Mapping Spatial Patterns and Environmental Drivers of Philippine Eagle Presence: Insights from Historical Sightings Data

J. D. Casisirano [1,2*]

[1] Department of Geodetic Engineering, University of the Philippines, Diliman, Quezon City, Philippines – (jarencecasisirano@gmail.com)
[2] Training Center for Applied Geodesy and Photogrammetry, University of the Philippines, Diliman, Quezon City, Philippines

KEY WORDS: Philippine Eagle, spatial statistics, point pattern analysis, GWR, MaxEnt

ABSTRACT:

The critically endangered Philippine Eagle, a symbol of the Philippines' biodiversity, faces significant threats from habitat destruction and environmental degradation. This study aimed to analyze the spatial patterns of eagle sightings and the environmental drivers influencing habitat suitability using advanced spatial statistical techniques. Elevation, river proximity, and forest cover were identified as key covariates influencing eagle presence. The workflow integrated point pattern analysis, kernel density estimation (KDE), Geographically Weighted Regression (GWR), and MaxEnt modeling to assess habitat preferences and predict suitable areas for conservation. Results revealed that **eagle sightings are highly clustered** in **mid-elevation forests (900–1,200 meters) near rivers (within ~500 meters)** and **strongly associated with dense forest canopies**, which account for 97% of sightings. The habitat suitability map generated through MaxEnt modeling highlighted priority areas for conservation and restoration. The study concludes that preserving mid-elevation forests and riparian zones is critical for the species' survival. Recommendations include incorporating additional variables such as prey availability in future studies, engaging local communities in conservation initiatives, and integrating advanced monitoring tools to adaptively manage eagle habitats. This integrative approach offers valuable insights for targeted conservation planning and enhanced research methodologies to protect the Philippine Eagle and its ecosystem.

1. INTRODUCTION

1.1 Background of the Study

The Philippine Eagle (*Pithecophaga jefferyi*), one of the largest and most majestic raptors in the world, is endemic to the Philippines. Revered as a national symbol, it is not only an emblem of the Philippines' rich biodiversity but also an indicator of forest health. However, this iconic species is critically endangered due to habitat destruction, hunting, and environmental degradation. With fewer than 400 individuals remaining in the wild (Ibañez et al., 2016), the urgency to protect this species is greater now more than ever.

The habitats of the Philippine Eagle are predominantly in forested areas across Luzon, Samar, Leyte, and Mindanao (Luczon et al., 2014). These forests provide essential resources, including prey availability and nesting sites. The eagle's survival is inextricably linked to these habitats, yet they are increasingly threatened by deforestation, agricultural expansion, and urbanization. The loss of forest cover has fragmented the eagle's territory, decreasing their chances of reproduction and survival. Moreover, the lack of spatially explicit studies makes it challenging to identify critical habitats that need immediate protection.

Spatial statistics and advanced modeling techniques offer robust tools to address these challenges. By analyzing historical sightings and environmental variables, it becomes possible to uncover patterns in the eagle's distribution and predict areas of potential habitat suitability. Such studies not only aid in understanding the species' ecological needs but also guide conservation policies and resource allocation.

For instance, analyzing the spatial distribution of eagle sightings begins with understanding whether these occurrences are clustered, random, or dispersed. Point pattern analysis provides the foundation for this exploration by quantifying spatial randomness and revealing underlying patterns. Methods like quadrat analysis divide the study area into smaller cells to identify regions of significant clustering, while Nearest Neighbor Analysis (NNA) calculates the average distances between sightings to detect local aggregations or dispersions. Ripley's K-function extends these insights further by examining clustering at multiple spatial scales, offering a nuanced understanding of how eagle sightings are distributed across their habitat.

Building upon these spatial patterns, Kernel Density Estimation (KDE) provides a powerful visualization tool to pinpoint areas of high sighting intensity. Unlike point pattern analysis, which focuses on statistical summaries, KDE translates the data into continuous density surfaces, highlighting hotspots of eagle activity. These density maps not only identify key regions where conservation efforts might be concentrated but also contextualize sightings in relation to environmental conditions.

Linking spatial patterns to environmental drivers can be achieved through concepts like Geographically Weighted Regression (GWR). Unlike traditional regression models that assume uniform relationships across space, GWR allows for an exploration of spatially varying influences (Páez, Farber, & Wheeler, 2011). This enables an examination of how factors such as elevation, proximity to rivers, and forest cover shape distributions differently across various parts of the landscape. By revealing local variations in these relationships, GWR provides a detailed perspective on how specific environmental covariates contribute to habitat suitability in different regions. This spatially explicit understanding is critical, as it highlights the

* Corresponding author

heterogeneity of eagle habitats and their dependence on localized environmental conditions.

Another framework for identifying potential habitats is Maximum Entropy (MaxEnt) modeling. This approach is particularly effective for presence-only datasets, as it leverages observed environmental conditions at sighting locations to infer areas of similar suitability (Baldwin, 2009). By applying the principle of maximum entropy, MaxEnt avoids making unnecessary assumptions about species distribution, focusing instead on identifying areas that closely resemble known habitats. The habitat suitability maps generated through MaxEnt offer valuable insights for conservation planning, drawing attention to regions where efforts such as protection or restoration might have the greatest impact.

These statistical and modeling approaches, when integrated thoughtfully, provide a comprehensive understanding of the spatial ecology of the Philippine Eagle. Concepts from point pattern analysis reveal the structure of eagle sightings, KDE highlights critical hotspots, GWR explores environmental drivers, and MaxEnt predicts suitable habitats. Together, these methods form a robust framework for identifying and understanding the factors influencing eagle distribution, supporting scientifically grounded conservation efforts.

1.2 Significance of the Study

The Philippine Eagle is not merely a species; it is a symbol of the Philippines' natural heritage. Protecting this apex predator means safeguarding the forests it inhabits and the countless other species that share its habitat. This study contributes to conservation efforts by:

- Identifying key environmental factors influencing eagle presence.
- Pinpointing hotspots of eagle sightings and potential suitable habitats.
- Providing spatially explicit maps that can guide conservation strategies and prioritize areas for habitat restoration.

The integration of exploratory spatial data analysis, Geographically Weighted Regression (GWR), and habitat suitability modeling through MaxEnt ensures a comprehensive approach. These methods allow for a nuanced understanding of the eagle's spatial ecology, highlighting regions critical for conservation. The outcomes are expected to support policymakers, conservationists, and local communities in creating effective strategies for the protection of the Philippine Eagle and its habitat.

1.3 Research Questions

This study aims to answer the following questions:

1. Are Philippine Eagle sightings spatially random, or do they exhibit clustering or dispersion patterns?
2. Where are the high-density hotspots of Philippine Eagle sightings?
3. How do environmental factors such as forest cover, elevation, and proximity to rivers influence the spatial variability of Philippine Eagle presence?
4. Where are areas with environmental conditions similar to those associated with Philippine Eagle sightings, and how can they inform potential habitat prediction?

1.4 Research Objectives

The overarching objective of this study is to analyze the spatial distribution of eagle sightings data in the study area and use spatial statistical concepts to derive useful and actionable insights from it. In particular, this study aims:

1. To examine the spatial distribution and randomness of Philippine Eagle sightings using point pattern analysis techniques.
2. To generate density maps of Philippine Eagle sightings and identify geographic hotspots.
3. To assess and map the spatially varying relationship between environmental covariates (e.g., forest cover, elevation, proximity to rivers) and Philippine Eagle sightings using Geographically Weighted Regression (GWR).
4. To predict potential habitats for the Philippine Eagle by modeling environmental conditions associated with historical sightings using MaxEnt.

2. METHODOLOGY

2.1 Study Area

The study area (shown as the rectangular area in Figure 1) encompasses approximately 15,535 hectares of forested land situated along the shared border between North Cotabato and Davao del Sur in Mindanao, Philippines. This region is characterized by its rugged terrain, dominated by the slopes of Mount Tinanan and Mount Unapan, which provide critical habitats for the Philippine Eagle (*Pithecophaga jefferyi*). The area is primarily dominated by forests and dense vegetation, interspersed with rivers such as the Luwang River, Tuli River, and Sibungan Creek forming a complex ecological network essential for the eagle's survival.

