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

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ABSTRACT:

Philippines is one of the countries classified with severe vulnerability to climate change. Some of the Philippines' deadliest and most destructive typhoons happened just very recently. This study focuses on Typhoon Ulysses, a destructive category-4 typhoon that hit the Philippines on November 11, 2020. This study explores the use of Sentinel-1 SAR data and Google Earth Engine to perform rapid flood mapping and damage assessment in the Cagayan River basin. A change detection approach was employed to delineate flood extent which was then subsequently used to extract statistics on exposed population, affected croplands, and affected urban areas within the study area. The results showed that the total area of the flood extent in the Cagayan River basin on November 16, 2020 was 71,455 hectares. Meanwhile, 75,418 hectares of cropland were affected within the basin and the estimated urban area affected was 5,642 hectares. Approximately 61,730 people were also exposed to flooding. In summary, Cagayan and Isabela are the two most affected provinces within the Cagayan River basin. It was apparent that croplands/agricultural areas were affected more severely than urban areas.

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, the urgency to protect this species has never been greater.

The habitats of the Philippine Eagle are predominantly in forested areas across Luzon, Samar, Leyte, and Mindanao. 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, reducing 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. 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 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. By applying the principle of

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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.
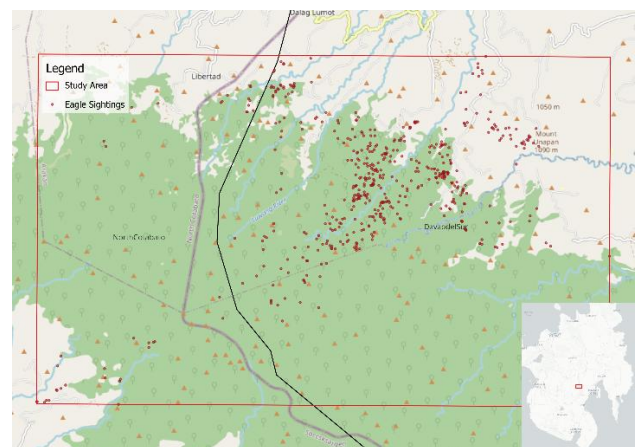

Figure 1 Vicinity Map of the Study Area.

The study focuses on identifying the patterns of environmental factors influencing eagle sightings within this ecologically significant environment.

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), which 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, 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=cfcb7609de5f478e b7666240902d4d3d). 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).

2.5 Analytical Framework

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

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2.5.1 Point Pattern Analysis

The spatial distribution of Philippine Eagle sightings was first analyzed using point pattern analysis to detect clustering, randomness, or dispersion.

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:

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

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.

Kernel Density Estimation (KDE): KDE was performed using the *density.ppp* function to create a continuous density surface of sightings, with a smoothing bandwidth (σ) set to 0.002. Diggle's method (*bw.diggle*) was also tested for optimal bandwidth selection. This ensured that the density estimates were neither over-smoothed nor overly fragmented. One-dimensional (1D) density plots for latitude and longitude were also generated using *geom_density()*, providing additional insights into linear spatial patterns. The KDE maps were visualized to highlight hotspots of eagle activity including density contours and a color gradient.

2.5.2 Geographically Weighted Regression (GWR) Analysis

Geographically Weighted Regression (GWR) was applied to investigate the spatially varying relationships between Philippine Eagle sightings and environmental covariates, providing spatially explicit insights into habitat suitability.

The preparation of data began with the extraction of covariate values from raster layers. 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, while 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 model 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 GWR model was then fitted using the *gwr()* function, with the presence of eagle sightings as the response variable and elevation, proximity to rivers, and forest cover as predictors. The model was executed adaptively to account for non-uniform spatial distributions within the study area.

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 the study area. Additionally,

local values were extracted and mapped to evaluate the explanatory power of the model in different regions

Visualization played a crucial role in interpreting the results. Separate maps were generated to show spatial variations in the coefficients for elevation, proximity to rivers, and forest cover categories (forest vs. others, rangeland vs. others). These maps used the *viridis* color palette for clarity and interpretability. A local map highlighted areas where the predictors most effectively explained the distribution of eagle sightings. Furthermore, a scatterplot was created to display the spatial distribution of presence and pseudo-absence points, ensuring the comprehensiveness of the study's coverage of the landscape

The GWR analysis revealed spatially varying insights into the role of environmental covariates in explaining eagle presence. Coefficient maps indicated localized effects of elevation and proximity to rivers, while forest cover categories exhibited variable influence across the study area. The local map identified regions where the predictors were most influential, offering valuable insights for targeted habitat conservation strategies.

2.5.3 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.

The environmental covariates used in the MaxEnt model included elevation, proximity to rivers, and forest cover. 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, ensuring 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, with random sampling ensuring reproducibility 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*) for reproducibility. The output configuration was set to *raw* format, allowing 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.

Model performance was evaluated using two key metrics. The first was the Area Under the Curve (AUC), extracted directly from the MaxEnt results, which measured the model's ability to distinguish between suitable and unsuitable habitats. The second was the mean suitability of test presence points, calculated by extracting predicted suitability values using the *extract()* function and averaging them. These metrics were saved as a CSV file (*maxent_model_evaluation.csv*) for documentation.

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.

3. RESULTS AND DISCUSSION

3.1 Results

The primary output of this study is a map shown in GEE map canvas with key statistics resulting from the geospatial analysis performed above (see Figure 4).

