Brooks et al. 2002; Newbold et al. 2015; Brooks et al. 2019), calling for strategic prioritisation in conservation interventions.

Visual comparison of the spatial outputs and quantitative assessment through sensitivity analysis provided insights into the trade-offs amongst these methods. The CRFD inflection point emerged as the most effective threshold, capturing approximately 90% of species occurrence records, with a relatively broad spatial footprint. This inflection represents a meaningful ecological boundary where species richness begins to decline sharply, thus encompassing both highly diverse and moderately rich areas that may support important ecological functions or act as corridors. Similar to findings in other protected landscapes (Kukkala and Moilanen 2012), this method strikes a balance between ecological significance and spatial inclusivity. The mean + 1 standard deviation and top 20% thresholds also performed well, each with a sensitivity of 83%, indicating their ability to include a substantial proportion of known species occurrences, while maintaining a moderate spatial extent. These thresholds may be appropriate when aiming for the middle ground between broad conservation planning and targeted protection. In contrast, the more conservative top 10% and top 5% thresholds identified only limited areas, resulting in significantly lower sensitivity values of 73% and 29%, respectively. While these thresholds are effective in isolating rare biodiversity hotspots, they exclude many moderately rich areas that could play vital roles in species persistence and ecosystem connectivity. Their use may be more appropriate for precision-focused interventions, such as micro-reserves or species-specific management zones. Relying solely on these "hyper-hotspots" can result in fragmented management units that are too small to resist edge effects or external anthropogenic pressures (Morelli et al. 2020). Given that the RSPL already holds legal protection status, threshold selection must consider not only ecological richness, but also spatial functionality and management feasibility. Hence, within the existing framework of the RSPL, the CRFD inflection point offers the most balanced approach for inclusive conservation planning, ensuring the protection of both primary biodiversity nodes and the functional buffer habitats required for long-term species persistence (Hansen et al. 2020).

Conclusions

This study demonstrates the utility of SDMs and richness mapping as evidence-based tools for identifying HCVAs within the RSPL. The high predictive accuracy of the models (Mean AUC = 0.905; Mean TSS = 0.717), reinforced by consistent cross-validation, supports the effectiveness of the selected variables in capturing the broader environmental gradients of the landscape. Crucially, the structural integrity of these models was ensured through VIF analysis and the Jackknife test, confirming that the primary determinants — topographic complexity (TRI, slope and elevation) and bioclimatic proxies — provided independent predictive power. Environmental response further revealed that fine-scale terrain heterogeneity and thermal constraints are the dominant drivers of suitability in this karst landscape. However, in accordance with a disciplined interpretation of these results, the models must be viewed as spatial hypotheses rather than immutable biological boundaries. Given that bioclimatic layers were interpolated from limited local sampling points and several species were modelled with constrained occurrence datasets, these outputs represent proxy gradients reflecting

landscape-scale transitions. By explicitly acknowledging these sensitivities, we frame this work as an exploratory decision-support tool intended to prioritise future ground-truthing and denser sensor deployment. Spatially, the identified heterogeneity — ranging from the restricted "suitability islands" of threatened avifauna to the broader tolerances of certain herpetofauna — emphasises the necessity for multi-scalar management. Species richness analysis successfully identified the northern and north-western sectors as primary biodiversity hotspots, offering spatially-explicit targets for high-priority zoning. The application of the CRFD inflection point provides a transparent framework for delineating HCVAAs, capturing 90% of known biodiversity occurrences.

Acknowledgements

The authors acknowledge the Department of Science and Technology – Philippine Atmospheric, Geophysical and Astronomical Services Administration (DOST-PAGASA) and the Department of Environment and Natural Resources – Protected Area Management Board (DENR-PAMB) for providing essential spatial datasets, microclimate data and technical reports used in this study. Financial support for conducting the analyses at the Geolab of the National University of Singapore was provided by the Department of Science and Technology – Science Education Institute (DOST-SEI) through its Research Enhancement/Sandwich Program. The authors also extend their gratitude to all the staff (Kris, Nura, Sakinah and Mrs. Chong) of the Department of Geography, National University of Singapore, for facilitating the use of the Geolab. The authors acknowledge the use of Google Gemini (Gemini 3 Flash) for technical assistance in developing the R-based geospatial workflows, optimising SDM validation scripts and providing editorial support for the refinement of the manuscript's statistical discussions.

