

Mapping Terrestrial Conservation: Showcasing Model Assessment for Map Performance Evaluation



ABSTRACT

Habitat preservation, conservation, and protection of threatened species require careful site selection procedures. The presence of several site-selection models encourages model assessments to determine their usefulness and functionality for conservation purposes. Map model assessments are not conventionally conducted between site selection models to understand the nature of their decision-making strategies and prioritization. Therefore, the objective of this study was to determine the relationship between a recently published site selection model, the Safe Zone with MaxEnt, representing the Species Distribution Model, and the Forest Landscape Integrity Index, representing an intact forest habitat. As expected, there was considerable variation among the three models due to their different algorithms and themes of concern; nevertheless, these had some level of agreement in selecting potential areas for conservation. In addition, this study presented a convenient method for map data collection and the analysis required for a comprehensive understanding of the model agreements and relationships with other models. The nature of the decision making of the Safe Zone model and its potential utility for selecting Strict Protection Zones was presented. This study highlighted the intersection of geospatial analysis, conservation, and model evaluation. Finally, study emphasized the importance of informed decision-making in environmental planning and management through rigorous map assessment. The limitations of this study include the varied pixel resolutions of global and local maps, temporal predictions, and the fact that the models to which the SZ was compared are limited to models and maps available in the area of interest.

Keywords: *model evaluation; map comparison; category agreements; map model relationships; safe zone for conservation*

John Aries G. Tabora^{1,2*}
Rico C. Ancog²
Patricia Ann J. Sanchez²
Mark Dondi M. Arboleda²
Ireneo L. Lit, Jr.³
Cristino L. Tiburan, Jr.⁴

¹ Department of Biological Sciences, College of Science and Mathematics, University of Southern Mindanao, Kabacan, North Cotabato, 9407, Philippines

² School of Environmental Science and Management, University of the Philippines Los Baños (UPLB) College, Laguna, Philippines 4031

³ Environmental Biology Division, Institute of Biological Sciences, UPLB, College, Laguna, 4030, Philippines

⁴ Institute of Renewable Natural Resources, College of Forestry and Natural Resources, UPLB, College, Laguna, 4030, Philippines

*corresponding author:
jgtabora@up.edu.ph

INTRODUCTION

Maps have become an essential tool in decision-making (Farhan *et al.* 2017; Tao 2013; Fletcher *et al.* 2015), especially with the advent of satellite technology and the “virtual globe” (Sheppard and Cizek 2009). Decision makers rely on maps and Geographic Information System (GIS) tools to designate geographic areas for conservation (Harris and Hazen 2006). Primarily used for navigation and territorial boundary identification, maps are now used in countless ways by every user. In the Philippines, the most common use is for analysis and comparisons of land use and land cover, similar to the study of Almadrone-Reyes and Dagamac (2022), on the correlation between vegetation cover and surface temperature. Geospatial data are processed and analyzed in a multitude of ways to be used in every human endeavor, as shown by Verburg *et al.* (2018) in a

book chapter, where they described a variety of modeling approaches and indicated their strengths and weaknesses. The usefulness of decisions dependent on spatial data is as effective as map quality; thus, as early as 1981, Fitzpatrick-Lins introduced the idea of comparing manual sampling with computer-based sampling techniques. Meanwhile, Foody (2004) and Foody (2006) introduced kappa coefficient analysis to compare maps.

In environmental conservation, species distribution and habitat maps were used by Cabeza and Moilanen (2003) and Önal (2004) as tools to select potential areas for protection. Various conservation site selection methods are commonly employed to identify the priority areas. The widely-used conservation planning approaches include Ecological Niche Modelling (ENM), which estimates the

likelihood of species occurrence in specific conservation areas (Peterson 2012; Ishihama, 2019); Ecosystem Services approach prioritizes areas based on the value and rank of ecosystem service they provide (Hummel 2019; Scolozzi 2014); and species-based prioritization which aims to conserve organisms with significant conservation status (McGeoch 2016). Puno (2019) used a stream drainage characterization strategy to select priorities for sub-watershed conservation based on the erosion potential. A customizable user-defined mapping algorithm is featured in online Marxan software (Serra-Sogas 2020). In the presence of several selection methods introduced for environmental conservation, comparing maps is a reasonable exercise for a comprehensive analysis of the resulting map.

There are different ways to perform map comparisons using different comparison measures (Stehman 1999). Comparing maps allows us to assess the accuracy of the classifications, methods, and analyses. (Foody 2013; Moral 2010; Hagen-Zanker and Martens 2008; Herold et al. 2008; Stehman 1999; Herold et al., 2008). Several maps have also been compared to determine the dynamics of the features over time (Tabora et al. 2023 (a); Son et al. 2015). Maps were also compared to describe features, determine locations, and correct issues.

No map model assessments have been conducted between site-selection models, particularly to understand the nature of prioritization for selecting conservation sites. New user-defined algorithm maps need to be compared to other well-established models, with distinct predispositions on the theme of their concern, to determine how they make decisions to appreciate their usefulness and functionality for conservation. The plausibility of the map alone is not sufficient for describing the new models being introduced as a decision-making tool. There is a need to support the claims of relationships using statistical tools to convince potential users of new mapping models. By conducting map model assessments, this study can

understand the resulting maps beyond their face values alone but with a more rigorous validation process.

The process presented in this study is a practical method for systematically evaluating the different aspects of model performance using common reference maps and statistical analyses to determine the agreements and relationships of the models being assessed. Recently, Tabora et al. (2023b) proposed the “Safe Zone” method of selection and a map showing the potential area for a Strict Protection Zone (SPZ) in a watershed in the southern Philippines. The Safe Zone (SZ) model was intended to augment the procedure of the Department of Environment and Natural Resources (DENR) in site selection, which is the focus of this study. The two models used to compare the SZ model in this study were the Maximum Entropy (MaxEnt) Model by Phillips (2006) and the Forest Landscape Integrity Index (Grantham 2020), which were also used as reference models to suggest conservation sites. This study sought to address the research question: Can model assessments provide a deeper understanding of the context of a new model?

The objective of this study was to assess the effectiveness of a newly developed mapping framework model (SZ) alongside other commonly utilized site selection models (FLII and Maxent). The study emphasizes the importance of map assessments in improving the understanding of the decision-making process related to site selection, particularly when using the newly developed model.

MATERIALS AND METHODS

The scheme started by describing how the three ecological models for comparison were pre-processed and extracted, followed by a description of sample collection (Figure 1). The analyses started with descriptive statistics, followed by agreement tests aimed at describing how the three models assigned increasing categories

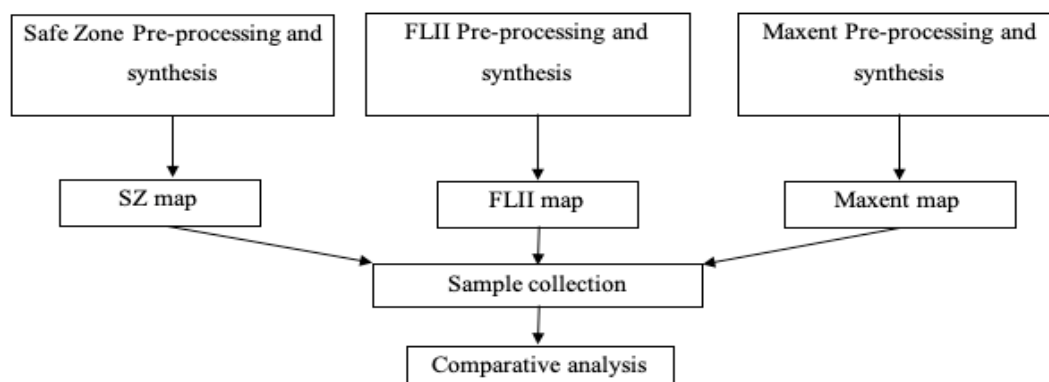


Figure 1. Schematic of the map comparison procedure.

for conservation. Finally, statistical analyses were used to present the relationships between the three models.

