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Abstract: *Landslide is a major concern in the Philippines due to its typhoon-prone environment since it is located at the Western Pacific Basin. To mitigate the impact of landslides, accurate and up-to-date information on rainfall-induced landslide areas is crucial. This study aims to determine rainfall-induced landslide areas using geospatial techniques in a specific region to identify the areas that are susceptible to rainfall-induced landslides by analyzing factors such as Elevation, Slope, Annual Precipitation, Distance to Streams, Land Use/Land Cover, Lithology, and Distance to Roads. These parameters were used for analytical hierarchy process (AHP) to create Localized Rainfall-induced Landslide Susceptibility Map. Among the parameters, Slope was identified as the main factor for rainfall-induced landslide. Overall, it resulted in that majority of the area of Butuan City having Moderate Susceptibility which covers 26.11% of the total. The map was validated using Area Under the Curve with the success rate of 93.6%.*

Keywords: landslide, analytical hierarchy process (AHP), rainfall-induced, Hazards, Geospatial Techniques.

1. INTRODUCTION

Landslides are natural disasters that have affected many parts of the world in recent years, causing numerous casualties and significant damage to infrastructure and settlements. Also, it is a general term used to describe the downslope movement of soil, rock, and organic materials under the effects of gravity and also the landform that results from such movement [1]. In the Philippines, landslides have become a recurring problem due to its topography and susceptibility to frequent typhoons and heavy rainfall [2]. Hence, to mitigate the impact of landslides, accurate and up-to-date information on rainfall-induced landslide areas is crucial.

Almost everywhere in the world, landslides brought on by rainfall are a frequent occurrence that result in hundreds of fatalities as well as billions of dollars' worth of damage each year. The Philippines is one of the nation's most vulnerable to this kind of hazard; from 1970 to 2023, it ranked fifth globally in terms of the frequency of landslide disasters (wet disasters) [3]. In the Philippines, typhoons are responsible for 42% of all landslides caused by rainfall, which account for roughly 46% of all landslides [4]. Patterns of rainfall can have a big impact on how dangerous landslides are to human life. The majority of the incidents occurred on both gentle and severe slopes near roads and highways in hilly areas [5].

Geographical Information Systems (GIS) have been instrumental in gathering, storing, analyzing, and presenting vast amounts of geographically related data, among other innovative technologies and methods for anticipating natural disasters and minimizing their effects on a community. Large-scale mapping has become more feasible because of GIS, which has also greatly improved mapping processes' productivity [6]. It is essential to conduct a scientific evaluation of places that are vulnerable to landslides in order to reduce any potential damage. Using GIS as a fundamental analytical tool for spatial and data management and manipulation, it is feasible to conduct a landslide susceptibility analysis [7].

In GIS, the Weighted Overlay is used to merge many data layers into a single result. But just adding or averaging these layers wouldn't take into consideration how important each component is in relation to the others. The Analytic Hierarchy Process (AHP) is useful in this situation. AHP offers a methodical approach for allocating weights to these various strata because AHP takes relative importance into account [8]. AHP makes it possible for experts or decision makers to compare variables pairwise and assess the relative importance of each. The experts' knowledge is incorporated into the weighing process. Thus, providing a methodical way to weight calculation, minimizing bias and guaranteeing consistency in weighting choices among various components and projects.

The topography of Butuan City, Philippines, consists of mountainous terrain that is in proximity to roads, hence presenting a notable hazard of landslides. The efficacy of authorities and communities in mitigating landslide risks is impeded by the requirement for more precise and up-to-date information, as well as comprehensive maps that identify areas prone to landslides. In the absence of adequate knowledge and spatial planning, individuals may choose to inhabit or conduct economic endeavors within areas that pose significant risks, hence increasing the likelihood of casualties, property destruction, and the interruption of critical services. In order to address this matter, it is imperative to gather and evaluate data pertaining to the topography, geological attributes, and precipitation patterns of the region to determine rainfall-induced landslide areas using geospatial technology.