Hosting institution

School of Environmental Science and Management, University of the Philippines Los Banos; GeoLab, Department of Geography, National University of Singapore; Science Education Institute of the Department of Science and Technology; Bohol Island State University

Ethics and security

CVAARRDEC Data Declaration: Specimen Collection Gratuitous Permit (GP) Number VII-2019-04 (DENR Region VII) and Prior Informed Consent (PIC) were secured before conducting the research. In addition, the study was approved by UPLB Research Ethics Board with assigned study protocol code UPLB REB 2025-0202.

Conflicts of interest

The authors have declared that no competing interests exist.

References

- Agresti A, Coull B (1998) Approximate is Better than “Exact” for Interval Estimation of Binomial Proportions. *The American Statistician* 52 (2): 119-126. <https://doi.org/10.1080/00031305.1998.10480550>
- Allouche O, Tsoar A, Kadmon R (2006) Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology* 43 (6): 1223-1232. <https://doi.org/10.1111/j.1365-2664.2006.01214.x>
- Alviola PA, Pulhin JM, Gevana D, J D (2020) Assessing the effectiveness of protected area management in the Philippines: The case of Rajah Sikatuna Protected Landscape. *Journal of Environmental Science and Management* 2 (23): 12-22.
- Aureo W, Reyes T, Mutia FC, Jose R, Sarnowski MB (2020) Diversity and composition of plant species in the forest over limestone of Rajah Sikatuna Protected Landscape, Bohol, Philippines. *Biodiversity Data Journal* 8 <https://doi.org/10.3897/bdj.8.e55790>
- Aureo W, Reyes Jr. T, Mutia FC, Tandang D, Jose R (2021) Floristic composition and community structure along the elevational gradient of Balinsasayao Twin Lakes Natural Park in Negros Oriental, Philippines. *One Ecosystem* 6 <https://doi.org/10.3897/oneeco.5.e56536>
- Aureo W, Decena SC (2023) Habitat alteration affects amphibian assemblages in Rajah Sikatuna Protected Landscape of Bohol, Philippines. *Herpetological Conservation and Biology* 18 (2): 348-361. URL: https://www.herpconbio.org/Volume_18/Issue_2/Aureo_Decena_2023.pdf
- Bakx A, Etard A, Weigelt P, Kreft H (2023) Global conservation prioritization for plant diversity under climate change. *Nature Ecology & Evolution* 7: 142-150. [In English]. <https://doi.org/10.1038/s41559-022-01978-z>
- Bartolino V, Maiorano L, Colloca F, Stefánsson G, GD r (2010) Modelling habitat preferences of demersal species: A case study of the Mediterranean Sea. *Marine Ecology Progress Series* (420)255-267. <https://doi.org/10.3354/meps08836>
- Birding2Asia (2014) Rajah Sikatuna Protected Landscape: Birdwatching site guide. <https://www.birding2asia.com/W2W/Philippines/RajahSikatuna.html>. Accessed on: 2024-5-24.
- BirdLife International (2014) Important Bird Areas factsheet: Rajah Sikatuna Protected Landscape. <http://www.birdlife.org>. Accessed on: 2024-5-24.
- Bracken FSA, McMahon BJ, J W (2022) Evaluating the performance of species distribution models in conservation planning. *Ecological Indicators* 142 (109174). <https://doi.org/10.1016/j.ecolind.2022.109174>
- Brooks T, Mittermeier R, Mittermeier C, Da Fonseca GB, Rylands A, Konstant W, Flick P, Pilgrim J, Oldfield S, Magin G, Hilton-Taylor C (2002) Habitat Loss and Extinction in the Hotspots of Biodiversity. *Conservation Biology* 16 (4): 909-923. <https://doi.org/10.1046/j.1523-1739.2002.00530.x>
- Brooks T, Pimm S, Akçakaya HR, Buchanan G, Butchart SM, Foden W, Hilton-Taylor C, Hoffmann M, Jenkins C, Joppa L, Li B, Menon V, Ocampo-Peñuela N, Rondinini C (2019)

Measuring Terrestrial Area of Habitat (AOH) and Its Utility for the IUCN Red List. *Trends in Ecology & Evolution* 34 (11): 977-986. <https://doi.org/10.1016/j.tree.2019.06.009>

