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ARTICLE

A Multi-Criteria GIS Approach to Landslide Risk Assessment: Application of FAHP in San Andres, Romblon, Philippines

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ABSTRACT: A landslide is the downslope movement of soil, rock, or debris driven by gravity, often triggered by natural or anthropogenic factors. The Philippines is highly susceptible to landslides due to its steep terrain, frequent typhoons, intense rainfall, and seismic activity, resulting in significant socioeconomic and environmental impacts. Despite increasing landslide occurrences in vulnerable coastal and mountainous municipalities in the Philippines, localized and integrated Geographic Information System (GIS)-based landslide risk assessments incorporating hazard, vulnerability, and exposure components remain limited in small island municipalities such as San Andres, Romblon. This study assesses landslide risk in the Municipality of San Andres, Romblon, using an integrated GIS and Fuzzy Analytic Hierarchy Process (FAHP) framework guided by the Sendai Framework for Disaster Risk Reduction to develop a comprehensive landslide risk assessment framework for localized disaster risk management and spatial planning. The study utilized the available multi-source geospatial, environmental, and socio-economic datasets spanning 2011–2024, including terrain, rainfall, land use, soil, and demographic information obtained from government agencies, remote sensing sources, and local community-based records. Risk was evaluated through three core components: hazard, vulnerability, and exposure. Hazard factors included soil type, landslide susceptibility, slope, elevation, and annual rainfall, while vulnerability incorporated socioeconomic and accessibility indicators. Exposure was represented by population, land use, household distribution, and proximity to evacuation facilities. Expert-based pairwise comparison was applied to derive parameter weights, with landslide susceptibility (34.98%) and distance to river (26.28%) identified as dominant hazard and vulnerability drivers, respectively, while land use/land cover (33.01%) and population density (32.93%) were the most influential exposure factors. The resulting landslide risk map revealed that 17.78% of the study area falls under very high risk, primarily concentrated in Marigondon Norte, Marigondon Sur, Victoria, and Matutuna. The findings provide a spatially explicit basis for targeted mitigation strategies, supporting local government units in implementing structural and non-structural interventions. This study demonstrates the effectiveness of GIS–FAHP integration in enhancing data-driven disaster risk reduction and resilience planning in landslide-prone regions.

KEYWORDS: Landslide; spatial analysis; disaster risk reduction; hazard; exposure; vulnerability; fuzzy logic; GIS

1 Introduction

Landslides are among the most destructive environmental hazards, commonly resulting from slope failures driven by complex interactions among geological, hydrological, climatic, and anthropogenic factors [1,2]. These events can lead to severe property damage, disruption of livelihoods, and significant loss of life in affected communities [3]. Landslides frequently occur in conjunction with extreme weather events such as typhoons; however, their timing, magnitude, and spatial distribution remain highly uncertain and difficult to predict [4,5]. Fundamentally, landslides involve the downslope movement of soil, rock, or debris, including boulder falls, rotational and translational slides, and debris flows, primarily governed by gravitational forces and slope instability [6,7]. The occurrence of landslides is influenced by both triggering and predisposing factors. Intense or prolonged rainfall, seismic activity, and human interventions such as deforestation and land-use change act as primary triggers, while slope gradient, lithology, soil composition, and drainage conditions serve as predisposing factors that control slope stability [8]. With increasing population growth, rapid urban expansion, infrastructure development in marginal lands, and environmental degradation, landslide risks are expected to intensify [9,10]. Globally, landslides have caused substantial socio-economic impacts; between 1998 and 2017, they affected approximately 4.8 million people and resulted in more than 18,000 fatalities, according to the World Health Organization [11]. Climate change further exacerbates landslide hazards by increasing the frequency and intensity of extreme precipitation events, particularly in steep and environmentally sensitive regions [12]. In countries such as Brazil, landslides remain one of the most prevalent and damaging natural hazards [13].

Landslides are recognized as one of the most significant geological hazards in mountainous and natural terrains, exerting profound effects on both environmental integrity and ecosystem stability [14,15]. A comprehensive understanding of landslide processes, including their spatial and temporal dynamics, is essential for minimizing associated risks and enhancing disaster preparedness [16]. The development of reliable landslide inventories, incorporating historical events and spatial distributions, is critical for assessing susceptibility and forecasting potential hazards [17]. Key factors influencing landslide occurrence include steep slopes, weak or unconsolidated geological materials such as clay and marl, deep valleys, and high rainfall intensity, all of which contribute to soil instability, erosion, and subsurface weakening [18–20]. Moreover, the increasing interaction of climatic variability, tectonic activity, and anthropogenic pressures has led to a noticeable rise in landslide frequency and severity, posing escalating threats to infrastructure, ecosystems, and human safety [19,21].

Advancements in geospatial technologies have significantly improved landslide assessment and mapping capabilities [22,23]. A Digital Elevation Model (DEM) serves as a fundamental dataset for representing terrain characteristics by capturing elevation variations of the Earth's surface while excluding vegetation and built structures [24,25]. Generated from satellite, aerial, or drone-based data, DEMs provide high-resolution topographic information essential for modeling natural hazards, including landslides and floods [26,27]. Higher-resolution DEMs, characterized by smaller grid sizes, enhance the accuracy of slope, elevation, and terrain-derived parameters, thereby improving the reliability of susceptibility and risk assessments [28,29].

Given the complexity and uncertainty inherent in landslide processes, robust analytical frameworks are required to support decision-making [29–31]. The FAHP, an extension of Saaty's Analytical Hierarchy Process (AHP), integrates fuzzy set theory to better represent uncertainty and vagueness in expert judgment, making it particularly suitable for complex environmental systems [32,33]. Multi-criteria decision-making (MCDM) approaches enable the integration of both qualitative and quantitative factors, reducing subjectivity and improving the objectivity of risk evaluation [34–36]. When coupled with GIS, FAHP has demonstrated strong capability in spatially explicit landslide risk assessment by systematically weighing multiple influencing parameters and minimizing uncertainties associated with expert-based evaluations [37]. This integration allows for the development of comprehensive risk maps that support informed planning and disaster risk reduction strategies [38].

The Philippines is among the most landslide-prone countries globally, ranking third among 41 nations in terms of landslide-related fatalities [39,40]. Its geographical setting, characterized by steep mountainous terrain, high annual rainfall, and frequent typhoon activity, significantly increases susceptibility to slope failures [41]. The Municipality of San Andres, Romblon, exemplifies these conditions due to its rugged topography and exposure to extreme climatic events. Historical records indicate recurring landslide incidents, including those in Sitio Naruntan (2019) and Sitio Hagimit (2022), triggered by Typhoon Tisoy, which caused disruptions to transportation networks and posed serious risks to local communities.

Recent studies have demonstrated the effectiveness of GIS-integrated multi-criteria decision-making techniques in landslide susceptibility and disaster risk assessment. These approaches improve spatial prediction accuracy and support evidence-based disaster mitigation planning in vulnerable communities. Karpouza et al. (2024) developed soil liquefaction and landslide hazard maps using GIS techniques and Peak Ground Acceleration (PGA) analysis to identify safe points and evacuation routes for schools in northeastern Peloponnese, Greece. Their study demonstrated how geospatial hazard mapping can support emergency planning, evacuation management, and risk-informed decision-making for vulnerable communities [42]. Another study from Bathrellos et al. (2024) investigated landslide causative factors in the tectonically active Glafkos River area in northwestern Peloponnese, Greece using GIS and statistical spatial analysis. Their study identified lithology, slope angle, distance from tectonic discontinuities, and proximity to drainage networks as significant factors influencing landslide occurrence. The results showed that steep slopes, areas near streams, and locations close to tectonic structures exhibited higher landslide susceptibility. Furthermore, the study achieved validation accuracies ranging from 76.5% to 79.5%, demonstrating the effectiveness of GIS-based spatial analysis for landslide susceptibility assessment and spatial planning [43]. Nwazelibe and Egbueri conducted a geospatial assessment of landslide-prone areas in Southern Anambra State, Nigeria using classical statistical models such as Frequency Ratio (FR), Shannon's Entropy (SE), Weight of Evidence (WoE), and Logistic Regression (LR). The study utilized twelve conditioning factors and high-resolution spatial datasets to generate landslide susceptibility maps and evaluate model performance. Their findings revealed that geological conditions, slope, elevation, rainfall, proximity to streams, land cover, vegetation indices, and stream power index significantly influenced landslide occurrence [44,45]. Recent advances in landslide susceptibility assessment have incorporated machine learning and ensemble modelling approaches to improve prediction accuracy and spatial analysis. Studies have applied methods such as Artificial Neural Networks (ANN), Boosted Regression Trees (BRT), Elastic Net models, and Support Vector Regression combined with optimization algorithms for landslide susceptibility mapping. These approaches demonstrated strong predictive capabilities in identifying landslide-prone areas using multiple conditioning factors such as lithology, slope, rainfall, topographic indices, and land use characteristics [46].

Despite increasing landslide occurrences in vulnerable municipalities in the Philippines, comprehensive localized landslide risk assessments integrating hazard, vulnerability, and exposure components using GIS–FAHP approaches remain limited, particularly in small and rural island municipalities [47]. This highlights the importance of developing a comprehensive landslide risk assessment approach that incorporates hazard, vulnerability, and exposure components. This study aims to assess landslide risk in the Municipality of San Andres, Romblon, using a GIS-based multi-criteria decision-making framework integrated with the FAHP. Compared with purely statistical or machine learning approaches, the GIS–FAHP framework provides a practical and interpretable method for integrating expert judgment, limited localized datasets, and multiple spatial parameters within data-constrained municipalities. By generating a detailed landslide risk map, the study provides a spatially explicit basis for identifying high-risk areas and supports the implementation of targeted mitigation strategies. The results are intended to assist local government units, urban planners, and disaster risk management agencies in improving preparedness and resilience. Furthermore, the methodology developed in this study can be applied to other regions with similar environmental and socio-economic conditions, contributing to broader efforts in disaster risk reduction and sustainable land-use planning. While national-level landslide susceptibility mapping has been extensive in the Philippines, local assessments that integrate community vulnerability remain sparse, underscoring the critical need for regional studies like this one [48].

Indeed, the province of Romblon, including the municipality of Odiongan and Santa Fe, frequently experiences typhoons and heavy rainfall that lead to significant natural hazards such as flooding and landslides, further emphasizing the need for robust risk assessments [32,35]. This particular vulnerability underscores the importance of employing advanced methodologies, such as multi-criteria decision analysis within a GIS framework, to effectively delineate and quantify landslide susceptibility [30,49,50]. Such an approach allows for a granular understanding of risk by integrating various geomorphological, hydrological, and anthropogenic factors, crucial for developing effective mitigation and adaptation strategies. Moreover, this study contributes to the field of geomatics through the integration of GIS-based spatial analysis, geospatial data processing, and multi-criteria decision-making techniques for landslide risk assessment and disaster risk reduction planning. Specifically, the integration of remote sensing data, such as those derived from open-source satellite imagery and digital elevation models, with multi-criteria decision analysis methods in a GIS environment, offers a powerful tool for generating accurate and precise landslide susceptibility models.