2. METHODOLOGY

2.1 Study Area

The study was conducted in Butuan City, Philippines (see Fig. 1), situated at approximately 8°57' North, 125°32' East, on the island of Mindanao. Butuan City, encompassing 81,728 hectares across 86 barangays, presents a distinctive landscape of urban zones, agricultural lands, and natural ecosystems, where predominant soil type is loam. [9].

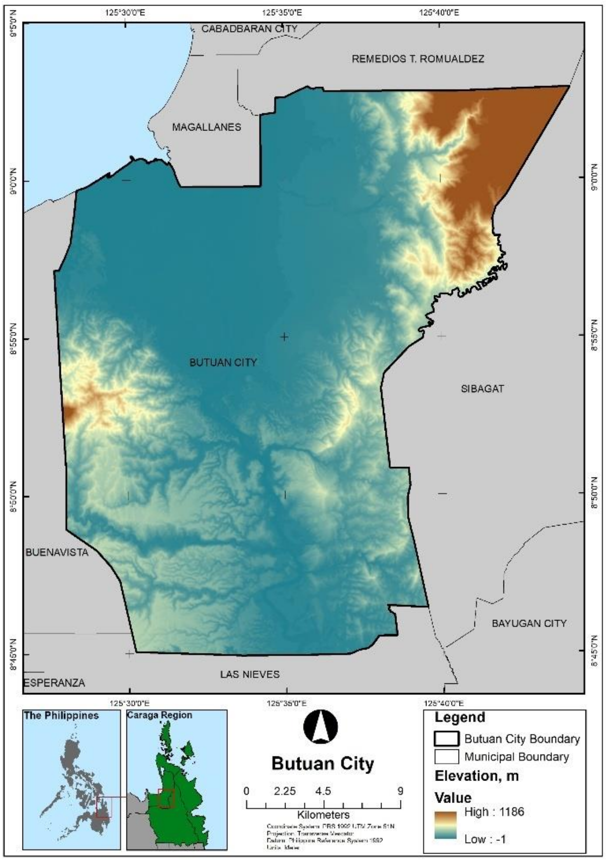

Fig. 1. Map of the Study Area.

2.2 Determination of Criteria

Various analyses based on the relevant literature were carried out in order to identify the datasets for this study to determine rainfall-induced landslides in Butuan City. Table 1 lists the datasets that were collected from various sources and analyzed using GIS methods. These datasets were only limited to availability from these mentioned sources.

Table 1. Criteria used with corresponding data source and type

DATASETS	DATA SOURCE	DATA TYPE
Digital Elevation Model (DEM)	Caraga Center for Geo-Informatics (CCGeo)	Raster
Satellite Images (Landsat 8)	USGS	Raster
Road Network	Humanitarian Data Exchange	Vector
Lithology	Mines and Geosciences Bureau Region XIII	Vector
Annual Rainfall Data	Climate Hazard Center	Vector

2.2.1 Elevation

The elevation layer was used in this study to determine high and low elevation locations. Although elevation doesn't always cause landslides directly, it can contribute to creating the conditions that lead to landslides. There might be less vegetation at higher altitudes than in lower ones [10]. Because vegetation holds soil in place, a lack of it might increase the risk of landslides on slopes [11].

2.2.2 Slope

More landslides occur on steeper slopes because they are less stable and more likely to be caused by other events like intense rain or earthquakes [12]. Also, steeper slopes mean a greater downward force due to gravity acting on earth materials [13]. This study utilized the slope layer to identify areas categorized from gentle slopes to very steep slopes.

2.2.3 Precipitation

Excessive rainfall leads to increased groundwater levels, and therefore increased pore water pressure. Additionally, it causes more surface runoff, which could exacerbate sliding tendencies by eroding the material at the slope's base. In the Philippines, rain is the primary cause of landslides, which provide a particularly serious risk when typhoons pass through at the same time as the southwest monsoon rains [14].

2.2.4 Distance to Streams

There is a statistical analysis indicating a strong relationship between the distribution of landslides and the distance to drainage [15]. Putting in another context, landslides are more likely to occur nearer the drainage [16].

