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GIS-Based Landslide Susceptibility Assessment of the Upper Marikina River Basin Protected Landscape, Rizal Province, Philippines, using Analytic Hierarchy Process

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Abstract

The Upper Marikina River Basin Protected Landscape (UMRBPL) suffers significant consequences from landslides, including fatalities, property damage, and environmental degradation. This study was conducted to assess the landslide susceptibility of UMRBPL using Analytic Hierarchy Process (AHP). The analysis identified that slope had the highest contribution to landslide with 28.04%, followed by land use and land cover (20.50%), average annual rainfall (20.08%), soil morphology (8.46%), typhoon frequency (8.08%), distance to lineament (7.74%), and soil geology (7.10%). Based on the landslide susceptibility, 1.80% with very high susceptibility, 46.39% of the area were classified as highly susceptible, 38.05% with moderately susceptible, 12.76% with low susceptibility, and only 1.00% with very low susceptibility. Validation of the susceptibility assessment through Area Under the Curve (AUC) analysis yielded a score of 0.87. Insights from AHP can facilitate informed decision-making for implementing mitigation strategies, such as slope stabilization and land use regulations. This study emphasizes the urgent need for proactive measures to safeguard vulnerable landscapes like UMRBPL from the devastating impacts of landslides.

INTRODUCTION

A river basin is commonly defined as the area of land drained by a river and its tributaries (Teclaff, 2012). The River Basin Coordinating Office of the Department of Environment and Natural Resources (2014) identified 20 major river basins spread all over the Philippines, recognized for their significant role in driving local and regional economies both inside and outside the basins and this includes the Upper Marikina River Basin Protected Landscape (UMRBPL).

The UMRBPL is critical for managing water flow to the National Capital Region (Santos, 2023), helping to prevent flooding from heavy rains and typhoons (Bungabong et al., 2023). The area includes urban and forested landscapes with compromised ecological functions, varied terrain, and is prone to rainfall-induced landslides, gullies, and flash floods that endanger local communities (Almarines and Lapitan, 2014). Approximately half of UMRBPL's land has been degraded by human activities, such as shifting agriculture, small-scale mining, timber-cutting, and poaching, necessitating urgent restoration (Palomar, 2015). Forest degradation and extractive industries, like mining and quarrying, have also increased sediment yield in the region (Castañeda and Racelis, 2023).

Over the last decades, catastrophic landslides have occurred, causing significant damage and impacting numerous areas which include the devastating landslide in Cherry Hills Subdivision in Antipolo City in 1999, and subsequent landslides in the municipalities of San Mateo in 2004, Taytay in 2017, and Rodriguez in 2018 (PAGASA, 2000). These events have led to irreplaceable damage to properties (Bagtasa, 2021), as well as disruption of infrastructures and displacement of communities (Ballano et al., 2017), and caused multiple fatalities, endangering the lives of many individuals, including children.

To mitigate landslide hazards, landslide susceptibility assessment is essential, as it provides understanding into the likelihood of landslides occurring in a specific area (Ercanoglu and Gokceoglu,

2004; Pourghasemi and Rahmati, 2018). Utilizing the Analytic Hierarchy Process (AHP) method that focuses on multi-criteria analysis offers a comprehensive approach, widely applicable across various industries and disciplines (Saaty, 1990; Sipahi and Timor, 2010). The UMRBPL landslide susceptibility assessment can serve as a crucial tool for land use planning, aiding in the avoidance of landslide-prone areas during development (Abino et al., 2015). It facilitates infrastructure planning in safe zones, enhances emergency response strategies, and raises public awareness about landslide risks, encouraging proactive measures to mitigate hazards. Thus, this study was conducted to assess the landslide susceptibility of the UMRBPL. Specifically, the study developed the relative weights of thematic factors using the Analytic Hierarchy Process (AHP) and validated the prediction accuracy of the overall landslide susceptibility

MATERIALS AND METHODS

Study Site

The study was conducted in Upper Marikina River Basin Protected Landscape (UMRBPL) which is a protected landscape within the Philippines in the Province of Rizal, overlapping the City of Antipolo, and the Municipalities of Baras, Rodriguez, San Mateo (Fig. 1). UMRBPL, with a total land area of 26,127.30 ha, was established through Presidential Proclamation (PP) no. 296 in 2011 and plays an important role in regulating the flow of water towards the highly urbanized National Capital Region (DENR-FMB, 2015). The protected river basin has a technical geographic definition of Latitude 14°39’08.82" North and Longitude 121°13’05.70" East which is identical to Corner No. 55 of the Marikina Watershed Reservation (Proclamation No. 585, s. 1990).

Data collection

Thematic factors

Open-source data and remotely sensed data were utilized as landslide thematic factors, including slope, land use and land cover, distance to lineaments, soil morphology, soil geology, average annual rainfall, and typhoon frequency as shown in Table 1. The thematic factors were selected based on data availability, study site characteristics and literature review. These data were used as landslide triggering factors by Abancó et al. (2021), DENR-ERDB (2011), Lagmay et al. (2020). Figure 2 shows the individual maps of the identified landslide thematic factors.

Table 1
Landslide thematic factors with data sources

Data	Source
Landslide Records	Historical data from LGU
Slope and Land use and land cover	NAMRIA (2020) through geoportal.gov.ph
Distance to lineament, soil morphology, and soil geology	PHIVOLCS (2015) and Geological Survey Division, Philippine Bureau of Mines (now Mines and Geoscience Bureau of DENR)
Average annual rainfall and Typhoon frequency	DOST – PAGASA (2022)

Slope is a fundamental factor in all landslide susceptibility assessments, especially in defining the topography of the study area. Steeper slopes, with their heightened gravitational potential, represent areas more prone to landslides.

Land use and land cover influence landslides by altering surface properties, impacting water infiltration, and potentially destabilizing slopes through changes in vegetation, soil characteristics, and human activities.

Soil morphology influences landslide susceptibility by affecting drainage capacity and cohesion. Soils with poor drainage or low cohesion, such as sand and silt, are more prone to landslides due to reduced stability and quick water passage, unlike clay textures with better water-holding capacity (Andriani et al., 2023).

Soil geology refers to the physical and chemical characteristics of the rock fragments, minerals, and particles that make up the parent material of soil. Geological formations impact soil properties, affecting factors such as permeability and shear strength.

The lineament map spatially characterizes linear formations such as faults or fractures. Proximity to these lineaments significantly contributes to landslide susceptibility due to increased structural weakness and reduced stability, which is a very important controlling factor in evaluating landslide susceptibility (Yilmaz 2009; Conforti et al. 2014). Generally, as the slope decreases, the potential for slope failure increases. The line data were utilized to illustrate their distances from UMRBPL using the buffer function of QGIS based on the DENR-ERDB Vulnerability Assessment Manual, 2011.

Landslides are associated with rainwater infiltration that may load and weaken the soil mantle and lead to abrupt soil mass release (Fan et al., 2020; Dechkamfoo et al., 2022). Heavy rainfall directly triggers landslides, and any alteration in rainfall patterns will consequently affect the occurrence of landslides (Andriani et al., 2023). The data were clipped to display only the annual rainfall for the area.

Typhoons are large-scale weather systems characterized by low-pressure centers, organized convection, and strong winds. In recent years, typhoons have occurred frequently, generated numerous landslides, and caused mass casualties and economic losses worldwide (Choy et al., 2020). The typhoon frequency was determined by investigating historical typhoon events and converting the data into a raster format for the entire area.