Therefore, this study aims to assess landslide risk in the Municipality of San Andres, Romblon, using an integrated GIS-based multi-criteria decision-making framework with the FAHP. The study systematically combines hazard, vulnerability, and exposure components to develop a comprehensive and spatially explicit landslide risk assessment framework. The succeeding sections present the methodology, parameter analysis, FAHP-based weighting process, and spatial risk mapping in a logically connected manner to support coherent interpretation of the results and provide geospatial information that may support localized disaster risk reduction, land-use planning, and community resilience initiatives.

2 Methodology

This study evaluates landslide risk in the Municipality of San Andres, Romblon, Philippines by following three key stages: gathering relevant data, analyzing parameters through the FAHP [18], and producing landslide risk maps. At the initial stage, essential information on factors such as elevation, slope, land use, soil characteristics, rainfall patterns, and proximity to roads and fault lines is obtained from online sources and various government and non-government databases. The GIS–FAHP approach was selected because it effectively integrates expert judgment and spatial multi-criteria analysis, particularly in areas where comprehensive historical landslide inventories and large training datasets required for machine learning approaches are limited. Specialists then apply a nine-point rating scale to determine the relative importance of each factor, and these values are processed using FAHP to support a structured multicriteria decision-making approach. GIS tools are utilized to integrate and analyze both primary and secondary datasets, enabling the creation of landslide susceptibility and risk maps [19]. These maps present a clear spatial overview of areas that are more likely to experience landslides, providing useful guidance for local authorities and disaster risk management teams. The schematic diagram of the study process is illustrated in Fig. 1.

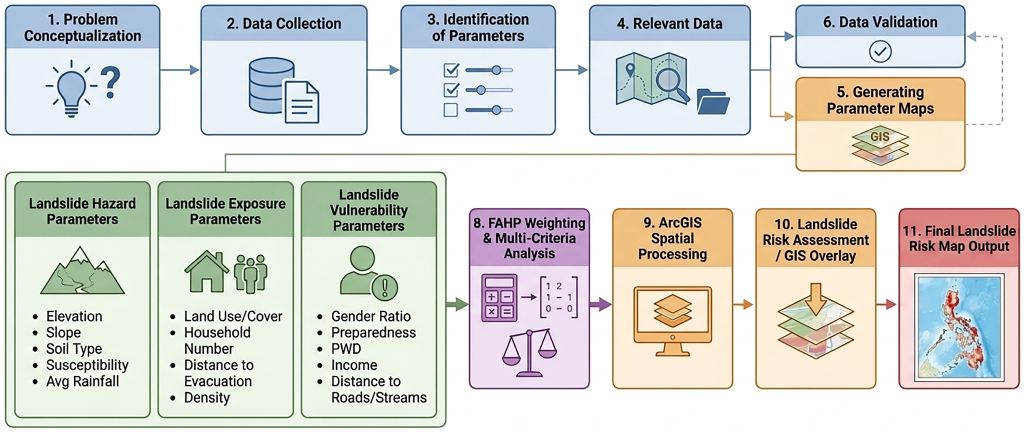

Figure 1: The proposed schematic diagram of the study.

2.1 Study Area

San Andres is a municipality in the province of Romblon [51], located in the central part of Tablas Island [52] at coordinates 12°31′22″ N and 122°0′37″ E. San Andres features a coastal landscape with rugged terrain, including hills, mountains, and steep slopes, particularly in its eastern portion facing the Sibuyan Sea. Given its geographical characteristics, San Andres is susceptible to landslides, making it crucial to assess landslide risks and develop risk maps. These maps can help mitigate potential hazards and support local government efforts to implement proactive disaster management measures to protect residents and infrastructure as shown in Fig. 2.

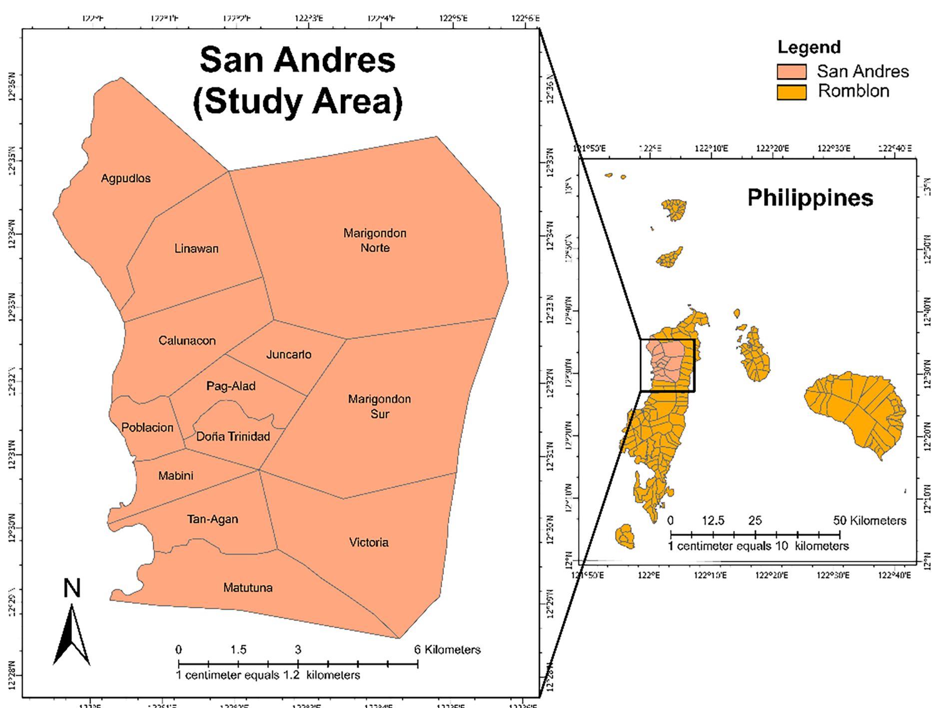

Figure 2: Municipal and barangay boundaries of the study area.

2.2 Data Collection and Preliminary Site Assessment

The research used relevant literature from previous studies and site investigation to gather information and data in this phase. Past landslide occurrences and potential risks in the study area were also surveyed and observed. Furthermore, the researcher conducted interviews with local officials. This stage focuses on reviewing related studies and gathering information about the study area. Essential data and knowledge contributing to landslide risk have been identified through online platforms that provide access to satellite-based data sets, different agencies, and site visits in the study areas [53]. This step also involves interviewing the disaster risk officials and barangay officials in the study area to gather information regarding landslide risk and occurrence.

Collecting precise details regarding the study location is necessary for this stage. This entails obtaining information on various factors such as the demographic profile in the study area, specifically the population density, gender ratio, disabled population, average income, evacuation facility, household number, and socioeconomic status [30,54,55]. These data were gathered from the local government unit and the community-based monitoring system. Furthermore, land use/land cover, annual average rainfall, and soil type were also collected. These data were acquired through request letters to the different affiliated agencies, such as the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA), the Department of Environment and Natural Resources (DENR), and the National Mapping and Resource Information Authority (NAMRIA).

Other relevant data, such as DEM and satellite images of the study area, are also gathered in this step. These data are important tools for mapping and creating accurate, updated, and spatially comprehensive data for analyzing the Earth's surface and reducing disaster risk [56,57]. The IfSAR Digital Terrain Model (DTM) was selected as the primary DEM, acquired through the National Mapping and Resource Information Authority, Department of Environment and Natural Resources.

2.3 Identification of Parameters

After gathering the data from the study area, the researchers adopted the method for disaster risk assessment offered by the Sendai Framework [58]. This method aids in identifying the crucial factors that should be considered while assessing the likelihood of landslides in San Andres, Romblon. Fig. 3 shows the relationship between parameters. By examining how risks, exposure, and vulnerabilities interact, the framework highlights how crucial it is to comprehend disaster risk [59]. This approach leads to the selection of hazard criteria, such as soil type, annual average rainfall, elevation, slope, and landslide susceptibility, all of which influence landslide risk. To ascertain the degree of risk to people and infrastructure, the framework additionally points out the necessity of evaluating exposure, such as land use/land cover, population density, household number, and distance to evacuation facilities, and vulnerability criteria, such as gender ratio, emergency preparedness, number of PWD, average income, distance to stream, and distance to roads. Table 1 shows the parameters of the landslide risk.

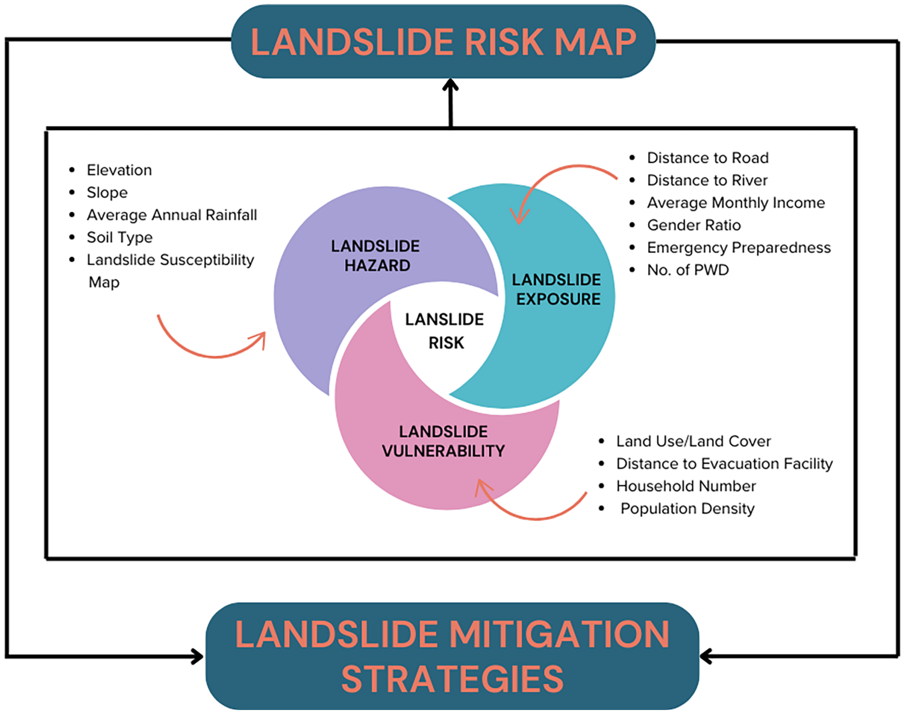

Figure 3: This Venn diagram shows the relationship between the parameters and the landslide risk assessment framework of the study.

Table 1: Parameters with the duration/year and source used for hazard, vulnerability, and exposure assessment.