2.2.5 Land Use/Land Cover

The biological and physical components that make up the Earth's surface are referred to as land cover. It consists of surfaces that have been altered by humans, including roads, houses, and farms, as well as natural elements like water bodies, woods, exposed rock or dirt. On the other hand, land usage refers to the socioeconomic seizure of the land [17]. Soil moisture and mechanical behavior are affected by land cover in a variety of ways. For instance, by mechanical anchoring and soil suction by roots, plants can improve slope stability and prevent soil erosion [18]. On the other hand, slope stability is frequently decreased by road development, slope cutting, deforestation, and building construction on hillslopes [19].

2.2.6 Lithology

Several studies show that the lithological characteristics of the ground surface have a significant influence on landslides [20]. The geologic/lithologic theme is typically considered as one of the predisposing variables for landslides in any assessment of landslide susceptibility that uses data-driven approaches [21]. Since lithological and structural variations frequently result in differences in the strength and permeability of rocks and soils, it is well known that geological factors have a significant impact on the occurrence of landslides [22]. The lithologic data used in this study was obtained from the Mines and Geosciences Bureau- Region XIII (MGB-XIII).

2.2.7 Proximity to Roads

Road construction alters vegetation; hence, roads may create landslides [23] [24]. Also, due to increased commercial activity in the vicinity of the roadways, there is an increase in human activity [25]. Moreover, vehicle vibrations from driving often cause rocks to shatter and loosen, causing uncontrollably large rock explosions [26]. Since they add more weight to the slope, road construction activities and the over vibration frequency can trigger and can cause landslides.

2.3 Reclassification of the Criteria

2.3.1 Preparation of Criteria Maps

Euclidean distance was employed in road and stream networks to calculate the distances from these networks. Distances were categorized into several classes based on the classification that was utilized in other publications. For other criteria, it was categorized into 5 groups based on the related literature.

Elevation plays a vital role in determining landslide vulnerability, where areas ranging from -0.8405 to 73.64 meters are considered very low risk (Rank 1), typically representing low-lying flatlands. As elevation increases, susceptibility also rises, with very high-risk areas (Rank 5) found between 758.0 to 1186 meters. These high-altitude zones are often steep and prone to mass movement due to gravitational pull and water infiltration [27][28]. Slope is another primary factor, as steeper terrain correlates strongly with landslide potential. Flat areas with 0–5° slope are deemed not susceptible, while steeper zones from 35° to 72.94° fall under the very high-risk category (Rank 5), where soil and rock are more likely to fail under stress [29].

Annual precipitation influences soil saturation and pore pressure, with areas receiving 470.4 to 576.2 mm of rainfall annually ranked as very high risk (Rank 5). Conversely, drier regions with 46.73 to 152.6 mm annual precipitation have very low susceptibility (Rank 1) to landslides [14]. Distance to stream also affects slope stability; proximity to water bodies increases erosion and saturation, thus enhancing landslide probability. Sites within 100 meters of a stream are labeled very high risk (Rank 5), while those more than 2000 meters away are considered very low risk (Rank 1) [30][31]. Land use and land cover (LULC) significantly contribute to susceptibility levels. Water bodies are least prone to landslides (Rank 1), whereas barren lands, lacking vegetation that stabilizes soil, are at very high risk (Rank 5). Built-up areas and croplands also show increased vulnerability due to anthropogenic disturbances [32]. Lithology, or rock type, further refines susceptibility classification. Alluvial and unconsolidated deposits are classified as very low risk (Rank 1), while tuffaceous and pyroclastic rocks in the N2 unit are deemed very high risk (Rank 5) due to their loose, erodible nature. Expert assessments highlight additional lithologic units, such as molasse sediments, ultramafic plutonics, and reef limestones, graded from low to high risk depending on their structural integrity and weathering characteristics. Lastly, distance to roads indicates human disturbance and slope modification. Areas closest to roads (0–100 m) show very high susceptibility (Rank 5), reflecting frequent slope cutting, drainage alteration, and vibrations. Conversely, locations 400.1 to 4299 meters away are classified as very low risk (Rank 1), typically undisturbed by infrastructure development [23].