The study site was a candidate protected area (PA) in the Southern Philippines, the Libungan River Watershed and Forest Reserve (LWFR) (**Figure 2**). It covers 52,820 ha with headwaters in the north and drains its rivers to the south towards the Ligawasan Marsh in Central Mindanao, Philippines. Closed forest is concentrated in the northern portion, covering 14% of the landscape. Croplands cover approximately 70% of the landscape. In the past 50 years, closed forests have decreased at a rate of 1.21 K%, whereas croplands have been increasing at a rate of 2.45 K% (*Tabora et al. 2023a*). A zoning strategy was recommended in the reference paper to be implemented in the landscape to preserve the remaining forest while providing space for agricultural production and other socioeconomic activities.

Ecological Models Pre-processing

The Safe Zone. This study adopted this section from the methodological framework for Safe Zone determination proposed by *Tabora et al. (2023b)* (**Figure 3**). The study performed the suggested preliminary steps to

synthesize the final SZ map. These steps involved scoring weights per Land Use and Land Cover based on a simplified scoring matrix to gauge the perceptions of local informants and experts. Land Use and Land Cover maps used in this study can be downloaded from figshare. doi:10.6084/m9.figshare.23258987.v2 and figshare. doi:10.6084/m9.figshare.23537772.v2 The scoring of weights includes positive and negative values that directly categorize the land-use type into factors (F) that contribute to threatened species and forest conservation.

First, the factors identified as positively contributing to conservation using key informant interviews (KII) were assigned F+. The weights of Land Cover (LC) types, such as closed forest, open forest, croplands, grasslands, and savanna, were determined by the highest number of threatened vertebrates per km² biodiversity survey of (*Tabora et al. 2023a*). By assigning weights to LC, it was converted to the Area of Habitat (AOH). Using QGIS, the weights were multiplied by the F+ and AOH rasters, making it the value of each map pixel (Equations 1 and 2).

$$\text{Local Habitat of the Organism (LHO)} = (F^+_1 W^{KII}) + (F^+_2 W^{KII}) \dots (F^+_n W^{KII}) + \text{AOH} \quad (1)$$

Where: F+ = factor identified as positively affecting conservation

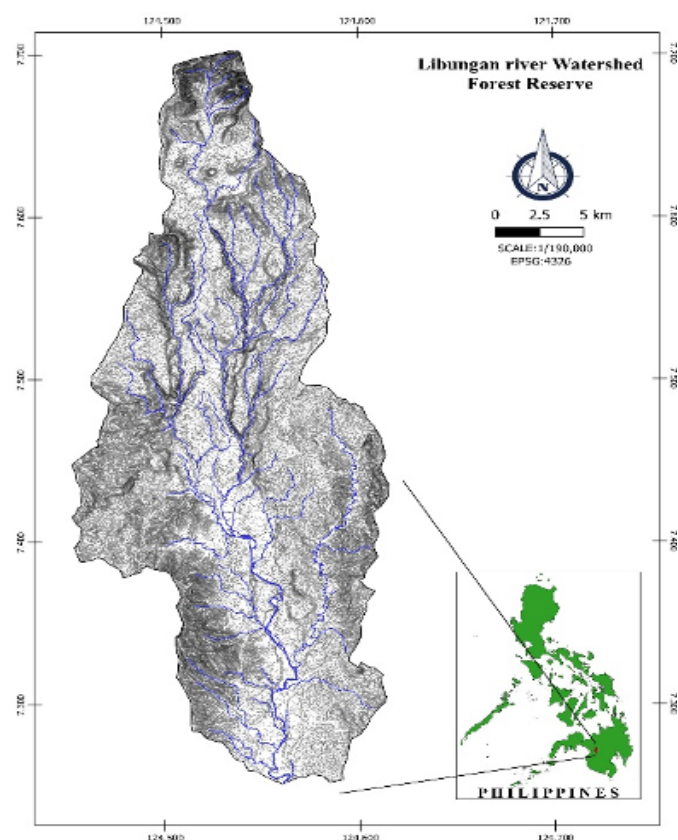


Figure 2. The Libungan River Watershed and Forest Reserve (LWFR) contours, drainage and relative location in the Philippines.

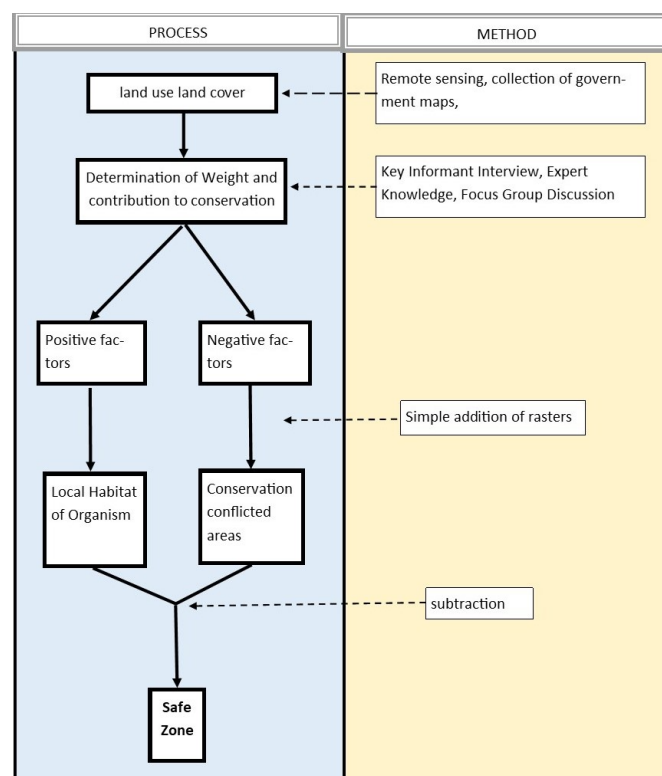


Figure 3. Schematic diagram of the process in synthesizing the 'Safe Zone' for threatened species conservation.

WKII= Weight based on Key Informant Interviews

$$AOH = (L_1 W^S) + (L_2 W^S) \dots (L_n W^S) \quad (2)$$

Where L = Land cover type

WS = Weight based on the highest number of threatened species recorded in a km² of land cover type.

Following the equation above, were added and all land-use types assigned as F+ and the AOH; the resulting map is the Local Habitat of the Organism (LHO).

Second, maps that negatively contributed to conservation were assigned as F⁻. The weights are multiplied by the raster pixels of each map. All the F⁻ maps were combined by adding rasters in QGIS; this area was called the Conservation Conflicted Areas (CCA) (Equation 3).

The equation for attaining CCA is:

$$CCA = (F_1^- W^{KII}) + (F_2^- W^{KII}) \dots (F_n^- W^{KII}) \quad (3)$$

Where: F⁻ = factor identified as negatively affecting conservation

W^{KII}= Weight based on Key Informant Interviews

Finally, CCA (Equation 4) rasters were subtracted from the LHO to synthesize the SZ. The Resulting SZ map was reclassified and categorized from very suitable to unsuitable, with an equal quantile of 100/5. The general equation used for the final map of the Safe Zone is:

$$SZ = LHO - CCA \quad (4)$$

The MaxEnt. The Maximum Entropy (MaxEnt) model developed by *Phillips (2006)* is a machine learning algorithm designed to predict the probability of occurrence of species based on environmental variables. The Maxent model is useful when species occurrence data are limited or incomplete (*Elith et al. 2011*). It is based on predictions of occurrence data, and the goal is to find a probability distribution that maximizes entropy (i.e., the least biased spot based on the available data). This strategy enables MaxEnt to incorporate complex connections between other variables (e.g., climate) despite the limited number of occurrences. It is widely used in ecology and conservation biology, with varying applications in identifying areas of high conservation value and drivers of species distribution and extinction. It is an open-source software with a user-friendly interface that allows researchers and practitioners to apply the model to their

own data (*Pang 2021; Malakoutikhah 2020; Avalos 2015*).