Parameters	Data Type	Duration/Year	Source	Reference
		Landslide Hazard Parameters		
Average Annual Rainfall	Interpolated Climatological Normal using Inverse Distance Weighted (IDW) technique tool in ArcGIS	2023	Center for Hydrometeorology and Remote Sensing (CHRS) and web search for weather station coordinates.	[60,61]
Slope	Derived from IfSAR Data Using Slope Tool in ArcGIS	2013	NAMRIA/DENR	[61–63]
Elevation	Derived from IfSAR Data	2013	NAMRIA/DENR	[64,65]
Soil Type	Shapefile	2011	Geoportal Philippines	[60,66]
Landslide Susceptibility			Mines and Geoscience Bureau (MGB), eFOI	[63]
		Landslide Vulnerability Parameters		
Average Income	Average Income of each barangay.	2023	Barangay Profile/Municipality of San Andres Community Based Monitory System (CBMS)	[67–69]
Number of Persons with Disabilities	Number of persons with disability in every barangay.	2024	Barangay Profile/Municipality of San Andres CBMS	[70–72]

(Continued)

Table 1 (continued)

Parameters	Data Type	Duration/Year	Source	Reference
Gender Ratio	Men to women gender ratio of every barangay.	2023	Barangay Profile/Municipality of San Andres CBMS	[30,73]
Emergency Preparedness	Emergency Preparedness during an expected situation like natural disasters.	2024	Survey Questionnaire	[30]
Distance to Road Network	Distance of the identified road network using the Euclidean Distance tool in ArcGIS	2022	Open Street Map	[63]
Distance to River Network	Distance of identified river network using the Euclidean Distance tool in ArcGIS	2022	NAMRIA	[74,75]
Landslide Exposure Parameters				
Land Use/Land Cover	Land cover map from Comprehensive Land Use Plan (CLUP)	2011	Municipality of San Andres CLUP	[63,76]
Household Number	Number of households in every barangay.	2022	Barangay Profile/Municipality of San Andres CBMS	[70–72,77]
Distance to the Evacuation Facility	Distance of identified evacuation facility using Euclidean Distance tool in ArcGIS	2022	Municipality of San Andres CBMS	[30]
Population Density	Computed from the population over the covered area of the barangay	2022	Municipality of San Andres CBMS	[70–72]

2.3.1 Landslide Hazard Parameters

Landslide disaster planning and mitigation can benefit from using landslide hazard maps [78]. Conducting a practical assessment of landslide hazards is essential to understand the various factors contributing to landslides comprehensively. Five (5) parameters are anticipated in this study, which are further discussed below: Rainfall significantly influences landslides by increasing soil moisture, which reduces soil strength and stability [79]. Intense or prolonged rainfall can saturate the soil, elevating pore water pressure and decreasing friction between soil particles, leading to slope failure. The amount, duration, and intensity of rainfall are critical factors in triggering landslides. This study utilized climatological records from the CHRS, encompassing 5-year data averages and corresponding latitude and longitude coordinates. Analysis for annual average rainfall was expressed in millimeters (mm) and was classified into five (5) categories. The slope was defined as the inclination of a surface or terrain, and the steeper the slope, the higher the risk of landslide occurrence [80]. If the slope is too steep or unstable, it can trigger landslides by causing the ground to become unstable and prone to movement. Slope values (in degrees) were categorized into five (5) groups. Landslides were more likely to occur on slopes with angles greater than 30 degrees [39,40]. A comprehensive slope map for the study area was generated through data from NAMRIA, such as DTM and ArcGIS tools for slope analysis. Elevation is crucial in landslides because higher slopes are more prone to gravity-driven movements [30]. Elevation data were measured in meters and were classified into five categories:

>100, 75–100, 50–75, 25–50, and 0–25. Steeper elevations increase shear stress on the soil, making slopes more susceptible to failure, especially when rainfall infiltrates and weakens the ground. Additionally, rainfall intensity may vary at higher altitudes, with orographic effects causing more precipitation on windward slopes, further increasing landslide risk. Lower elevations, especially valleys, can also be affected by debris flows from landslides at higher elevations. Different soil types also vary in drainage, cohesion, and stability properties [81,82]. The soil types in the study area were classified into seven (7) groups: clay, clay loam, complex, hydrosol, loam, sandy clay loam, and sandy loam. These soil classifications aid in understanding the area most susceptible to landslides. Landslide susceptibility is a crucial hazard parameter as it provides data regarding the potential occurrence of landslides in a certain area. Landslide susceptibility was classified into four (4) groups: high, low, moderate, and very high. A shapefile of this data was requested from the Mines and Geosciences Bureau through their online portal.

2.3.2 Landslide Vulnerability Parameters

Vulnerability is a complex and dynamic concept influenced by social, economic, political, and environmental factors and can vary across different spatial and temporal scales [83,84]. The United Nations Office for Disaster Risk Reduction (UNDRR) defines vulnerability as "the conditions determined by physical, social, economic, and environmental factors or processes, which increase the susceptibility of an individual, community, assets, or systems to the impacts of hazards." Identifying the prone communities likely to be more affected by landslides can enhance the effectiveness and impartiality of disaster risk reduction and response initiatives. This can facilitate the development of a more resilient community in the Municipality of San Andres, Romblon. The study comprises demographics and disaster risk reduction data from the San Andres local government unit for assessment.

Assessing the social and economic factors in the Municipality of San Andres is crucial as they play an important role in identifying the area most vulnerable during disasters such as landslides. These factors, such as average income, number of people with disabilities, and gender ratio, influence how individuals and communities experience, respond to, and recover from disasters.

The study focuses on analyzing several factors, such as emergency preparedness, distance to road network, and distance to river network. Data for these factors were gathered by utilizing data from the Municipal Planning and Development Office of San Andres and the OpenStreetMap website.

2.3.3 Landslide Exposure Parameters

Exposure was defined by the UNDRR as the presence of people, infrastructure, housing, and environmental resources in hazard-prone areas [58]. It focuses on identifying at-risk populations and infrastructure and their potential economic losses. Exposure was categorized into four groups: household number, distance to evacuation facility, population density, and land cover data. Household and population data were gathered from the barangay profile and CBMS by the local government office of the Municipality of San Andres. Through Google Earth Pro, coordinated evacuation facilities were pinpointed. Based on the CLUP of the Municipality of San Andres, shapefile data on land use were obtained from the NAMRIA.

Exposure parameters are crucial in identifying landslide-prone areas as they aid in determining the extent to which people, buildings, infrastructure, and economic activities are at risk. Analyzing these parameters can provide possible preventive measures, improve land-use planning, and enhance disaster preparedness strategies in the Municipality of San Andres.

2.3.4 Convert All Collected Data into Parameter-Specific Maps

A GIS was utilized to map each factor. It aids in capturing, storing, and analyzing spatial and geographic data. GIS combines several kinds of data, including maps, satellite photos, and statistical data, to support transportation, environmental management, urban planning, and disaster response decision-making. It allows users to layer and evaluate spatial data to find patterns, similarities, and variations. Due to technological innovations, real-time data analysis and visualization using GIS is increasingly widespread in internet-based programs, mobile devices, and artificial intelligence. This research study uses ArcGIS specifically as the main application in creating maps. Developed by the Environmental Systems Research Institute (ESRI), ArcGIS is a GIS-based tool that can produce standard Web Services and make numerous network GIS.

2.4 Evaluation and Assessment of Parameters Using the FAHP

Experts from different fields, such as water resources engineers, risk-reduction specialists, civil engineers, geodetic engineers, and end-users, have contributed and participated in this study to evaluate the weight of each parameter. These experts represent different academic institutions, government agencies, private offices, and end-users from LGU-San Andres. Through their expertise, the parameters were evaluated to determine the importance of each factor by comparing them to each other in pairs and assigning weights using a nine-point scale, also known as the FAHP, which measures the intensity of their importance using pairwise comparison questionnaires and risk assessment. Experts assess the parameters through online and printed materials.

At this stage, the determining process was broken down into separate components and depicted in a hierarchical diagram with at least three levels: goal, criteria, and indicators. The FAHP structure, shown in Fig. 4, placed the primary aim at the top of the hierarchy and selected it as the best option. The lower levels of the hierarchy included decision rules or criteria that contributed to making the best choice, which can be further elaborated and enlarged depending on the decisions or standards evaluated. Finally, the lowest layer of the hierarchy comprises alternatives or signs that decision-makers should examine.

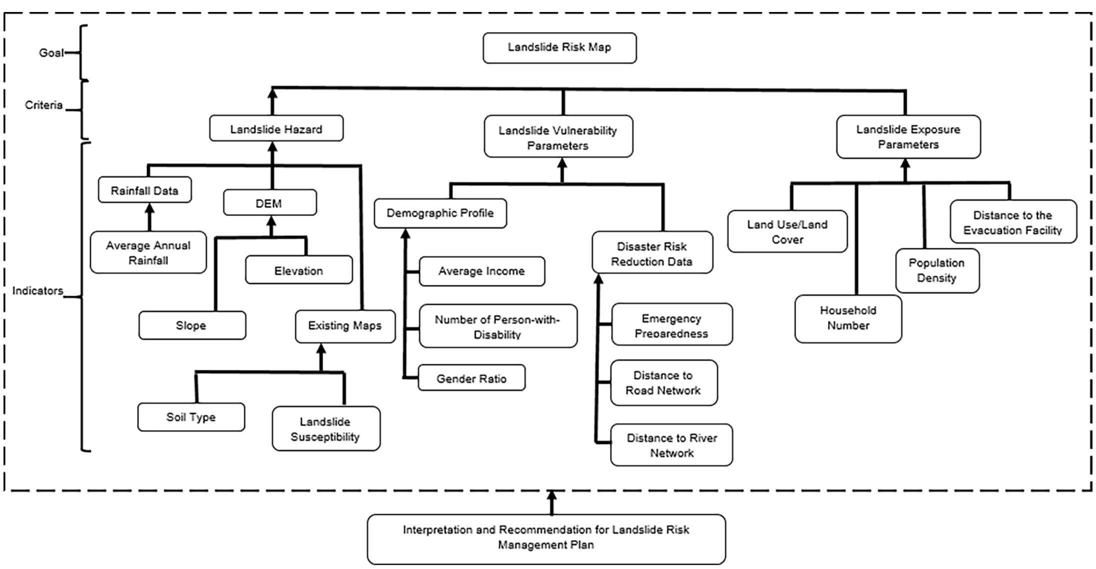

Figure 4: MCDA hierarchy tree for landslide risk assessment in FAHP framework.

The relative level of importance evaluated by twenty (20) experts was calculated through FAHP, which applied the geometric mean method to achieve the normalized weight value of its parameters as indicators and create a comprehensive landslide risk map. The questionnaire was divided into three criteria: Hazard parameters, Vulnerability parameters, and Exposure parameters [30,32,51]. Its indicators were presented in a matrix-based structure; relative importance was provided to undergo the pairwise comparison technique. The assignment of feature weights was based on the relative importance of each indicator in influencing landslide hazard, vulnerability, and exposure within the study area. Experts evaluated each parameter through pairwise comparison using Saaty's nine-point scale integrated with triangular fuzzy numbers to minimize uncertainty in judgment. Indicators considered to have a stronger influence on landslide occurrence and disaster impact, based on previous studies, local environmental conditions, historical landslide observations, and expert knowledge, were assigned higher relative weights during the FAHP evaluation process.

The weighing method of the FAHP process was the same as that of the AHP. However, FAHP handles decisions with uncertainty and imprecision compared with AHP, which assumes certainty. Giving FAHP the weighing scale presented in Table 2 acknowledges that decision-makers may have vague preferences.

Table 2: The scale for pairwise comparison techniques [85,86] used for FAHP.