Together, these parameters form a comprehensive framework for assessing landslide-prone areas, guiding land use planning and hazard mitigation strategies.

2.4 Analytical Hierarchy Process (AHP) Analysis

To decide on the final weights assigned to different thematic levels and their associated attributes, the Analytic Hierarchy Process (AHP) is utilized as a decision-making tool. Using this analysis it will determine component weights for mapping rainfall-induced landslide-prone areas, taking into account the relative contributions of the main themes to rainfall-induced landslides. Establishing a decision hierarchy is the initial phase in the AHP approach. The primary objective of this method is to rank the established criteria by their importance by assigning weights to each of them. The pool of professionals and experts specializing in landslides and related natural hazards was consulted and it includes experts from different agencies such as the Mines and Geosciences Bureau (MGB), City Disaster Risk Reduction Management Office (CDRRMO), Provincial Disaster Risk Reduction Management Office (PDRRMO), and Department of Environment and Natural Resources. AHP employed a preference matrix to ascertain the required weights connected to each of the distinct criterion map layers. The matrix compares and aggregates all relevant criteria.

Table 2. Fundamental Scale for Pairwise Comparison.

Intensity of Importance	Definition
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very Strong Importance
9	Extreme Importance
2, 4, 6, 8	Intermediate Values
Reciprocals: ½, ⅓, ¼, etc.	These intensities can be used for elements that are very close in importance.

The Consistency Ratio (CR) helps identify potential errors in judgment, guiding improvements based on its value [8]. According to Saaty (1998), pairwise comparison results are considered reasonably consistent if the CR is ≤ 0.1. To calculate the weights for each variable, a pairwise comparison matrix was constructed. The consistency of the comparisons within this matrix was then evaluated by calculating the consistency ratio using Equation 1.

$$CR = \frac{CI}{RI} \qquad \text{Eq. 1}$$

Where, CI represents Consistency Index (Eq. 2), and RI represents Random Index (based on matrix size (n).

$$CR = \frac{\lambda max - n}{n - 1} \qquad \text{Eq. 2}$$

Where, n represents Number of criteria used, and λmax is the principal eigenvalue of the matrix.

The generated outputs of this study were assessed and validated by the landslide data provided by the Butuan City Disaster Risk Reduction Office. Field observations were also used to confirm the landslides that were recorded. A total of eleven (11) recorded landslides were shown in the map, ranging from 2021 to 2023.

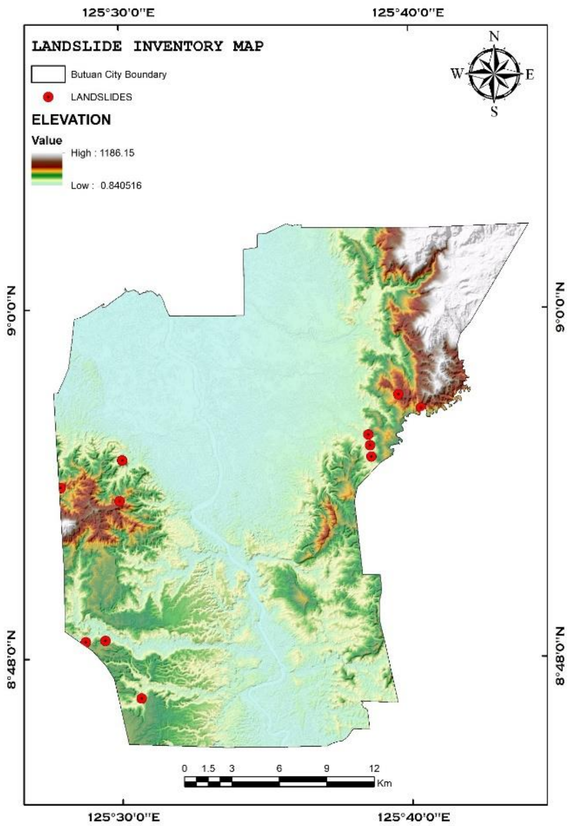

Fig. 2. Landslide Inventory Map of the Study Area.