Survey from Experts

Researchers surveyed identified experts relevant to watershed management and Disaster Risk Reduction Management (DRRM). They were asked to answer a questionnaire that compared each thematic factor/s to another thematic factor/s. The questionnaire indicated a nine-point importance scale, in which, similar to a Likert scale, the experts were asked to mark the degree of importance of each thematic factor over the others. The questionnaire guided the experts to create pairwise comparisons between two thematic factors needed to measure landslide susceptibility. Table 2 shows the sample survey questionnaire distributed to experts.

Table 2
Sample survey form for determining the weights of the thematic factors using analytic hierarchy process

Indicator	Factor Weighing Scale									Indicator
	Equal									
Slope	9	7	5	3	1	3	5	7	9	Land use and land cover
Land use and land cover	9	7	5	3	1	3	5	7	9	Distance to lineament
Distance to lineament	9	7	5	3	1	3	5	7	9	Soil Morphology
Soil Morphology	9	7	5	3	1	3	5	7	9	Soil Geology
Soil Geology	9	7	5	3	1	3	5	7	9	Average annual rainfall
Average annual rainfall	9	7	5	3	1	3	5	7	9	Typhoon frequency
Land use and land cover	9	7	5	3	1	3	5	7	9	Typhoon frequency
Distance to lineament	9	7	5	3	1	3	5	7	9	Slope
Soil Morphology	9	7	5	3	1	3	5	7	9	Land use and land cover
Soil Geology	9	7	5	3	1	3	5	7	9	Distance to lineament
Average annual rainfall	9	7	5	3	1	3	5	7	9	Soil Morphology
Typhoon frequency	9	7	5	3	1	3	5	7	9	Soil Geology
Average annual rainfall	9	7	5	3	1	3	5	7	9	Slope
Slope	9	7	5	3	1	3	5	7	9	Typhoon frequency
Average annual rainfall	9	7	5	3	1	3	5	7	9	Land use and land cover
Soil Geology	9	7	5	3	1	3	5	7	9	Slope
Typhoon frequency	9	7	5	3	1	3	5	7	9	Soil Morphology
Distance to lineament	9	7	5	3	1	3	5	7	9	Average annual rainfall
Land use and land cover	9	7	5	3	1	3	5	7	9	Soil Geology
Slope	9	7	5	3	1	3	5	7	9	Soil Morphology
Typhoon Frequency	9	7	5	3	1	3	5	7	9	Distance to lineament

The diagram of importance/probability functions as a balance machine, where more than one side is inclined to the left or right, the more significant the element is compared to the parameter on the other side. When the balance is exactly or near the middle (the value is 1), there is an equal chance that both of the compared parameters will occur (equal probability). To compare each factor, experts were composed based on the knowledge of six (6) experts and individuals with comprehensive expertise in

disaster risk reduction management and who had knowledge of the Upper Marikina River Basin Protected Landscape. There is no set minimum sample size for AHP analysis, according to the literature currently available on its uses in management and engineering. Sample sizes ranging from four to nine were utilized in several research studies (Arizapa et al., 2015; Thanki et al., 2016; and Veisi et al., 2016).

The decided number of experts in this study was also used by Gacu et al. (2022) and Zhou et al. (2023). According to Saaty et al., (2015), if an expert is knowledgeable and experienced in a field, he may provide judgments without jeopardizing correctness by including others who might not be as qualified.

Landslide Inventory

All versions of susceptibility mapping methods involve the production of a landslide inventory (Solaimani and Mousavi, 2013). To compile a landslide inventory, the research began by collecting historical data on specific landslide events that had occurred in the study area. The distribution of past landslide incidents was spatially assessed using historical data from various sources and mandated agencies. Studies to identify landslides are traditionally expensive and time-consuming; however, advancements in technology and the accessibility of high-resolution remote sensing data now allow for the identification of landslides using satellite images and aerial photographs. The identification of landslides was based on Google Earth Landslide Practical authored by Mihir and Malamud (2014).

Using temporal analysis in geotagging landslides using Google Earth Pro contributes to the development of more accurate landslide susceptibility maps. Additionally, in the research of Psomiadis et al. (2020), Google Earth Pro offers several advantages for geotagging landslides. It provides a user-friendly interface, making it accessible to researchers with varying levels of expertise. Its extensive database of high-resolution imagery and the ability to switch between historical imagery enables the identification of changes in landscapes over time, aiding in landslide monitoring.

Data Analysis

Assessment of Landslide Thematic Factors

A detailed flow chart of methodology indicates the framework of the landslide susceptibility process as shown in Fig. 3. Reclassification of each factor was based on the Vulnerability Assessment Manual of DENR-ERDB (2011) as shown in Table 3 and weighted overlay analysis was performed.

Table 3
Reclassification value and its description for the different thematic factors

Thematic Factors	Class	Description
Slope	1	Not steep (< 8%)
	2	Slightly steep (8.1–18%)
	3	Fairly steep (18.1–30%)
	4	Moderately steep (30.1–50%)
	5	very steep (> 50%)
Land use and land cover	1	Does not favor any landslide (closed forest)
	2	Slightly favor minor landslide (open forest; plantations)
	3	Moderately favor landslide (shrubs; natural grassland)
	4	Highly favor minor landslide (agricultural/cultivated; pasture land; built-up)
	5	Highly favor major landslide (bare)
Soil morphology	1	Clay with high organic matter
	2	Clay with low organic matter
	3	Sandy soil
	4	Silty soil with high organic matter
	5	Silty soil with low organic matter
Distance to lineament	1	There are fault lines beyond 8 km
	2	There are fault lines within 5–8 km
	3	There are fault lines within 2–5 km
	4	There are fault lines within 0.5-2 km
	5	Fault lines run 0.5 km from the area
Average annual rainfall	1	Very low rainfall (< 100mm)
	2	Low rainfall (100.1-200mm)
	3	Moderate rainfall (200.1-300mm)
	4	High rainfall (300.1-500mm)
	5	High rainfall (300.1-500mm)
Typhoon frequency	1	Very low frequency (1)

Thematic Factors	Class	Description
	2	Low frequency (2–3)
	3	Moderate frequency (4–6)
	4	High frequency (7–8)
	5	Very High frequency (> 8)

Source: DENR-ERDB (2011)

Analytic Hierarchy Process

The task was completed using the Analytic Hierarchy Process (AHP) after implementing the Simple Numerical Rating, which is a multi-criteria decision-making technique. AHP is based on the consistency of the degree of importance of each thematic factor to another (Saaty, 1977). Table 4 shows the degree of preference to be used in pairwise comparison.