Scale	Verbal Comparison of Factor Importance	Importance Level	Scale of a Fuzzy Number
9	Extremely		(9, 9, 9)
7	Very Strongly		(6, 7, 8)
5	Strongly	More Important	(4, 5, 6)
3	Moderately		(2, 3, 4)
1	Equally Important		(1, 1, 1)
1/3	Moderately		(¼, 1/3, ½)
1/5	Strongly	Equally Important	(1/6, 1/5, ¼)
1/7	Very Strongly		(1/8, 1/7, 1/6)
1/9	Extremely	Less Important	(1/9,1/9,1/9)

To illustrate the membership degree of value, a Triangular Fuzzy number in Fig. 5 was used, consisting of the lower bound (l), the minimum possible value, the modal value (m), and the upper bound (u). A triangular number was converted into three fuzzy numbers to quantify uncertain decisions under different conditions. The Triangular Number Design Approach model helps expert choices be flexible, allowing absolute judgment and proportioning indicators or criteria into numerical values.

The representation of a triangular fuzzy number was denoted by Eq. (1) as follows:

$$P = (l, m, u) \tag{1}$$

Fig. 6 shows the equivalent numerical values of a Fuzzy number, as indicated in Table 2, that is needed to expand the multi-criteria judgment based on the expert's relative scale. Each scale was specified from lowest to moderate or highly crisp numerical numbers. The membership degree for the degree of uncertainty can only range from 0 to 1 to enable better reasoning.

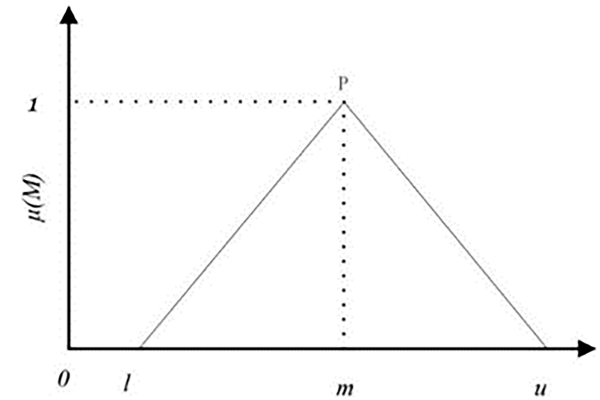

Figure 5: Triangular fuzzy number (P).

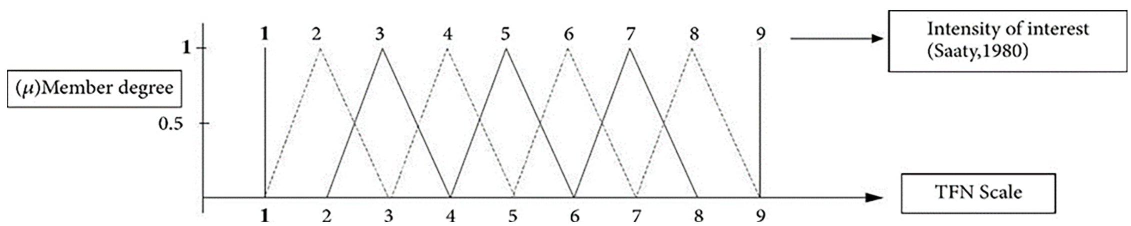

Figure 6: Graph of fuzzy triangle set.

The membership function M(μ) is defined by the equation below as shown in Eq. (2):

$$Mu\mu_M x = \left\{ \begin{array}{ll} 0\,(x < l) & \\ \dfrac{x-l}{m-l} & (l \leq x \leq m) \\ \dfrac{u-x}{u-m} & m \leq x \leq u \\ 0\,(x \geq u) & \end{array} \right\} \tag{2}$$

Following the replacement of numerical crisp values at individual fuzzy scale numbers from the pairwise comparison obtained from each expert, relative importance was evaluated for each parameter under the fuzzy geometric Mean method. However, fuzzy numbers may appear in their reciprocals. To determine its equivalent fuzzy intermediate values, shown below in Eq. (3), where the upper value is written at the left and the lower at the right:

$$\hat{A}^{-1} = (l, m, u)^{-1} = \left(\frac{1}{u}, \frac{1}{m}, \frac{1}{l}\right) \tag{3}$$

Eqs. (4)–(6) present the calculation of the fuzzy geometric mean by multiplying all lower, middle, and upper points, and then solving for the nth root.

$$l_\mu = (l_1 \times l_2 \times l_3 \times \ldots \times l_n)^{\frac{1}{n}} \tag{4}$$

$$m_\mu = (m_1 \times m_2 \times m_3 \times \ldots \times m_n)^{\frac{1}{n}} \tag{5}$$

$$u_\mu = (u_1 \times u_2 \times u_3 \times \ldots \times u_n)^{\frac{1}{n}} \tag{6}$$

Fuzzy weights were determined by dividing the sum of the geometric mean of l_u, $m_{u,}$ and u_u. The calculation is expressed by the following equations below (Eqs. (7)–(9)).

$$l = l_n \times \left(\frac{1}{\sum u_\mu}\right) \tag{7}$$

$$m = m_n \times \left(\frac{1}{\sum m_\mu}\right) \tag{8}$$

$$u = u_n \times \left(\frac{1}{\sum l_\mu}\right) \tag{9}$$

Derived fuzzy weights of l_u, $m_{u,}$ and u_u proceed to solving their mean values as outlined in Eq. (10) to get the average of individual indicators w_n.

$$w_n = \frac{l_{n+m_n+u_n}}{3} \tag{10}$$

Normalization of weights occurs if the sum of these weights resulted to not exactly one, thus each calculated equivalent weight of each indicator was divided by the sum of the calculated weights. Moreover, the FAHP computational procedures, including the derivation of Eqs. (1)–(10), particularly triangular fuzzy numbers, fuzzy geometric mean, and weight normalization, were adopted from established methods in the literature [32,87].

2.5 Development of Landslide Risk Map

In this step, data assessed using FAHP were layered using GIS modeling to create a comprehensive landslide risk map. This map allows the researchers to assess the severity of the landslide in the area. It was also a tool to create precautionary measures and mitigate landslides, and it was then passed to the local Municipality of San Andres, Romblon.

The normalized weights calculated were integrated into ArcGIS to create map indices. Using "Polygon to Raster" in the ArcGIS tool, parameters represented in different file types were converted into raster format. For example, land cover data used in this study was initially in shapefile format and was converted to raster. Once converted, the raster data is reclassified and normalized on a scale from one (1) to five (5). This normalization reflects the accuracy and relative importance of each decision-making and ensures that more critical parameters have a greater impact on the result. The "Raster Calculator" tool in ArcGIS was employed to generate the landslide hazard index map, vulnerability index map, and landslide exposure index map, the "Raster Calculator" tool in ArcGIS was employed. The landslide index maps were classified into five (5) categories: very low, low, moderate, high, and very high risk. Maps generated were checked and assessed for accuracy to ensure they met the study's objective. Information derived from the landslide hazard index map, landslide vulnerability index map, and landslide exposure index map was further evaluated by qualified individuals to ensure all inputs meet the desired output of each criterion. Some experts in the field of geotechnical engineers, civil and water resource engineers, municipal/local government, or risk-reduction specialists, including mentors, were consulted for further recommendations, immediate action for any errors, and verification.

Although additional causative factors such as land cover change, seismic activity, drainage density, and proximity to faults may further improve susceptibility analysis, the present study utilized parameters with reliable and locally available spatial datasets. The selected parameters were validated through expert consultation and supported by previous landslide assessment studies employing GIS-based FAHP approaches.

3 Results

The study deals with the analysis of data for determined parameters, risk evaluation and assessment results using FAHP, and the municipality's Landslide Management Plan. The findings may help the local administration and LGU-San Andres end-users make effective and efficient plans for considering landslide incidents.

3.1 Data Analysis for Identified Parameters

Data analysis for identified parameters involves several steps to ensure accurate and comprehensive results. It begins with site investigation, data collection, and gathering spatial and non-spatial datasets, including maps and demographic information, focusing on parameters from relevant literature and previous research studies, as well as the historical landslide occurrences through manual reading and internet searches. Preprocessing the data collection involves manual reading and preparing the datasets for compatibility with ArcGIS tools. Relevant data were gathered during the data analysis phase. For further analysis, relevant data included demographic data, land use/land cover, rainfall data, soil type, and other data sources, such as DEMs and satellite images. Several parameters were included in the study for different criteria: for hazard assessment are average annual rainfall, slope, elevation, soil type, and landslide susceptibility; for vulnerability assessment, the number of persons with disabilities, average income, gender ratio, emergency preparedness, distance to road, and distance to the river; and for exposure assessment are population density, land use/land cover, households number, and distance from evacuation center. After this spatial analysis, parameters are mapped using ArcGIS techniques by including these factors in a comprehensive model to assess the potential impact of landslide exposure and vulnerability for identifying high-risk zones as feasible. Before weighing variables for increased accuracy, results are validated by comparing variables with field surveys and historical data before weighing variables for increased accuracy. The findings aim to be visualized through maps and serve as a basis for informed decision-making, ensuring the safety and sustainability of communities within the study area.

3.2 Landslide Hazard Parameters

This study determined five (5) key parameters that significantly influence landslide occurrence, which were systematically analyzed. These parameters include average annual rainfall, slope, elevation, soil type and landslide susceptibility. Each factor was carefully evaluated to understand its relative contribution and the results of this modeling process are illustrated in Fig. 7. The annual average rainfall influences soil saturation, slope stability, and landslide likelihood. It was examined using IDW, a method in ArcGIS. Using equal intervals, five (5) classes were created using the interpolation findings. The resulting map in Fig. 7a shows an average yearly rainfall ranging from 2670 to 2710 mm and higher. Slope affects runoff speed, soil stability, and landslide susceptibility. The reclassified slope layers are shown in Fig. 7b, categorized in degrees. The colors on the map are coded, with red denoting the lowest slopes and green representing the highest slopes. The majority of the map exhibits slopes ranging between 14 to 21 degrees. The slope map also plays a role in influencing both the likelihood of a landslide occurring and the speed at which materials flow once the slope fails in the soil creep. Elevation affects slope stability and landslide occurrence. The elevation map of the area is shown in Fig. 7c, which was acquired from NAMRIA using IfSAR DTM. Five (5) levels of elevation, ranging from 0 to 100 m above the water surface, are used to classify elevations. These elevation levels, which are impacted by the terrain's slope, are crucial in predicting the possible rate of landslides. The map also shows that the higher the elevation, the higher the risk of an area. The map shapefile provides spatial data used to identify and analyze landslide-prone areas. The map shown in Fig. 7d, was obtained from Geoportal Philippines and then cropped to fit the boundaries of the study area. Based on the Hydrologic Soil

Group (HSG), the soils are divided into seven categories (A, B, C, D, E, F, and G) according to their potential for runoff in landslide risk. Mitigation efforts such as slope stabilization, vegetation planting, and drainage systems are essential. Proper land use and controlled water flow help reduce risks for disaster preparedness in San Andres.