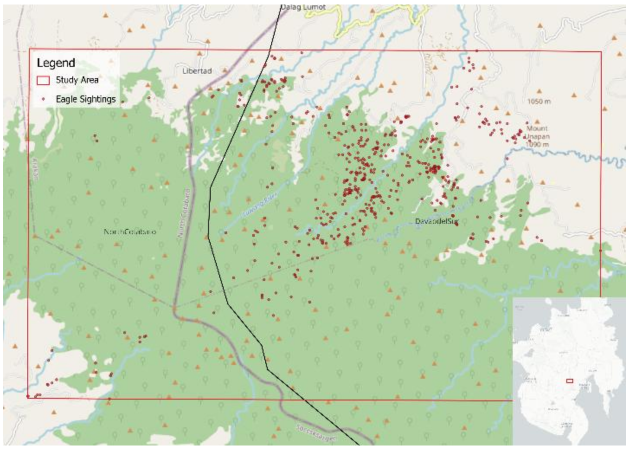

Figure 1 Vicinity Map of the Study Area

The study focuses on identifying the patterns of environmental factors influencing eagle sightings within this ecologically significant environment. Having delineated the study area encompassing key eagle sightings, the next step involved assembling datasets that capture relevant environmental covariates and species occurrence points.

2.2 Data

The primary datasets used in this study were sourced from open-access platforms, mostly through online geospatial portals. The eagle sightings data were obtained from the Global Biodiversity Information Facility (GBIF) under the dataset titled "Philippine Eagle Occurrence Records" (https://www.gbif.org/dataset/7bfbd7bb-fdd8-44ff-ab28-7f92c2d55ee3). GBIF is a global research infrastructure that provides open access to biodiversity data contributed by researchers and institutions worldwide. The dataset includes georeferenced records of Philippine Eagle sightings in decimal degrees (WGS 84) representing a comprehensive inventory of the species' known occurrences.

Elevation data were acquired from the Shuttle Radar Topography Mission (SRTM) through the SRTM Downloader plugin in QGIS. SRTM provides high-resolution (30m) digital elevation models (DEMs). These are crucial for analyzing topographic influences on the distribution of species. The elevation dataset captures terrain variations critical for understanding the nesting and hunting preferences of the Philippine Eagle.

The river network data (which was eventually used to calculate proximity to rivers) were derived from OpenStreetMap (OSM) river network information. It was accessed using the Quick OSM plugin in QGIS. This dataset provides detailed vector representations of river networks which were then processed to calculate the Euclidean distance from each raster cell to the nearest river. River proximity is an essential factor for species dependent on water sources for ecological stability, providing not only a source of water for eagles but also a place to hunt preys.

Lastly, forest cover data were sourced from the ESRI 2020 Land Use/Land Cover (LULC) dataset (*https://www.arcgis.com/home/item.html?id=cfcb7609de5f478eb7666240902d4d3d*). The ESRI LULC dataset provides a globally consistent land cover classification derived from Sentinel-2 imagery, ensuring high accuracy in delineating forested and non-forested areas. The dataset was reclassified into three categories: forest (1), rangeland (2), and others (0), reflecting habitat types most relevant to the Philippine Eagle.

2.3 Tools and Software

The analysis was conducted using a combination of R and QGIS, utilizing the following tools and packages:

- **QGIS**
    - **SRTM Downloader Plugin**: Used to acquire high-resolution digital elevation data for the study area.
    - **Quick OSM Plugin**: Used to download and preprocess river network data from OpenStreetMap (OSM).
    - **Raster Processing**: QGIS was used for clipping datasets to the study area, reprojecting layers to WGS 84, and resampling raster layers to a consistent resolution of 10 meters.
- **R**
    - **spatstat**: For point pattern analysis, including quadrat analysis, nearest neighbor analysis, Ripley's K-function, and kernel density estimation (KDE).
    - **GWmodel**: For geographically weighted regression, including bandwidth selection and spatial coefficient mapping.
    - **raster**: For handling environmental raster data, such as elevation, proximity to rivers, and forest cover.
    - **dismo**: For MaxEnt modeling and habitat suitability analysis.
    - **ggplot2**: For creating detailed visualizations, including maps and statistical plots.
    - **MASS**: For additional spatial and statistical modeling needs.
    - **viridis**: For visually appealing and interpretable color scales in maps and plots.
    - **sp**: For spatial data manipulation, including handling presence and pseudo-absence points.
    - **rJava**: Required for running MaxEnt within the R environment.

2.4 Data Preprocessing

Preprocessing was conducted in QGIS to ensure consistency and spatial alignment of all datasets:

- Clipping: All datasets were clipped to the bounding box of the study area. The bounding box is the extent of the point dataset extracted using QGIS' calculate extent tool.

- Reprojection: All raster datasets were reprojected to the same coordinate reference system (EPSG:4326 - WGS 84) to maintain spatial consistency.

- Resampling: All raster datasets were resampled to a uniform resolution of 10 meters using bilinear interpolation for continuous data (elevation and proximity to rivers) and nearest neighbor interpolation for categorical data (forest cover).

In addition to ensuring the datasets were prepared with consistent spatial resolution and extent, it is important to acknowledge the nature of the Philippine Eagle sighting data. This forms the foundation for the choice of analysis techniques. Given that the Philippine Eagle occurrence data comprises only presence records, specific methodologies were adopted to account for the absence of direct absence data as detailed in the following section.

2.5 Handling Presence-Only Data

The Philippine Eagle sightings dataset consisted of presence-only records. While presence-only data are valuable for identifying where species have been observed, the absence of systematic absence points poses challenges for traditional statistical analyses (Zarnetske, Edwards, & Moisen, 2007). This study addressed these limitations by employing two complementary approaches: pseudo-absence generation and MaxEnt modelling.

Pseudo-absence points were generated using random sampling across the study area, excluding known presence locations, to enable regression-based analyses such as Geographically Weighted Regression (GWR). This allowed comparisons of environmental conditions between observed and assumed absence points.

For presence-only modeling, MaxEnt provided a robust alternative by leveraging background points as proxies for absences. Background points represent the range of environmental conditions across the study area and allow MaxEnt to predict habitat suitability without requiring explicit absence data.

The understanding of presence-only data and its inherent challenges informs the selection of analytical approaches employed in this study which includes Geographically Weighted Regression and Maximum Entropy modeling. These methods allow for the extraction of valuable ecological insights despite the limitations of the data format.

2.6 Analytical Framework

The analysis combined spatial statistics and predictive modeling to address the research objectives comprehensively employing rigorous statistical techniques and detailed methodologies.

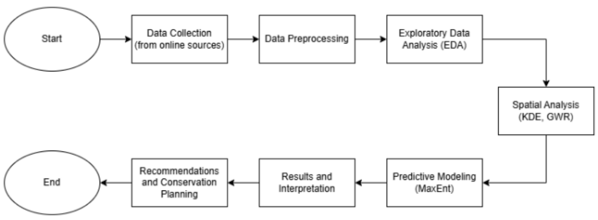

Figure 2 Methodology Flowchart

2.6.1 Point Pattern Analysis

The spatial distribution of Philippine Eagle sightings was first analyzed using point pattern analysis to detect clustering, randomness, or dispersion. The analyses done were the following:

Quadrat Analysis: Quadrat analysis was implemented using the *quadratcount* function in the *spatstat* package. The study area was divided into a 5 x 5 grid and the number of sightings in each quadrat was counted. The *quadrat.test* function was applied to perform a chi-square test for spatial randomness providing insights into clustering or dispersion patterns within the dataset.

Nearest Neighbor Analysis (NNA): The average nearest neighbor distance was calculated using the *nndist* function. The expected distance under complete spatial randomness (CSR) was estimated using the formula:

$$E(d) = 1 / (2 * \text{sqrt}(\lambda))$$

where λ (lambda) represents the point density calculated using the *intensity(ppp_data)* function. The Nearest Neighbor Index (NNI) was computed as:

NNI = Observed Mean Distance / Expected Mean Distance

This index indicated whether the sightings were clustered (NNI < 1) or dispersed (NNI > 1).

Ripley's K-function: Ripley's K-function was used to assess spatial dependence across multiple scales. Using the *Kest* function, the cumulative number of points within varying distances from each point was calculated and compared to CSR expectations. The graphical plot of observed K(r) against expected K(r) under CSR provided scale-dependent insights into clustering and dispersion.

Having established the spatial distribution of eagle sightings through point pattern analysis, Kernel Density Estimation (KDE) was utilized to visualize these patterns as continuous density surfaces to highlight specific hotspots.