This study preprocessed MaxEnt Species Distribution Model (SDM) maps using a reference list of threatened species from the SZ. The list of organisms was based on the Global Biodiversity Information Facility, also known as *GBIF (2021)* data to increase the number of records to the national level to increase the efficacy of SDM (*Rondinini 2006*). The study excluded species with insufficient GBIF data points to generate significant contributions to the model projections. This study further truncated the GBIF data by removing samples older than 1990 years, preserved specimens, and museum specimens. Sample points that fell beyond the expected habitat (e.g., *C. syrichta* in built-up areas or on the sea) were also removed from the GBIF data. It was presumed that some data points in built-up areas were in holding facilities, such as zoos, farms, and caged pets, that did not represent their natural habitat. The 11 species with sufficient samples and significant contributions for the SDM inside LWFR are the following: *Buceros hydrocorax* (Rufous hornbill), *Basilornis mirandus* (Apo myna), *Chloropsis flavipennis* (Philippine leafbird), *Carlito syrichta* (Philippine tarsier), *Dicaeum anthonyi* (Yellow-crowned flowerpecker), *Macaca fascicularis* (Philippine macaque), *Otus mirus* (Mindanao scops owl), *Penelopides affinis* (Mindanao hornbill), *Rhinomyias goodfellowi* (Slaty-backed jungle flycatcher), *Sus philippensis* (Philippine warty pig), and *Trichoglossus johnstoniae* (Mindanao lorikeet).

The following environmental factors were downloaded from WorldClim (*Fick 2017*): annual mean temperature, mean diurnal range, isothermality, temperature seasonality (standard deviation × 100), maximum temperature of the warmest month, minimum temperature of the coldest month, annual temperature range, mean temperature of wetter quarter, mean temperature of driest month, mean temperature of warmest quarter, mean temperature of coldest quarter, annual precipitation, precipitation of wettest month, precipitation of driest month, precipitation seasonality (coefficient of variation), precipitation of wettest quarter, precipitation of driest quarter, precipitation of warmest quarter, and precipitation of coldest quarter. Using Maxent's Graphical User Interface (GUI) default settings, this study generated the SDM for each species (*Pang et al. 2021*)

This study normalized the pixel scores to within the range of 0–100. The resulting normalized Philippine distribution map of the species was cropped onto an LWFR polygon. The resulting SDM rasters are added to

form a single MaxEnt SDM raster.

Each pixel of the final raster had total scores for the 11 species modeled. Note that the map generated by MaxEnt extends up to the entire boundaries of the Philippine archipelago; however, this study cropped the maps to the LWFR area to make them comparable to other models. The resolution of the resulting map was reclassified to 30 x 30 m to make it similar to the SZ. Suitability was classified using five quantile intervals, where the upper 20% was assigned as the 'very suitable' and the lowest 20% was the 'unsuitable' to make it similar to the classification used by SZ (Tabora *et al.* 2023b).

The FLII. The Forest Landscape Integrity Index (FLII) integrates data on observed and inferred forest pressures and lost forest connectivity to generate the first globally consistent continuous index of humid forest integrity, as determined by the degree of anthropogenic modification. With cloud computing and massive datasets, FLII was the first global initiative to quantify the ecological integrity of forests. The study of Grantham (2020) showed that 40% of the world's forests have high integrity. Their outputs were used by the Convention on Biological Diversity and the Convention on Climate Change as references.

The Forest Landscape Integrity Index was downloaded from their website (<https://www.forestlandscapeintegrity.com/home>) and cropped the LWFR raster using QGIS. The FLII raster was reclassified to fit a resolution similar to that of the SZ (30 m x 30 m). Although FLII was originally categorized as 'high integrity' to 'low integrity' of forest, this study converted the classification to 'very suitable (highest 20%) and 'unsuitable' (lowest 20%) similar classification of Tabora *et al.* (2023b) with the SZ and MaxEnt for uniformity. Simultaneously, the raster pixel scores were normalized in the range of 0-100.

Data collection

The purposive sampling method covered all raster surfaces at regular intervals with equal spacing within the LWFR polygon. Sampling points were generated in QGIS vector research tools, establish fixed point intervals. A distance of 300 x 300 m per sampling point was established. This is 1/10 of the model maps' actual raster size of 30 x 30 pixels. This implies that the sample size was approximately 10% of the total population of pixels. A fixed interval was used to allow the samples to efficiently represent the differences in the location and area occupied by the tested map variables (Figure 4).

An average of ±5,862 sampling points inside the

LWFR polygon using vector tools in QGIS was established. These points were used to sample raster pixel data. The resulting maps of the three models have numerical values in their pixels. The sampling points that landed on a specific pixel collected its value. The numerical values were then converted to weighted categorical values of 1–5 (1 = unsuitable, 5 = very suitable). Different sets of data were collected from the sampling points of the categorical maps. The samples extracted from the shapefile points were transformed into *.asc files.

Data analysis

The classification of the SZ, FLII, and MaxEnt models was compared by first normalizing the data matrix. In addition to the three models, the presence-absence data of the reference maps used in synthesizing the SZ was included in the analysis. The reference maps were areas occupied by closed forest (clsdforst), open forest (opnforst), cropland (crplnd), grassland (grslnd), alienable and disposable lands (A&D), timberland (tmbrlnd), Certificate of Ancestral Domain Title (CADT), Certificate of Land Ownership Awards (CLOA), Integrated Social Forestry (ISF), Forest Land Grazing Management Agreement (FLGMA), Network

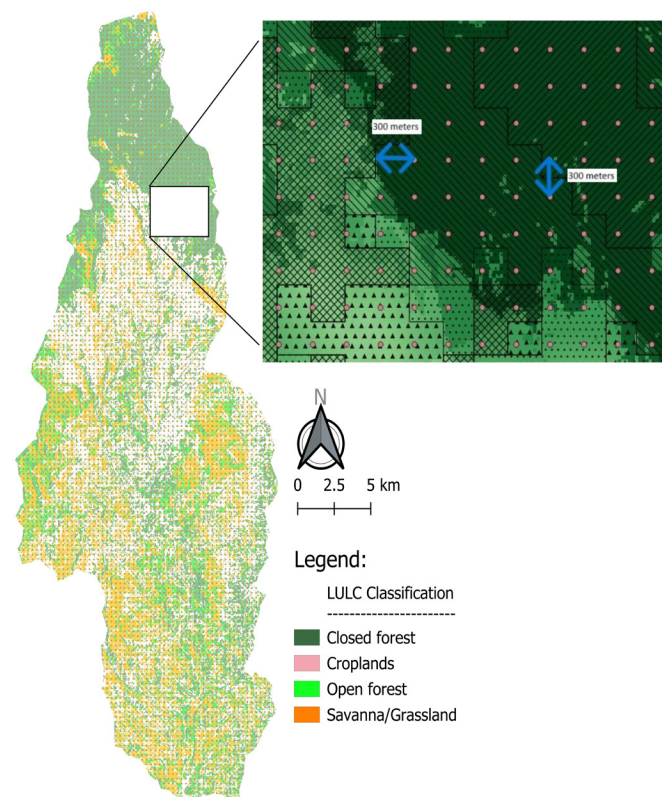


Figure 4. Distribution of Sampling Points over Land-use Land Cover Types with 2021 Land Cover Classification as Background.

of Protected Areas for Agriculture and Agro-Industrial Development (NPAAD), and Strategic Agriculture and Fisheries Development Zones (SAFD). This study also sampled the Digital Elevation Model (DEM) and raw slope values. The distance to roads (roads) and settlements (stlmnt) was collected by determining the 'distance to hub' value where the grid points were the reference, and the hub was the converted lines to points of roads and stlmnt. Points near the hub had small values (in meters), whereas points away from the hub had higher values.