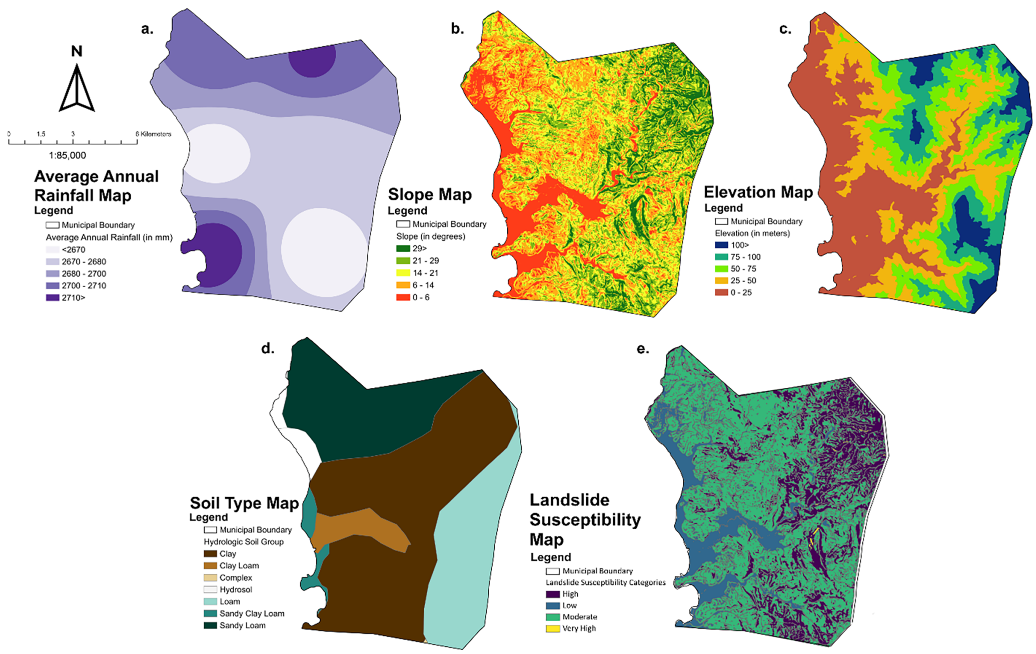

Figure 7: Produced map for landslide hazard parameters including average (**a**) annual rainfall (**b**) slope (**c**) elevation, (**d**) soil type, and (**e**) landslide susceptibility.

Landslide susceptibility influences the likelihood and spatial distribution of landslides. The municipality of San Andres' landslide susceptibility map, which provides spatial analysis, is displayed in Fig. 7e. The landslide risk within the study area is categorized into four levels: very high susceptibility, high susceptibility, moderate susceptibility, and low susceptibility. This helps residents comprehend the hazards connected to their area, allowing them to take proactive steps like retrofitting their homes, taking part in exercises for readiness, and following evacuation protocols in an emergency. It is an important tool for long-term sustainable development planning and short-term disaster risk mitigation.

3.3 Landslide Vulnerability Parameters

Landslide vulnerability assessment was important for developing effective risk reduction and mitigation techniques. The study considered multiple parameters influencing landslide vulnerability, as shown in Fig. 8. Demographic factors such as average monthly income, number of persons with disabilities per barangay, proportion of men to women, emergency preparedness, proximity of roads or highways, distances to the river network were analyzed to determine physical susceptibility.

In Fig. 8a, the number of persons with disabilities per barangay is displayed, revealing that the majority number of PWD across several barangays is in the parts of Calunacon, Matutuna, Tan-Agan, and Marigondon Sur that fall into the 30 to 36 residents. Barangay Doña Trinidad and Victoria have the lowest average number, 15 to 22 people. Notably, Barangay Poblacion has the highest number of persons with disabilities, consisting of between 44 and 50 people within the area. Number of persons with disabilities affects evacuation capacity and overall landslide vulnerability.

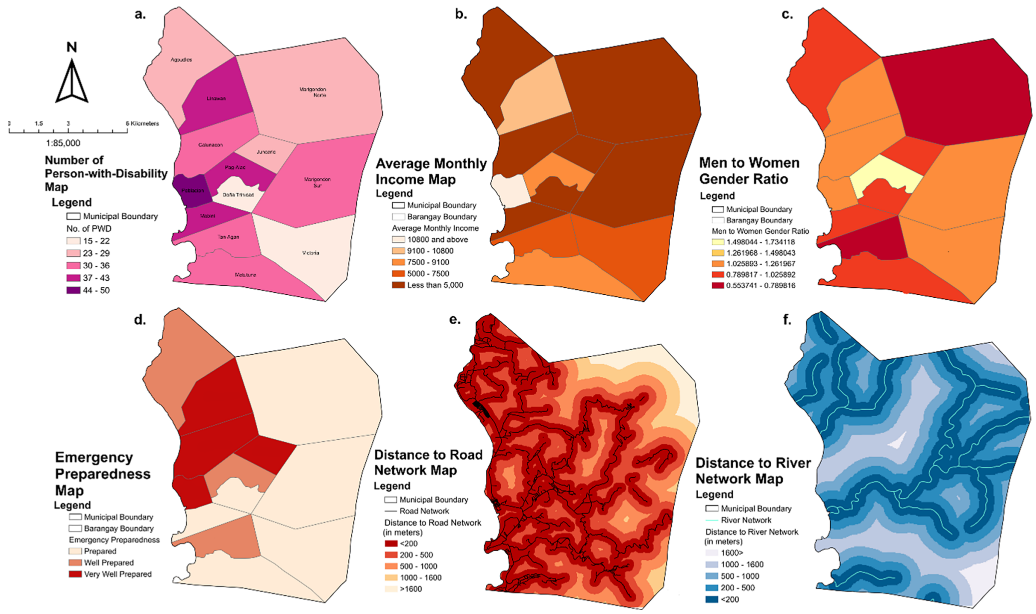

Figure 8: Landslide vulnerability incorporated parameters including (**a**) number of persons with disability, (**b**) average monthly income, (**c**) men to women gender ratio, (**d**) emergency preparedness, (**e**) distance to road network, and (**f**) distance to river network.

Average monthly income affects resilience and ability to cope with landslide impacts. It was categorized into five (5) classes: less than 5000, 5000 to 7500, 7500 to 9100, 9100 to 10,800, and 10,800 and above shown in Fig. 8b. The map reveals that the average monthly income of Barangay Mabini, Doña Trinidad, Juncarlo, Marigindon Norte, Agpudlos, Calunacon, and Marogondon Sur is less than 5000.

Proportion of men to women affects labor availability and community. It is observed in Fig. 8c that in the Municipality of San Andres, there generally appears a higher proportion of men to women in Barangay Pag-Alad only, while the range of other barangays indicates nearly equal proportions of men and women. In particular, the overall gender ratio for San Andres leans slightly toward fewer men compared to women, with a ratio of 0.9397.

Emergency preparedness maps show landslide response capacity. It indicates which barangays are better equipped to handle landslide risks is depicted shown in Fig. 8d. Disaster preparedness was categorized into three (3) classes: Prepared, Well Prepared, and Very Well Prepared. Barangays such as Poblacion, Linawan, Calunacon, Juncarlo, and Linawan were categorized as very well prepared. At the same time, Barangay Tan-Agan, Pag-alad, and Agpudlos fall into the category of well-prepared. Barangay Doña Trinidad, Mabini, Matutuna, Victoria, Marigondon Sur, and Marigondon Norte fall into the prepared classification; these areas are potentially less equipped to handle landslides and have a limited disaster management infrastructure.

Fig. 8e shows the proximity of roads or highways to the furthest communities or residences regarding road connectivity. The classified data from this map indicated that, for most barangays, the distance between the farthest sitios and the nearest roadways is between 200 and 1600 m. However, the nearest road distances beyond 200 m are the closest to the road network. In contrast, the northeastern and southeastern parts of the municipality which extend the distance to 1600 m, are significantly far from the road network, implying more limited access to transportation and services. Proximity to roads affects landslide evacuation.

Proximity to rivers influences landslide risk. The distances to the river network are classified into five (5) levels: greater than 1600, 1000–1600, 500–1000, 200–500 m, and less than 200 m shown in Fig. 8f. Buildings and residences within 200 m of the river may receive large volumes of runoff water. Saturated soil near rivers can become unstable, triggering landslides or debris flows, which erosion caused by river currents can weaken riverbanks, making nearby slopes more prone to collapse. Generally, communities close to rivers could face compounded risks of flooding and landslides during extreme weather events, making them more susceptible and vulnerable to landslide-related events.

3.4 Landslide Exposure Parameters

Population density increases the number of people exposed to landslide hazards. The map shown in Fig. 9a indicates that Barangay Victoria, Marigondon Sur, Marigondon Norte, and Juncarlo have the lowest population density, followed by Agpudlos, Linawan, Calunacon, and Matutuna then Doña Trinidad. Barangay Mabini, Pag-Alad, and Tan-Agan represent moderate population density. In contrast, Barangay Poblacion shows that areas with high-density populations are more vulnerable to disasters due to higher population concentration.

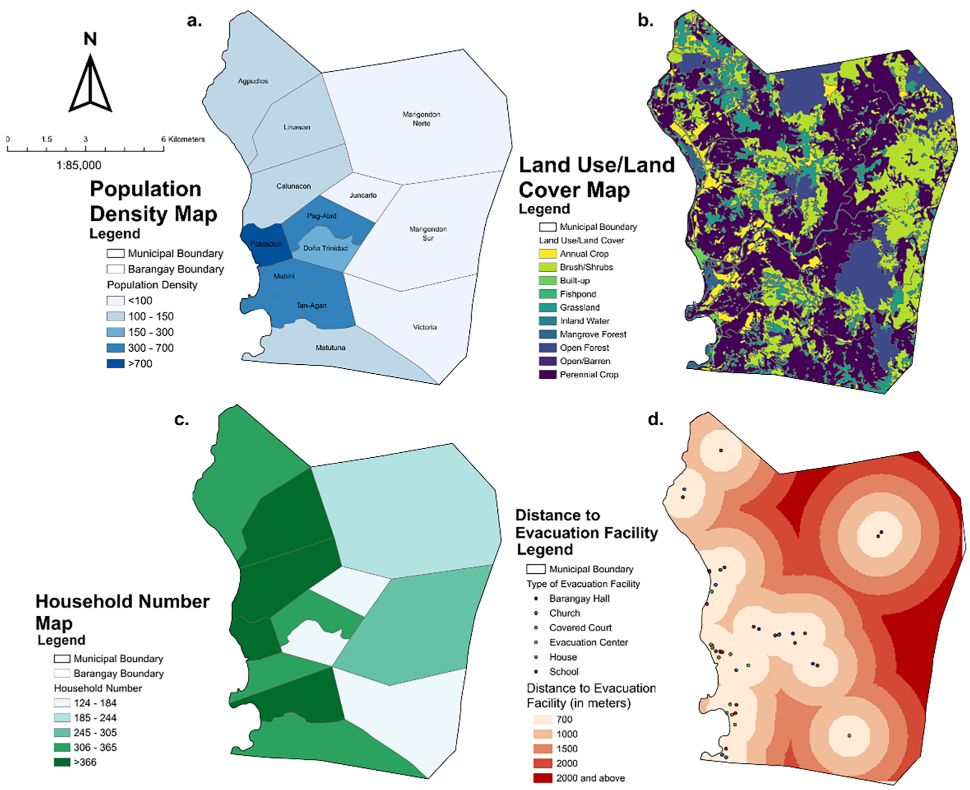

Figure 9: Parameters influencing landslide exposure: (**a**) population density, (**b**) land use/land cover, (**c**) household number, and (**d**) distance to evacuation facility.