Kernel Density Estimation (KDE): KDE was performed using the *density.ppp* function to create a continuous density surface of sightings with the smoothing bandwidth (σ) automatically determined using Diggle's method (*bw.diggle*). This approach ensured that the density estimates achieved a balance between over-smoothing and excessive fragmentation accurately reflecting the spatial distribution of eagle sightings. One-dimensional (1D) density plots for latitude and longitude were also generated using *geom_density()*. These provided additional insights into linear spatial patterns. The KDE maps were visualized to highlight hotspots of eagle activity including density contours and a color gradient.

While KDE effectively highlights hotspots of eagle activity, it does not account for the environmental covariates that may drive these patterns. To bridge this gap, the environmental covariates used in the analysis were visualized and explored to better understand their spatial patterns and relationships before employing Geographically Weighted Regression (GWR).

2.6.2 Exploratory Analysis and Visualization of Covariates

The environmental covariates analyzed included elevation, proximity to rivers, and forest cover. These covariates were visualized to provide insights into their spatial distributions and potential influence on eagle presence.

1. **Elevation**: The elevation raster was visualized using a continuous gradient map. This showcased variations in topography across the study area. The visualization highlighted areas of higher elevation where eagle sightings are concentrated.

2. **Proximity to Rivers**: Proximity to rivers was mapped using a similar gradient to identify areas closer to river networks as these regions are often associated with eagle habitats.

3. **Forest Cover**: Forest cover, a categorical variable, was reclassified into three categories: forest, rangeland, and others. A custom color palette was applied to distinguish these categories. A legend was included to provide clarity. This map emphasized the dominance of forested areas within the study region which aligns with the ecological requirements of the Philippine Eagle.

Additionally, the relationships between these covariates and their interaction with the eagle sightings data were further explored through scatterplots and density plots. This exploratory analysis served as a critical step in identifying the individual contributions of covariates to the presence of eagles, providing a foundation for the GWR analysis.

2.6.3 Geographically Weighted Regression (GWR) Analysis

Geographically Weighted Regression (GWR) was then applied to investigate the spatially varying relationships between Philippine Eagle sightings and environmental covariates. Environmental variables, including elevation, proximity to rivers, and forest cover, were extracted at the eagle sighting locations using the *extract()* function from the **raster** package. Forest cover was reclassified into three categories: forest, rangeland, and others, and converted into a factor variable for analysis. To address the absence of sightings in certain areas, 500 random pseudo-absence points were generated within the study area using the *spsample()* function. Environmental covariates were also extracted for these pseudo-absence points and their presence label was set to 0 while actual sightings were labeled as 1. This combined dataset of presence and pseudo-absence points ensured a balanced dataset for the analysis. Missing values in continuous covariates, such as elevation and proximity to rivers, were replaced with their respective mean values. Meanwhile, missing forest cover values were imputed with the mode category (forest). Latitude and longitude coordinates were then converted into a matrix for GWR analysis, forming the *coords* variable.

The GWR fitting process began with the selection of adaptive bandwidths using cross-validation via the *gwr.sel()* function in the GWmodel package. This step ensured that each local regression incorporated an optimal subset of data points, accounting for spatial heterogeneity. The model was executed adaptively to address the non-uniform spatial distribution of eagle sightings within the study area. However, given the dominance of forest cover in both presence and pseudo-absence points (97% of presence data in forest), the GWR analysis was refined to focus exclusively on forested areas to minimize bias and improve ecological relevance. This adjustment ensured that the relationships between predictors and eagle presence were assessed within the species' primary habitat.

Once the model was fitted, local coefficients for each covariate were extracted from the spatial data frame (SDF) output of the GWR model. These coefficients were visualized using **ggplot2**, producing maps that displayed the spatial variability in the influence of each predictor across forested areas. Separate maps were generated to highlight the coefficients for elevation and proximity to rivers, as well as forest cover categories (forest vs. others, rangeland vs. others). A local map was also created to show regions where the predictors most effectively explained the spatial distribution of eagle sightings. These visualizations used the **viridis** color palette for clarity and interpretability. Additionally, to ensure comprehensive coverage of the landscape, a scatterplot was generated to illustrate the spatial distribution of presence and pseudo-absence points.

While GWR provides localized insights into the environmental factors influencing eagle presence, its reliance on pseudo-absence points introduces limitations particularly in extending predictions to the broader landscape. To overcome this limitation, Maximum Entropy (MaxEnt) modeling was employed as a complementary approach. MaxEnt's presence-only framework enables the prediction of potential habitats across the entire study area. The subsequent analysis transitions to MaxEnt to identify potential habitats for the Philippine Eagle using a more generalizable modeling framework.

2.6.4 MaxEnt Habitat Suitability Modeling

To predict the potential habitat suitability for the Philippine Eagle, Maximum Entropy (MaxEnt) modeling was employed. This presence-only modeling technique leverages known occurrence points and environmental variables to identify areas with similar ecological conditions providing insights into potential habitats (Phillips, Anderson, & Schapire, 2006).

The environmental covariates used in the MaxEnt model included the three mentioned covariates. Elevation and proximity to rivers were aggregated to approximately 30m resolution using the mean function to represent topographic variability and distances, respectively. Forest cover was aggregated using the modal function to maintain categorical integrity, distinguishing between forest, rangeland, and other categories. These covariates were stacked into a single raster dataset using the *stack()* function in the **raster** package to ensure consistent resolution and extent across all layers. Eagle sighting records were filtered to retain only those within the spatial extent of the raster stack. The filtered dataset was then split into 70% training and 30% testing subsets to validate the model's predictive accuracy. The reproducibility of the random sampling was ensured through the *set.seed(123)* function.

The MaxEnt model was implemented using the *maxent()* function from the **dismo** package. The training subset of presence points and the environmental raster stack were used as inputs to the model. Model outputs were saved in a specified directory (*./maxent_results_coarse*). The output configuration was set to *raw* format to allow for flexible post-processing of suitability scores. Once trained, the MaxEnt model was used to predict habitat suitability across the entire study area. This prediction was performed using the *predict()* function, generating a continuous raster surface of suitability scores where higher values indicated greater ecological similarity to known eagle habitats.

The habitat suitability map was visualized using both base R plotting functions and enhanced visualizations. A raster plot displayed suitability scores with labeled axes and a descriptive title while semi-transparent red contours, created using the *contour()* function, delineated suitability levels. Observed presence points were overlaid using *points()* to provide a direct comparison of predictions and known occurrences. The resulting map was exported as both a GeoTIFF file (*eagle_habitat_suitability_coarse.tif*) and a PNG image for documentation and presentation purposes.

The model performance was evaluated using multiple metrics to provide a comprehensive assessment. The Area Under the Curve (AUC), extracted directly from the MaxEnt results, measured the model's ability to distinguish between suitable and unsuitable habitats. Higher values indicated better predictive performance. The mean suitability of test presence points was also calculated by extracting predicted suitability values using the *extract()* function and averaging them. This provided insight into the model's predictive accuracy for known presence locations. Additional evaluation metrics included sensitivity (true positive rate), specificity (true negative rate), total skill score (TSS), accuracy, and precision. Sensitivity and specificity quantified the model's ability to correctly identify suitable and unsuitable areas. The TSS combined these metrics to evaluate the overall discriminatory power of the model. Accuracy measured the proportion of correctly predicted points and precision captured the reliability of positive predictions. These metrics were saved in a CSV file (*maxent_evaluation_metrics.csv*) for documentation and further analysis.

The MaxEnt modeling process provided valuable insights into the potential distribution of suitable habitats for the Philippine

Eagle. The habitat suitability map highlighted regions with conditions favorable for the species while the evaluation metrics quantified the model's predictive performance, complementing the spatial analyses from point pattern analysis and GWR.

2.7 Assumptions and Limitations

This study relied on several assumptions during data preparation, analysis, and modeling to address the research questions effectively. Pseudo-absence points were generated randomly across the study area assuming a uniform representation of background habitat availability. Many of these points were located in forested areas which are known to be suitable habitats for the Philippine Eagle (Lewis, 1986). This approach, while practical, does not explicitly delineate unsuitable habitats and may affect the accuracy of predictive models like MaxEnt. The environmental covariates used in the analysis—elevation, proximity to rivers, and forest cover—were selected based on their ecological relevance and data availability. However, this assumes that these covariates are the primary determinants of habitat suitability. This may overlook other potential factors such as prey availability and human disturbance which were excluded due to data limitations.