Numerical data were used for the descriptive statistics. The same data were used for correlation analysis. Weighted categorical data were used in kappa coefficient analyses. The overlap of map models was visually inspected using the QGIS raster and vector tools.

Exploratory Spatial Data Analysis (ESDA) was performed using GEODA software (*Anselin 1995*). The ESDA allows patterns to be found from the data to describe the spatial distribution and identify atypical spatial observations. Parallel coordinate analysis was used as a visual representation of the score distribution of the three models. This shows variations in how each model scores the same pixel.

The Scatter Plot matrix shows the pairwise relationship between each model and another. The SZ vector points extracted from the sampling points was plotted in a Cartesian coordinate system against FLII and MaxEnt vector points and vice-versa. This process was performed using JASP statistical software (*JASP Team 2023*) standard procedures.

The JASP statistical software to analyze the kappa coefficients, synthesize the correlation matrix, and perform principal component analysis. Cohens' Kappa was used to analyze the agreement between the three models. Fleiss' kappa was used to reveal the agreements or disagreements between the categories (1 to 5) in the map models.

A Spearman correlation matrix was presented to measure the strength and direction of the linear relationship of the models plus other landscape features mentioned above (reference maps) for a better understanding of how the different models decide. This analysis was previously used by *Paenen (2019)* and *Ramachandra (2016)* to elucidate the role of anthropogenic forces in forest transitions, socio-economic and bio-geophysical variables, and climatic zoning.

Principal Component Analysis (PCA) was used

to present the patterns in the dataset. Promax oblique rotation was set in the analysis to allow factors to correlate and maximize interpretability by simplifying the factor patterns. This analysis showed whether the models belonged to the same group and how other landscape features grouped themselves with the models. *Farhan et al. (2017)* used PCA to examine the effectiveness of morphometric parameters in a watershed prioritization study.

The contextual explanation of the relationships among geographic phenomena was discussed along with a presentation of the analyses. The spatial distribution of the categories identified in the mapping process was described and compared repeatedly using different analyses and graphical presentations. The produced maps and analyses were examined and interpreted based on the context of the landscape and their application as a tool for selecting conservation areas for threatened species.

RESULTS AND DISCUSSION

Descriptive statistics

All models' suitability classifications portray similar locations of the 'very suitable' sites at the Northeastern part of the Libungan River Watershed and Forest Reserve (LWFR) landscape with few exemptions (**Figure 5**). The Safe Zone (SZ) model showed its highest points within the closed forest area but removed the areas devoid of a forest, based on the LWFR land cover classification. It also reduced the areas with land use intended for socialized development. The Forest Landscape Integrity Index (FLII), on the other hand, had sporadic variations in scores along the landscape. MaxEnt shows a distinctive classification of the 'very suitable' site placed mostly within the closed forest, while the rest of the landscape scores were low with smooth transitions.

Some sources of uncertainties may have caused some of the variations in classification. For example, the resolution of the three models varied but only resampled to 30×30 m. The land cover classification of SZ and FLII may have affected the accuracy of the base maps. Finally, MaxEnt, being a probabilistic model, may have some miscalculations due to very few presence points and too many points that may cause autocorrelation.

To verify the locations of different classifications over the SZ map (**Figure 6**), the study overlapped FLII and Maxent over the SZ map. FLII's very suitable site of FLII is 50% wider than the very suitable site of SZ. In addition, FLII also has suitable sites on the western

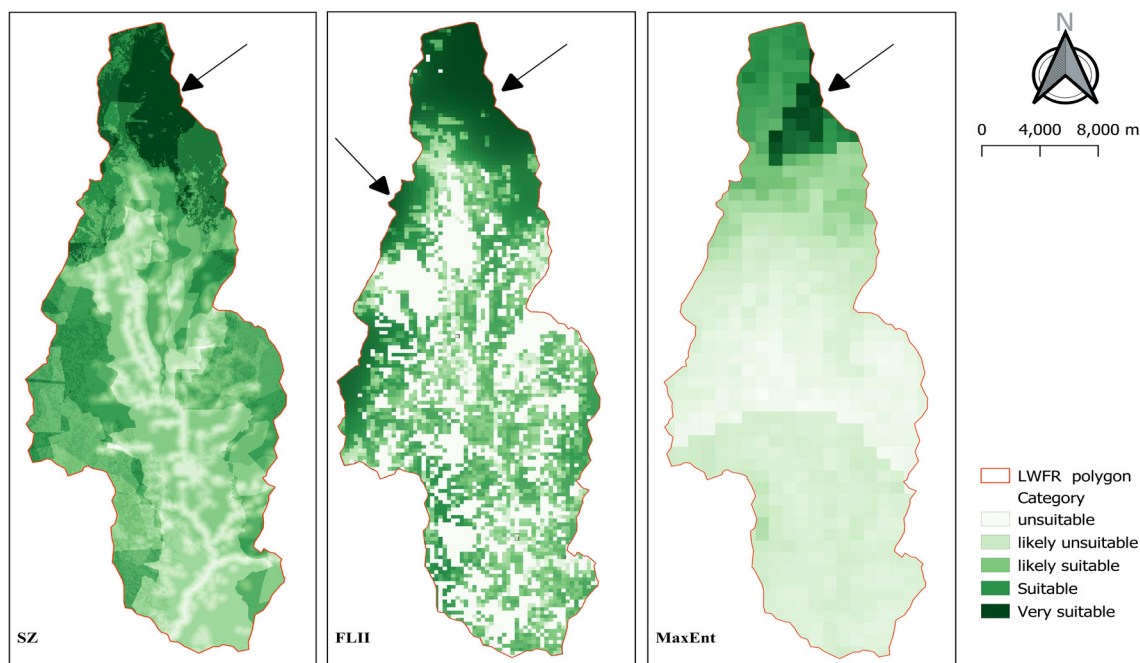


Figure 5. Side-by-side comparison of spatial distribution of suitability categories for Safe Zone, Forest Landscape Integrity Index, and MaxEnt in Libungan River Watershed and Forest Reserve. Note: The black arrow emphasizes the location of 'very suitable' sites.

side of the watershed where closed forests are located. On the other hand, MaxEnt's very suitable site is approximately 45% of the very suitable site of the SZ. The 'likely unsuitable' areas for the MaxEnt occupies 'unsuitable' areas of SZ. These areas were the valley areas of the LWFR, and the climatic conditions may have influenced the MaxEnt classification hinted at by the middle portion along the mountain range having a different classification from the valleys (**Table 1**).

The extent of high categories (very suitable) is the widest in FLII and the smallest in MaxEnt. The high categories occupy the northern tip of the LWFR, where most of the closed forests are located in FLII. In addition, there are also some 'very suitable' categories in the western middle part of the landscape based on FLII. Low categories (unsuitable) were placed near the central part of the watershed for FLII, with high similarity to SZ. The central portion of the LWFR is occupied by cropland landcover, and alienable and disposable land use assignment. Meanwhile, the lower categories of Maxent occupy most of the southern 70% of the landscape.