- Buckland ST, Studeny AC, Magurran AE, al. e (2022) Monitoring biodiversity change through effective sampling and robust statistical methods. *Ecological Indicators* 135 (108538). <https://doi.org/10.1016/j.ecolind.2021.108538>
- De Alban JDT, Acaylar AL, Yokohata T, Ooba M, al. e (2015) Mapping deforestation and forest degradation using Landsat time-series imagery in tropical forests of Cambodia. *International Journal of Remote Sensing* 2 (36): 544-567. <https://doi.org/10.1080/01431161.2014.999879>
- Department of Environment and Natural Resources (2019) Rajah Sikatuna Protected Landscape General Management Plan. Department of Environment and Natural Resources – Protected Area Management Board, Philippines. DENR.
- Department of Science and Technology - Philippine Atmospheric, Geophysical and Astronomical Services Administration (2023) Philippines weather and climate data services. DOST PAGASA. URL: <https://www.pagasa.dost.gov.ph>
- Dormann C, Elith J, Bacher S, Buchmann C, Carl G, Carré G, Marquéz JG, Gruber B, Lafourcade B, Leitão P, Münkemüller T, McClean C, Osborne P, Reineking B, Schröder B, Skidmore A, Zurell D, Lautenbach S (2012) Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography* 36 (1): 27-46. <https://doi.org/10.1111/j.1600-0587.2012.07348.x>
- Dullinger I, Wessely J, Bossdorf O, Dawson W, Essl F, Gatttringer A, Klonner G, Kreft H, Kuttner M, Moser D, Pergl J, Pyšek P, Thuiller W, van Kleunen M, Weigelt P, Winter M, Dullinger S (2016) Climate change will increase the naturalization risk from garden plants in Europe. *Global Ecology and Biogeography* 26 (1): 43-53. <https://doi.org/10.1111/geb.12512>
- Elith J, H. Graham* C, P. Anderson R, Dudík M, Ferrier S, Guisan A, J. Hijmans R, Huettmann F, R. Leathwick J, Lehmann A, Li J, G. Lohmann L, A. Loiselle B, Manion G, Moritz C, Nakamura M, Nakazawa Y, McC. M. Overton J, Townsend Peterson A, J. Phillips S, Richardson K, Scachetti-Pereira R, E. Schapire R, Soberón J, Williams S, S. Wisz M, E. Zimmermann N (2006) Novel methods improve prediction of species' distributions from occurrence data. *Ecography* 29 (2): 129-151. <https://doi.org/10.1111/j.2006.0906-7590.04596.x>
- Elith J, Leathwick J (2009a) Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annual Review of Ecology, Evolution, and Systematics* 40 (1): 677-697. <https://doi.org/10.1146/annurev.ecolsys.110308.120159>
- Elith J, Leathwick J (2009b) Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annual Review of Ecology, Evolution, and Systematics* 40 (1): 677-697. <https://doi.org/10.1146/annurev.ecolsys.110308.120159>
- Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ (2011) A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions* 17 (1): 43-57. <https://doi.org/10.1111/j.1472-4642.2010.00725.x>
- Fawcett T (2006) An introduction to ROC analysis. *Pattern Recognition Letters* 27 (8): 861-874. <https://doi.org/10.1016/j.patrec.2005.10.010>
- Fielding A, Bell J (2002) A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* 24 (1): 38-49. <https://doi.org/10.1017/s0376892997000088>