The dominance of forested areas in the dataset (97% of presence points) required adjustments in the Geographically Weighted Regression (GWR) analysis to focus on forested regions. This assumes that the environmental effects on eagle presence are consistent within forests, potentially overlooking spatial variability in non-forested areas. Additionally, the raster layers for environmental covariates were downsampled to ~30m resolution, assuming that this scale adequately captures key habitat features while balancing computational efficiency. However, this coarser resolution might overlook finer-scale habitat variations that could influence eagle distribution.

The use of presence-only data for Philippine Eagle sightings assumes that the absence of sightings reflects a lack of observations rather than true absence. This limitation was partially addressed by generating pseudo-absence points, but the interpretation of results remains constrained by this assumption (Iturbide et al., 2015). In the MaxEnt model, threshold-based metrics were calculated using the 10th percentile of training presence points, an approach commonly used in habitat modeling. However, this threshold is somewhat arbitrary and may not fully reflect ecological reality. Lastly, the study area was defined by a bounding box encompassing all eagle sightings assuming that ecological and spatial processes influencing habitat suitability are confined within this boundary. Broader-scale influences beyond the study area were not considered. These assumptions, while necessary to complete the study, introduce limitations that should be addressed in future research

3. RESULTS AND DISCUSSION

3.1 Results and Discussion

This section presents the key findings from the spatial and statistical analyses of Philippine Eagle sightings and environmental covariates. The results are discussed in relation to the research questions, integrating insights from point pattern analysis, kernel density estimation, geographically weighted regression, and MaxEnt modeling, with implications for conservation strategies.

3.1.1 Point Pattern Analysis

The spatial distribution of Philippine Eagle sightings was visualized using a point pattern representation (Figure 3). Each point represents an individual sighting recorded within the study area. The raw visualization highlights the geographic scope and density of sightings providing an initial indication of clustering in certain regions. This foundational visualization sets the stage for subsequent spatial analyses, such as point pattern analysis and hotspot identification, which delve deeper into the spatial characteristics and patterns of the data

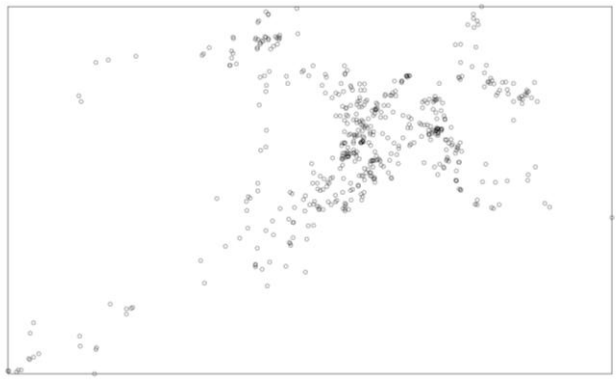

Figure 3 Plot of the Philippine Eagle Sightings data

The quadrat analysis was performed to evaluate the spatial distribution of Philippine Eagle sightings across the study area. By dividing the region into a grid of 25 quadrats, the number of sightings in each tile was tallied. The results revealed a pronounced clustering pattern with central quadrats exhibiting high densities—exceeding 100 sightings in some areas—while peripheral quadrats showed sparse or no sightings (Figure 4).

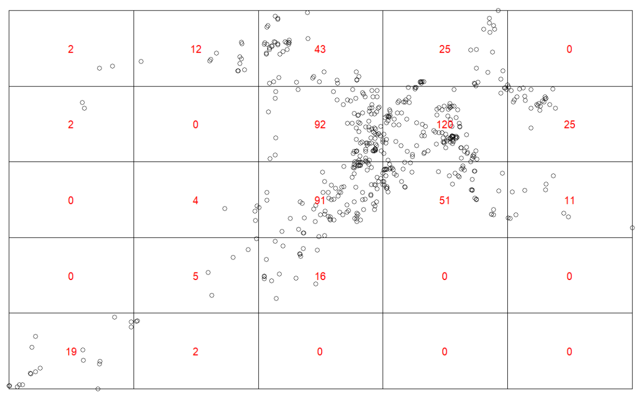

Figure 4 Quadrat Analysis

A Chi-squared goodness-of-fit test was conducted to assess whether the distribution deviates from complete spatial randomness (CSR). The test yielded a highly significant result ($X^2 = 1296.3$, df = 24, p-value < 2.2e-16), rejecting the null hypothesis of CSR. This confirms that the sightings are non-random and clustered, likely reflecting localized environmental influences. These findings set the stage for subsequent analyses to identify the drivers behind these patterns.

The Nearest Neighbor Analysis was conducted to further assess the spatial arrangement of Philippine Eagle sightings. The mean nearest neighbor distance (NND) among sightings was calculated to be 0.00096 degrees. This reflects the average proximity of individual points to their closest neighbor. Under the assumption of complete spatial randomness (CSR), the expected nearest neighbor distance was determined to be 0.00247 degrees based on the point density of the study area. Comparing these values, the Nearest Neighbor Index (NNI) was computed as 0.39, which is significantly less than 1. This indicates a high degree of clustering as sightings are much closer to each other than would be expected under random conditions. These results align with the quadrat analysis reinforcing the notion of spatial clustering in eagle sightings.

Ripley's K-function was employed to evaluate the spatial clustering of Philippine Eagle sightings at various scales. The K-function (black line) represents the observed spatial point pattern, while the theoretical K-function under complete spatial randomness (CSR) is indicated by the $K_{pois}(r)$ curve (blue dashed line). Deviations of the observed K-function above the CSR line suggest clustering at corresponding scales of r.

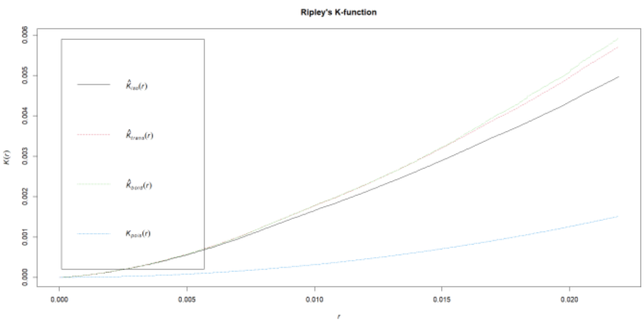

Figure 5 Ripley's K-function graph

As shown in Figure 5, the observed K-function consistently exceeds the CSR curve indicating significant clustering of sightings across all tested spatial scales. This suggests that the Philippine Eagle sightings are not randomly distributed but rather exhibit a pattern of aggregation. This analysis complements the findings from Quadrat and Nearest Neighbor analyses, reinforcing the conclusion of spatial clustering in the eagle presence data.

Kernel Density Estimation (KDE) was applied to analyze the spatial distribution of Philippine Eagle sightings, with the optimal bandwidth determined using the **Diggle bandwidth selector** (R Documentation, n.d.). This method balances detail and smoothness, ensuring a reliable representation of density variations. The 2D density surface, visualized in Figure 6, overlays individual sighting points with a gradient color scale where warmer colors (e.g., yellow) signify higher densities. The highest density regions appear centrally within the study area, indicating clusters of eagle activity.

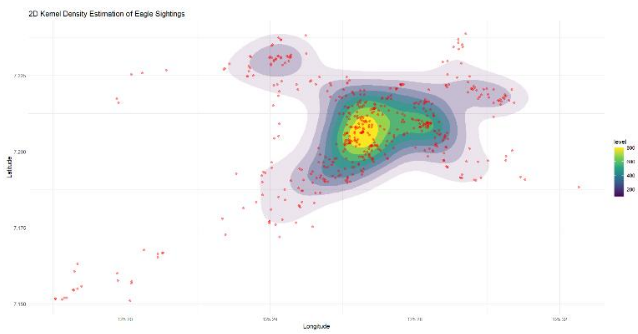

Figure 6 KDE plot of the Eagle Sightings data

The 1D density plots for latitude (Figure 7) and longitude (Figure 8) also provide a visual representation of the spatial distribution of Philippine Eagle sightings along individual spatial dimensions. The latitude density plot shows a concentration of sightings within the range of approximately **7.15°N to 7.23°N**, with a peak density around **7.20°N**, tapering off toward the northern and southern edges of the study area. Similarly, the longitude density plot highlights clustering within the range of **125.20°E to 125.32°E**, with the highest density observed around **125.26°E**. These plots complement the two-dimensional kernel density estimates by isolating variations along a single axis offering additional insights into the spatial patterns of the eagle sightings.