The extracted normalized values of each sampling point ($\pm 5,862$) were between 54 and 34 average values for the three models. The distribution of scores varied (**Figure 7**), where SZ tapered in the upper and low scores, the FLII ballooned on middle and lower values, and the MaxEnt ballooned on the lower scores. The narrow distribution of scores at the higher level of

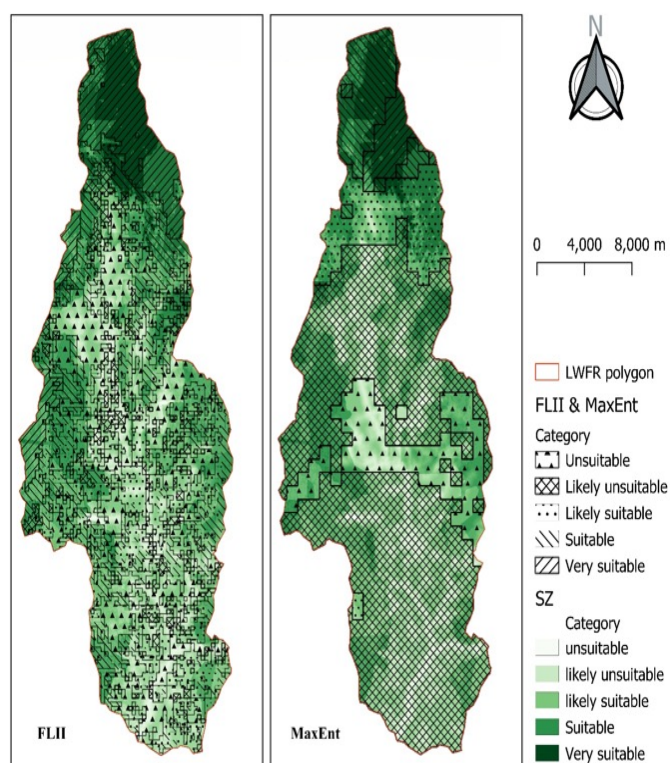


Figure 6. A. Safe Zone as base (green) over Forest Landscape Integrity Index; B. Safe Zone as base (green) over MaxEnt.

MaxEnt signifies strict selection based on environmental variables, leaving most of the landscape with low scores. The variances in the pixel score distribution also indicate a difference in the selected categories of each model.

Table 1. Percent (%) area covered by each category for Safe Zone, Forest Landscape Integrity Index, and MaxEnt in the Libungan River Watershed and Forest Reserve.

Category	SZ		FLII		MaxEnt	
	%	area(has)	%	area(has)	%	area(has)
Very suitable	8.00	4,225.60	14.43	7,619.87	3.35	1,769.27
Suitable	26.93	14,224.43	20.04	10,587.23	7.47	3,945.72
Likely suitable	44.07	23,277.77	28.33	14,964.02	9.85	5,202.25
Likely unsuitable	20.00	10,564.00	0.07	38.17	66.75	35,255.51
Unsuitable	1.00	528.20	37.13	19,610.71	12.58	6,647.25
Total	100.00	52,820.00	100.00	52,820.00	100.00	52,820.00

Rater agreement test

Pixels were converted into five categorical values. The study used Cohen's kappa weighted agreement test with a confidence interval of 95%. This was to understand how each model agrees with the other models (**Table 2**). SZ had a stronger agreement with FLII than with MaxEnt. This result may have caused by the similarities of patchiness of SZ and FLII categorization in LWFR while the MaxEnt's categorization is almost monotonous in almost 80% of the landscape.

Fleiss' Kappa shows agreements among the categories (**Table 3**). The highest agreement among the three models was in category 5. This area represents the suggested potential area of the SPZ. This means that Maxent and FLII agree more with SZ in finding the potential conservation area for threatened species, but slightly agree on category 4 and very low or no agreements on other categories.

Krippendorff's alpha showed an overall agreement of 0.277, which is below the 0.60 standard for acceptable agreement.

Relationship tests

Parallel coordinate analysis revealed the distribution of the same sampling points in the three models (**Figure 8**). Variances were also present based on high angular lines, meaning that some samples for SZ were scored differently in the other models. The polarity of high scores (red line equivalent to >87) on the right side (**Figure 8**) represents a substantial similarity of the three models; however, some points were scored lower by FLII, and Maxent was represented by high angular lines pointing towards the left of the graph. the selection of the 'very suitable' has high similarity (red lines) with FLII but is reduced in volume with Maxent. This result is a validation of the high similarity of 'very suitable' areas of all three map models. Meanwhile, the second level (70-80 scores) for SZ was mostly rated similarly to

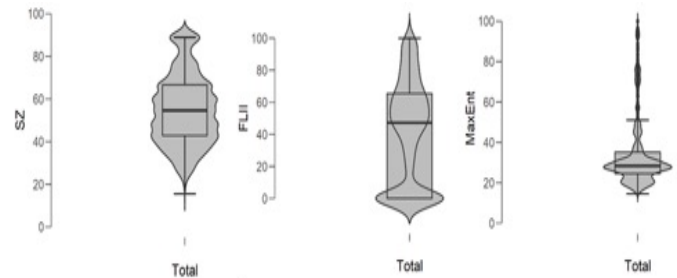


Figure 7. Boxplot distribution of Libungan River Watershed and Forest Reserve sample points from the Safe Zone, Forest Landscape Integrity Index, and MaxEnt models.

Table 2. Cohen's weighted Kappa of Safe Zone, Forest Landscape Integrity Index, and Maxent in the Libungan River Watershed and Forest Reserve.

Ratings	Weighted Kappa	Agreement	Lower	Upper
Average Kappa	0.402	Moderate		
SZ - MaxEnt	0.333	Fair	0.315	0.351
SZ - FLII	0.410	Moderate	0.392	0.428
MaxEnt - FLII	0.463	Moderate	0.443	0.483

Note. 5851 items and 3 raters.

Confidence intervals (95%) are asymptotic

Table 3. Fleiss' Kappa agreement between the categories of the Safe Zone, Forest Landscape Integrity Index, and Maxent in the Libungan River Watershed and Forest Reserve.

Ratings	Fleiss' Kappa	Agreement	Lower	Upper
Overall	0.016	Fair	0.008	0.024
1 - Unsuitable	-0.074	No	-0.089	-0.059
2 - Likely unsuitable	-0.072	No	-0.087	-0.057
3 - Likely suitable	-0.030	No	-0.045	-0.015
4 - Suitable	0.107	Fair	0.092	0.122
5 - Very suitable	0.491	Moderate	0.476	0.506

Note. 5851 items and 3 raters.

Confidence intervals (95%) are asymptotic

FLII but placed in the lower 20 for Maxent.

Most of the SZ pixel scores in the range of 50-70 were

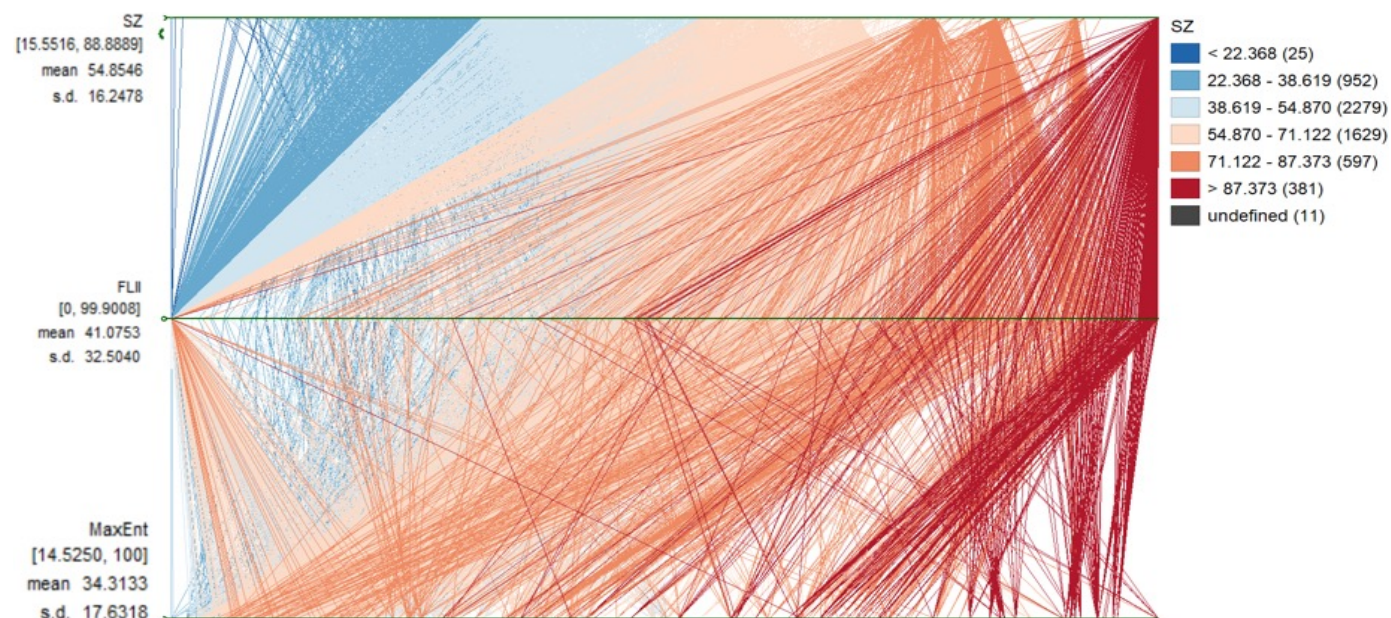


Figure 8. Parallel coordinate plot comparison of the Safe Zone, Forest Landscape Integrity Index, and Maxent models using 5 quantile classification.

scored from 1 to ~80 by FLII and were usually scored from 10 to 40 by MaxEnt. The SZ pixels with scores of 50 and below were mostly scored by FLII at around <10 and by MaxEnt at 10–30.