Table 4
The matrix of the scale of judgment in analytic hierarchy process

Preference	Definition	Explanation
1	Equally Important	Both factors are equally important
3	Slightly Important	The factor has a few more effects than the other one
5	More Important	One factor is more effective as compared to the other one
7	Particularly Important	A factor has higher importance than the other one
9	Most Important	A factor has the highest possibility of affecting the occurrence of landslide over the other factor
2,4,6,8	Intermediate Values	The degree of importance is in between the above scales

Source: Saaty (1977)

The reliability of the pairwise comparison judgments is correlated with AHP's output. This process is necessary to compute the consistency of the assessment and determine the consistency ratio (CR) before making a decision. The evaluation matrix is thought to have passed the consistency assessment

if CR ≤ 0.1. On the other hand, if CR > 0.1, the matrix has failed the consistency evaluation and needs to have its scale to be adjusted. The formula below presents the eigenvalue formula (maximum) of the judgment matrix.

$$\lambda max = \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)i}{Wi} \quad (1)$$

Where *n* is for the number of thematic factors, *A* is the judgment matrix, *W* is the weighting factor and *Wi* is the component of the weight vector W, which was derived using the judgment matrix A. The weights were obtained by normalizing any of the rows or columns of A since, if the pairwise comparisons are reliable, the matrix A will be ranked one and λmax = n. The consistency is determined by the relatedness of the entries, and the consistency index (CI) will be determined using the equation below.

$$CI = \left(\frac{\lambda max - n}{n-1}\right) \quad (2)$$

The decision-maker can determine whether the assessments were calculated as the CIs and the random index (RI) quotient using the final CR as presented in the formula above (Eq. 2). One possibility for this stage is that the judgment will be deemed inconsistent if the proportion is more than 0.1. A consistency ratio must therefore be less than 0.1 or 10%. If the evaluation is uncertain, the process is repeated until the CR is within the desired scale. Following the findings of the assessment, the user concluded. The next step is to integrate the landslide thematic factors weights and associated classes employing the Multi Criteria Overlay Analysis (MCOA) for raster data which served as the foundation for defining the landslide susceptibility zone of UMRBPL.

Weighted Overlay Analysis and Reclassification

To determine the overall susceptibility classes, reclassified variables were overlaid with the weights of the different factors. To lower the data discreteness of the reclassified thematic factors (Apduhan, 2021; Wen, 2015), normalization was done. Five classes were used in this study and these were 0.00-0.20 as very low, 0.20–0.40 as low, 0.40–0.60 as moderate, 0.60–0.80 as high, and 0.80-1.00 as “very high”.

Validation of the Landslide Susceptibility Map

After generating the landslide susceptibility map of UMRBPL, it was compared to the inventory of historical landslide events and statistically validated using the Receiver Operating Characteristics (ROC) curve method. Landslides were purposely assigned to create 70% training data sets and 30% validation data sets while maintaining their spatial distribution. The ROC curve, known for assessing how well a classification system fits its data, was utilized, with the Area Under the Curve (AUC) serving as a measure of predictive effectiveness. A higher AUC value, closer to 1.00, indicates better map accuracy.

The validation landslide datasets, representing observed landslides, were used to evaluate the map's performance, while the training landslide datasets were used to construct the map. The interpretation of results, based on AUC, follows criteria where 0.70 to 0.80 is considered acceptable, 0.80 to 0.90 is excellent, and above 0.9 is outstanding. The LSM map performance was assessed by comparing it to a random classifier with an AUC of 0.50 (no discrimination) and an ideal classifier with an AUC of 1.00 (perfect classification). For cross-validation, the dataset was divided into multiple subsets, and ROC analysis was repeated on each to calculate AUC values, ensuring result stability and generalizability (Luque-Fernandez et al., 2019).

RESULTS AND DISCUSSION

Reclassification of the different Thematic Factors

Figure 4 presents the susceptibility rating of UMRBPL based on the thematic factors. In the slope as shown in Fig. 4a, very low susceptibility has an area of 1,892.37 ha, constituting 7.24% of the total region. Low susceptibility covers 2,193.23 ha (8.39%) while moderate susceptibility spans an area of 3,968.34 ha, representing 15.19% of the region. High susceptibility has an area of 8,972.66 ha (34.34%) and very high susceptibility covers 9,100.68 ha (34.83%). As the steepness of the slope increases, the probability of landslide occurrence also increases (Lee and Min, 2001). Previous and current results indicate the presence of a correlation between slope and other (normally unconsidered) geo-environmental factors (Capitani et al., 2013). The LULC (Fig. 4b) has a very low susceptibility covering 9.96% of the total area, low susceptibility spanning 16.47%, moderate susceptibility accounting for 59.81%, high susceptibility including 13.72%, and very high susceptibility observed in 0.0004% of the area. The results show that barren land/settlement being the most susceptible, while forests and water bodies are less susceptible. Barren lands exhibit the highest susceptibility due to the absence of deep plant roots (Anbalagan, 1992; Arora, 1997). Woodland, shrub/bush/grassland, and cropland show varying levels of susceptibility (ERDB, 2011; Mekonnen et al., 2022), with shrubs and brushlands having moderate susceptibility due to shallow roots, higher than coniferous and broadleaf forests (Asada and Minagawa, 2023).

Soil morphology (Fig. 4c) shows that areas with high susceptibility dominate UMRBPL, covering 17,122.75 ha or 65.54% of the total area. Low susceptibility areas make up 9,004.56 ha, or 34.46%. No areas fall under very low, moderate, or very high susceptibility categories. The undifferentiated Antipolo soil is classified as high susceptibility, while Antipolo and Binangonan clays are classified as low susceptibility. Soils with higher clay content form stable slopes due to high shear strength, whereas sandy or coarse loam, which have lower shear strength, form unstable slopes. Soils with high silt content are more erosion-prone compared to clayey and sandy soils (Fonseca, 2017). Slopes with high sand content in areas of intensive rainfall are the most susceptible to landslides (Arora, 2008). Susceptibility ratings across different soil geologic categories in UMRBPL (Fig. 4d) revealed very low susceptibility areas (K or undifferentiated) dominate 67.70% of the total area (17,687.89 ha). Moderate susceptibility areas (N1 or Pleistocene) account for 5,257.57 ha (20.12%), high susceptibility areas (QUP or Pliocene)

cover 2,645.70 ha (10.13%), and very high susceptibility areas (N2 or Upper Pliocene – Pliocene) span 550.67 ha (2.11%). Soil geology influences landslide occurrence by affecting the strength and permeability properties of the bedrock (Silalahi et al., 2019), as geologic units vary in composition, structure, and cohesion, impacting their resistance to motion (Fell et al., 2008).

Landslide susceptibility is influenced by proximity to lineaments, with increased fracturing and weathering leading to higher susceptibility (Farrokhnia et al., 2010). Figure 4e illustrates susceptibility ratings, with 33.89% classified as low susceptibility, 30.26% as very low, 25.29% as moderate, 7.51% as high, and 3.05% as very high, indicating areas with the highest risk. In terms of average annual rainfall (Fig. 4f), UMRPBL is classified as having low susceptibility to landslides. Intense or prolonged rainfall infiltrates the soil, increasing water content and pore pressure, which decreases soil weight and cohesion, thus reducing its support capacity and promoting slope failure (Dechkamfoo et al., 2022). Chan et al. (2018) found that substantial rainfall over short periods increases landslide occurrences, reducing stable areas. Rainfall accumulation can trigger mass movement based on infiltration capacity, permeability, and soil type, even after rain events (Ramos et al., 2022). Both short periods of heavy rain and prolonged moderate rain can initiate landslides, especially in areas with steep terrain, weak geological formations, or poor drainage. Slopes are generally stable under natural or half-saturated conditions but are highly likely to cause damage during extreme rainfall (Sui et al., 2022).