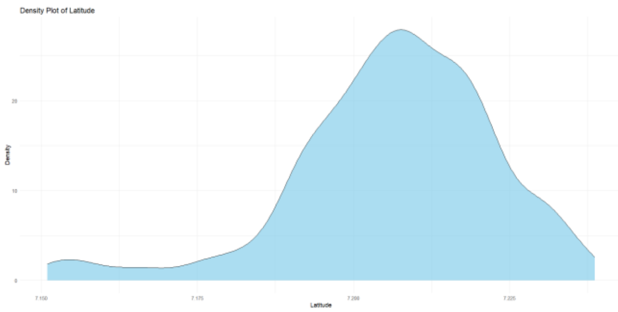

Figure 7 One-dimensional density plot for latitude

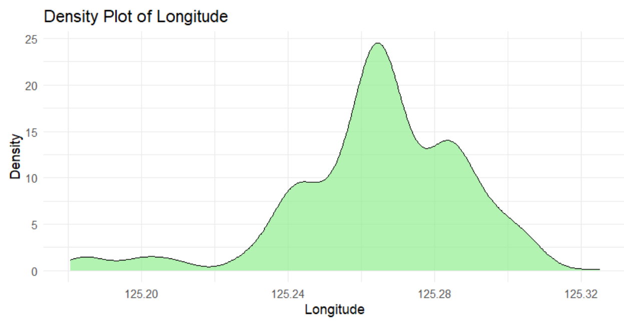

Figure 8 One-dimensional density plot for longitude

3.1.2 Spatial Distribution and Environmental Covariates

The spatial patterns of the environmental covariates provide a critical backdrop for understanding the ecological preferences of the Philippine Eagle.

Elevation shows a gradient ranging from lowlands (~600 meters) to highlands (~1,800 meters), highlighting the diverse terrain within the study area.

Proximity to Rivers indicates varying accessibility to water resources with areas closer to river networks characterized by lower values. These zones may represent potential corridors for eagle movement or hunting grounds.

Forest Cover, classified into three categories (Others, Forest, Rangeland), reveals the dominance of forested areas interspersed with patches of rangeland and non-forest zones. The visualization underscores the predominance of forests within the eagle's observed habitat, aligning with its known preference for dense forest cover. Together, these covariates form the ecological conditions against which eagle habitat suitability is analyzed.

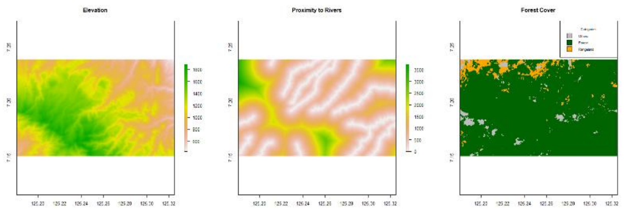

Figure 9 Environmental covariates: elevation (left), river proximity (middle), and land cover (right)

A bar plot illustrating the proportion of eagle sightings across different forest cover categories (Figure 10) reveals that the overwhelming majority of sightings (approximately over 90%) are located in forested areas. This finding underscores the species' strong reliance on forested habitats, consistent with their known ecological preference for mature, dense forests. Minimal sightings are observed in rangeland and other categories, which collectively constitute less than 3% of the total records. This distribution emphasizes the critical role of forests in supporting Philippine Eagle populations and highlights areas with sparse or no forest cover as unsuitable habitats.

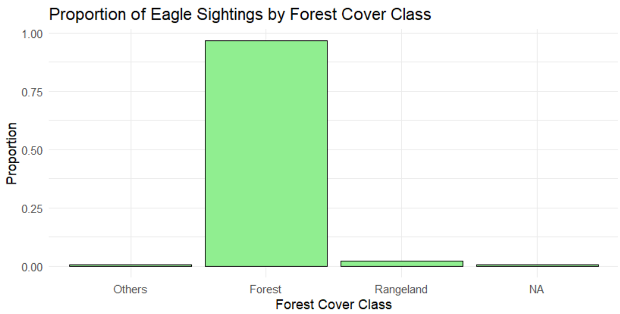

Figure 10 Proportion of eagle sightings per land cover type

The 2D density-scatter plot (Figure 11) explores the relationship between elevation and proximity to rivers by overlaying a density surface of eagle sightings. The density contours and color gradient reveal that eagle sightings predominantly occur at mid-range elevations between approximately 900 and 1200 meters above sea level and within 500 meters of rivers. The highest density (indicated by the yellow and green regions) suggests that these areas offer favorable conditions for the Philippine Eagle, possibly due to the availability of prey and forest cover near river systems. The density distribution further indicates a gradual decline in sightings as the proximity to rivers increases beyond 1000 meters while sightings remain sparse at elevations higher than 1500 meters.

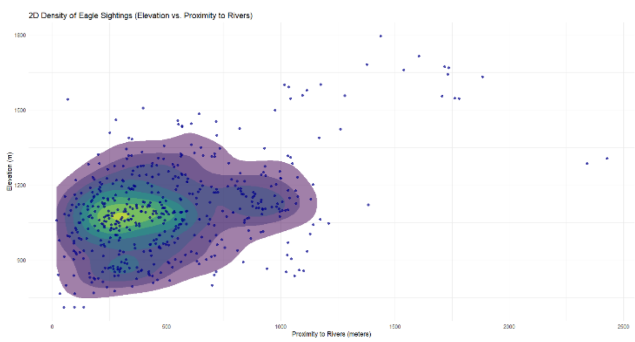

Figure 11 Scatter plot of Eeevation and river proximity for Eagle Sightings with 2D density

This KDE plot provides critical insights into potential core habitats, highlighting areas of conservation priority. The integration of density surfaces with occurrence points enhances understanding of spatial patterns and allows stakeholders to pinpoint high-density regions for targeted conservation strategies. By combining robust statistical methods with visualization, KDE offers a comprehensive tool for ecological analysis.

This pattern underscores the ecological importance of riparian zones and mid-elevation forests for the Philippine Eagle. This highlights the species' known preference for habitats that offer a mix of forest cover and access to water. Such insights are crucial for conservation planning as they emphasize the need to preserve riparian and mid-elevation habitats within the eagle's range.

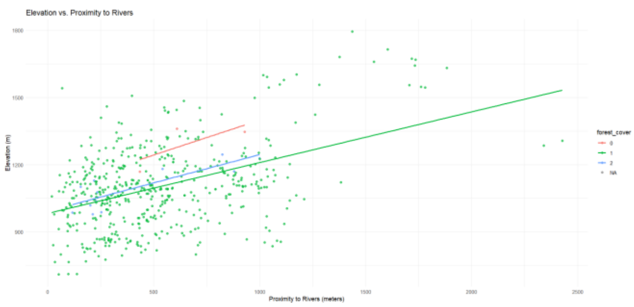

Figure 12 Scatterplot of elevation and proximity to rivers by land cover type

The scatterplot with trend lines in Figure 12 demonstrates the relationship between elevation and proximity to rivers differentiated by land cover classes. Among the categories, the **Forest** class (1) exhibits the longest trend line, attributable to the larger number of eagle sightings in forested areas. In contrast, the shorter trend lines for **Others** (0) and **Rangeland** (2) reflect fewer data points within these classes limiting their spatial representation.

Across forest cover (1) and rangeland (2) classes, a positive relationship is evident between elevation and proximity to rivers. The steeper trend for the **Forest** category suggests a stronger preference of the Philippine Eagle for higher elevations further from rivers when located in forested areas. This highlights the ecological importance of forested habitats at elevated terrain for the species.

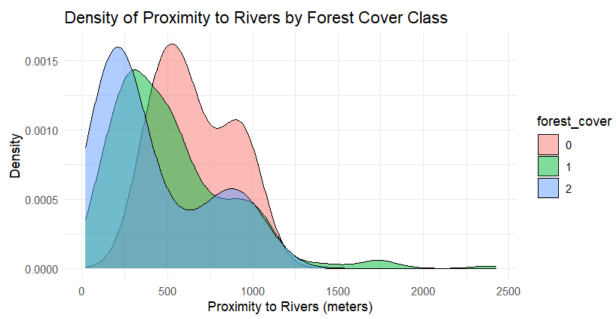

Figure 13 Density of proximity to rivers for eagle sightings by land cover type

The density plot (Figure 13) illustrates the variation in proximity to rivers across forest cover classes. The **Forest class (1)** exhibits a broader distribution with a peak density near 500 meters suggesting that eagle sightings are more common within intermediate distances from rivers in forested areas. In contrast, the **Others (0)** and **Rangeland (2)** classes show density peaks also closer to rivers indicating that sightings in these areas are generally closer to riverbanks. However, it is important to note that the "Others" and "Rangeland" classes combined account for only about 5% of the total data points, which may influence the apparent density patterns and their interpretability

The boxplot of proximity to rivers by forest cover class reveals distinct variations across categories (Figure 14). The "Forest" class exhibits the widest range of proximities spanning from nearly 0 meters to over 2,000 meters with a median around 500 meters. This indicates the flexibility of eagles in utilizing forested habitats regardless of proximity to rivers. In contrast, "Rangeland" and "Others" show narrower ranges and lower medians, suggesting these habitats are less frequently used and are located farther from rivers on average.