Based on the scatter plot matrix (**Figure 9**), the SZ is slightly more related to MaxEnt (0.6) than to FLII (0.5). SZ has deviations in the lower scores with MaxEnt, but runs along the projection from approximately 30 % and up. While FLII has its deviations from the projection at the upper 30%, the amplitude is higher than MaxEnt's. This means that SZ and MaxEnt are more similar in selecting the 'very suitable' habitat than FLII. The SZ

and FLII were more similar in the lower categories.

The FLII is more related to SZ than to MaxEnt (0.4). FLII and MaxEnt had their greatest deviation at the lower 20% and slightly more sample deviations at higher pixel scores. The FLII and SZ, with a strong amplitude of difference, have lower and higher scores, respectively.

MaxEnt is more related to SZ (0.6) than to FLII (0.4). As previously described, the most remarkable difference between the two models is the lower portion of the scores, whereas the FLII varies more with MaxEnt at the higher level of scores.

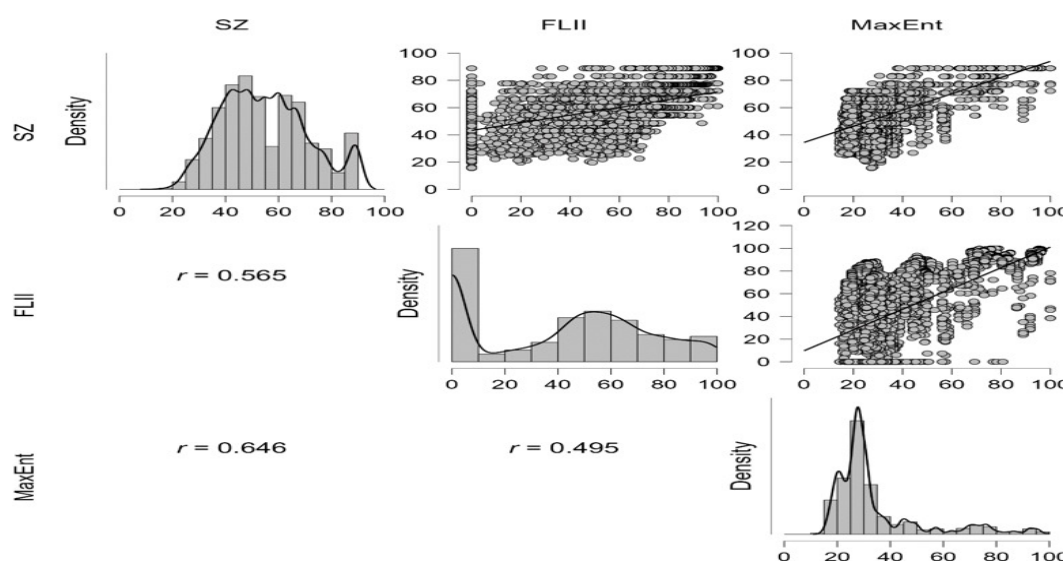


Figure 9. Scatter Plot Matrix and Histograms Showing Pairwise Relationships for Safe Zone, Forest Landscape Integrity Index, and MaxEnt models..

Spearman correlation (**Figure 10**) showed that SZ was more correlated to FLII than MaxEnt, MaxEnt was more correlated to SZ than to FLII, and FLII was more correlated to SZ than MaxEnt. The analysis of the other LU maps in the landscape, it showed that, the SZ is highly correlated with increasing distance from settlements and roads. This means that the 'highly suitable' areas of the SZ model are located farther from roads and settlements. The high correlation of SZ to DEM shows that the higher scores in the SZ classification are also located at high elevations, and even if the SZ equations do not include elevation, most of the closed forests in the LWFR landscape are located at higher elevations, which influences the SZ $\times$ DEM relationship. The high correlation of SZ to timberland was possible because the highly suitable areas were exclusively located in the Timberland land-use classification of LWFR. The SZ was negatively correlated with croplands, Alienable and Disposable lands (A and D), Strategic Agriculture and Fisheries Development Zones (SAFDZ), and Certificate of Ancestral Domain Title (CADT). Although the algorithm used by SZ declared that croplands have a positive low score value (+2) as habitat, its location that overlaps with the negatively classified A and D, roads, settlements and CADT resulted in the downgrading of most cropland scores.

As expected, FLII decisions have a positive relationship with Land Use Land Cover (LULC), which contains and supports forest conservation. For example, croplands have the strongest negative relationship with FLII due to the low density of trees; A and D are land use types intended for settlement and development; CADT areas in this watershed were used for croplands; and Forest Land Grazing Management Agreement (FLGMA) has limited trees because land use is intended for grazing animals and pasture lands.

MaxEnt was negatively correlated with open forests, croplands, and grasslands. This does not mean that the threatened species in the models are not found in those habitats, but the pattern shows that the pixels of MaxEnt go down in locations of open forest, cropland, and grasslands. MaxEnt's relationship was also negative for A and D, CADT, FLGMA, and SAFD. Climatic factors might have affected the relationship between MaxEnt's very suitable area and the Land Use and Land Cover mentioned above.

Local maps were included in the analysis to provide a proper understanding of the landscape and the models. Nevertheless, the result presentation was limited to important land-use maps. For instance, closed forests were highly correlated with SZ, FLII, and MaxEnt,