- Fitzpatrick MC, Sanders NJ, Ferrier S, Long DG, Weiser MD, Dunn RR, Svenning JC (2015) How will climate change affect the distribution of European birds? *Ecography* 10 (38): 933-943. <https://doi.org/10.1111/ecog.01349>
- Gardner T, Barlow J, Chazdon R, Ewers R, Harvey C, Peres C, Sodhi N (2009) Prospects for tropical forest biodiversity in a human-modified world. *Ecology Letters* 12 (6): 561-582. <https://doi.org/10.1111/j.1461-0248.2009.01294.x>
- GBIF (2023) GBIF Occurrence Download. URL: <https://www.gbif.org/citation-guidelines#occDataDownload>
- Guisan A, Thuiller W, Zimmermann N (2017) Habitat Suitability and Distribution Models. *Science Advances* 1(2): e1500052 <https://doi.org/10.1017/9781139028271>
- Hansen AJ, Kormos CF, Mittermeier RA, Locke H, Neugarten RA, Watson JE, Geldmann J (2020) Global conservation and management of tropical forest biodiversity: A bio-cultural perspective. *Biotropica* 2 (52): 295-310. <https://doi.org/10.1111/btp.12738>
- Hijmans R, Phillips S, Leathwick J, Elith J (2017) dismo: Species Distribution Modeling. CRAN: Contributed Packages <https://doi.org/10.32614/cran.package.dismo>
- Hijmans R (2020) terra: Spatial Data Analysis. CRAN: Contributed Packages <https://doi.org/10.32614/cran.package.terra>
- Hosmer D, Lemeshow S, Sturdivant R (2013) Applied Logistic Regression. Wiley Series in Probability and Statistics <https://doi.org/10.1002/9781118548387>
- Hughes A, Satasook C, Bates PJ, Bumrungsri S, Jones G (2011) Explaining the causes of the zoogeographic transition around the Isthmus of Kra: using bats as a case study. *Journal of Biogeography* 38 (12): 2362-2372. <https://doi.org/10.1111/j.1365-2699.2011.02568.x>
- IPBES (2019) Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. URL: <https://ipbes.net/global-assessment>
- Jarnevich C, Stohlgren T, Kumar S, Morisette J, Holcombe T (2015) Caveats for correlative species distribution modeling. *Ecological Informatics* 29: 6-15. <https://doi.org/10.1016/j.ecoinf.2015.06.007>
- JAXA (2019) ALOS World 3D (AW3D30) - 30m resolution global digital surface model. URL: <https://www.eorc.jaxa.jp/ALOS/en/aw3d30>
- Kark S, Levin N, Grantham H, Possingham H (2009) Between-country collaboration and consideration of costs increase conservation planning efficiency in the Mediterranean Basin. *Proceedings of the National Academy of Sciences* 106 (36): 15368-15373. <https://doi.org/10.1073/pnas.0901001106>
- Körner C (2007) The use of 'altitude' in ecological research. *Trends in Ecology & Evolution* 22 (11): 569-574. <https://doi.org/10.1016/j.tree.2007.09.006>
- Kukkala A, Moilanen A (2012) Core concepts of spatial prioritisation in systematic conservation planning. *Biological Reviews* 88 (2): 443-464. <https://doi.org/10.1111/brv.12008>
- La Marca E, Tognelli MF, Savy V, Lavilla EO, Lyra ML, Pérez-Mellado V, Nori J (2019) Towards a comprehensive reassessment of conservation status of amphibians in the tropical Andes region. *Diversity and Distributions* 25 (3): 378. <https://doi.org/10.1111/ddi.12874>
- Lantican CB (2001) The Science and Practice of Crop Production. Southeast Asian Regional Center for Graduate Study and Research in Agriculture (SEARCA) and the University of the Philippines Los Baños (UPLB).

