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Development and Prioritization of Flood Vulnerability Indicators for Nabunturan, Davao de Oro

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ABSTRACT

Flooding remains one of the most prevalent and destructive natural hazards, threatening infrastructure, livelihoods, and communities worldwide. This study conducted a systematic assessment of flood vulnerability in Nabunturan, Davao de Oro, a municipality prone to recurrent flooding. Utilizing the UNESCO-IHE flood vulnerability indicators, the research examined the Social, Economic, Environmental, and Physical components of vulnerability. These indicators were categorized into three subdimensions—exposure, susceptibility, and resilience—and were evaluated using the Fuzzy Delphi Method (FDM) to achieve expert consensus, followed by the Analytical Hierarchy Process (AHP) to prioritize key factors influencing flood vulnerability. The study identified and prioritized 27 flood vulnerability indicators, with normalized weights (ranging from 0 to 1) derived from the Fuzzy Delphi Method (FDM) and Analytical Hierarchy Process (AHP), reflecting the relative importance of each factor. Higher-weighted indicators serve as the basis for prioritization of risk reduction actions and resilience-building efforts. The study revealed the indicators with the highest weights per component, arranged in exposure, susceptibility, and resilience, respectively. Social Component: Population in Flood-prone Areas (0.3114); Past Experience (0.4314); Shelters/Hospitals (0.2685). Economic Component: Land Use (0.5230); Quality of Infrastructure (0.6149); Amount of Investment (1.0). Environmental Component: Degraded Area (1.0); Rainfall (0.5091); Green Area (1.0). Physical Component: Topography (0.2958); Frequency of Occurrence (1.0); Dikes/ Levees (1.0). The weighted indicators can support the computation of a Flood Vulnerability Index (FVI), informing Barangay Disaster Risk Reduction and Management Plans (BDRRMPs), enhancing the Climate and Disaster Risk Assessment (CDRA), and guiding targeted risk reduction and adaptation programs.

Keywords: Analytical Hierarchy Process (AHP), Disaster Risk Reduction (DRR), Delphi Fuzzy Method (FDM), Flood Vulnerability Index (FVI), UNESCO-IHE Institute for Water Education

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INTRODUCTION

Flooding remains one of the most recurrent and destructive natural hazards globally, contributing to significant economic losses, population displacements, and the disruption of critical infrastructure (UNDRR, 2019). The growing frequency and severity of flood events in recent decades have been closely linked to the intensifying impacts of climate change, particularly rising sea levels, altered precipitation regimes, and unsustainable land-use changes (IPCC, 2021). Situated along the typhoon-prone western Pacific belt, the Philippines consistently ranks among the most climate-vulnerable countries worldwide. From 2000 to 2019, it placed fourth globally in the Global Climate Risk Index, underscoring its chronic exposure to extreme weather events and the socio-economic consequences they entail (Eckstein et al., 2021).

This national vulnerability is mirrored at the municipal level, particularly in regions like Nabunturan, Davao de Oro. A landlocked municipality characterized by a mix of mountainous terrain and lowland settlements, Nabunturan faces compound flood risks. From 2014 to early 2022, the municipality experienced 13 notable flood events. During January 26–31, 2019, flooding caused by heavy rains, about 241 families across the municipality were affected, and total damages to properties, including infrastructure and agriculture, amounted to approximately ₱12,720,461.11 (CDRA, 2022). Municipal disaster reports and vulnerability assessments confirm that floods frequently disrupt agriculture, damage homes, and threaten livelihoods in multiple barangays. Similar conditions have been documented in neighboring provinces such as Davao Oriental, where flood exposure correlates strongly with population settlements near rivers and altered land cover (Cabrera and Lee, 2018).

While the Disaster Risk Reduction and Management (DRRM) frameworks have been institutionalized in the Philippines through the Philippine DRRM Act of 2010, challenges in shifting from reactive to proactive approaches persist (Orencio and Fujii, 2013; Bankoff and Hilhorst, 2009). Many local interventions continue to prioritize emergency response, often with limited integration of proactive, evidence-based vulnerability assessments. This tendency may be partly due to the scarcity of localized, multidimensional data needed to support anticipatory planning (Nakasu and Amrapala, 2023). Orencio and Fujii (2013) observed that several Philippine LGUs still tend to adopt reactive, response-oriented strategies rather than proactive vulnerability reduction. These systemic challenges can constrain local governments' ability to allocate resources efficiently, potentially contributing to recurring disaster losses and slow recovery (Cutter and Finch, 2008).

Flood vulnerability is inherently multidimensional, encompassing not only physical exposure but also social susceptibility and adaptive capacity. These three dimensions—exposure, susceptibility, and resilience—jointly determine the severity of a population's response to flood hazards and must be systematically assessed to inform risk reduction (Nasiri and Shahmohammadi-Kalalagh, 2013; Cardona et al., 2012; Rehman et al., 2019). However, many flood risk models continue to prioritize topographical and hydrological parameters while overlooking socio-economic and environmental indicators. This imbalance can result in assessments that miss critical vulnerabilities, particularly among marginalized or underserved communities.

Recent advances in spatial analytics and decision-support frameworks offer tools to address this gap. Geographic Information Systems (GIS), when combined with Multi-Criteria Decision-Making (MCDM) techniques such as the Analytical Hierarchy Process (AHP), enable the integration of diverse indicators into comprehensive vulnerability assessments. For example, Efraimidou and Spiliotis (2024) employed a GIS-DEMATEL framework to evaluate flood risks in northeastern Greece, highlighting how such methods can model interdependencies among indicators. Nevertheless, many existing approaches lack participatory validation, and the absence of expert-informed indicator selection undermines the local applicability of findings (Jamshed et al., 2020).

To address these methodological and contextual gaps, this study introduces a localized, indicator-based flood vulnerability assessment for Nabunturan, Davao de Oro. The approach integrates the Fuzzy Delphi Method (FDM) to validate a set of indicators—categorized under social, economic, environmental, and physical domains—and the AHP to derive expert-informed weights based on their perceived importance. These indicators are further structured by subdimensions of exposure, susceptibility, and resilience, ensuring theoretical coherence and practical applicability (Lee et al., 2013; Mourato et al., 2023).