UMRPBL is classified as having very low susceptibility to landslides in terms of typhoon frequency (Fig. 4g). Rainfall from typhoons is crucial for landslide initiation on hillslopes, where topographic and geologic conditions may be conducive, but rain infiltration and soil saturation are essential triggers (Yang et al., 2018). Intense rain from tropical storms or typhoons can trigger new landslides and debris flows (Harp et al., 2021). Frequent typhoons significantly contribute to landslides, as evidenced by the devastation in Infanta, Quezon from successive typhoons in 2004 (Macandog, 2012). Typhoon-induced erosion can remove vegetation that stabilizes slopes, and strong winds can topple trees and loosen soil, increasing landslide risks. These factors make typhoons a potent catalyst for landslides, especially in mountainous or hilly areas, posing serious threats to communities and infrastructure. Constant-intensity rainfall tends to induce deep landslides, while increasing rainfall produces shovel-shaped slopes (Taili et al., 2020).

Overall Landslide Susceptibility of UMRPBL

Analytic Hierarchy Process

Landslides vary in behavior, movement, and distribution across locations and times, influenced by various factors (Shano et al., 2020). Understanding these factors is crucial for Landslide Susceptibility Assessment, which helps identify the most significant factors in predicting landslides. However, not all conditioning factor maps may be globally or locally accessible due to issues such as data non-compliance, unavailability, and structural errors (Meena et al., 2022).

The mean weights of thematic factors, as shown in Table 5, highlight slope as the most influential factor in landslide susceptibility within the UMRPBL, with a mean weight of 28.04%, underscoring its topographical significance (Psomiadis et al., 2020; Wubalem, 2021; Leonardi et al., 2022). Other thematic factors show varying weights due to differences in geographic, geologic, and climatic characteristics of study sites, reflecting the complex nature of landslide susceptibility assessments. LULC, with a mean weight of 20.50%, highlights the importance of human activities and vegetation cover on landslide susceptibility, while soil morphology and distance to lineament also contribute significantly with mean weights of 20.08% and 8.46%, respectively. Other factors such as average annual rainfall, typhoon records, and soil type have comparatively lower mean weights.

Table 5
Mean weights of landslide thematic factors after analytic hierarchy process

Landslide Thematic Factors	Weights (%)
Slope	28.04
Land Use and Land Cover	20.50
Average Annual Rainfall	20.08
Soil Morphology	8.46
Typhoon Frequency	8.08
Distance to Lineament	7.74
Soil Geology	7.10
Total	**100.00**

The computed consistency of expert responses, with a mean of 0.0886, was compared to Saaty's consistency criterion, which values close to zero are considered consistent (Saaty, 1977). This consistency ratio supports the experts' judgments as logically coherent and lacks significant contradictions. Cox et al. (2000) and Soma (2003), referring to Saaty, agreed that consistency ratios up to 0.10 are acceptable, thus enhancing the reliability of pairwise comparisons and the accuracy of prioritizing and weighting factors influencing landslide susceptibility.

Overall Landslide Susceptibility Rating

As shown in Fig. 5, "very high" susceptibility areas are the most critical for landslides, characterized by steep slopes, specific LULC, soil traits, and proximity to fault lines, like the Philippines West Valley Fault, which increase susceptibility (Eco et al., 2015; Luzon et al., 2016; Kato and Lee, 2022). These fault lines act as zones of weakness in the earth’s crust (Tubog et al., 2023, emphasizing the importance of geological hazard assessments in susceptibility mapping (Abancó et al., 2021; Nath et al., 2021; Bloom et al., 2022). The "high susceptibility" areas show significant landslide risk, though less than "very high" zones, featuring moderately sloped terrain and diverse land use such as agriculture and barren lands (Dill

et al., 2021; Zou et al., 2021; Advincula and Padrones, 2024). Effective landslide risk management remains crucial (Roccati et al., 2021).

Under "moderate susceptibility" areas, the largest portion of the study area, have moderately steep slopes and diverse land cover, including shrub/brushlands and open forests, with soils like K and QVP. Though less prone than "high" and "very high" zones, they need attention in landslide risk management (Roccati et al., 2021). Regions under “low susceptibility” with slightly steep slopes and land uses like built-up areas and grasslands, have reduced risk but are not immune to landslides due to natural and human-induced factors (Sargeant et al., 2020; Bibentyo et al., 2024).

Finally, "very low susceptibility" areas demonstrate minimal landslide risk, characterized by non-steep slopes, closed forests, and inland water bodies, with soil types like K and N1 predominating and considerable distance from fault lines (Asurza-Veliz, 2022). Despite minimal risk, preparedness is necessary as external factors can still contribute to instability and potential landslides (Asurza-Veliz, 2022).

Landslide Inventory

A total of 125 landslides within UMRBPL were spatially assessed, identified, and purposely selected using Google Earth. The points were then imported into QGIS to generate the inventory map, as shown in Fig. 6. A landslide inventory map provides significant data regarding the distribution of landslide occurrences within a particular area (Wu et al., 2022). This information contributes to a more comprehensive comprehension of the behavior of landslides and facilitates the evaluation of landslide susceptibility.

The ROC Area Under the Curve (AUC) as reflected in Fig. 7, is indicative of the efficiency and accuracy of the AHP method (Bopche and Rege, 2021), with a value of 0.87 supporting high accuracy in landslide susceptibility assessment in the UMRBPL (El Jazouli et al., 2019). AUC values close to 1 signify high accuracy, while values near 0.5 suggest low accuracy.

Validation results, according to Shahabi and Hashim (2015), demonstrate acceptable agreement between susceptibility maps and current landslide data, indicating reliability, as evidenced by the increasing percentage of landslides with susceptibility degree (Kumar and Anbalagan, 2016). Despite its subjectivity, the AHP method is a valuable tool for generating landslide susceptibility maps, yielding reliable results useful for disaster-related studies (Anchima et al., 2023; Arizapa et al., 2015; Asmare, 2023; Bhat et al., 2023; Tubog et al., 2023).

CONCLUSION

The study used the Analytic Hierarchy Process (AHP) to assess landslide susceptibility of UMRBPL, creating a detailed susceptibility map that categorizes areas by risk level. It is therefore concluded that more than half of Upper Marikina River Basin Protected Landscape is susceptible to landslides (moderate to very high susceptibility). The integration of AHP and geospatial data provided insights into

the spatial distribution and influencing factors of landslide susceptibility in the UMRBPL. Experts' judgments were consistent and regarded slope and soil geology as highest and lowest contributing thematic factors, respectively. Lastly, validation of the susceptibility assessment through the Receiver Operating Characteristics (ROC) curve method demonstrated its accuracy, with an Area Under the Curve (AUC) value of 0.87, indicating its effectiveness in identifying landslide-prone areas. This validation process strengthens the assessment's credibility and utility in informing decision-making for landslide risk management. The researchers further propose detailed site-specific investigations to develop targeted mitigation measures in UMRBPL. Public awareness campaigns should be conducted to educate communities about landslide risks and its preventive measures. Significantly, vulnerability assessment anchored to the climate change framework such as exposure, sensitivity, and adaptive capacity should also be done, considering the LSA as a baseline data.

Declarations

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STATEMENT ON CONFLICT OF INTEREST

The authors declare no conflicts of interest, whether actual or perceived, that could potentially influence the impartiality or objectivity of the research findings presented in this manuscript.