- Li J, Heap A (2014) Spatial interpolation methods applied in the environmental sciences: A review. *Environmental Modelling & Software* 53: 173-189. <https://doi.org/10.1016/j.envsoft.2013.12.008>
- Liu C, White M, Newell G (2013) Selecting thresholds for the prediction of species occurrence with presence-only data. *Journal of Biogeography* 40 (4): 778-789. <https://doi.org/10.1111/jbi.12058>
- Lu B, Wang Y, Zhang Y, Fu B, Wang Y (2018) Conservation priority areas in China: Matching biodiversity protection and ecosystem services, e0192730. *PLoS ONE* 2 (13). <https://doi.org/10.1371/journal.pone.0192730>
- Mallari N, Collar NJ, McGowan P, SJ M (2013) Philippines protected areas: A paradox in urgent need of expansion. *Oryx* 47 (1): 18-26. <https://doi.org/10.1017/S0030605311001804>
- Mancera KF, Lapuz M (2021) Mapping ecosystem services in Philippine watersheds: Implications for decision making. *One Ecosystem* 6 (e65191). <https://doi.org/10.3897/oneeco.6.e65191>
- Maxwell S, Cazalis V, Dudley N, Hoffmann M, Rodrigues AL, Stolton S, Visconti P, Woodley S, Kingston N, Lewis E, Maron M, Strassburg BN, Wenger A, Jonas H, Venter O, Watson JM (2020) Area-based conservation in the twenty-first century. *Nature* 586 (7828): 217-227. <https://doi.org/10.1038/s41586-020-2773-z>
- Merow C, Smith M, Silander J (2013) A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography* 36 (10): 1058-1069. <https://doi.org/10.1111/j.1600-0587.2013.07872.x>
- Morelli TL, Barrows CW, Ramirez AR, Cartwright JM, Ackerly DD, Eaves TD, Ebersole JL, Krawchuk MA, Letcher BH, Mahalovich MF, Meigs GW, Michalak JL, Millar CI, Quiñones RM, Stralberg D, Thorne JH (2020) Climate-change refugia: biodiversity in the slow lane. *Frontiers in Ecology and the Environment* 18 (5): 228-234. <https://doi.org/10.1002/fee.2189>
- Myers N, Mittermeier R, Mittermeier C, da Fonseca GB, Kent J (2000) Biodiversity hotspots for conservation priorities. *Nature* 403 (6772): 853-858. <https://doi.org/10.1038/35002501>
- Naimi B, Hamm NS, Groen T, Skidmore A, Toxopeus A (2013) Where is positional uncertainty a problem for species distribution modelling? *Ecography* 37 (2): 191-203. <https://doi.org/10.1111/j.1600-0587.2013.00205.x>
- Newbold T, Hudson L, Hill SL, Contu S, Lysenko I, Senior R, Börger L, Bennett D, Choimes A, Collen B, Day J, De Palma A, Díaz S, Echeverria-Londoño S, Edgar M, Feldman A, Garon M, Harrison MK, Alhousseini T, Ingram D, Itescu Y, Kattge J, Kemp V, Kirkpatrick L, Kleyer M, Correia DLP, Martin C, Meiri S, Novosolov M, Pan Y, Phillips HP, Purves D, Robinson A, Simpson J, Tuck S, Weiher E, White H, Ewers R, Mace G, Scharlemann JW, Purvis A (2015) Global effects of land use on local terrestrial biodiversity. *Nature* 520 (7545): 45-50. <https://doi.org/10.1038/nature14324>
- Ocampo FA, Ramos P, MB A (2022) Conservation gaps in protected areas under climate change: Insights from the Philippines. *Biological Conservation* 271 (109574). <https://doi.org/10.1016/j.biocon.2022.109574>
- O'Donnel M, Ignizio D (2012) Bioclimatic predictors for supporting ecological applications in the conterminous United States. *Data Series* <https://doi.org/10.3133/ds691>
- Pearson R, Raxworthy C, Nakamura M, Townsend Peterson A (2006) ORIGINAL ARTICLE: Predicting species distributions from small numbers of occurrence records: a

test case using cryptic geckos in Madagascar. *Journal of Biogeography* 34 (1): 102-117. <https://doi.org/10.1111/j.1365-2699.2006.01594.x>