3. RESULTS AND DISCUSSIONS

3.1 Reclassified Parameters

Seven factors were evaluated in order to create a map that showed which regions in Butuan City, Agusan del Norte were susceptible to landslides caused by rainfall: elevation, slope, annual precipitation, distance to streams, land use/cover, lithology, and distance to roads (as shown in Fig. 3). Each criterion was examined by five experts to determine which is most important in identifying places that are susceptible to landslides caused by rainfall. The data gathered from different institutions and agencies were reclassified, which served as the input in the Weighted Overlay. Before overlaying, these data were projected, clipped, and converted into raster layers. The scale for the reclassified maps was one (1) for Very Low and five (5) for Very High. Based on the average weighted criterion total, maps that will aid in characterizing the susceptibility of rainfall-induced landslide-prone areas in Butuan City were produced using the input criteria for the overlay.

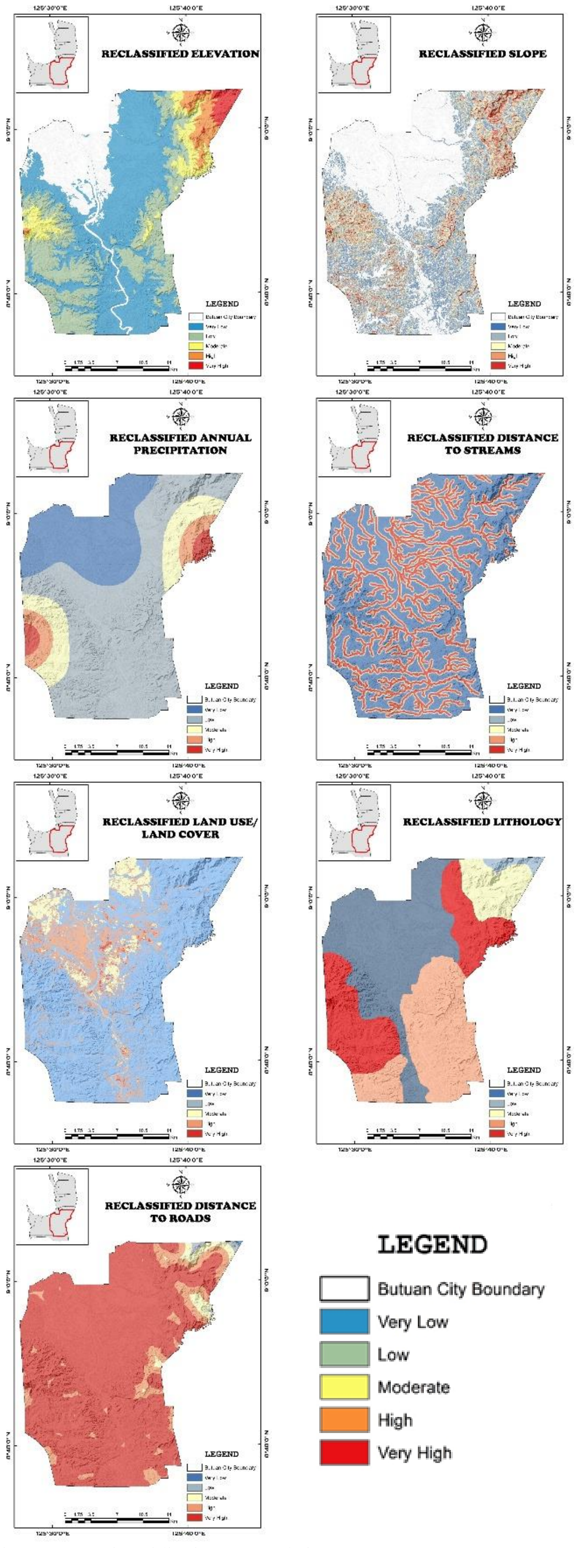

Fig. 3. Reclassified maps of the parameters.