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AUTHORS' CONTRIBUTION

All authors contributed to the conception and design of the study, as well as the acquisition of data. C.G.S. Almoite, J.L. Bucasan, and R.T. Bona performed the analysis and interpretation of the data. All authors were involved in drafting the manuscript and revising it critically for important intellectual content. All authors reviewed and approved the final version of the manuscript to be published. Specifically, here are the specific contribution of the authors:

a. Conception and design of study: C.G.S. Almoite, J.L. Bucasan, R.T. Bona, R.I.C. Lumbres
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f. Approval of the version of the manuscript to be published: C.G.S. Almoite, J.L. Bucasan, R.T. Bona, R.I.C. Lumbres

DECLARATION ON ETHICS APPROVAL

As this study involved an anonymous numerical survey of experts providing professional opinions within their field of expertise, it did not fall under the mandate for formal institution ethics committee approval. The study ensures participant anonymity and the voluntary nature of the study.

DECLARATION ON CONSENT TO PARTICIPATE

An informed consent was obtained from all individual experts included in the study. Participants were notified of the purpose of the study, and their voluntary completion of the Analytical Hierarchy Process (AHP) survey constituted their consent to participate.

DECLARATION ON CONSENT TO PUBLISH

Not applicable. The data collected was strictly numerical and was processed in aggregate, no identifying information, names, or specific institutional affiliations were recorded or are included in this publication

OTHER DECLARATION

This study is not a clinical trial, hence, no registration/s were done to conduct this study.

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Figures

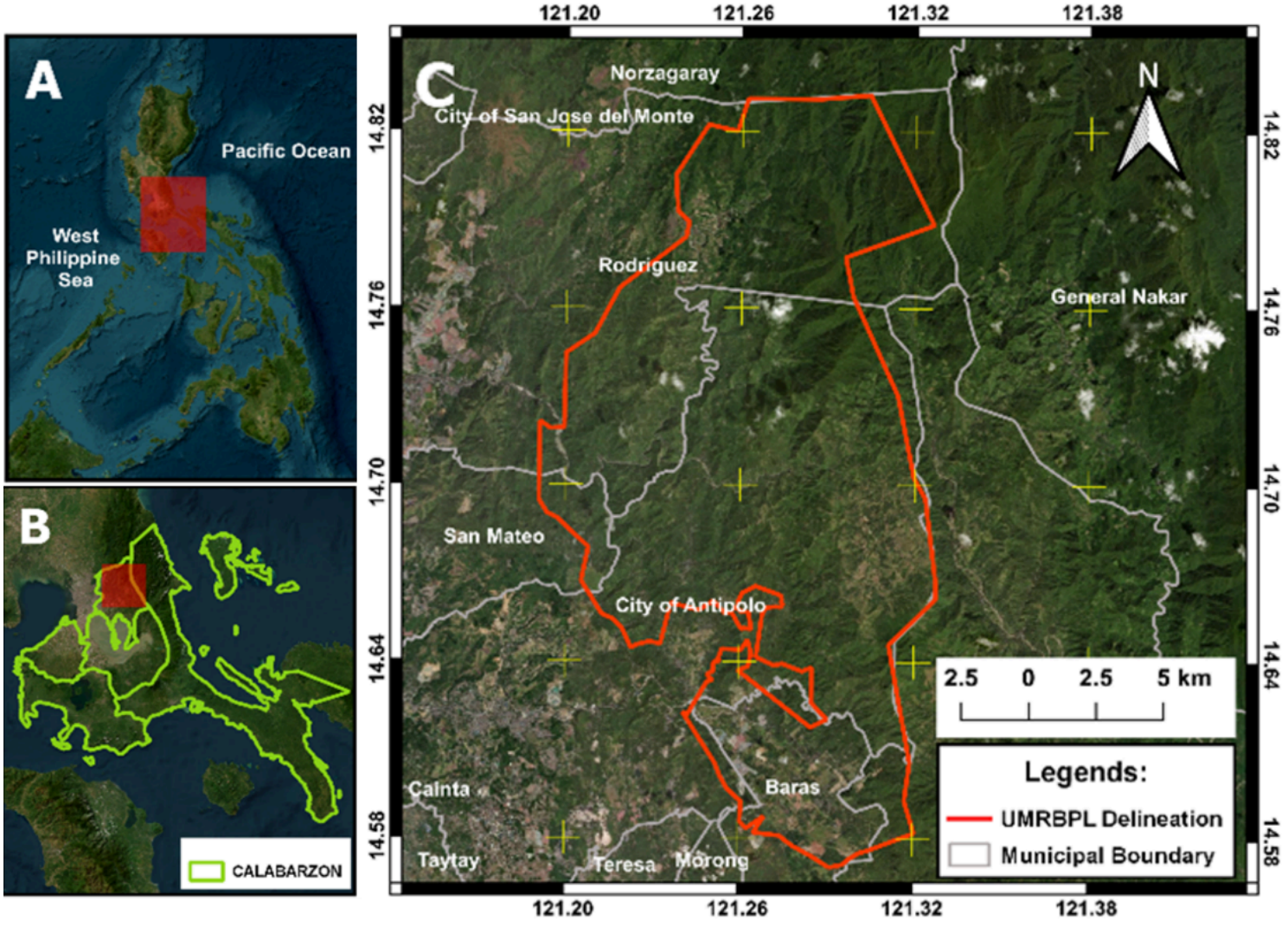


Figure 1

Location map of UMRBPL showing (A) its specific location in the Northern part of the Philippines, (B) the specific location in the northern part of CALABARZON, (C) the satellite image with boundary of UMRBPL and the political boundaries of the municipalities surrounding the UMRBPL