The primary output of this study is a set of weighted flood vulnerability indicators derived through AHP, offering an empirically grounded framework for prioritizing flood-related risks across barangays. These weights not only support the generation of spatial flood vulnerability maps but also serve as decision-support inputs for land use planning, infrastructure development, and local DRRM programming in Nabunturan (Saaty, 2008). In doing so, the study contributes to the expanding literature on quantitative, participatory risk assessment and demonstrates the utility of hybrid FDM-AHP frameworks in climate-vulnerable municipalities (Fatemi et al., 2017; Birkmann et al., 2013).

This study aims to develop and prioritize social, economic, environmental, and physical flood vulnerability indicators for Nabunturan, Davao de Oro, utilizing the Fuzzy Delphi Method (FDM) for expert validation and the Analytical Hierarchy Process (AHP) for weighting. The results will guide the identification of priority areas for flood risk management and support the formulation of localized policy strategies and resilience measures aligned with municipal and barangay-level climate adaptation and disaster preparedness planning.

MATERIALS AND METHODS

Description of the study area

Nabunturan, located in the northeastern part of Davao de Oro, Philippines, is positioned at 7°41' north latitude and 125°27' east longitude (Figure 1). It is situated 88 kilometers from Davao City and 33 kilometers from Tagum City. As the capital town of Davao de Oro, Nabunturan served as the province's administrative and economic center, supporting a blend of urban and rural communities, with a population of 84,340 (Philippine Statistics Authority, 2021). Nabunturan shared boundaries with Montevista to the north, New Corella to the west, Mawab to the southwest, Maco and Mabini to the south, Maragusan to the southeast, New Bataan to the east, and Compostela to the northeast. The municipality covered approximately 26,999 hectares, comprising 28 barangays and 40 sitios, all interconnected by a network of roads and bridges (Municipality of Nabunturan, 2024).

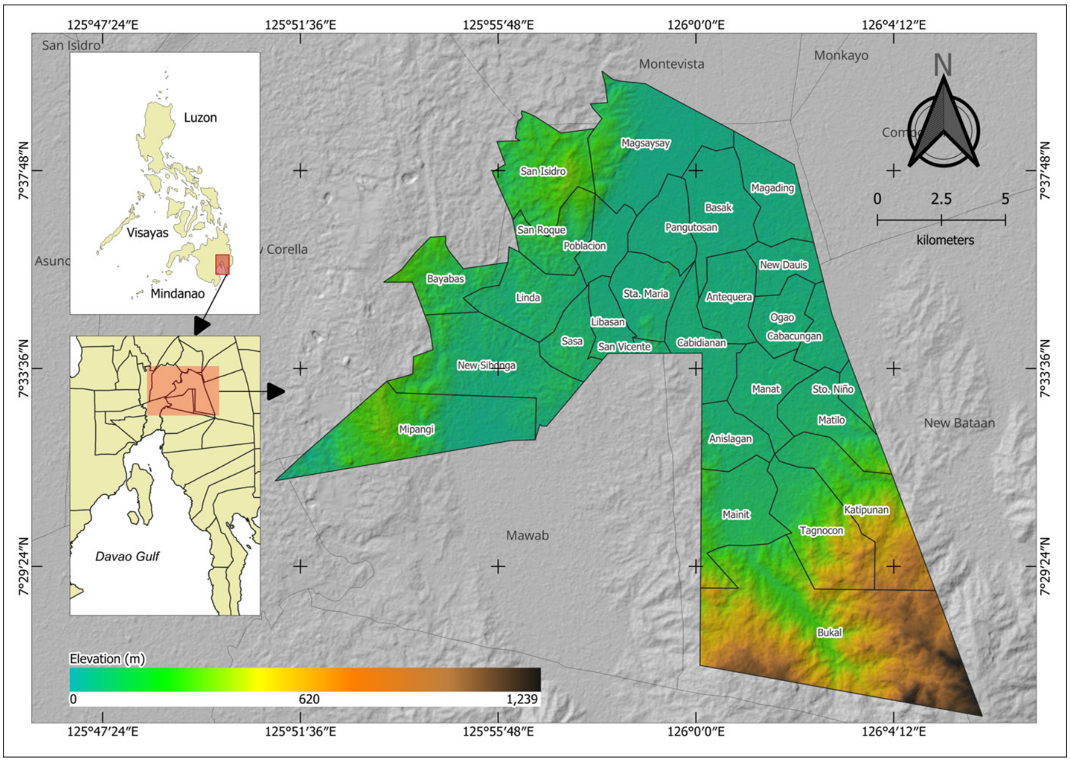

Figure 1. Map of Nabunturan, Davao de Oro, showing the 28 barangays covered in the study.

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The geographic characteristics of Nabunturan make most areas susceptible to flooding and landslides. Disasters significantly disrupt economic activities, particularly agriculture, which occupies 16,512.96 hectares of the municipality's land and serves as the primary livelihood. Public health is also threatened by waterborne diseases and delayed medical access during floods. Despite existing evacuation policies and centers, displacement disrupts community well-being. Flooding often damages roads and infrastructure, and while residents have adapted to recurring hazards, resilience alone cannot fully protect lives and property. Notably, Super Typhoon Pablo caused ₱500 million in agricultural losses and over ₱200 million in infrastructure damages (CDRA, 2022).

Data collection and instrument

This study employed a descriptive quantitative research design, firmly grounded in ethical standards and community engagement principles. The initial stage involved the distribution of courtesy letters to barangay leaders to formally request consent for participation in the research process. This protocol served as a foundational step in establishing rapport, building trust, and fostering collaboration with local stakeholders—an essential aspect for ensuring the validity and reliability of the data collected. Subsequently, formal approval and consent were sought from the local government unit to ensure alignment with local governance protocols and secure community endorsement.