This pattern underscores the role of rivers in shaping eagle habitat use within forests while limiting their utilization in other land cover types (Brown, Stevens, & Yates, 1998). The inclusion of outliers in "Forest" highlights eagles' occasional use of forest patches that are more distant from water sources, possibly due to resource availability or territorial behavior.

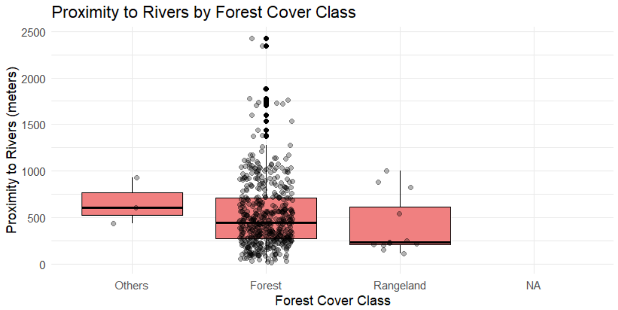

Figure 14 Proximity to rivers for different land cover classes

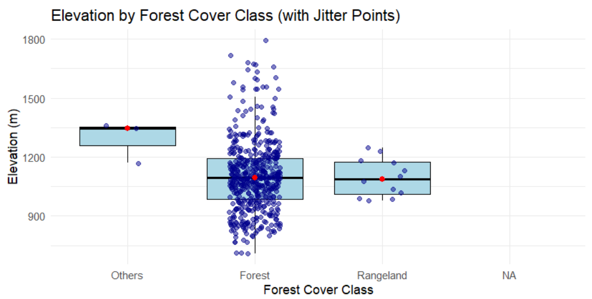

Figure 15 Elevation distribution across land cover classes

The boxplot for elevation across forest cover classes reveals that eagle sightings within the "Forest" class span a broad range of elevations, with the median elevation around 1,200 meters (Figure 15). In contrast, the "Others" category, though less frequent, is predominantly associated with higher elevations, clustering above 1,200 meters with a narrower distribution. This suggests that non-forested habitats classified as "Others" may represent specific high-altitude areas where eagles occasionally occur.

The "Rangeland" class exhibits a similar pattern to "Forest," albeit with a narrower range and fewer sightings. These findings highlight the predominant association of eagle sightings with forested habitats while occasional use of high-altitude "Others" areas could reflect unique ecological conditions or landscape features suitable for eagles. The results underscore the importance of considering elevation as a factor influencing habitat preferences across different land cover types.

3.1.3 Exploring Spatial Variability Using Geographically Weighted Regression (GWR)

To prepare the dataset for Geographically Weighted Regression (GWR), 500 random pseudo-absence points were generated within a bounding box encompassing the Philippine Eagle sightings, complementing the 520 presence points. Covariate values—elevation, proximity to rivers, and forest cover—were extracted for both presence and pseudo-absence points. Missing values were imputed using the mean for continuous variables (elevation and proximity to rivers) and the mode for categorical variables (forest cover). The final dataset (n = 1,020) spanned elevations from 537 m to 1,820 m (mean: 1,150.4 m) and proximity to rivers from 2.007 m to 3,457.078 m (mean: 681.216 m). The "forest" category dominated the forest cover variable with 963 points (94.4%) while "others" and "rangeland" accounted for 18 (1.8%) and 39 (3.8%) points, respectively. This dataset provided a robust basis for exploring spatially varying relationships in the GWR analysis.

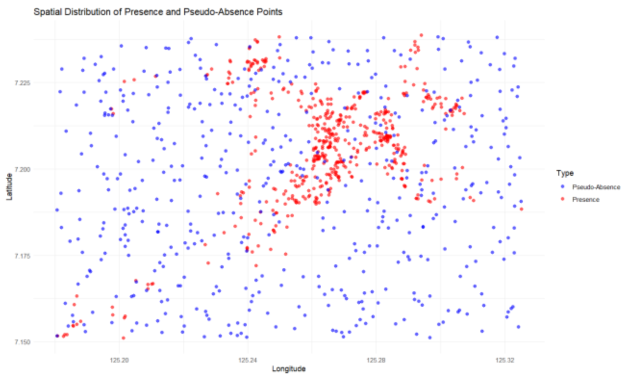

Figure 16 Spatial distribution of presence and pseudo-absence points

Figure 16 illustrates the spatial distribution of presence (red) and generated pseudo-absence (blue) points across the study area. The presence points, representing known Philippine Eagle sightings, are significantly clustered particularly in the central and northern regions, consistent with the species' preference for forested areas. In contrast, the pseudo-absence points are uniformly distributed across the landscape ensuring adequate representation of potential habitat absence regions and providing a balanced dataset for spatial analysis. This spatial separation highlights the importance of carefully sampling pseudo-absence data to capture landscape variability while avoiding over-representation of dominant land cover types, such as forest, thereby enhancing the robustness of subsequent GWR and MaxEnt analyses.

The GWR model was implemented to examine the spatially varying relationships between eagle presence and environmental covariates with an adaptive bandwidth approach ensuring localized variations were effectively captured. The optimal adaptive bandwidth, approximately **0.0308**, minimized the cross-validation score to **139.80** incorporating 1,020 spatial observations. This approach allowed the model to account for spatial heterogeneity in the influence of elevation, proximity to rivers, and forest cover, providing localized insights into the environmental factors shaping eagle presence.

The spatial variation in the elevation coefficient (Figure 17) highlights the localized influence of elevation on the presence of Philippine Eagles. Positive coefficients, predominantly observed in the northeastern part of the study area, indicate that higher elevations are positively associated with eagle presence. This aligns with the ecological understanding that Philippine Eagles prefer higher altitudes likely due to cooler temperatures and reduced human disturbances. Conversely, negative coefficients, observed in some areas to the south, suggest that lower elevations in these regions may also support eagle presence possibly due to other favorable conditions such as proximity to forested areas, reduced competition, or availability of prey.

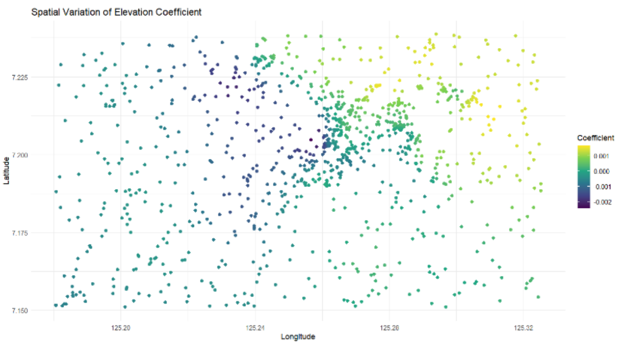

Figure 17 Spatial variation of the elevation coefficient across the study area

The gradient in the coefficients reflects the spatial heterogeneity in habitat preferences. This emphasizes that elevation alone cannot fully explain eagle distribution. The interplay between elevation and other covariates, such as forest cover or proximity to rivers, may contribute to these localized patterns. This spatial variability underscores the importance of considering multiple environmental factors when assessing habitat suitability for conservation planning.

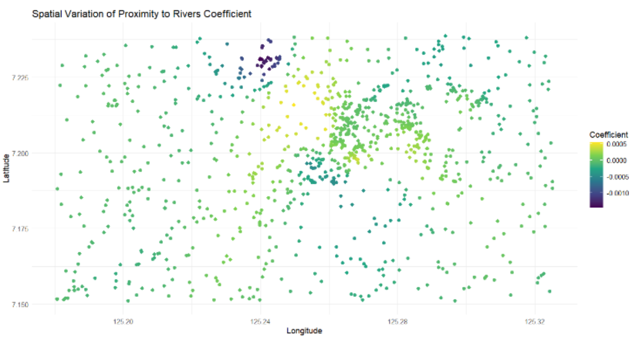

Figure 18 Spatial variation of the river proximity coefficient across the study area

The spatial variation in the coefficient for proximity to rivers (Figure 18) underscores the localized role of water sources in influencing Philippine Eagle presence. Positive coefficients in the central and southeastern regions suggest that these areas benefit from proximity to rivers, likely due to the availability of prey species and dense vegetation near water sources. Conversely, negative coefficients in the northeastern parts imply that eagles may also thrive farther from rivers, potentially due to the presence of other factors like forest cover or suitable nesting sites. This spatial heterogeneity reflects the adaptability of the eagles to varying environmental conditions while reinforcing the importance of water sources in certain areas for their habitat suitability.