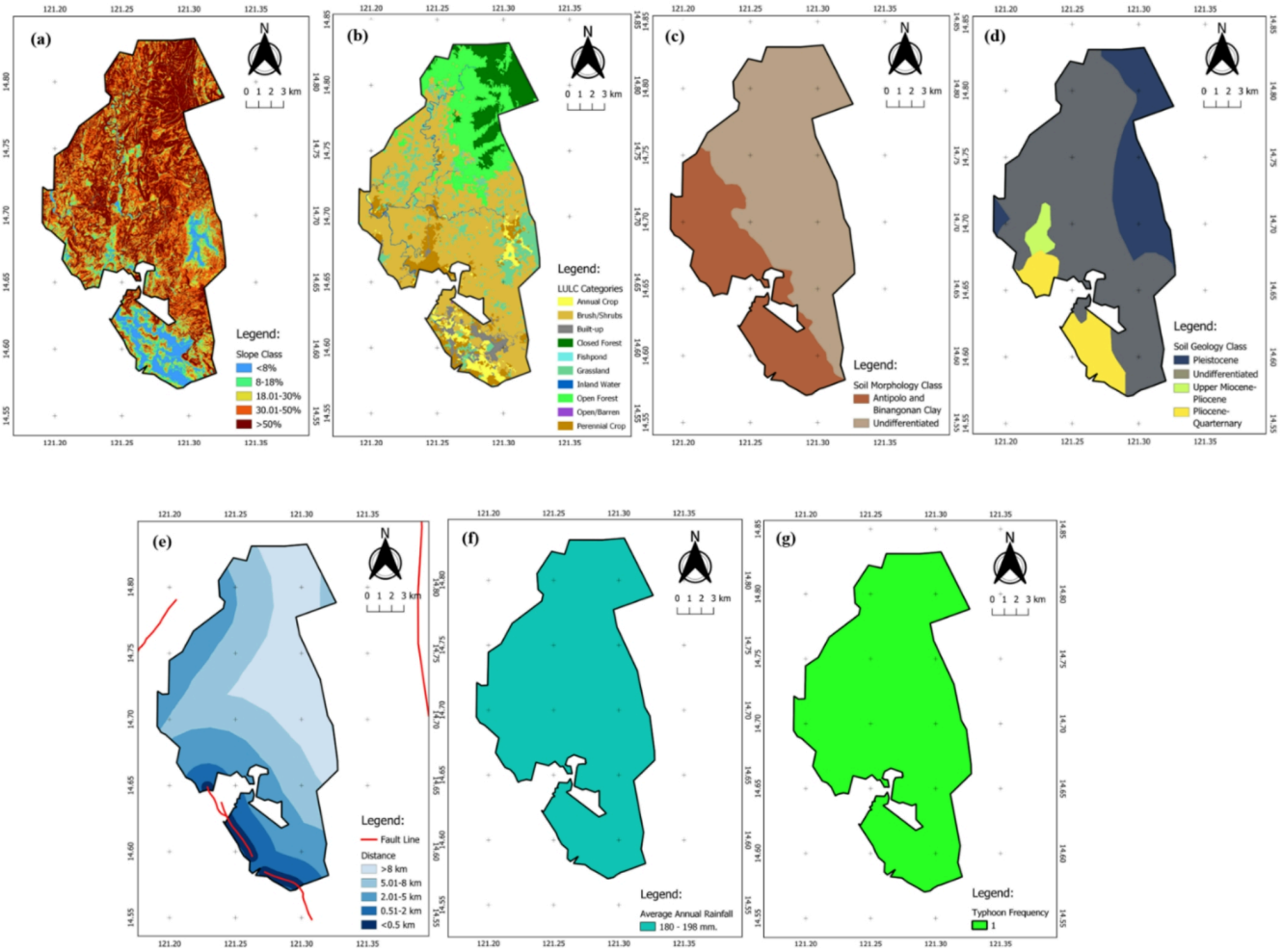


Figure 2

Thematic factors such as (a) slope, (b) land use and land cover, (c) soil morphology, (d) soil geology, (e) distance to lineament, (f) average annual rainfall, and (g) typhoon frequency that were used in the landslide susceptibility of UMRBPL