Figure 2 shows the phases conducted in this study. Following the ethical groundwork, the data collection process incorporated expert opinion surveys to evaluate flood vulnerability indicators. This study employed a structured questionnaire adapted from the UNESCO-IHE Institute of Water Education, a globally recognized framework for flood risk assessments and water-related research (Balica, 2012). The questionnaire was meticulously developed to gather empirical data on the social, economic, environmental, and physical indicators of flood vulnerability and to be used to identify vulnerability indicators specific to Nabunturan, Davao de Oro (Abdullah and Yusof, 2018; Pelone et al., 2024; Pelone and Sanchez, 2024). The Fuzzy Delphi Method (FDM) survey was conducted face-to-face using printed questionnaires in August 2024, allowing direct engagement with experts for richer data validation. Meanwhile, the Analytical Hierarchy Process (AHP) survey was conducted asynchronously through Google Forms in March 2025, ensuring broader expert participation while accommodating their availability.

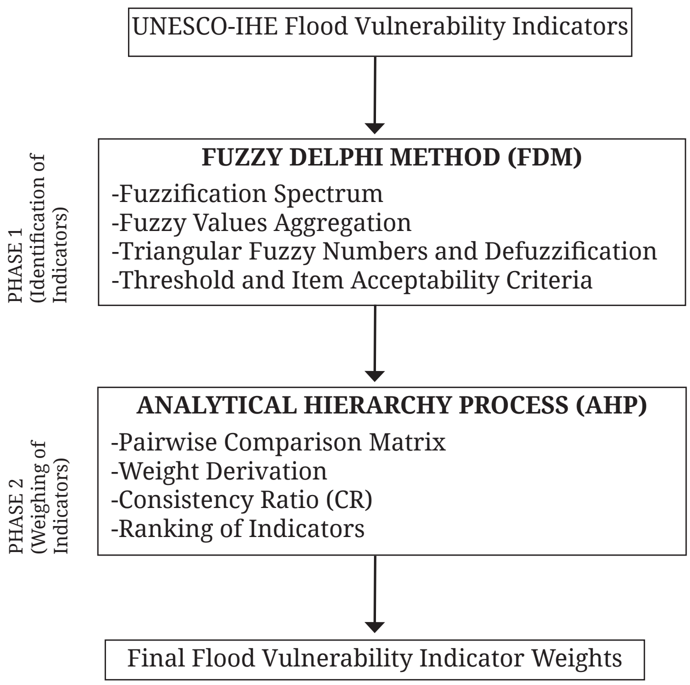

Figure 2. Integrated FDM–AHP Approach for Developing Flood Vulnerability Indicator Weightsw

A five-point Likert scale (see Table 2) was used to assess the perceived influence of each vulnerability component, where 1 represented "Very Low Influence" and 5 indicated "Very High Influence.", was utilized to systematically assess the varying degrees of influence of each vulnerability component. This methodological approach enabled a nuanced quantification of vulnerability factors, minimizing subjectivity while ensuring analytical rigor (Ismail, Mohamed, and Hamzah, 2019)

The FDM was employed to enhance indicator accuracy through expert consensus, enabling systematic evaluation of each indicator's weight and relevance. The Triangular Fuzzy Number (TFN) method was applied to transform Likert-scale responses into fuzzy numerical values, reducing ambiguity and improving decision-making accuracy (Hsu and Sandford, 2007)

In the second phase of expert validation, the AHP was employed to systematically rank and prioritize flood vulnerability indicators. A pairwise comparison approach was utilized, allowing experts to assign weights to various vulnerability components based on their perceived significance in flood susceptibility (Saaty, 1980). The AHP methodology provided a structured, objective framework for multi-criteria decision-making, ensuring that social, economic, environmental, and physical flood vulnerability factors were appropriately weighted according to expert judgment and empirical data (Balica and Wright, 2010).

Expert Panel and Validation Procedures

The selection of experts followed established guidelines for FDM and AHP-based studies. Seventeen (17) experts participated in the FDM survey, representing fields such as disaster risk management, flood vulnerability research, environmental science, and urban and environmental planning. The panel included 4 experts from the Municipal Planning and Development Office (MPDC) – Nabunturan, 2 from the Municipal Agriculture Office (MAGRO), 1 from the Municipal Disaster Risk Reduction and Management Office (MDRRMO), 6 from the Provincial Disaster Risk Reduction and Management Office (PDRRMO) – Davao de Oro, and 4 from the Provincial Planning and Development Office (PPDO) – Davao de Oro.

For the AHP process, a separate panel of 11 experts was convened, comprising 2 from the academe, 3 from the City Disaster Risk Reduction and Management Office (CDRRMO), 2 from MDRRMO, 1 from the Office of Civil Defense (OCD), 2 from the PDRRMO, and 1 from the MPDC. The sample sizes align with best practices in previous flood risk modeling studies, which recommend a minimum of 10 experts for FDM and 5–10 for AHP to ensure methodological robustness (Habibi et al., 2015; Mohamed Yusoff et al., 2021).

Both the FDM and AHP experts were purposively selected based on their specialized knowledge and relevance to the study's focus areas. For the FDM process, experts were drawn primarily from the Nabunturan LGU and the Provincial Government of Davao de Oro, as these professionals possess direct experience and contextual understanding of the municipality's flood dynamics, disaster risk patterns, and local governance structures. Their localized insights were critical in identifying and validating relevant flood vulnerability indicators.

For the AHP phase, the panel included experts from outside Nabunturan to introduce broader technical perspectives and minimize potential biases that may arise from localized familiarity. This inclusion of external experts ensured a balance between local knowledge and wider methodological rigor, consistent with best practices that recommend incorporating diverse expert views to enhance the generalizability and robustness of multi-criteria decision analyses (Hsu and Sandford, 2007)

Selection criteria required that all experts possess a minimum of five years of professional experience in disaster risk management, environmental planning, flood vulnerability research, or closely related fields. This methodological approach strengthens the credibility and validity of the study outcomes, as recommended in expert elicitation and decision-making studies.