The spatial variations in the coefficients for land cover categories (Forest vs. Others and Rangeland vs. Others) (Figures 19 and 20) underscore the critical role of forested habitats in influencing Philippine Eagle presence. For the Forest vs. Others comparison, positive coefficients dominate the study area particularly in the central and southern regions. This highlights the strong association between eagle sightings and forested habitats. These findings are consistent with the eagle's dependency on dense forest canopies for nesting and hunting. In contrast, the Rangeland vs. Others coefficients reveal predominantly negative values in the northern and central regions, suggesting that rangelands are generally less suitable for eagle presence. However, localized positive coefficients in the southern parts suggest occasional utilization of rangeland areas potentially due to their proximity to forest edges or the availability of prey. Together, these results emphasize the importance of maintaining extensive forest cover while addressing habitat fragmentation, ensuring that rangelands near forests provide transitional habitats that can support eagle movement and survival in fragmented landscapes.

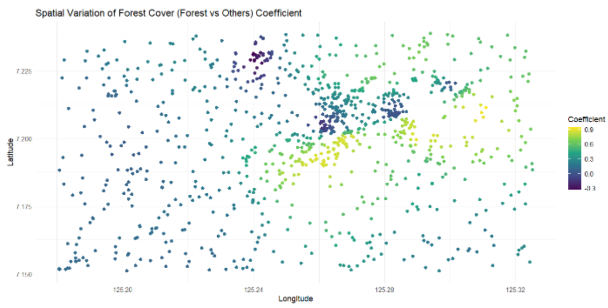

Figure 19 Spatial variation of the land cover coefficient (Forest vs. Others) across the study area

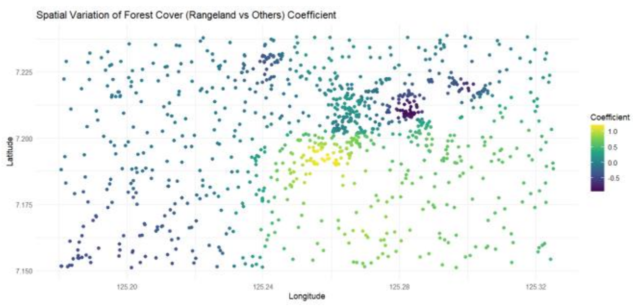

Figure 20 Spatial variation of the land cover coefficient (Rangeland vs. Others) across the study area

The spatial distribution of local R-squared (R^2) values (Figure 21) illustrates the variability in the explanatory power of the Geographically Weighted Regression (GWR) model across the study area. Local R^2 values range from 0.01 to 0.53 reflecting how well the model explains the variability in eagle presence at different locations. The mean local R^2 is approximately 0.25 with most values clustering between 0.13 and 0.34 (interquartile range). This indicates that, on average, the selected environmental covariates (elevation, proximity to rivers, and forest cover) moderately explain eagle presence.

Areas with higher local R^2 values, represented by green and yellow colors (closer to 0.5), are scattered across the western and southern parts of the study area. These regions suggest that eagle presence is more strongly influenced by the selected environmental predictors in those locations. Conversely, lower local R^2 values, shown by purple colors, dominate the central and western-most parts of the study area. This suggests that additional, unmeasured factors may play a more significant role in influencing eagle presence in these areas.

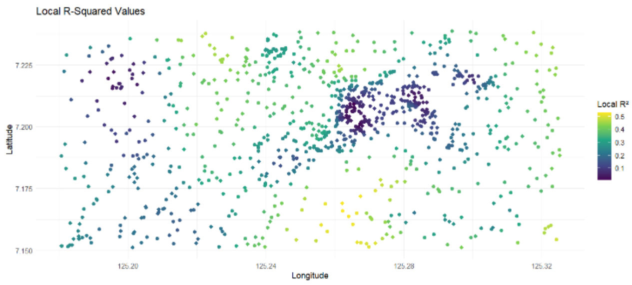

Figure 21 Spatial distribution of local R-squared (R²) values across the study area

The relatively low mean local R² value of 0.25 highlights the limitations of the selected covariates in fully capturing the complexity of eagle habitat preferences. Future studies may benefit from exploring additional predictors, such as prey availability, anthropogenic disturbance, or vegetation structure, to improve model accuracy. Despite these limitations, the spatial heterogeneity in local R² values underscores the utility of GWR in identifying where specific covariates are more or less effective in explaining species distributions, providing insights for targeted conservation strategies.

3.1.4 Predicting Habitat Suitability Using MaxEnt

To optimize computational efficiency and align with the ecological scale of the analysis, raster layers (elevation, proximity to rivers, and forest cover) were downsampled to approximately 30m resolution using an aggregation factor of 3. Mean values were used for continuous variables, while the modal value was applied for categorical data. The final raster stack had dimensions of 323 × 533 and covered the full extent of the study area. This step ensured that the analysis was both computationally manageable and ecologically relevant.

To ensure that presence points aligned with the raster extent of the environmental covariates, points falling outside the raster bounds were excluded, leaving 519 valid presence points. The presence data was then split into training (70%) and testing (30%) subsets, comprising 363 and 156 points, respectively. This step ensured that the model was trained and validated on spatially consistent and representative data enhancing the reliability of predictions.

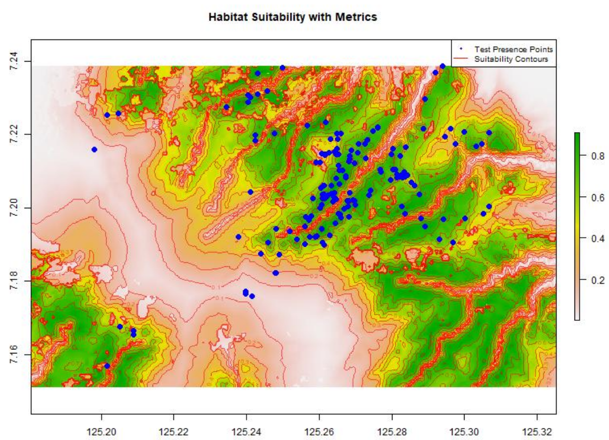

Figure 22 Predicted philippine eagle habitat suitability map

The habitat suitability map (Figure 22) provides a spatially explicit prediction of Philippine Eagle habitats, highlighting areas with high suitability closely aligned with known presence points. Test presence points showed a mean suitability value of 0.673, suggesting that the model captures key environmental variables associated with suitable habitats. The map also demonstrates the spatial heterogeneity of suitability with high-suitability areas primarily concentrated in regions characterized by specific environmental conditions. Contours overlaid on the suitability map provide further clarity showcasing the gradation of habitat suitability across the landscape. These patterns indicate the robustness of the model in delineating areas of ecological importance for the species.

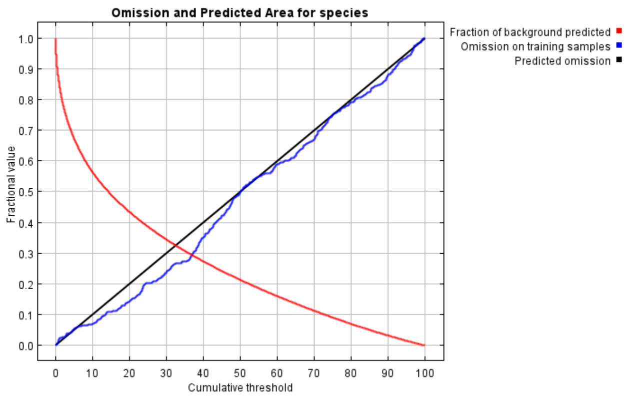

Figure 23 MaxEnt omission plot

The evaluation metrics substantiate the model's performance. The omission plot (Figure 23) illustrates a close alignment between predicted and observed omissions which affirms the model's reliability. The Receiver Operating Characteristic (ROC) curve (Figure 24) demonstrates a strong discriminative ability, with an Area Under the Curve (AUC) of 0.759, which exceeds the benchmark for acceptable performance. This AUC value highlights the model's capacity to effectively distinguish between suitable and unsuitable habitats based on environmental predictors. Further, the threshold-based predictions revealed high sensitivity (0.891) indicating the model's strong ability to identify true positives. Meanwhile, specificity (0.51) showed moderate performance in avoiding false positives.