Land use affects landslide susceptibility by influencing soil stability and runoff patterns. It has been classified, depicted in Fig. 9b, into ten (10) general classes based on the various land-use and land-cover types. The map illustrates that perennial crops dominantly cover the majority of the land portion of the municipality. Open forest areas and brush/shrubs are prominent, particularly in the municipality's eastern and northern sections, indicating elevated or less accessible parts. Grassland is mainly found in scattered, less fertile areas throughout the map, which is also evident.

Fig. 9c illustrates the range of households in each barangay within the municipality. Barangay Tan-Agan, Poblacion, Linawan, and Calunacon have more than 366 households, which makes them stand out and implies significant exposure and settlements. On the contrary, Barangay Victoria, Doña Trinidad, and Juncarlo have the fewest households, between 124 and 184, indicating sparse populations spread over larger areas with limited facilities or services that may be offered due to the lowest number of houses. Household distribution determines population exposure during landslides.

Spatial placement and capacity of evacuation sites affect effective disaster management in landslide-prone areas. Along with their optimal coverage, Fig. 9d shows the location and types of facilities designated as evacuation locations in each barangay in the Municipality of San Andres, Romblon. This map displays the number of residents that can be accommodated and cared for in the event of a disaster, as well as the locations and spots of these centers that are within reasonable walking distance and easily accessible for the residents. Table 3 lists the evacuation areas and capacity for the Municipality of San Andres.

Table 3: List of evacuation areas of San Andres, Romblon, Philippines with their floor area (sqm) capacity.

Evacuation Area	Type of Facility	Floor Area (sqm)	Capacity	
			1.5 sqm/Person	3.5 sqm/Person
Barangay Matutuna				
Matutuna Elem. School	School	1590	1060	454
Matutuna Foursqure Matutuna	Church	132	88	38
IFI	Church	130	87	37
Residents' House	House	105	70	30
Barangay Tan-Agan				
Barangay Public Plaza	Covered Court	453	302	129
Resident's House	House	147	98	42
Tan-Agan ES	School	1750	1167	333
Tan-Agan HS	School	1800	1200	514
Barangay Mabini				
Evacuation Center	Evacuation Center	300	200	86
Mabini Church	Church	145	97	41
Multi-Purpose Hall	Barangay Hall	645	430	184
Barangay Poblacion				
Poblacion Church	Church	500	333	143
Poblacion ES	School	1945	1297	556
Poblacion HS	School	1872	1248	535
Poblacion RSU	School	2236	1490	639
Resident's House	House	150	100	43
Barangay Calunacon				
Barangay Public Plaza	Covered Court	430	287	123
Calunacon ES	School	870	580	249
Resident's House	House	150	100	43
Calunacon Church	Church	144	96	41
Barangay Linawan				
Barangay Public Plaza	Covered Court	631	421	180
Linawan Church	Church	123	82	35
Linawan ES	School	1373	915	392
Resident's House	House	126	84	36

(Continued)

Table 3 (continued)

Evacuation Area	Type of Facility	Floor Area (sqm)	Capacity	
			1.5 sqm/Person	3.5 sqm/Person
Barangay Agpudlos				
Barangay Public Plaza	Covered Court	450	300	129
Agpudlos ES	School	1603	1069	458
Agpudlos RSU	School	1725	1150	493
Health Center	Center	126	84	36
Agpudlos Church	Church	105	70	30
Barangay Doña Trinidad				
Doña Trinidad Church	Church	90	60	26
Doña Trinidad HS	School	1100	733	314
Doña Trinidad ES (Geminiano)	School	800	533	229
Barangay Marigondon Sur				
Multi-Purpose Hall	Barangay Hall	380	253	109
Marigondon Sur ES	School	1064	709	304
Barangay Victoria				
Health Center	Center	150	100	43
Barangay Marigondon Norte				
Multi-Purpose Hall	Barangay Hall	470	313	134
Marigondon Norte ES	School	245	163	70
Barangay Pag-Alad				
Multi-Purpose Hall	Barangay Hall	452	301	129
Pag-Alad ES	School	226	151	65
Barangay Juncarlo				
Multi-Pupose Hall	Barangay Hall	430	287	123
Juncarlo ES	School	515	343	147

To approximate each room's capacity for a comfortable stay in these shelters, the total floor areas were calculated to estimate the number of people. The Barangay Tan-Agan and Poblacion have estimated capacities ranging from 1018 to 2767 and 1916 to 4468, notably exceeding their ideal coverage. This ensures the emergency response efforts are as effective as possible. Conversely, other areas had calculated capacities that were below their ideal coverage, indicating that there would not be enough space to evacuate to cater to the affected residents during a calamity.

3.5 Evaluation and Assessment of Parameters

This landslide assessment included an evaluation and assessment of contributing factors utilizing the FAHP as a tool to weigh the assigned parameters to each factor derived using a pairwise comparison questionnaire that has been distributed among the 20 experts, including the Civil Engineer, Water Resource Engineer, Geodetic Engineer, end-user of LGU-San Andres, and an individual with extensive experience and knowledge in Disaster Risk Reduction.

A hierarchy diagram with at least three levels, goal, criterion, and indicator, was used to structure the decision-making process. The landslide hazard map, landslide vulnerability map, and landslide exposure map were among the bottom levels of the hierarchy that indicated criteria that helped achieve the goal.

This study shows the level of indicators for identified parameters, including the average annual rainfall, slope, elevation, soil type, landslide susceptibility, number of persons with disabilities, average income, gender ratio, emergency preparedness, distance from the road, distance from the river, population density, land use/land cover, household number, and distance to evacuation facility.

The relevance of every group or classification determined the values that were allocated. Each parameter was given a feature weight based on the class presented. The levels were categorized and specified using distinctions ranging from 1 to 5, where 5 represents the highest priority and 1 represents the lowest. The feature weights given to each indicator are shown in Table 4.

Table 4: Parameters with their designated feature weight.

Indicators	Feature Class	Feature Weight
	Landslide Hazard Parameters	
Average Annual Rainfall (mm)	<2670	1
	2670–2680	2
	2680–2700	3
	2700–2710	4
	2710>	5
Slope (degrees)	29>	5
	21–29	4
	14–21	3
	6–14	2
	0–6	1
Elevation (m)	100>	5
	75–100	4
	50–75	3
	25–50	2
	0–25	1
Soil Type	Clay	5
	Clay Loam	4
	Complex	1
	Hydrosol	5
	Loam	3
	Sandy Clay Loam	2
	Sandy Loam	5
Landslide Susceptibility	Very High Susceptibility	5
	High Susceptibility	4
	Moderate Susceptibility	3
	Low Susceptibility	1
	Landslide Vulnerability Parameters	
	15–22	1
	23–29	2

(Continued)

Table 4 (continued)

Indicators	Feature Class	Feature Weight
Number of Person-with-Disability	30–36	3
	37–43	4
	44–50	5
Average Income	10,800 and above	1
	9100–10,800	2
	7500–9100	3
	5000–7500	4
	Less than 5000	5
Gender Ratio	1.498044–1.734118	5
	1.261968–1.498043	1
	1.025893–1.261967	2
	0.789817–1.025892	3
	0.553741–0.789816	4
Emergency Preparedness	Prepared	5
	Well Prepared	3
	Very Well Prepared	1
Distance to Road (m)	Less than 200	5
	200 to 500	4
	500 to1000	3
	1000 to 1600	2
	1600 above	1
Distance to River (m)	1600 above	1
	1000 to 1600	2
	500 to 1000	3
	200 to 500	4
	Less than 200	5
Landslide Exposure Parameters		
Population Density	>700	5
	300–700	4
	150–300	3
	100–150	2
	<100	1
Land Use/Land Cover	Annual Crop	1
	Brush/Shrubs	1
	Built-Up	1
	Fishpond	1
	Grassland	3
	Inland Water	1

(Continued)

Table 4 (continued)

Indicators	Feature Class	Feature Weight
	Mangrove Forest	1
	Open Forest	5
	Open/Barren	5
	Perennial Crop	4
Household Number	307 > 366	5
	306–365	4
	245–305	3
	185–244	2
	124–184	1
Distance to Evacuation Facility	700	1
	1000	2
	1500	3
	2000	4
	2000 above	5

After the feature weight was assigned, pairwise comparison questionnaires were used, which (20) experts in the field and end-users evaluated and participated in the landslide risk assessment. Expert judgment, experience, knowledge, and comprehension are used to determine various factors' relative importance and contribution. To determine which component or indicators have a greater influence on triggering landslides, they use a nine-point rating system to compare two parameters at a time based on relevance and impact. Frequently incorporated into GIS-based mapping for hazard modeling, weights indicate the impact of each parameter in landslide susceptibility analysis, supporting risk assessment and mitigation tactics. Table 5 provides the qualifications and credentials of the qualified responders.

Table 5: Respondents' credentials for the pairwise comparison technique for landslide hazard, landslide vulnerability, and landslide exposure parameters.

Respondent	Field Expertise/Project Involvement	Agency/Institution/Project	Years in Service
1	Geodetic Engineer	Meridian Land (Surveying Office)	9
2	Geodetic Engineer	GeoPhil Land Surveying	7
3	Water Resource Engineer	Odiongan Water District	7
4	Civil Engineer	Tablas Mega Construction	12
5	Civil Engineer	DPWH-Romblon DEO	8
6	Civil Engineer II/Unit Head ESROW	DPWH-Romblon DEO	10
7	Water Resource Engineer	Romblon State University	4
8	Civil Engineer II	DPWH-Romblon DEO	6
9	Civil Engineer II	DPWH-Romblon DEO	4
10	Civil Engineer II	DPWH-Romblon DEO	6
11	Project Engineer	Philippine Foundation	5
12	Civil Engineer II	DPWH-Romblon DEO	7
13	Civil Engineer, Assistant	DPWH-Romblon DEO	4
14	Municipal Disaster Risk Reduction Management-Assistant	Local Government Unit, San Andres	7
15	Admin Assistant II	Local Government Unit, San Andres	7
16	Local Disaster Risk Reduction Management Officer II	Local Government Unit, San Andres	9

(Continued)

Table 5 (continued)

Respondent	Field Expertise/Project Involvement	Agency/Institution/Project	Years in Service
17	Local Disaster Risk Reduction Management Officer	Local Government Unit, San Andres	6
18	Barangay Captain	Barangay Hall, San Andres	8
19	Barangay Captain	Barangay Hall, San Andres	2
20	Barangay Captain	Barangay Hall, San Andres	1

The survey was conducted by experts from many agencies and organizations, including Odiongan Water District, GeoPhil Land Surveying, Philippine Foundation, Tablas Mega Construction, Department of Public Works and Highways-Romblon DEO, and Local Government Unit-San Andres, who responded and cooperated in the survey distributed. The questionnaires were also completed by specialists from an academic institution, an end user from LGU-San Andres, and a Disaster Risk Reduction Officer. This research study used an online platform and printed questionnaires to distribute and gather the pairwise comparison survey.