By integrating UNESCO-IHE indicators, Fuzzy Delphi, and AHP methodologies, this study ensures a scientifically rigorous and data-driven approach to flood vulnerability assessment. The findings derived from these instruments provide critical insights into Nabunturan's flood risk profile, reinforcing evidence-based disaster mitigation strategies, land-use planning, and climate resilience initiatives (Pelone et al., 2024; Balica, 2013).

Data Analysis

Fuzzy Delphi Method (FDM)

The FDM is an enhanced version of the Delphi Method (Table 1) that utilizes triangulation statistics to determine the level of consensus among the expert panel (Shelton and Creghan, 2015). As presented on Table 1, it was implemented in this study to identify the flood vulnerability indicators, reducing the possibility of ambiguity, diversity, and discrepancy in the perspectives provided by subject matter experts, enhancing the overall quality of the selected items (Manakandan et al., 2017).

Table 1. The subsequent phases of Fuzzy Delphi Method as stated by Habibi et al. (2015).

Fuzzy Delphi Method (FDM)
1. Identification of a suitable spectrum for the fuzzification of linguistic expressions.
2. Fuzzy aggregation of the fuzzified values.
3. Triangular Fuzzy Numbers and the Defuzzification Process.
4. Selection of the threshold and item acceptability criteria.

The fuzzy spectra presented in Table 2 were employed in this study to represent a five-point Likert scale. The data analysis began by determining the TFN for each indicator, which involves organizing the three parameters: m_1, m_2, and m_3. Specifically, m_1 denotes the lowest possible value assigned by the experts, m_2 reflects the most plausible or reasonable value, and m_3 indicates the highest possible value. These values collectively form the fuzzy interval used to capture the uncertainty and subjectivity inherent in expert evaluations.

Table 1. Triangular fuzzy numbers for a 5-point Likert scale.

Linguistic Expressions	Linguistic Equivalent	Fuzzy Number
Very High Influence	5	(0.6, 0.8, 1)
High Influence	4	(0.4, 0.6, 0.8)
Moderate Influence	3	(0.2, 0.4, 0.6)
Low Influence	2	(0, 0.2, 0.4)
Very Low Influence	1	(0, 0, 0.2)

Defuzzification of the resultant values was essential to finalize the aggregation of expert opinions using fuzzy logic. Mohamed Yusoff et al. (2021) state that the utilization of the FDM technique necessitates the inclusion of the triangular fuzzy numbers and the defuzzification process as essential components. Triangular fuzzy numbers have two specific criteria that must be met. The first condition is that the value of threshold (d) must be less than or equal to 0.2. When the result is 0.2 or lower, the experts reach a consensus.

Equation (1) is the formula for the calculation of the threshold (d) value. (Mohamed Yusoff et al., 2021).

$$d\,(M,m) = \sqrt{\left(\tfrac{1}{2}\left[(M_1 - m_1)^2 + (M_2 - m_2)^2 + (M3_3 - m_3)^2\right]\right.} \quad (1)$$

where:

M = the mean value of a fuzzy number,
m = represents a fuzzy number assigned by each expert for each item.

The defuzzification process has been made in the data analysis process in the FDM. It is the process of determining the relative weight value of each criterion to decide the sequence of the weight value and the importance level of each indicator (Hao-Chang, 2020). The defuzzification value for every item has to be more than the α-cut value = 0.5. In this process, the equation presented below was used.

Equation (2) is the formula for determining the defuzzification value. (Mohamed et al., 2019; Abdullah and Yusof, 2018; Pelone and Sanchez, 2024).

$$A=\frac{1}{2}*(m_1+m_2+m_3) \qquad (2)$$

where:
m = mean.

The next criterion for the defuzzification is the necessity of obtaining a level of agreement among experts, expressed as a percentage. In accordance with the traditional Delphi process, a suggestion is deemed acceptable if the consensus among the expert group exceeds 75%. The formula below was used in the study (Equation 3).

Equation (3) is the formula for the calculation of consensus percentage.

$$\left[\frac{(\sum Experts*\sum Items)-(Total\ Responses>0.2)}{(\sum Experts\ \sum * Items)}\right]*100 \qquad (3)$$

Analytical Hierarchy Process (AHP)

The AHP is a robust multi-criteria decision-making (MCDM) method developed by Saaty (1980, 2005), designed to tackle complex problems by structuring them into a hierarchical framework. It facilitates systematic evaluation of alternatives by incorporating both qualitative and quantitative factors through expert judgment, as presented on Table 3. Central to the AHP methodology is the use of pairwise comparisons, wherein experts evaluate the relative importance of criteria, enabling the construction of a reciprocal matrix that yields normalized priority weights (Abdullah and Yusof, 2018; Vaidya and Kumar, 2006).

Table 3. Schematic representation of the AHP framework used for flood vulnerability indicator weighting (Adapted from Saaty, 2005).

ANALYTICAL HIERARCHY PROCESS (AHP)
-Pairwise Comparison Matrix -Weight Derivation -Consistency Ratio (CR) -Ranking of Indicators

This method has been extensively applied in disaster risk management, particularly in flood vulnerability assessments, due to its ability to integrate subjective expert insights with analytical rigor (Rehman et al., 2019). In this context, AHP allows for the prioritization of vulnerability indicators across domains such as social, economic, environmental, and physical dimensions. The process involves deriving consistency ratios (CR) to ensure logical coherence in judgments, followed by ranking based on computed weights, thus promoting transparency and evidence-based decision-making (Saaty, 2008; Pelone and Sanchez, 2024). The application of AHP ultimately strengthens the reliability of indicator-based assessments used in planning, resource allocation, and policy formulation.

Pairwise Comparison Matrix Construction

The process begins by constructing a pairwise comparison matrix, where experts evaluate the relative importance between each pair of indicators. The equation used is as follows:

$$a_{ij}=\frac{w_i}{w_j} \text{ for } \quad i,j=1,2,\ldots,n \qquad (4)$$

where:

a_{ij} = is the relative importance of indicator i over j,
w_i, w_j = are the weights of indicators i and j,
n = is the total number of indicators being compared.