3.2 Generated Weight from AHP

Five experts considered the seven chosen parameters and were rated on a discrete nine-value scale. Through the AHP Pairwise comparison, the weights percentage per criterion were obtained. The table below shows the acquired weight for each criterion the experts determined. Based on the table below, the criterion to be highly considered as top factor for determining rainfall-induced landslides is the Slope, followed by Annual Precipitation, Elevation, Lithology, Land Use/Land Cover, Distance to Streams, and Distance to Roads. The Average Final Weights of the parameters are 25.68%, 25.64%, 14.74%, 14.14%, 9.62%, 5.92%, and 4.26%.

Table 3. AHP Final Individual Weight Criterion.

Criteria	Average Criteria Weights	Average Final Weights (%)	Ranks
Elevation	0.14742842	14.74	3
Slope	0.25675782	25.68	1
Annual Precipitation	0.25642079	25.64	2
Distance to Streams	0.05915073	5.92	6
Land Use/Land Cover	0.09621383	9.62	5
Lithology	0.14138136	14.14	4
Distance to Roads	0.04264704	4.26	7

In the Consistency Ratio (CR) analysis for the pairwise comparison matrix used in the Analytic Hierarchy Process (AHP) to evaluate the relative importance of criteria contributing to rainfall-induced landslides, the CR value of 0.039 falls well below the 0.10 threshold, demonstrating that the experts' judgments are consistent and reliable. With seven criteria (n = 7), the computed maximum eigenvalue (λ_{max}) is 7.309. Using the standard formula, the Consistency Index (CI) is calculated as 0.052. Given the Random Index (RI) of 1.32 for a 7x7 matrix, the resulting Consistency Ratio is 0.039 or 3.9%. According to Saaty (1998), a CR value less than or equal to 0.10 is considered acceptable, indicating that the level of inconsistency in the judgments is within a tolerable range. In this case, the weight assignments derived from this comparison matrix can be confidently used in the subsequent landslide susceptibility analysis, as they reflect a sound and rational decision-making process.

3.3 Rainfall-induced Landslide Susceptibility Map

Employing AHP for mapping rainfall-induced landslide-prone areas was successfully generated. Fig. 4 displays the weighted Localized Rainfall-induced Landslide Susceptibility map of Butuan City, Agusan del Norte, classified into different classifications: Very High Susceptible, High Susceptible, Moderate Susceptible, and Low Susceptible. The results were based on the average weights assigned through AHP and judged by the selected experts.

Table 4 shows the area covered and its percentage for each classification of rainfall-induced landslide susceptibility. The classification for Moderate Susceptible areas has the highest covered area with 16973.72 hectares and is 26.11% of the total area, it is then followed by High Susceptible Areas covering 16776.17 hectares with 25.81% of the total area, Very High Susceptible areas cover 2145.15 hectares with 3.30% of the total area, Low Susceptible areas cover 271.73 hectares with 0.42% of the total area, and lastly, Not Susceptible areas cover 28828.95 hectares with 44.36% of the total area.