- Pebesma EJ (2004) Multivariable geostatistics in S: the gstat package. *Computers & Geosciences* 30 (7): 683-691. <https://doi.org/10.1016/j.cageo.2004.03.012>
- Phillips S, Anderson R, Schapire R (2006a) Maximum entropy modeling of species geographic distributions. *Ecological Modelling* 190: 231-259. <https://doi.org/10.1016/j.ecolmodel.2005.03.026>
- Phillips S, Anderson R, Schapire R (2006b) Maximum entropy modeling of species geographic distributions. *Ecological Modelling* 190: 231-259. <https://doi.org/10.1016/j.ecolmodel.2005.03.026>
- Phillips SJ, Dudík M, Schapire RE (2009) Maxent software for modeling species niches and distributions. Version 3.3.3k. URL: http://biodiversityinformatics.amnh.org/open_source/maxent/
- Pulhin JM, Gevana D, Peras R, et al. (2016) Forest landscape restoration in the Philippines: The role of governance. D. World Forestry Congress. urban, South Africa..
- Ramos PF, De Alban JDT, Ocampo FA, Diesmos AC, Mallari NAD (2021) Bridging spatial gaps for threatened Philippine biodiversity using expert-based and data-driven models. *Environmental Conservation* 4 (48): 265-274. <https://doi.org/10.1017/S0376892921000143>
- R Core Team (2023) R: A Language and Environment for Statistical Computing. R: A language and environment for statistical computing <https://doi.org/10.32614/r.manuals>
- Santora J, Veit R (2013) Spatio-temporal persistence of top predator hotspots near the Antarctic Peninsula. *Marine Ecology Progress Series* 487: 287-304. <https://doi.org/10.3354/meps10350>
- Thomas CD, Betts RA, Boyd IL, Gonzalez A, Hill JK, Leadley P, Malhi Y, Mace GM, Oliver TH, Purvis A, Scholes RJ (2024) Biodiversity in the Anthropocene: Assessing future options for conservation. *Nature Ecology & Evolution* <https://doi.org/10.1038/s41559-024-02345-3>
- Valavi R, Guillera-Aroita G, Lahoz-Monfort J, Elith J (2021) Predictive performance of presence-only species distribution models: a benchmark study with reproducible code. *Ecological Monographs* 92 (1). <https://doi.org/10.1002/ecm.1486>
- Watson JM, Dudley N, Segan D, Hockings M (2014) The performance and potential of protected areas. *Nature* 515 (7525): 67-73. <https://doi.org/10.1038/nature13947>
- Wilson MF, O'Connell TJ, Brownstein J, Dettmers R, White RJ (2007) Predictive mapping of bird biodiversity using remotely sensed data. *Remote Sensing of Environment* 3 (106): 385-398. <https://doi.org/10.1016/j.rse.2006.09.006>
- Wisz MS, Hijmans RJ, Li J, Peterson AT, Graham CH, Guisan A, (2008a) Effects of sample size on the performance of species distribution models. *Diversity and Distributions* 14 (5): 763-773. <https://doi.org/10.1111/j.1472-4642.2008.00482.x>
- Wisz MS, Hijmans RJ, Li J, Peterson AT, Graham CH, Guisan A, the NCEAS Predicting Species Distributions Working Group (2008b) Effects of sample size on the performance of species distribution models. *Diversity and Distributions* 5 (14): 763. <https://doi.org/10.1111/j.1472-4642.2008.00482.x>
- Xu W, Xiao Y, Zhang J, Yang W, Zhang L, Hull V, Wang Z, Zheng H, Liu J, Ouyang Z (2017) Conservation of biodiversity hotspots in China: The effectiveness of nature reserves. *Biological Conservation* 209: 70-77. <https://doi.org/10.1016/j.biocon.2017.02.011>

- Zhang Y, Kumar M, Xu J, Zhang W, Yang X (2020) Global SDM performance comparison of threatened tree species. *Ecological Modelling* 420 (108982). <https://doi.org/10.1016/j.ecolmodel.2019.108982>
- Zhang Y, Li J, Wei W, Chen X, Wang L, Zhao Y (2024) Integration of environmental and remote sensing data in species distribution modeling: A new framework for conservation planning. *Remote Sensing of Environment* 312 (113597). <https://doi.org/10.1016/j.rse.2024.113597>
- Zipkin EF, DiMatteo A, Ray J, Rossman S, Royle JA (2015) Long-term monitoring of birds at protected and unprotected sites in Africa. *Biological Conservation* 182: 195-203. <https://doi.org/10.1016/j.biocon.2014.12.027>
- Zuur A, Ieno E, Elphick C (2009) A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution* 1 (1): 3-14. <https://doi.org/10.1111/j.2041-210x.2009.00001.x>

Supplementary materials

Suppl. material 1: Species Occurrence

Authors: Wilbert Aureo

Data type: Excel (.csv)

[Download file](#) (50.18 kb)

Suppl. material 2: Bioclimatic Raw Data

Authors: Wilbert Aureo

Data type: Excel

[Download file](#) (42.40 kb)

Suppl. material 3: Topographic Variables

Authors: Wilbert Aureo

Data type: Raster (.tif)

[Download file](#) (23.01 MB)

Suppl. material 4: List and formula of bioclimatic variables

Authors: Wilbert AUreo

Data type: Word

[Download file](#) (14.15 kb)

Suppl. material 5: MaxEnt Settings and Configuration

Authors: Wilbert Aureo

Data type: Word file

Brief description: List of the MaxEnt settings used in the species distribution modelling.

[Download file](#) (15.08 kb)

Suppl. material 6: Sensitivity analysis (NTP vs. MaxSSS)

Authors: Wilbert Aureo

Data type: Excel file

Brief description: Sensitivity analysis showing the Reduction that serves as a basis for the threshold selection.

[Download file](#) (9.34 kb)