This matrix serves as the foundation for calculating the weights of each criterion through reciprocal judgments (Abdullah and Yusof, 2018; Pelone and Sanchez, 2024).

Normalization of the Comparison Matrix

Once the matrix is completed, normalization is performed by dividing each element in a column by the maximum value of that column:

$$a_{ij}^{norm}=\frac{a_{ij}}{\max a_{ij}}, \forall i,j \qquad (5)$$

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This normalization process ensures uniformity and transforms the matrix values into a comparable scale, enabling the derivation of consistent priority vectors (Abdullah and Yusof, 2018; Pelone and Sanchez, 2024).

Derivation of Weights Using Eigenvector

The eigenvector (w_i) is calculated by taking the average of each row in the normalized matrix:

$$w_i = \frac{\hat{a}_i}{n}, \forall i \qquad (6)$$

where:

$\hat{a}_i$ =is the sum of the normalized row values for the indicator i,
n is the number of criteria.

This step yields the priority weights of each indicator, representing their relative importance in decision-making (Saaty, 2005).

Consistency Check

The next step is verifying the internal consistency of the pairwise comparison matrix, which is crucial for ensuring the reliability of expert judgments. The Consistency Index (CI) is computed using the formula:

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (7)$$

where λ_{max} is the maximum eigenvalue of the matrix and n is the number of criteria or indicators being compared. The CI is then compared to the Random Index (RI) (see Table 4), which is a standard reference value that depends on the matrix size. Saaty (2005) provided RI values for matrices of various sizes, as shown in Table 4.

Table 4. Ratio Index (Saaty, 2005).

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

The consistency ratio (CR) is then computed to assess the acceptability of the CI value:

$$CR = \frac{CI}{RI} \qquad (8)$$

where RI is the random index, dependent on matrix size n, as shown in Table 4 (Saaty, 2005).

A matrix is considered consistent if the CR is less than or equal to 0.10 (10%), indicating that the pairwise comparisons are logically sound (Abdullah and Yusof, 2018; Pelone and Sanchez, 2024; Saaty, 2005). If the CR exceeds this threshold, the matrix must be revised by the panel of experts to improve its consistency.

Final Weight Derivation and Ranking

The final step involves the extraction of the priority vector, which contains the final weights of the indicators. This is expressed as:

$$W' = (d'(A1), d'(A2), \ldots, d'(An))T \qquad (9)$$

This weight vector is then used to rank the indicators from most to least significant in terms of their contribution to flood vulnerability. The derived rankings guide decision-makers in prioritizing actions and resource allocation for flood mitigation (Abdullah and Yusof, 2018; Pelone and Sanchez, 2024).

RESULTS

Validated Flood Vulnerability Indicators

The FDM was employed to identify and validate relevant flood vulnerability indicators under four key components: Social, Economic, Environmental, and Physical. The initial list of indicators was derived from the UNESCO-IHE Flood Vulnerability Indicator framework (Balica, Wright, and van der Meulen, 2012), which provided a comprehensive foundation based on internationally recognized parameters. A panel of 17 experts was engaged to evaluate each indicator using a 5-point Likert scale. Their responses were converted into triangular fuzzy numbers to facilitate analysis. Indicators that met the established acceptance criteria—specifically, a threshold value (d) of ≤ 0.2, an expert consensus level of ≥ 75%, and a defuzzified score (α-cut) of ≥ 0.5—were deemed valid and carried forward to the next phase of the study.

Social Flood Vulnerability Indicators

Social vulnerability pertains to the degree to which a population is predisposed to and incapable of withstanding adverse impacts of natural hazards, particularly due to social, economic, and demographic constraints. It encapsulates not only the exposure of individuals to hazards but also their limited capacity to cope with, adapt to, and recover from such events (Cutter et al., 2003; Wisner et al., 2004). In the context of flooding, vulnerability is intensified by unequal access to resources, poor housing conditions, inadequate infrastructure, and systemic social inequalities. These conditions render certain groups disproportionately at risk and hinder their ability to respond effectively to disaster impacts (Birkmann, 2006; Razzaghi Asl et al., 2025).

Table 5 presents the validated social flood vulnerability indicators through the FDM. From the total of 19 social indicators evaluated, 11 indicators were accepted after meeting the inclusion criteria: a defuzzified score (α-cut) ≥ 0.5, consensus ≥ 75%, and a threshold value (d) ≤ 0.2. The indicators were classified into three subdimensions: Exposure, Susceptibility, and Resilience, following the social component structure adapted from recent vulnerability frameworks (Abarquez and Murshed, 2004).

Table 5. FDM results for Social Flood Vulnerability Indicators.

Component	Indicator	Fuzzy score	*d Value*	Consensus (%)	Verdict
	Population in a flood-prone area	0.706	0.144	82.35	Accepted
	Rural population	0.647	0.126	88.24	Accepted
	Chi000000000ld Mortality	0.435	0.228	47.06	Rejected
	Transboundary River Commission	0.565	0.202	47.06	Rejected
	Past Experience	0.671	0.137	88.24	Accepted
	Awareness & Preparedness	0.635	0.174	70.59	Rejected
	Communication Penetration Rate	0.635	0.155	70.59	Rejected
SOCIAL	Warning system	0.706	0.122	88.24	Accepted
	Evacuation Roads	0.635	0.174	70.59	Rejected
	Disabled People	0.647	0.144	82.35	Accepted
	Human Development Index	0.576	0.169	58.82	Rejected
	Population density	0.553	0.131	76.47	Accepted
	Cultural Heritage	0.475	0.213	47.06	Rejected
	Population growth	0.541	0.140	76.47	Accepted
	Slums	0.518	0.144	76.47	Accepted
	Cadastral Survey	0.451	0.165	70.59	Rejected
	Shelters/Hospitals	0.600	0.188	94.12	Accepted
	Emergency Service	0.706	0.122	88.24	Accepted
	Institutional Capacity	0.647	0.126	82.35	Accepted

Under the Exposure subdimension, the indicators Population in Flood-Prone Area, Rural Population, Population Density, and Population Growth were accepted. These indicators emphasize spatial concentration and demographic pressure in flood-prone areas—conditions strongly linked to increased disaster risk in rural and peri-urban settlements (Zhou et al., 2022).