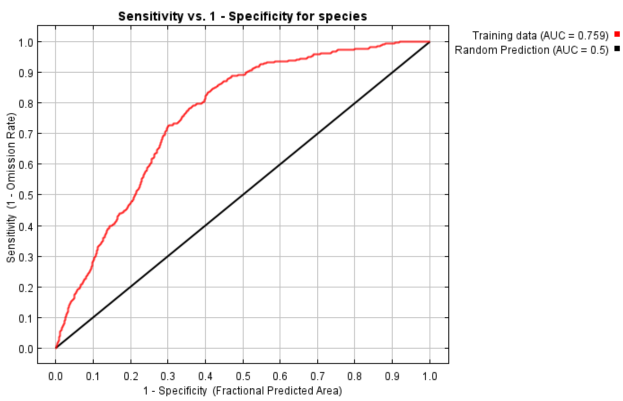

Figure 24 MaxEnt ROC curve

Other key metrics such as the True Skill Statistic (TSS = 0.401) and overall accuracy (56.14%) reflect a balance between predictive reliability and variability in environmental conditions across the study area. However, the precision score (0.221) underscores some limitations potentially arising from overlap in environmental characteristics between suitable and unsuitable habitats. These metrics collectively provide valuable insights into the model's predictive ability with the relatively high sensitivity and AUC values underscoring its effectiveness in habitat suitability assessment. The results validate the MaxEnt model as a powerful tool for habitat prediction, with potential applications in conservation planning and species management.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

The findings of this study highlight critical environmental characteristics that influence the habitat suitability of the critically endangered Philippine Eagle. The species exhibits a strong preference for **mid-elevation forests (900–1,200 meters)**, which provide optimal conditions for nesting and hunting. Additionally, proximity to rivers—typically within **500 meters**—emerges as a significant factor, likely due to the availability of prey and water resources. Forested habitats are overwhelmingly associated with eagle presence, accounting for approximately **97% of sightings**, underscoring the eagle's dependency on dense canopies for survival.

Spatial analyses revealed significant clustering of eagle sightings, particularly in central regions with overlapping favorable environmental conditions, such as abundant forest cover, proximity to rivers, and suitable elevations. The integration of spatial statistical methods, such as Geographically Weighted Regression (GWR) and MaxEnt modeling, provided localized and generalizable insights into habitat suitability, with results confirming the importance of preserving riparian zones and mid-elevation forests. However, areas of low model performance suggest additional unmeasured factors, such as prey availability or human disturbance, may also influence eagle distribution.

This study affirms the ecological importance of forested areas and highlights the Philippine Eagle's adaptability to varying environmental conditions within its primary habitat. Conservation efforts should prioritize protecting these core habitats while addressing the threats of deforestation and habitat fragmentation.

4.2 Recommendations

To enhance the research on Philippine Eagle habitat suitability, several methodological improvements are recommended. First, future studies should incorporate additional environmental variables beyond elevation, river proximity, and forest cover. Factors such as prey availability, human disturbance, and climate conditions could provide a more comprehensive understanding of the eagle's habitat preferences. Advanced modeling techniques such as ensemble species distribution models could also be utilized to compare and validate habitat predictions. High-resolution satellite imagery and LiDAR data should be employed to capture fine-scale habitat characteristics while long-term monitoring programs are essential to validate model predictions over time. Moreover, areas with low model performance should be investigated further to identify unmeasured factors influencing habitat suitability. Collaborating with ecologists, local conservationists, and other stakeholders could provide valuable insights to improve data collection and analytical approaches.

In addition to improving the research framework, specific conservation actions are necessary to protect the critically endangered Philippine Eagle. The conservation of **mid-elevation forests (900–1,200 meters) near riparian zones** should be prioritized as these habitats provide essential nesting and hunting grounds. Efforts to reduce deforestation and restore degraded habitats must be intensified with a focus on maintaining forest connectivity to support eagle movement and breeding. Riparian zones should be safeguarded by establishing buffer zones to minimize habitat degradation and ensure the availability of prey and water resources. Expanding conservation zones to include **transitional habitats**, such as rangelands near forest edges, can further support eagle populations by serving as secondary habitats and movement corridors.

Community engagement and policy support play a critical role in ensuring the success of conservation efforts. Local communities should be involved in promoting sustainable land-use practices that prioritize eagle habitats while ecotourism initiatives can provide economic benefits and raise awareness of conservation needs. Additionally, existing legal frameworks protecting eagle habitats must be updated and spatially explicit habitat maps should be integrated into land-use planning to ensure informed decision-making. Advanced conservation strategies should leverage real-time monitoring tools, such as machine learning and satellite-based habitat assessments, to adaptively manage conservation efforts in response to emerging threats.

By improving this research methodology and implementing targeted conservation actions, the long-term survival of the Philippine Eagle can be secured, contributing to the preservation of the Philippines' rich biodiversity and ecological heritage

ACKNOWLEDGMENT

The author of this paper thanks Professor Francisco N. de los Reyes of the University of the Philippines (UP) Diliman's School of Statistics, also the Director of the UP Office of Admissions, for providing the author with valuable insights during his lectures in spatial statistics.

GITHUB REPOSITORY

You may view the Github repository of this project here. The repository contains the working scripts used for the analysis, the output graphs, and the documents produced in this work. The datasets, however, are not included in the repository. Please look at Section 2.2 for the information about the datasets used in the study or contact the author if you plan to replicate this work.

REFERENCES

Baldwin, R. (2009). Use of Maximum Entropy Modeling in Wildlife Research. *Entropy*, 11, 854-866. https://doi.org/10.3390/e11040854.

Brown, B., Stevens, L., & Yates, T. (1998). Influences of fluctuating river flows on Bald Eagle foraging behavior. *The Condor, 100*(4), 745–748. https://doi.org/10.2307/1369759

Esri. (n.d.). Land Use/Land Cover (LULC) [Dataset]. Retrieved from https://www.arcgis.com/home/item.html?id=cfcb7609de5f478eb7666240902d4d3d

GBIF.org (30 December 2024) GBIF Occurrence Download [Dataset]. Retrieved from https://doi.org/10.15468/dl.793caq

Ibañez, J., Sumaya, A., Tampos, G., & Salvador, D. (2016). Preventing Philippine Eagle hunting: what are we missing?. *Journal of Threatened Taxa*, 8, 9505-9511. https://doi.org/10.11609/JOTT.2301.8.13.9505-9511.

Iturbide, M., Bedia, J., Herrera, S., Hierro, O., Pinto, M., & Gutiérrez, J. M. (2015). A framework for species distribution modelling with improved pseudo-absence generation. *Ecological Modelling, 312*, 166–174. https://doi.org/10.1016/j.ecolmodel.2015.05.018

Lewis, R. (1986). A rain-forest raptor in danger. *Oryx*, *20*(3), 170–175. https://doi.org/10.1017/S0030605300020032

Luczon, A., Fontanilla, I., Ong, P., Basiao, Z., Sumaya, A., & Quilang, J. (2014). Genetic diversity of the Critically Endangered Philippine Eagle Pithecophaga jefferyi (Aves: Accipitridae) and notes on its conservation. *Journal of Threatened Taxa*, 6, 6335-6344. https://doi.org/10.11609/JOTT.O3748.6335-44.

Páez, A., Farber, S., & Wheeler, D. (2011). A Simulation-Based Study of Geographically Weighted Regression as a Method for Investigating Spatially Varying Relationships. *Environment and Planning A*, 43, 2992 - 3010. https://doi.org/10.1068/a44111.

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, *190*(3–4), 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026

R Documentation. (n.d.). *bw.diggle function*. Retrieved January 5, 2025, from https://rdrr.io/cran/spatstat.core/man/bw.diggle.html

Zarnetske, P., Edwards, T., & Moisen, G. (2007). Habitat classification modeling with incomplete data: pushing the habitat envelope. *Ecological applications: a publication of the Ecological Society of America*, 17 6, 1714-26. https://doi.org/10.1890/06-1312.1.