	SZ	FLII	MaxEnt	clsdforst	Opnforst	crplnd	grslnd	slope	DEM	roads	stlmnt	A&D	tmbrlnd	CADT	CLOA	ISF	FLGMA	NPAAD	SAFD
SZ	—																		
FLII	0.537 ***	—																	
MaxEnt	0.394 ***	0.326 ***	—																
clsdforst	0.583 ***	0.547 ***	0.583 ***	—															
Opnforst	0.125 ***	0.146 ***	-0.041 **	-0.087 ***	—														
crplnd	-0.587 ***	-0.466 ***	-0.354 ***	-0.507 ***	-0.434 ***	—													
grslnd	0.138 ***	-0.021	-0.051 ***	-0.147 ***	-0.128 ***	-0.473 ***	—												
slope	0.336 ***	0.258 ***	0.043 ***	0.107 ***	0.143 ***	-0.255 ***	0.141 ***	—											
DEM	0.664 ***	0.413 ***	0.581 ***	0.586 ***	0.097 ***	-0.473 ***	0.012	0.26 ***	—										
roads	0.665 ***	0.524 ***	0.345 ***	0.473 ***	0.135 ***	-0.497 ***	0.118 ***	0.313 ***	0.362 ***	—									
stlmnt	0.759 ***	0.515 ***	0.434 ***	0.508 ***	0.18 ***	-0.574 ***	0.163 ***	0.321 ***	0.615 ***	0.693 ***	—								
A&D	-0.762 ***	-0.381 ***	-0.247 ***	-0.313 ***	-0.223 ***	0.448 ***	-0.142 ***	-0.38 ***	-0.593 ***	-0.441 ***	-0.557 ***	—							
tmbrlnd	0.757 ***	0.38 ***	0.247 ***	0.313 ***	0.221 ***	-0.441 ***	0.141 ***	0.385 ***	0.596 ***	0.435 ***	0.557 ***	-0.978 ***	—						
CADT	-0.287 ***	-0.157 ***	-0.044 ***	-0.189 ***	-0.077 ***	0.101 ***	0.118 ***	-0.04 **	-0.469 ***	0.226 ***	-0.149 ***	0.212 ***	-0.22 ***	—					
CLOA	0.174 ***	0.13 ***	0.16 ***	0.074 ***	0.134 ***	-0.205 ***	0.123 ***	0.159 ***	0.2 ***	0.145 ***	0.224 ***	-0.35 ***	0.348 ***	-0.088 ***	—				
ISF	0.1 ***	0.017	0.173 ***	0.009	0.027 *	0.02	-0.056 ***	-0.001	0.161 ***	-0.034 **	0.012	-0.12 ***	0.12 ***	-0.073 ***	-0.001	—			
FLGMA	0.061 ***	-0.058 ***	-0.265 ***	-0.095 ***	0.068 ***	-0.044 ***	0.106 ***	0.062 ***	-0.032 *	-0.052 ***	-0.017	-0.169 ***	0.169 ***	-0.051 ***	-0.127 ***	-0.037 **	—		
NPAAD	0.251 ***	0.231 ***	0.29 ***	0.315 ***	0.065 ***	-0.269 ***	0.004	0.093 ***	0.329 ***	0.26 ***	0.285 ***	-0.186 ***	0.188 ***	-0.115 ***	0.146 ***	-0.04 **	-0.058 ***	—	
SAFD	-0.106 ***	-0.073 ***	-0.184 ***	-0.122 ***	0.012	0.094 ***	-0.031 *	0.094 ***	-0.078 ***	-0.204 ***	-0.158 ***	-0.212 ***	0.205 ***	-0.06 ***	0.055 ***	-0.047 ***	0.058 ***	-0.074 ***	—

* p < .05, ** p < .01, *** p < .001

Figure 10. Spearman correlation matrix showing the Safe Zone, Forest Landscape Integrity Index, MaxEnt models, and other references maps from the Libungan Watershed and Forest Reserve landscape closed forest (clsdforst), open forest (opnforst), cropland (crplnd), grassland (grslnd), alienable and disposable lands (A&D), timberland (tmbrlnd), Certificate of Ancestral Domain Title (CADT), Certificate of Land Ownership Awards (CLOA), Integrated Social Forestry (ISF), Forest Land Grazing Management Agreement (FLGMA), Network of Protected Areas for Agriculture and Agro-Industrial Development (NPAAD), Strategic Agriculture and Fisheries Development Zones (SAFD). Digital Elevation Model (DEM), slope values (slope), distance to roads (roads) and distance to settlements (stlmnt). Blue text= emphasis of the research (relationship of SZ $\times$ FLII $\times$ MaxEnt); red text = negatively correlated maps to the three models.

indicating similar priorities in the models. Conversely, the open forest was weakly correlated with SZ and FLII but negatively correlated with MaxEnt. All models showed a negative correlation with croplands. Grassland was weakly correlated with SZ because it considered the presence of the survey results of two threatened species per square kilometer of grassland land cover classification. Alienable and disposable areas are the landscape's leading areas for agriculture and infrastructure development; they were negatively correlated to all models, but are more robust to SZ and less robust to MaxEnt. CADT and SAFD were also weakly correlated in all three models. The increasing distance of roads and settlements increases with the classification scores of the models; this means

that suitability is higher at points farther away from the roads and settlements, and the reverse is to A&D.

The PCA resulted in six components (**Figure 11**) based on the eigenvalue. The component-loading table shows the contributions of these variables. At the same time, the component correlation figure showed the strength of the relationship between principal components. The directions of these relationships are indicated by green arrows for positive connections and red arrows for negative relationships, while the line thickness represents the strength of the relationship. The study focused on component 1 (RC1), which contains the three models being compared.

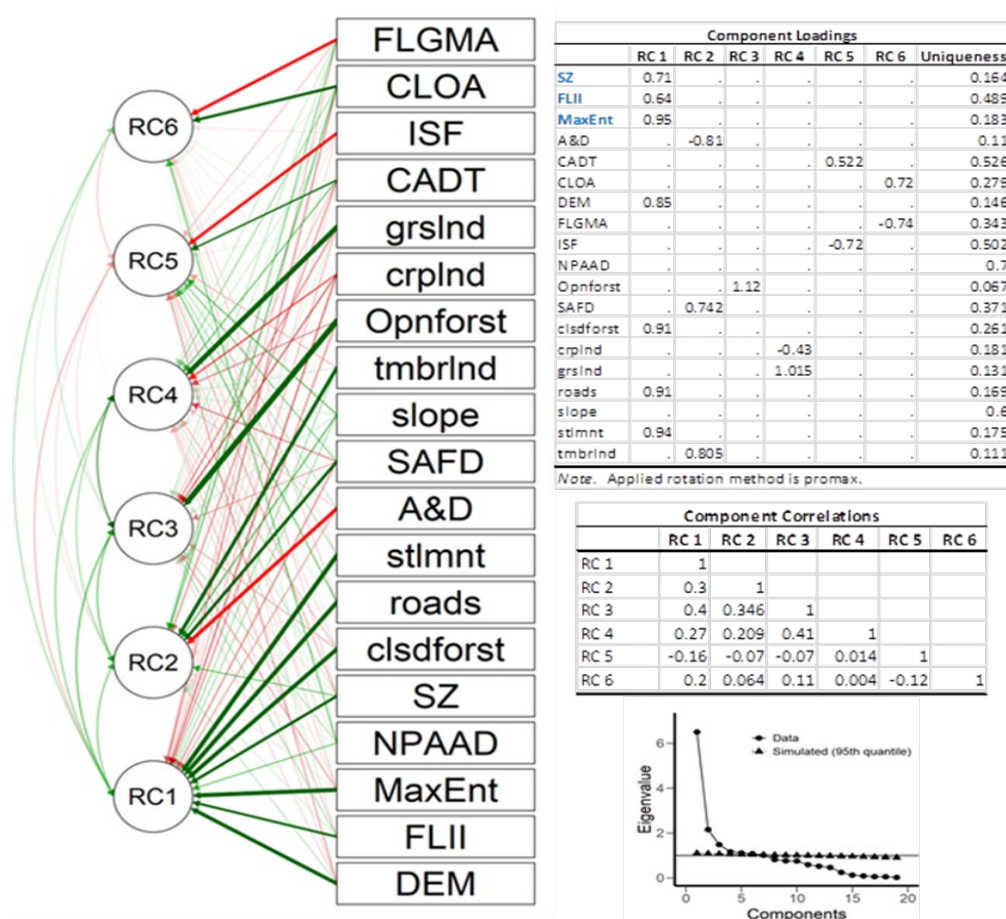


Figure 11. The relationships of the principal components (circles) and variables (boxes). Note that: Green are positive relationships, while red are negative relationships. Wider arrows = higher loading. Values of component loadings and the correlations are shown in the inset tables. RC = relation component, closed forest (clsdforst), open forest (opnforst), cropland (crplnd), grassland (grsInd), alienable and disposable lands (A&D), timberland (tmbrInd), Certificate of Ancestral Domain Title (CADT), Certificate of Land Ownership Awards (CLOA), Integrated Social Forestry (ISF), Forest Land Grazing Management Agreement (FLGMA), Network of Protected Areas for Agriculture and Agro-Industrial Development (NPAAD), Strategic Agriculture and Fisheries Development Zones (SAFD). Digital Elevation Model (DEM), slope values (slope), distance to roads (roads) and distance to settlements (stimnt).