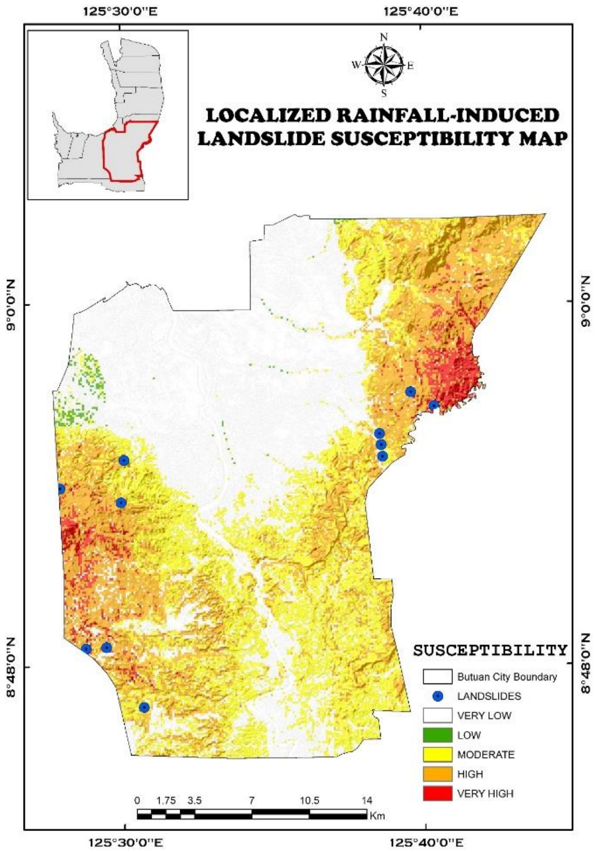

Fig.4. Localized Rainfall-induced Landslide Susceptibility Map.

Table 4. Area covered and percentage for each classification for rainfall-induced landslides.

Value	Susceptibility	Area (ha)
1	Not Susceptible	28828.95
2	Low Susceptible	271.73
3	Moderate Susceptible	16973.72
4	High Susceptible	16776.17
5	Very High Susceptible	2145.15
	Total	64995.73

This study was validated through the data that was acquired from the Butuan City Disaster Risk Reduction Management Office (CDRRMO). With a total of 11 validated landslides, it shows that eight 9 recorded landslides belong to High Susceptible areas, and 2 in Very High Susceptible areas. In addition, the Area Under the Curve (AUC) analysis was also conducted to reliably assess the predictive capacity of a proposed landslide model. Eleven (11) recorded landslides were used to test the AUC, with reclassification and projection of the final map (Localized Rainfall-induced Landslide Susceptibility Map) for calculation. The graph (Fig. 5) demonstrates the success rate for the Weighted Overlay Landslide Susceptibility Model at 93.6%.

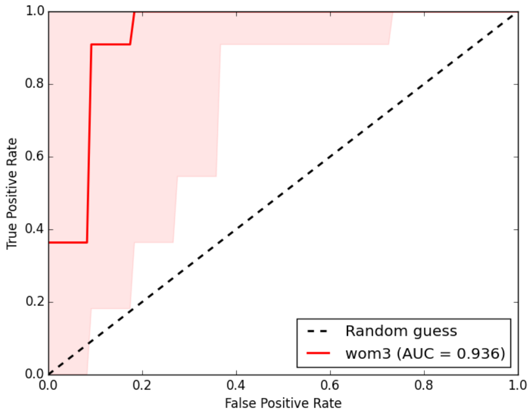

Fig. 5. Area Under the Curve

4. CONCLUSIONS AND RECOMMENDATIONS

Mapping rainfall-induced landslide-prone areas utilizing geospatial techniques is done in this study. This localized susceptibility map was made possible through the combination of expert viewpoints, geospatial datasets, and cutting-edge GIS technology. The Weighted Overlay analysis was employed to the seven geospatial datasets: elevation, slope, annual precipitation, distance to streams, land use/cover, lithology, and distance to roads. Through the Analytical Hierarchy Process (AHP), it was revealed that slope was the main factor impacting landslide susceptibility with a significant weight of 25.68%, followed by annual precipitation and elevation, with significant weights of 25.64% and 14.74%, respectively. Further analysis of the mapped rainfall-induced landslide-prone areas shows that that a substantial portion of Butuan City, approximately 16973.72 hectares or 26.11% of the total area, is mostly moderate susceptible areas. While very highly susceptible areas cover 2145.15 hectares or 3.30% of the total area. The validity and dependability of the susceptibility map were confirmed by validation using landslide data obtained from the Butuan City Disaster Risk Reduction Management Office (CDRRMO). The landslide susceptibility model's strong predictive ability was demonstrated by the high success rate of 93.6% obtained from the Area Under the Curve (AUC) analysis.

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