In a pairwise comparison matrix, experts use Saaty's 1 to 9 scale system to compare and evaluate each criterion to another that measures the level of significance, which denotes that the higher the number, the greater the importance. The matrix is normalized by dividing each element by the sum of its columns once it has been generated; each column must total one (1) and must be 100 percent. The row values are then averaged to determine the relative importance of each indicator, yielding priority weights and showing each factor's contribution to the overall evaluation. In this investigation, 20 expert judgments are validated and analyzed by calculating the weight of their corresponding responses and answers. In addition, the consistency of expert judgments was evaluated using the Consistency Index (CI) and Consistency Ratio (CR). A CR value of less than 0.10 was considered acceptable. All pairwise comparisons satisfied this threshold with a 0.091 value of CR, ensuring the reliability of the derived weights. Maintaining consistency enhances each criterion's reliability and relative significance in determining landslide risk.

In summary, pairwise comparison matrices provide a methodical way to ascertain the relative weight of different criteria. They also facilitate data-driven and knowledgeable decision-making in risk assessment and hazard management for the alternative options for that specific criterion, which is computed in the linear combination (LC). The product was initially calculated to obtain the weights of each criterion.

Table 6 presents the final weighted criteria for landslide hazard, vulnerability, exposure parameters, and their computed percentage for each indicator. This work produced and constructed risk assessment models, disaster management plans, and landslide maps using ArcGIS by ranking elements according to their respective importance and influence based on their results index value for landslide risk.

Table 6: Final weights and percentage weights of every parameter for hazard, vulnerability, and exposure criteria for landslide assessment.

Indicators	Weights	Percentage Weights
Landslide Hazard Parameters		
Average Annual Rainfall (mm)	0.222818	22.28%
Slope (degrees)	0.183818	18.38%
Elevation (m)	0.126409	12.64%
Soil Type	0.117106	11.71%
Landslide Susceptibility	0.349849	34.98%

(Continued)

Table 6 (continued)

Indicators	Weights	Percentage Weights
Landslide Vulnerability Parameters		
Number of Person-with-Disability	0.133130	13.31%
Average Income	0.137814	13.78%
Gender Ratio	0.084553	8.46%
Emergency Preparedness	0.164022	16.40%
Distance to Road (m)	0.217701	21.77%
Distance to River (m)	0.262780	26.28%
Landslide Exposure Parameters		
Population Density	0.329342	32.93%
Land Use/Land Cover	0.330098	33.01%
Household Number	0.185747	18.57%
Distance to Evacuation Facility (m)	0.154814	15.48%

3.6 Development of Landslide Risk Map

This visually represents the spatial distribution of landslide hazard, vulnerability, and exposure within a specific area, as shown in Fig. 10. These maps provide a comprehensive overview of landslide risks. Using GIS, it involved a raster calculator, raster conversion, raster extraction, reclassifying, and layer clipping that produced a map for each criterion by calculating and weighting the feature parameters in the FAHP.

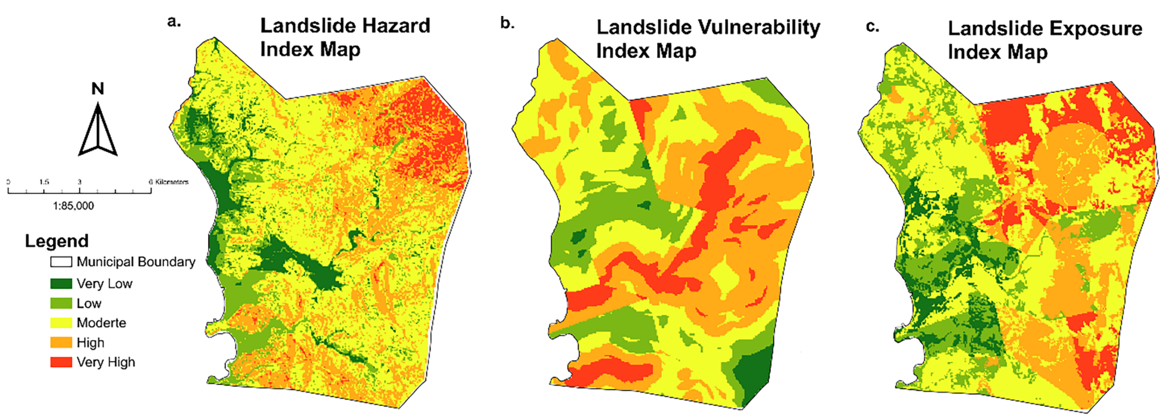

Figure 10: Hazard Geographic Information System (GIS)-generated map: (**a**) landslide hazard index, (**b**) landslide vulnerability index, (**c**) landslide exposure index.

The landslide hazard index map of San Andres, which was created in ArcGIS using a raster calculator tool, incorporates all five (5) criteria, as depicted in Fig. 10a. Five (5) hazard levels were identified: very low (green), which gives 7.10% of the distribution of the total area; low (green-yellow), which is bound to 13.07%; moderate (yellow), is composed of 47.30%, high (orange) that has 26.78%, and lastly, extremely high (red) that contributes 5.75%. Based on the map showed that the areas with very high to high hazards were primarily located in high elevations and steep slopes, especially in the barangay of Marigondon Norte and some portions of Marigondon Sur, Matutuna, Tan-again, Mabini, and Juncarlo. It was observed that the terrain features and inclined landscape areas can make them even more susceptible to landslide risk. To sum up, the higher the elevation and stiffness of an area's slope, the more landslides could occur.

As shown in Fig. 10b, the Landslide Vulnerability Index Map yielded six (6) indicators that interpreted the exposure level. The distribution covers 2.22%, 15.65%, 33.64%, 36.89%, and 11.60% of the total study area. The map shows that the barangays of Mabini, Matutuna, Marigondon Sur, Marigondon Norte, and Doña Trinidad are indicated as having high and very high vulnerability. While the moderate areas are Victoria, Linawan, Agpudlos, and Pag-alad, the rest of the barangays have evidence of low vulnerability levels.

A landslide exposure index map of San Andres, Romblon, was created by integrating the exposure parameters into the ArcGIS-based tool, as seen in Fig. 10c. The classifications determined the illustration of the entire area of the municipality that represents green, which is very low exposure (6.98%), followed by yellow green for low exposure (17.23%), yellow for moderate exposure (41.86%), orange for high exposure (21.73%), and red for extremely high exposure (12.41%). Based on the map, there is a high danger of exposure in several places in Barangay Marigondon Norte, Juncarlo, and Victoria.

A spatial overlay analysis was conducted to validate the landslide risk map by comparing it with documented landslide occurrences. The results show that most recorded landslides are located within high and very high-risk zones, indicating good agreement between the model output and actual events. As shown in Fig. 11, the landslide risk map data were combined with the landslide hazard, landslide vulnerability, and landslide exposure index maps utilizing FAHP and integrating them into ArcGIS to emphasize and understand the municipality's prone areas. These maps used an equal approach of weighing the parameters composed of five levels: very low, low, moderate, high, and very high, which are distinguished using equal intervals on the landslide risk map. Very low risk (green) represents 9.67% of the entire land area, including the barangay Poblacion and Calunacon, which fall under the low-risk category. At the same time, the low-risk (yellow green) was distributed to 20.18% of the total area. These compromised the other barangays, such as Pag-alad and Tan-agan. Furthermore, the range between moderate risk (yellow) covers 26.90% of the total area. These areas included are Mabini, Linawan, Doña Trinidad, and some parts of Agpudlos. In addition, the barangays of Marigondon Sur, Victoria, Matutuna, some portions of Juncarlo, and Agpudlos are under high risk, which is composed of 25.45% of the total area. Lastly, the very high risk (red) is distributed over 17.78% of the entire land, including Marigondon Norte, some parts of Marigondon Sur, Matutuna, and Victoria. Overall, this risk map serves as a critical tool for local authorities, urban planners, and disaster response teams to ensure the safety and sustainability of the future of San Andres, Romblon.

The landslide history map of the Municipality of San Andres, Romblon, is presented in Fig. 12. The map provides a spatial comparison between the generated landslide risk zones and the documented historical landslide occurrences recorded by the local government unit. Black point markers represent the available recorded landslide events within the municipality. Barangay Marigondon Norte recorded the highest number of documented landslide occurrences with seven (7) events, followed by Marigondon Sur with two (2) events, while Doña Trinidad, Agpudlos, Victoria, and Juncarlo each recorded one (1) occurrence. The overlay analysis showed that most of the documented landslide events were located within areas classified as high and very high landslide risk, indicating reasonable agreement between the GIS–FAHP model output and the observed landslide-prone locations. However, due to the limited availability of detailed landslide inventory datasets, including geotagged records, temporal information, photographic documentation, and comprehensive field observations in remote areas with limited communication access, advanced quantitative validation methods such as ROC/AUC and prediction rate analysis could not be fully implemented in this study.

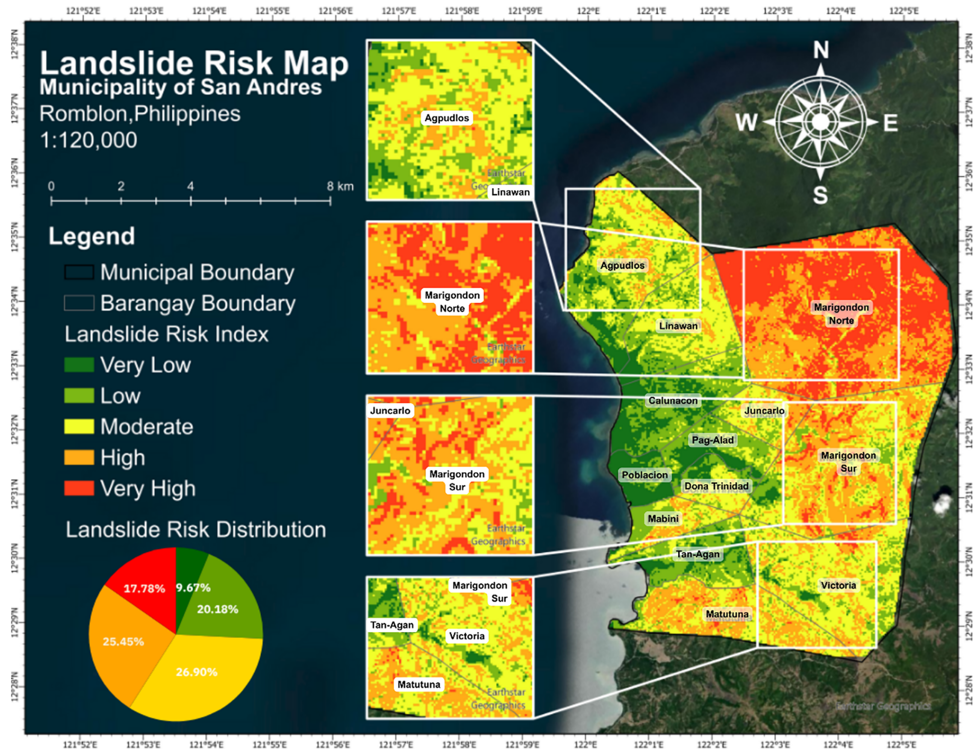

Figure 11: Landslide risk map of the Municipality of San Andres.