Habitat Suitability with Contours and Points
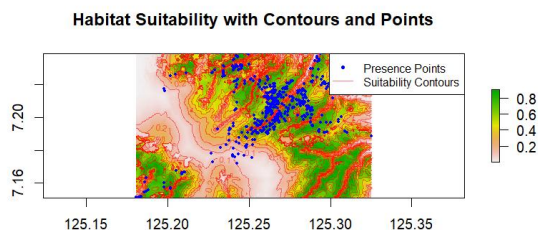
3.2 Discussion

It is important to note the specific advantages and disadvantages of using SAR, GEE, and this rapid flood mapping and damage assessment approach. By understanding the pros and cons, we can continue to leverage its strengths and continuously work to address its limitations to further improve our results.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

This study has successfully demonstrated rapid flood mapping and damage assessment in the Cagayan River basin using Sentinel-1 SAR data and GEE. Satellite-derived flood maps were produced, and meaningful statistics were also extracted for the damage assessment.

4.2 Recommendations

While this study has successfully shown that rapid flood mapping and damage assessment can be done using Sentinel-1 SAR data

and the cloud geospatial computing platform, GEE, there is still a lot of room for potential improvements.

REFERENCES

Brusola, K. S., Castro, M., Suarez, J., David, D., Ramacula, C. J., Capdos, M., Viado, L., Dorado, M., & Ballaran, V. Jr. (2023). Flood mapping and assessment during Typhoon Ulysses (Vamco) in Cagayan, Philippines using synthetic aperture radar images. https://doi.org/10.1007/978-3-031-24506-0_4

Curlander, J. C., & McDonough, R. N. (1991). *Synthetic Aperture Radar: Systems and Signal Processing*. Wiley.

Del Rosario, E. D. (2011, August 9). *Final Report on Typhoon "Yolanda" (Haiyan)*. Philippine National Disaster Risk Reduction and Management Council. pp. 77–148. Archived from the original PDF on November 5, 2020. Retrieved June 16, 2024

Del Rosario, E. D. (2014, April). *Effects of Typhoon Yolanda (Haiyan)*. National Disaster Risk Reduction and Management Council (NDRRMC). Retrieved June 16, 2024

Department of Environment and Natural Resources (DENR). (Year). *Climate-Responsive Integrated Master Plan for Cagayan River Basin*. Retrieved from https://rbco.denr.gov.ph/masterplans/cagayanexecutivesummary.pdf

Department of Social Welfare and Development - Disaster Response Operations Monitoring and Information Center (DSWD-DROMIC). (2021, April 19). Terminal Report on Typhoon Ulysses. Retrieved from https://dromic.dswd.gov.ph/typhoon-ulysses-08-nov-2020/

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18-27.

Henderson, F M, & Lewis, A J. (1998) *Principles and applications of imaging radar. Manual of remote sensing: Third edition, Volume 2*. United States.

Lillesand, T. M., Kiefer, R. W., & Chipman, J. W. (2015). *Remote Sensing and Image Interpretation* (7th ed.). Wiley

Mata, C.B., Balderama, O.F., Alejo, L.A., Bareng, JL.R., Kantoush, S.A. (2022). Satellite-based flood inundation and damage assessment. J Robot Auto Res, 3(2), 209-219.

National Geographic Society. (2019). National Geographic Atlas of the World (11th ed.). National Geographic.

Pandey, A.C., Kaushik, K., & Parida, B.R. (2022). Google Earth Engine for Large-Scale Flood Mapping Using SAR Data and Impact Assessment on Agriculture and Population of the Ganga-Brahmaputra Basin. *Sustainability*, 14(4), 4210. https://doi.org/10.3390/su14074210

Patel, K. (2020, November 12). Vamco thrashes the Philippines. *NASA Earth Observatory*. Retrieved from https://earthobservatory.nasa.gov/images/147525/vamco-thrashes-the-philippines

Sapigao, H. L. (2023, December 15). More intense typhoons to come this century, UP study warns. *University of the Philippines – Diliman College of Science's Institute of Environmental Science and Meteorology (UPD-CS IESM)*. Retrieved from https://science.upd.edu.ph/more-intense-typhoons-to-come-this-century-up-study-warns

Tumaneng, R. D., Morico, K. E. R., & Principe, J. A. (2024). Remote sensing and Google Earth Engine for rapid flood mapping and damage assessment: A case of Typhoon Goni (Rolly) and Vamco (Ulysses). *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-4/W8-2023, 445–452. https://doi.org/10.5194/isprs-archives-XLVIII-4-W8-2023-445-2024

United Nations. (n.d.). What is climate change? Retrieved June 16, 2024, from https://www.un.org/en/climatechange/what-is-climate-change.

United Nations Environment Programme. (n.d.). Facts about climate emergency. Retrieved June 16, 2024, from https://www.unep.org/facts-about-climate-emergency?gad_source=1&gclid=CjwKCAjwmrqzBhAoEiwAXVpgorP0HL4crXufXCklaIf6no1hxkODpBBGzw9iZjXOcpAorLrbMD4ejBoC3oYQAvD_BwE.

United Nations Office for Outer Space Affairs (UNOOSA). (2019). Recommended Practice: Google Earth Engine Flood Mapping. Retrieved from https://www.un-spider.org/advisory-support/recommended-practices/recommended-practice-google-earth-engine-flood-mapping/step-by-step