The Susceptibility subdimension included Past Experience, Disabled People, and Slums. These reflect the heightened vulnerability of groups with limited coping capacity or constrained mobility during floods. Past disaster experience has also been recognized as a proxy for perceived risk and awareness, influencing future preparedness (Alves et al., 2021).

For Resilience, four indicators were validated: Shelters/Hospitals, Warning System, Emergency Service, and Institutional Capacity. These represent adaptive capacities at the household

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and governance levels that enable communities to respond effectively to flooding. Recent studies have shown that robust institutional systems and access to emergency infrastructure significantly reduce post-disaster impacts (Mavhura, 2017).

Economic Flood Vulnerability Indicators

The economic indicators that passed the FDM screening include Land Use, Quality of Infrastructure, Amount of Investment, Unemployment, Urbanized Area, and Industries (see Table 6). These indicators reflect critical structural and financial conditions that influence a community's susceptibility to flood-related disruptions.

Land Use and Urbanized Area are essential for understanding how spatial development patterns contribute to surface runoff and exposure. Densely built environments with inadequate zoning often exacerbate flood impacts, particularly in low-lying and unregulated settlements. The inclusion of Quality of Infrastructure and Amount of Investment points to the importance of robust physical systems and financial allocation in mitigating risks and supporting recovery (Mavhura, 2017).

Table 6. FDM results for Economic Flood Vulnerability Indicators.

Component	Indicator	Fuzzy score	*d Value*	Consensus (%)	Verdict
ECONOMIC	Land Use	0.706	0.122	88.24	Accepted
	Inequality	0.447	0.131	76.47	Rejected
	Quality of infrastructure	0.729	0.100	94.12	Accepted
	Amount of Investment	0.694	0.112	94.12	Accepted
	Economic Recovery	0.659	0.166	70.59	Rejected
	Storage capacity over yearly discharge	0.529	0.154	70.59	Rejected
	Unemployment	0.541	0.140	76.47	Accepted
	Life expectancy Index	0.435	0.116	82.35	Rejected
	Flood Insurance	0.494	0.136	82.35	Rejected
	Dams Storage capacity	0.624	0.166	70.59	Rejected
	Urbanized Area	0.671	0.137	88.24	Accepted
	Industries	0.647	0.126	82.35	Accepted
	Contact with River	0.612	0.155	70.59	Rejected
	Recovery time	0.494	0.145	76.47	Rejected
	Drainage system	0.635	0.155	70.59	Rejected
	Infrastructure Management	0.682	0.138	70.59	Rejected

From a labor and production perspective, Unemployment and Industries highlight economic fragility and exposure in the event of flood disasters. High unemployment can weaken household resilience, while disruptions to industrial zones may cause cascading economic losses at the municipal scale (Nguyen et al., 2021). These findings reinforce the view that economic vulnerability is shaped not only by income levels but also by the configuration of assets, development priorities, and employment dynamics.

Environmental Flood Vulnerability Indicators

The environmental indicators that passed the FDM validation include Rainfall, Degraded Area, Urban Growth, and Green Area (see Table 7). These indicators highlight key ecological and landscape factors that significantly influence flood exposure and the environmental system's capacity to cope with such hazards.

Table 7. FDM results for Environmental Flood Vulnerability Indicators.

Component	Indicator	Fuzzy score	*d Value*	Consensus (%)	Verdict
ENVIRONMENTAL	Rainfall	0.788	0.022	100.00	Accepted
	Degraded Area	0.706	0.122	88.24	Accepted
	Unpopulated Area	0.486	0.202	52.94	Rejected
	Forested Area	0.627	0.204	76.47	Rejected
	Types of Vegetation	0.553	0.202	41.18	Rejected
	Natural Reservation	0.647	0.180	70.59	Rejected
	Evaporation rate	0.494	0.147	52.94	Rejected
	Urban Growth	0.553	0.131	76.47	Accepted
	Ground Water Level	0.612	0.177	64.71	Rejected
	Environmental Recovery	0.588	0.158	52.94	Rejected
	Green Area	0.659	0.166	76.47	Accepted

Rainfall, with the highest consensus and lowest threshold (d = 0.022), was strongly validated by the experts. This emphasizes the direct relationship between rainfall intensity and flood occurrences, as excessive precipitation remains a primary trigger of flood events (Robbani et al., 2020). Degraded Area, also highly rated, reflects the vulnerability created by land degradation processes such as deforestation, erosion, and urban encroachment, which exacerbate runoff and reduce natural absorption capacity (El Mazi et al., 2022).

Urban Growth signifies expanding impervious surfaces that hinder water infiltration and increase surface runoff, further aggravating flood risks in developing areas. Meanwhile, the inclusion of Green Area underscores the importance of vegetation cover in mitigating flood impacts by enhancing water retention and regulating runoff patterns (Liu et al., 2014; Sohn et al., 2020).

Physical Flood Vulnerability Indicators

Among the physical indicators assessed, six were validated by the expert panel: Topography, Number of Days with Rainfall, Frequency of Occurrence, Dikes/Levees, Flood Water Depth, and Proximity to River (see Table 8). These indicators encapsulate the geophysical attributes that directly influence flood behavior, exposure levels, and the overall impact on affected communities.

Table 8. FDM results for Physical Flood Vulnerability Indicators.