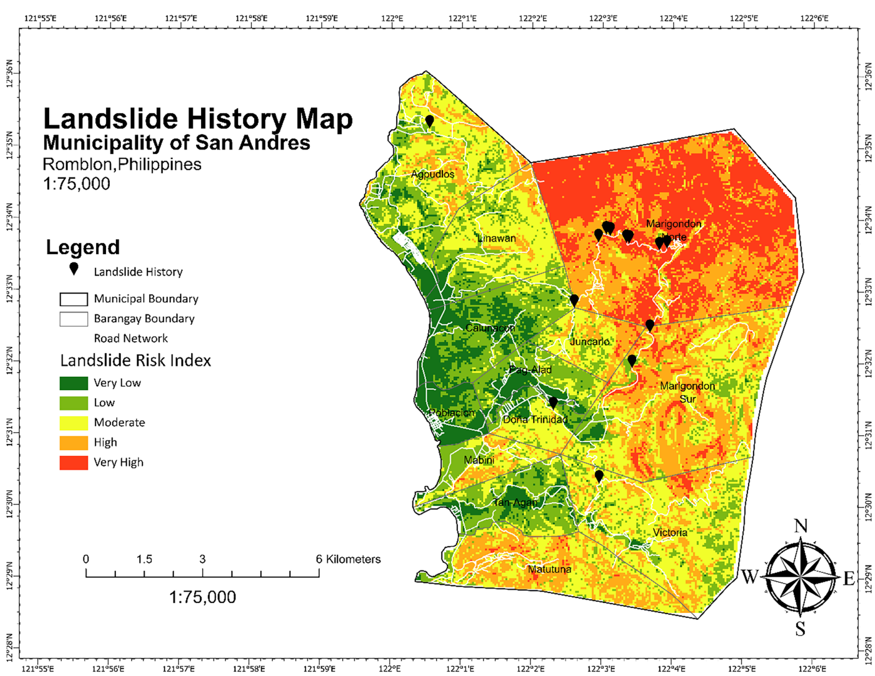

Figure 12: Validation of the GIS–FAHP landslide risk map using documented historical landslide occurrences. Most landslide events fall within high and very high-risk areas.

4 Discussion

Landslides remain a persistent and complex hazard in the Municipality of San Andres, Romblon, primarily due to the interplay of geomorphological characteristics, climatic conditions, and anthropogenic influences [88]. The municipality's steep terrain, coupled with frequent exposure to typhoons and intense rainfall, creates conditions highly conducive to slope instability [41]. The results of this study confirm that landslide occurrence is not governed by a single factor but rather by the dynamic interaction of hazard, vulnerability, and exposure components. By integrating these dimensions using a GIS-based FAHP, this study provides a holistic and spatially explicit understanding of landslide risk, addressing both physical susceptibility and socio-economic sensitivity.

The application of FAHP in this study effectively reduced subjectivity in parameter weighting by incorporating expert judgment under uncertainty, thereby strengthening the reliability of the landslide risk map derived. Compared with traditional AHP or simple weighted overlay methods, FAHP allows for a more flexible and realistic representation of decision-making processes, particularly in complex environmental systems where precise data may be limited [89]. The consistency of the results with previous studies conducted in landslide-prone regions of the Philippines, such as Baguio City, further validates the robustness of the adopted methodology [90].

From a hazard perspective, the results indicate that topographic and hydrological factors—particularly slope, elevation, rainfall, and landslide susceptibility—are dominant controls on landslide occurrence. Areas characterized by steep slopes and higher elevations, such as Marigondon Norte and portions of Marigondon Sur and Matutuna, exhibit significantly higher hazard levels. This finding aligns with established geomorphological principles, where increased slope gradient enhances shear stress while reducing slope stability [80]. Additionally, the influence of rainfall as a triggering mechanism is evident, as higher precipitation levels contribute to increased pore water pressure and reduced soil cohesion, ultimately leading to slope failure [91]. Soil characteristics further reinforce this pattern, as clay-rich and loamy soils, known for their high-water retention capacity, are more prone to saturation and instability [92].

Beyond physical susceptibility, the study highlights the critical role of socio-economic vulnerability in shaping overall landslide risk [93]. Barangays with lower income levels, higher numbers of persons with disabilities, and limited access to infrastructure were found to be more vulnerable to landslide impacts [94]. These findings emphasize that disaster risk is not solely determined by environmental conditions but is significantly influenced by the capacity of communities to anticipate, cope with, and recover from hazard events [83]. The limited accessibility to road networks and evacuation facilities in several barangays further exacerbates vulnerability, as it restricts timely evacuation and emergency response during landslide events. This underscores the importance of integrating infrastructure planning and social protection measures into disaster risk reduction strategies.

Exposure analysis reveals that population distribution, land use patterns, and settlement density play a substantial role in determining the extent of potential losses [95]. Areas with higher population density and larger household concentrations, such as Poblacion and Calunacon, are at greater risk due to the increased number of people and assets exposed to hazard-prone zones. Furthermore, land use practices, particularly the expansion of settlements and agricultural activities in steep or unstable areas, contribute to increased exposure and amplify landslide risk. The limited spatial coverage and accessibility of evacuation facilities identified in this study further highlight critical gaps in disaster preparedness infrastructure.

The integration of hazard, vulnerability, and exposure components into a comprehensive landslide risk map provides a more realistic representation of disaster risk conditions within the municipality [96]. The concentration of very high-risk zones in the northeastern and southeastern portions of San Andres indicates priority areas for intervention. These findings support the need for targeted, location-specific mitigation strategies rather than uniform, generalized approaches. Structural measures such as check dams, slope stabilization, and gabion walls are recommended to control runoff and reduce slope instability. However, non-structural measures, including land-use zoning, early warning systems, community-based disaster preparedness programs, and public awareness campaigns, are equally critical in enhancing resilience.

The dominance of landslide susceptibility and rainfall-related factors is consistent with findings from previous studies in landslide-prone areas, where slope and precipitation were identified as primary drivers [49]. Proximity to river systems contributes to soil saturation and slope instability, while land use and population density reflect increasing human exposure in hazard-prone zones. Importantly, this study highlights the value of data-driven and spatially explicit approaches in disaster risk reduction [97]. By integrating geospatial analysis with expert-based decision-making, the developed framework provides local government units with actionable insights for planning and policy development. The approach also demonstrates scalability and transferability, as it can be adapted to other municipalities with similar environmental and socio-economic conditions.

Despite its strengths, several limitations should be acknowledged. The study integrates multi-temporal datasets due to the limited availability of updated and consistent spatial data. While relatively stable parameters such as elevation and soil type are unlikely to change significantly over time, variations in land use and socio-economic data may influence the accuracy of the results. This limitation is acknowledged and should be considered when interpreting the landslide risk map. Future studies are recommended to utilize temporally consistent data sets to improve model reliability. The reliance on available datasets and expert judgment may introduce uncertainties, particularly in areas with limited or outdated data. Additionally, the static nature of the analysis does not fully capture temporal variations in rainfall patterns, land use changes, or climate-driven impacts. Future studies may incorporate time-series data, climate projections, and advanced modeling approaches such as machine learning or hybrid hydrological models to further enhance predictive capabilities.

This study reinforces the importance of integrating physical, social, and spatial dimensions in landslide risk assessment. The findings provide a strong scientific basis for improving disaster preparedness, guiding infrastructure development, and promoting sustainable land-use planning. Similar GIS-based landslide susceptibility studies conducted in Greece, Nigeria, and other hazard-prone regions identified slope, rainfall, geological conditions, and hydrological proximity as dominant landslide conditioning factors. The findings of the present study are generally consistent with these previous studies, although the relative influence of each factor varies depending on local environmental and geographic conditions [98]. The identified high-risk areas are characterized by steep slopes, intense rainfall exposure, unstable soil conditions, and proximity of residential settlements to landslide-prone terrain. Human activities such as vegetation clearing, land conversion, and settlement expansion near steep slopes may further contribute to increased landslide susceptibility within vulnerable barangays. By addressing both the causes and consequences of landslides, the study contributes to the broader goal of building resilient communities in hazard-prone regions.

5 Conclusion

The study supports Sustainable Development Goal (SDG) 11 by contributing to safer and more resilient communities through evidence-based disaster risk reduction and spatial planning. Furthermore, the generated landslide risk maps support SDG 13 by promoting climate adaptation and proactive hazard mitigation strategies in vulnerable municipalities. This research study assesses the risk of landslides in the Municipality of San Andres, Romblon, which has developed a landslide map using an ArcGIS-based tool and multi-criteria decision analysis that features the hazard map, vulnerability map, and exposure map. The previous records prove that the landslide posed a risk to economic status, caused property damage, and put lives at risk. This comprehensive and accurate evaluation fosters sustainable land use planning and community resilience.

The Sendai Framework is used to organize the criteria developed in the FAHP to evaluate and assess the danger of landslides. ArcGIS is utilized in the relevant data parameters for this research. Relevant data, on the other hand, comes from previous research investigations, relevant literature, satellite photos, and the DEM for topography features, respectively. Several factors under hazard were included, such as soil type, landslide susceptibility, slope, elevation, and average annual rainfall. Meanwhile, the vulnerability assessment includes the number of people, the average income, the gender ratio, emergency preparedness, and the distance to the road and river. Lastly, the exposure characteristics comprised the number of households, land use/land cover, population density, and distance to the evacuation facility. After further analysis, the found parameters were compared in a pairwise comparison to determine their weight based on expert judgment, which was then incorporated into the FAHP. The computed weights for hazard parameters are as follows: soil type (11.71%), landslide susceptibility (34.98%), slope (18.38%), elevation (12.64%), and average annual rainfall (22.28%). For vulnerability parameters are the number of persons with disabilities (13.31%), the average income (13.78%), the gender ratio (8.46%), emergency preparedness (16.40%), distance to the road (21.77%), and distance to the river (26.28%). For exposure parameters such as number of households (18.57%), land use/land cover (33.01%), population density (32.93%), and distance to the evacuation facility (15.48%). The map produced for the municipality's landslide risk reveals varying levels of risk value across the entire land area. The distribution includes 9.67% (very low risk), 20.18% (low risk), 26.90% (moderate risk), 25.45% (high risk), and 17.78% contributed as very high risk. The assessment for landslide risk found that out of thirteen (13) barangays evaluated, only the barangays Marigondon Norte, Marigondon Sur, Victoria, and Matutuna were identified as very high risk and considered landslide-prone areas.

In summary, the study demonstrated the significance of a landslide risk solution map in improving landslide prevention strategies by addressing risk factors such as exposure, vulnerability, and hazard. By implementing proactive mitigation measures and well-informed planning, engineers, urban planners, stakeholders, and community members can reduce the danger of landslides. This data makes it easier to prioritize locations that need urgent attention. Hence, future research should consider these limitations to improve and develop landslide risk assessment techniques and encourage environmental behaviors for a more sustainable and better environment. This study demonstrates the effectiveness of integrating GIS and FAHP in assessing landslide risk. The findings provide a valuable basis for local government units in developing targeted mitigation strategies and improving disaster preparedness. Future research should focus on incorporating updated datasets and advanced validation techniques to further enhance model accuracy.

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