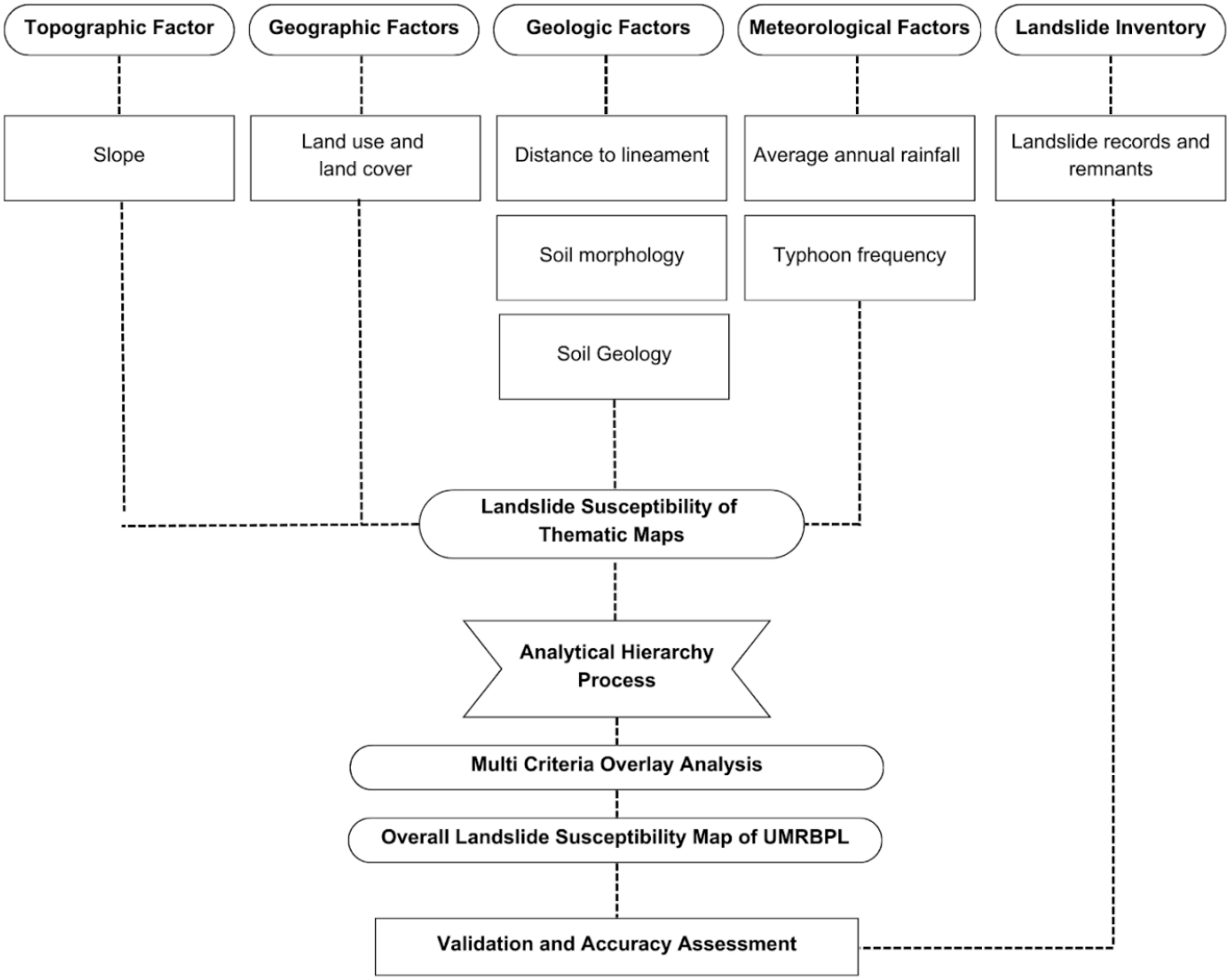


Figure 3

Schematic diagram of landslide susceptibility assessment of UMRBPL

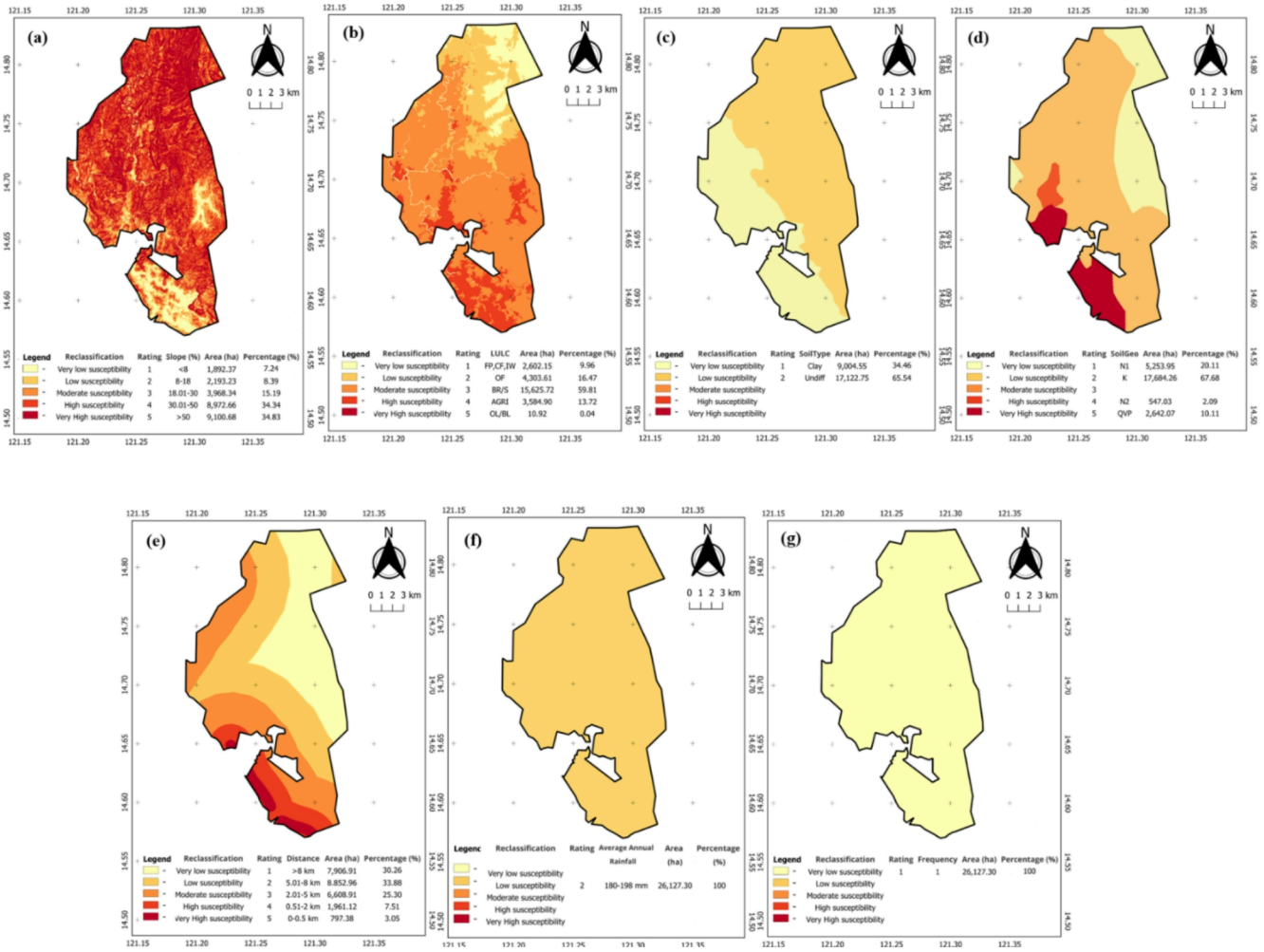


Figure 4

Susceptibility maps based on thematic factors including (a)slope, (b) land use and land cover, (c) soil morphology, (d) soil geology, (e) distance to lineament (f) average annual rainfall, (g) typhoon frequency

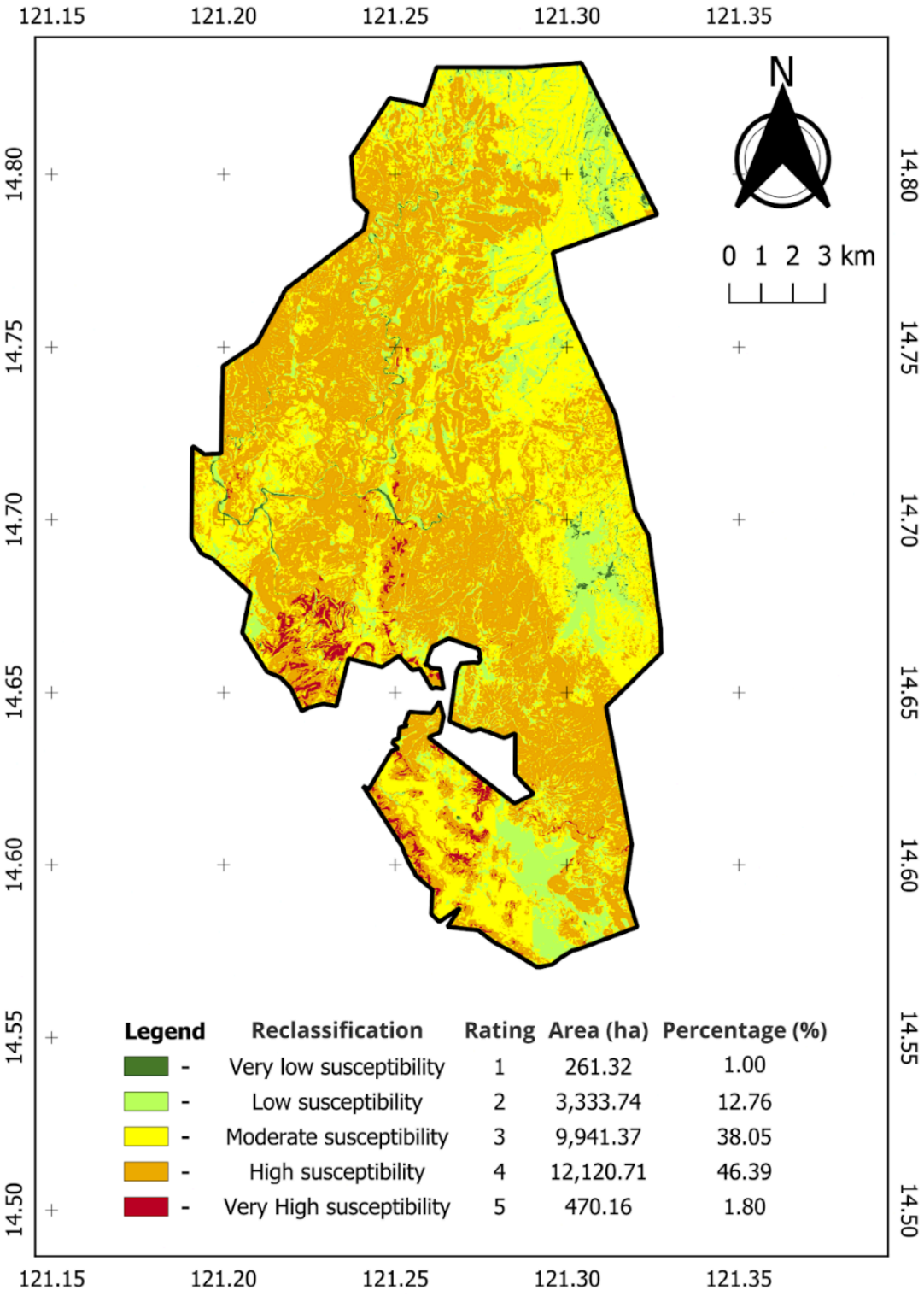


Figure 5

Overall landslide susceptibility map of Upper Marikina River Basin Protected Landscape Validation of the Landslide Susceptibility Map