Component	Indicator	Fuzzy score	*d Value*	Consensus (%)	Verdict
PHYSICAL	Topography	0.765	0.058	100.00%	Accepted
	Number of days with rainfall	0.776	0.042	100.00%	Accepted
	River Discharge	0.647	0.216	76.47%	Rejected
	Frequency of occurrence	0.729	0.108	94.12%	Accepted
	Evaporation Rate/Rainfall	0.624	0.208	70.59%	Rejected
	Flood Duration	0.659	0.166	70.59%	Rejected
	Dam's Storage capacity	0.647	0.216	70.59%	Rejected
	Sedimentation Load	0.635	0.155	70.59%	Rejected
	Contact with River	0.635	0.174	64.71%	Rejected
	Dikes/Levees	0.682	0.138	82.35%	Accepted
	Flood Water Depth	0.741	0.083	100.00%	Accepted
	Building Codes	0.612	0.155	70.59%	Rejected
	Proximity to river	0.694	0.149	76.47%	Accepted

Topography and Number of Days with Rainfall received perfect consensus scores (100%) with low d-values, highlighting the experts' strong agreement on their critical role. Steep or low-lying terrains can accelerate runoff or accumulate floodwaters, making topography a fundamental determinant of flood risk (Tayyab et al., 2021). Similarly, the frequency of rainfall days increases the cumulative saturation of the soil, leading to reduced infiltration and higher surface runoff.

The Frequency of Occurrence also garnered strong consensus, emphasizing the importance of historical flood events in forecasting future risk patterns. Flood Water Depth, another highly rated indicator, reflects the severity of flooding and its potential to damage property and endanger lives (Khosravi et al., 2016). The structural role of Dikes/Levees in mitigating flood spread was also recognized, aligning with infrastructure-based risk reduction strategies.

Weights and Prioritization of Indicators

The AHP allows for the systematic weighting of criteria based on expert judgments, ensuring objectivity and consistency in decision-making (Saaty, 2008; Vaidya and Kumar, 2006). In this study, validated indicators from the FDM were subjected to AHP pairwise comparison to derive relative weights, rank their importance, and check consistency (see Table 9). Indicators with higher weights are considered more critical for flood vulnerability assessment, thereby providing evidence-based guidance for risk reduction planning.

Table 9. Analytical Hierarchy Process (AHP) Results.

Component	**Subdimension**	**Indicator**	**AHP Weight**	**Rank**	**Consistency Ratio**
SOCIAL	Exposure	Population in Flood Prone Area	0.311	1	0.057
		Rural population	0.235	2	
		Population Density	0.233	3	
		Population Growth	0.220	4	
	Susceptibility	Past Experience	0.431	1	0.048
		Disabled People	0.327	2	
		Slums	0.242	3	
	Resilience	Shelters/Hospitals	0.269	1	0.056
		Warning System	0.267	2	
		Emergency Service	0.248	3	
		Institutional Capacity	0.217	4	
ECONOMIC	Exposure	Land Use	0.523	1	0.033
		Industries	0.268	2	
		Urbanized Areas	0.209	3	
	Susceptibility	Quality of Infrastructure	0.615	1	0.000
		Unemployment	0.385	2	
	Resilience	Amount of Investment	1.000	1	0.000
ENVIRONMENTAL	Exposure	Degraded Area	1.000	1	0.000
	Susceptibility	Rainfall	0.509	1	0.000
		Urban Growth	0.491	2	0.000
	Resilience	Green Area	1.000	1	0.000
PHYSICAL	Exposure	Topography	0.296	1	0.045
		Number of days with heavy rainfall	0.254	2	
		Flood Water Depth	0.227	3	
		Proximity to River	0.223	4	
	Susceptibility	Frequency of Occurrence	1.000	1	0.000
	Resilience	Dikes/Levees		1	

As presented in Table 9, the indicator with the highest weight in the social component is Past Experience (0.431), highlighting the community's historical encounters with flood events as the most influential factor for social susceptibility. This is followed by Disabled People (0.327), indicating the heightened risk of vulnerable populations, while Population in Flood Prone Area (0.311) ranked highest among exposure-related indicators. Shelters/Hospitals (0.269) led among resilience indicators, slightly ahead of Warning System and Emergency Service.

In the economic component, Land Use (0.523) dominated the exposure subdimension, while Quality of Infrastructure (0.615) emerged as the most critical under susceptibility, emphasizing structural conditions in economic vulnerability. Amount of Investment was given full weight (1.000) in resilience, showing the experts' unanimous agreement on its critical importance in economic recovery and risk mitigation.

For the environmental dimension, Degraded Area (1.000) and Rainfall (0.509) were identified as the most important indicators for exposure and susceptibility, respectively. Green Area also received full weight (1.000), signifying its essential role in flood absorption and ecosystem buffering capacity.

Lastly, in the physical domain, Topography (0.296) and Number of Days with Rainfall (0.254) were prioritized under exposure. Both Frequency of Occurrence and Dikes/Levees received the highest weight (1.000) in their respective subdimensions, reinforcing their fundamental roles in flood prediction and physical protection.

Policy Implications and Localized Strategies for Flood Resilience

The strategic application of flood vulnerability assessment results lies in their institutional integration into the policy and planning mechanisms of LGUs, thereby transforming empirical outputs into actionable governance tools. In the case of Nabunturan, the weighted indicators identified through the FDM and AHP serve not merely as diagnostic variables but as entry points for operationalizing anticipatory, risk-informed development.

The weighted indicators identified through the FDM and AHP processes provide a robust empirical basis for enhancing disaster risk management planning in Nabunturan. Specifically, they offer actionable insights for refining the CDRA, Barangay Disaster Risk Reduction and Management Plans (BDRRMPs), and the development of a localized Flood Vulnerability Index (FVI) (Balica et al., 2012; Rufat et al., 2015; Khajehei et al., 2020).

The CDRA, as the municipality's foundational risk assessment tool, can integrate the weighted indicators to improve the granularity and relevance of hazard exposure, sensitivity, and adaptive capacity metrics (Nakasu and Amrapala, 2023). Embedding these empirically derived indicators into the CDRA will strengthen its ability to inform spatial risk layers, prioritize hazard-prone areas, and support anticipatory planning (UN-Habitat, 2019; World Bank, 2021).