The three models were loaded in RC1, together with closed forests, areas far from roads and settlements, and higher elevations. These landscape components were the determining factors for the three LWFR models. All other land cover types (grassland, open forest, and cropland) and A and D had a negative relationship with RC1. MaxEnt has the greatest load in RC1 among the three models, whereas SZ shares its load with RC2. The RC2 group comprises SAFD and Timberland, with a strong negative loading on A&D. This is because the ‘very suitable’ area of the SZ favors closed forests. SAFD is located in the closed forest in LWFR; the timberland contains a closed forest; in contrast, A&D has no closed forest.

Map comparison

The maps compared in this study are all used as a basis for suggesting conservation sites. However, different algorithms and thematic objectives were used. The map comparison exercise revealed that all three models exhibited similar decision-making by having a similar location of “very suitable” areas in the landscape (at the northern end of the watershed). The moderate agreement between the maps is understandable because each model has different objectives in identifying categories. The low agreement in the lower categories (1 to 4) greatly affected Krippendorff’s alpha. Those lower categories are less critical than category 5 because, in the search for a potential SPZ or a CH, the highest category is the only choice, while other areas will only fall in management areas or be removed from protected areas. This study only chose the highest category because it aligns with the IUCN’s description of a protected area, that is, essential for biodiversity conservation, functioning natural ecosystems, and refuge of species (*Dudley 2008*). The remaining lower categories have the potential to be disturbed in the future.

It should be noted that FLII is biased towards forest cover (*Grantham 2020*), while Maxent is biased towards species distribution (*Phillips 2006*); thus, the agreement is expected to be not ‘near perfect (1.0)’. However, this exercise revealed that the SZ, as a new selection methodological framework, is leaning towards the decisions of forest cover compared to species distribution.

Since the MaxEnt’s contributory factors are limited to the climatic parameters, it depicts that the SZ model is inclined to identify potential habitats of the species of concern based on climatic conditions or the “bioclimatic envelope model”; in this paper, the 13 threatened species list of LWFR (*Tabora et al. 2023*). The smooth transitions of the MaxEnt model correspond with climatic change

as the elevation increases in the north, and wind patterns and temperature patterns are affected by global systems. The resulting map of SZ covers 100% of the bioclimatic envelope produced by MaxEnt SDM, making the SZ decision relevant to threatened species conservation. As mentioned by *Rose and Burton (2009)*, bioclimatic envelopes follow the ecological niche principle, which describes species distribution based on climatic conditions. Meanwhile, the FLII downloaded data removes areas without intact forests or places them in a lower category.

The SZ, on the other hand, had large patches that are affected by different layers of land-use types with different weight scores. Because the SZ algorithm used 12 land use types, these combinations were patchy. This study noted that some closed forest areas were removed from the highest suitability category because of an overlap with a negative conservation value; in this case, the CLOA areas. The negative value of CLOA is caused by the notion that CLOAs are open to agricultural activities, such as palm oil plantations in Southeast Asia (*Colchester et al. 2011*).

The intactness of the closed forest in the area selected by the SZ model is incidental; this result may not occur if the LULCs used are fragmented and intersecting. The intactness factor, however, can be included in the categorization process if stakeholders desire this feature to make it intentional. The intactness of a habitat is an important factor that is used as an indicator of ecosystem health (*Scholes and Biggs 2005*).

All the models were selected for high elevations. This may also be incidental, because the land cover with the highest score is a closed forest located at higher elevations. As found by *Mallari et al. (2015)*, most of the low elevations were designated for ‘multiple use zone’ (*Mallari et al. 2015*). The geomorphology was not included in the algorithms of the three models. The authors expected that decision-making may differ if the models are used in areas with intact lowland forests.

The smaller space assigned by the MaxEnt model does not necessarily mean that it is an inferior model; rather, it shows the limitations of climatic parameters in selecting conservation sites. The broader areas assigned by FLII represent land cover with intact forest, which does not mean that it is superior to other models. The purpose of the comparison is not to determine which model is superior but rather to understand the nature of the decision-making of the SZ methodological framework.

The relationship of land cover is more potent with the

SZ model because the forest has the highest importance weights in the SZ algorithm because of the multiplier effect of the number of endangered species found in it. The SZ's most desirable area is smaller than that of FLII by deducting areas with existing development plans from potential areas for conservation. This also means that the SZ responds more to the local situation, which is essential for management and monitoring.

Although MaxEnt and FLII are designed for global applications with coarser resolutions, SZ requires fine-grained local information and may not be readily applicable on a global scale. The capacity of the SZ model for future projections has not yet been tested, although several authors have used MaxEnt to predict potential species habitat changes (Wei *et al.* 2018).

The SZ map used local perceptions, the best available maps, and LULC to determine a potential conservation area. The best available maps were reliable maps provided by appropriate and authorized agencies. The SZ's user-defined algorithm includes the four major land cover types and places more weight on the land cover that houses more threatened species. The impact of this algorithm is evident when comparing the SZ model with the MaxEnt and FLII models.

The three models' imperfect fit of the 'very suitable' area is caused by several factors such as pixel resolution, variance in land cover base data, local land use maps used by SZ mode, and the importance weights for the SZ model. The relationship between SZ and MaxEnt signifies its plasticity toward species distribution, whereas its relationship with FLII also signifies its disposition for closed forest habitats.

While the global models provide an overview of the wider regions and landscapes, the local map synthesis, such as the SZ, provides a higher relationship to factors that affect habitats in the landscape. SZ also has a higher repulsion to vital land use types that are important for locals for development and socio-economic activities. The SZ approach facilitates the effective management of candidate protected areas. In economically challenged nations, the imperatives of conservation and development must advance in tandem to ensure sustainable progress (Brown 2003). As concluded by Omoding *et al.* (2020), stakeholder perceptions can significantly improve management.

CONCLUSION AND RECOMMENDATIONS

The map model assessment study yielded valuable

insights into the performance and applicability of the new user-defined algorithm in the context of conservation decision-making. The comparison between SZ, FLII, and MaxEnt sheds light on the decision-making process of the SZ, that is, it is more biased towards habitat compared to species distributions. By contrasting their outcomes, this study gained a deeper understanding of how the new algorithm operates and where it diverges from the established approaches. Cross-validation of the map models using land use and land cover (LULC) data provided crucial information regarding the accuracy and reliability of the mapped areas. Understanding how well the algorithm aligns with actual landscape features is essential for effective conservation planning. Statistical analysis provides quantitative values of the model agreements and relationships.

Potential challenges in map model assessments include the selection of models for comparison. The sampling procedure was set at 30×30 m in this study because the reference map for comparison used that resolution size; however, when used with other models, the resolution of the sampling points can be adjusted to fit the models for comparison.

It is recommended that new site selection maps be compared with standard models to clarify their usefulness and applicability. In the Philippine context, where the traditional procedure of determining "forestlands" for conservation relies heavily on the slope and elevation of the landscape, this comparison procedure may provide insight into how to understand the maps generated for decision-making purposes.

Based on the model assessment, it is concluded that the SZ model is a potential tool for selecting conservation sites. The SZ model can also be compared with other models not included in this study to further understand its decision-making. The authors believe that the degree of similarities and differences may vary if the three algorithms are applied in a different area of concern and if the temporal perspective is included in the models.

Further testing of the SZ strategy is recommended for other protected area zoning in the Philippines. Some modifications may be applied based on the available data and purpose of the selection process. The method can also be tested to select potential biodiversity corridors connecting Protected Areas or Key Biodiversity Areas.

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DISCLAIMER

The model presented is based on the best available data collected in 2020 under the office of the CENRO Midsayap. Other maps not in the repository of that office may not have been included in the algorithm and did not affect the final resulting map.

DECLARATION OF INTERESTS

The authors declare that they have no known competing financial interests.