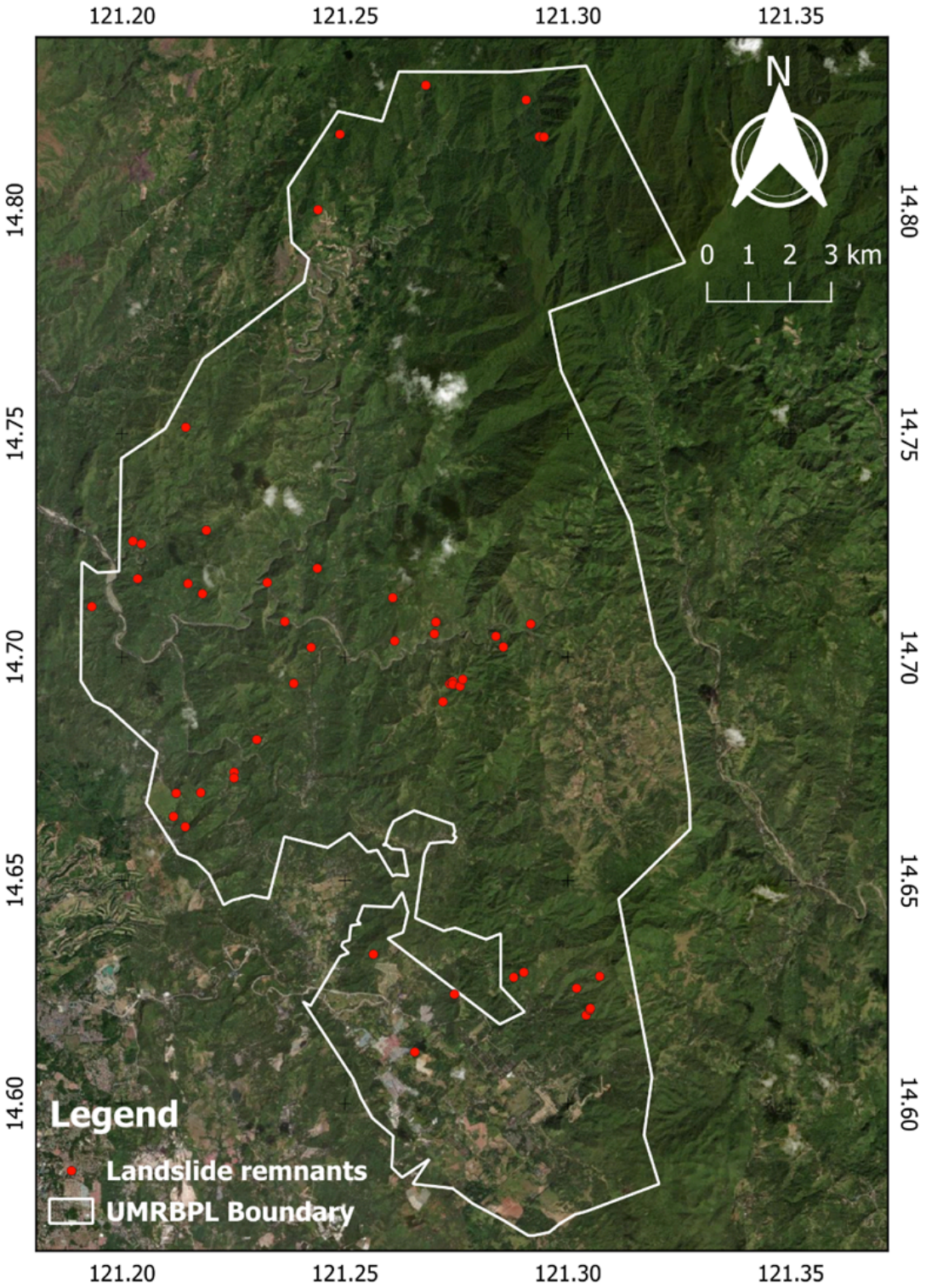


Figure 6

Geotagged landslide remnants in UMRBPL using Google Earth Pro *ROC Curve*

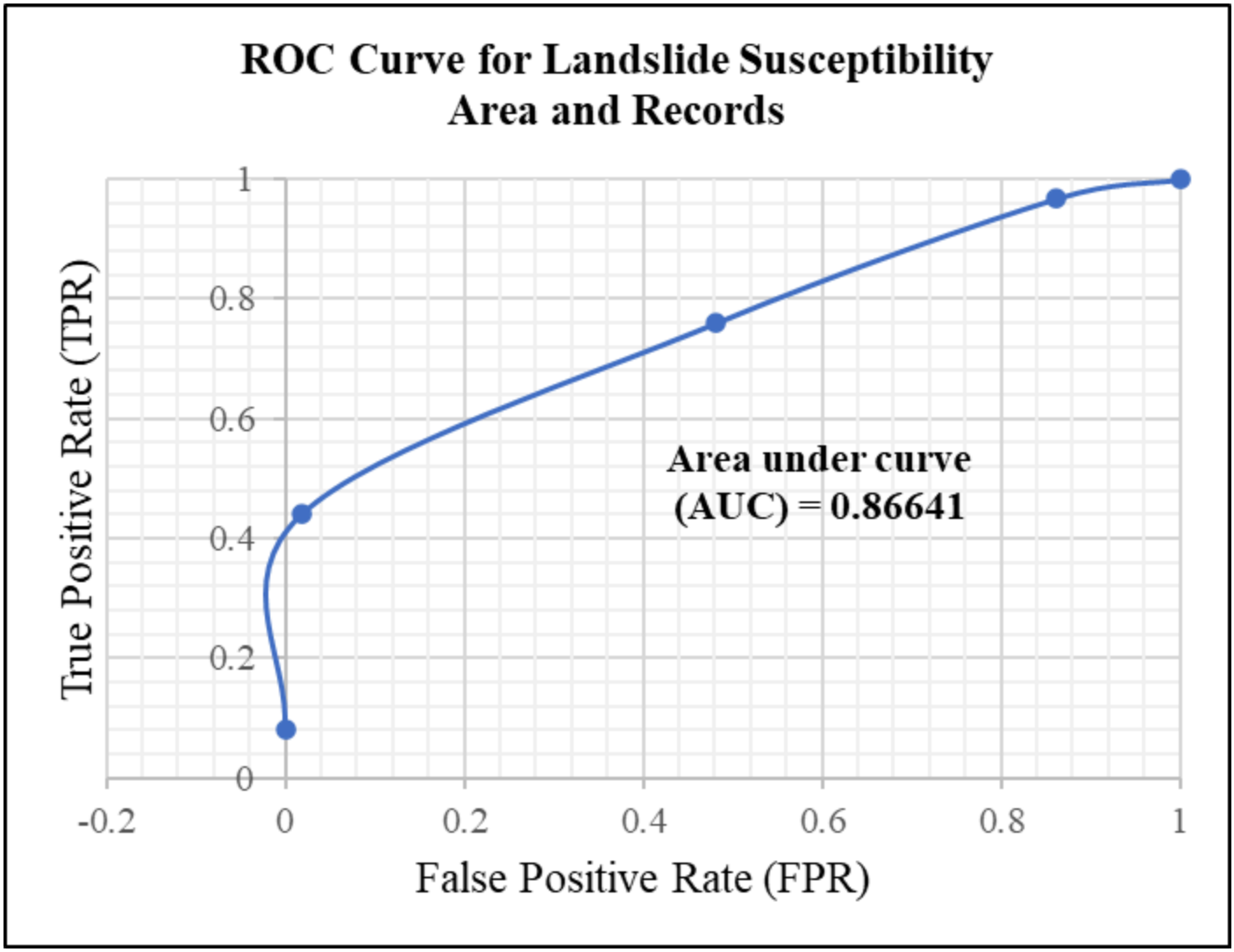


Figure 7

Receiver Operating Characteristic (ROC) curve for landslide susceptibility area and records of Upper Marikina River Basin Protected Landscape