At the barangay level, the BDRRMPs may adopt the validated indicators to enhance risk profiling and guide the prioritization of preparedness and mitigation measures. For instance, indicators related to social vulnerability (e.g., population in flood-prone areas, disabled populations) and infrastructure resilience (e.g., quality of infrastructure, access to emergency services) can inform contingency planning, evacuation strategies, and community-based early warning systems (Gaillard and Mercer, 2013). Integrating these indicators will ensure that the BDRRMPs are grounded in both scientific evidence and the social realities of the most vulnerable groups.

Moreover, the study's weighted indicators provide the foundation for constructing a Flood Vulnerability Index (FVI) tailored to Nabunturan's context. The FVI will allow for the aggregation of normalized indicator scores into composite vulnerability ratings at the barangay level (Balica et al., 2012; Rufat et al., 2015; Khajehei et al., 2020). This index can serve as a decision-support tool for local officials to allocate resources strategically, prioritize risk reduction investments, and monitor changes in flood vulnerability over time.

By aligning the CDRA, BDRRMPs, and the FVI within a shared, indicator-based framework, Nabunturan can transition from reactive disaster response to anticipatory, resilience-focused planning. This integration will promote coherence across local governance instruments and support more targeted, data-driven disaster risk reduction efforts (Cutter and Finch, 2008; Abdullah and Yusof, 2018; Saaty, 2008).

The convergence of CDRA, BDRRMPs, and the FVI through a shared, indicator-based framework ensures that risk reduction is not siloed but mainstreamed across governance levels. This alignment strengthens institutional coherence, improves risk visibility in planning instruments, and reinforces the LGU's pursuit of sustainable, climate-resilient development.

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DISCUSSION

This study successfully identified and validated 27 flood vulnerability indicators for Nabunturan, Davao de Oro, encompassing social, economic, environmental, and physical dimensions. Through the FDM and the AHP, it developed an empirically grounded framework for assessing and prioritizing flood risks in a localized, data-driven manner.

Social Dimension

The social dimension revealed that Past Experience (0.431), Disabled People (0.327), and Population in Flood-Prone Areas (0.311) were the most significant indicators. The prioritization of Past Experience reflects how historical flood exposure shapes both community awareness and adaptive capacity. Communities with frequent flood experiences often develop coping mechanisms and risk perceptions that can either strengthen resilience or, in some cases, lead to risk normalization, where repeated exposure leads to underestimation of danger. This aligns with Cutter et al. (2003), who emphasized that disaster experience is a core driver of vulnerability and adaptive behaviors.

The high weight assigned to Disabled People highlights the disproportionate vulnerability of marginalized populations in disaster contexts. Studies like Rufat et al. (2015) stress the importance of integrating social equity into vulnerability assessments, noting that socially sensitive groups often face systemic barriers in preparedness, response, and recovery. In the Philippines, Orencio and Fujii (2013) have noted that LGUs frequently struggle to address the compounded vulnerabilities of such groups, partly due to resource constraints and reactive governance.

Meanwhile, Population in Flood-Prone Areas emphasizes the risks associated with demographic exposure. High-density settlements in flood-prone zones amplify potential casualties and damages, which is consistent with findings by Cutter et al. (2003) and reflects broader patterns of urban expansion into hazard-prone areas driven by socio-economic pressures.

Economic Dimension

In the economic dimension, the highest weights were observed for Amount of Investment (1.000), Quality of Infrastructure (0.615), and Land Use (0.523). The dominance of Amount of Investment highlights the vulnerability of economic assets, particularly in developing regions where key investments such as marketplaces, transportation hubs, and agricultural infrastructures are often located in hazard-prone areas. Khajehei et al. (2020) and World Bank (2021) underline that while such investments drive local economic growth, they can also become significant liabilities when exposed to flooding.

The importance of Quality of Infrastructure reflects how resilient physical systems can mitigate or exacerbate flood impacts. Poorly constructed roads, bridges, and drainage systems can lead to cascading failures during flood events, turning moderate hazards into disasters. This supports Rufat et al. (2015), who found that infrastructure quality is not only a determinant of direct flood damage but also of the speed and effectiveness of post-disaster recovery.

Land Use further underscores the critical role of spatial planning. Improper zoning and land use conversions often lead to settlements in high-risk zones, exacerbating exposure and complicating evacuation and response efforts. This confirms findings from Khajehei et al. (2020), who argued for the integration of flood risk assessments into urban and regional land use planning.

Environmental Dimension

For the environmental dimension, Degraded Area (1.000), Green Area (1.000), and Rainfall (0.509) received the highest priority weights. The top ranking of Degraded Area reflects how land degradation—caused by deforestation, mining, and unsustainable land management—reduces natural flood absorption capacities. This increases runoff, exacerbates flood peaks, and contributes to soil erosion. The importance of this indicator echoes Balica et al. (2012) and Khajehei et al. (2020), who demonstrated that environmental degradation directly correlates with heightened flood risks.

Conversely, the equal prioritization of Green Area highlights the role of Nature-based Solutions (NbS). Vegetation not only acts as a physical barrier to slow floodwaters but also improves soil infiltration and stabilizes slopes. UN-Habitat (2019) and UNDRR (2022) advocate for preserving and restoring green spaces as a sustainable, cost-effective method for reducing flood vulnerability while co-delivering ecological and social benefits.

Rainfall was recognized as a key hazard driver. While it is an uncontrollable variable, its predictive capacity for flood risk is crucial, particularly in climate change scenarios where extreme precipitation events are becoming more frequent and intense.

Physical Dimension

The physical dimension identified Frequency of Occurrence (1.000), Dikes/Levees (1.000), and Topography (0.296) as the most significant indicators. The high weighting of Frequency of Occurrence confirms that past flood patterns are essential for anticipating future risks. This is consistent with Cutter et al. (2003), who emphasized that hazard frequency must be central in vulnerability and capacity assessments.

The equal priority of Dikes/Levees underscores the role of structural measures in managing flood hazards. While not foolproof, properly designed and maintained flood control infrastructures can significantly reduce exposure and damage. However, Khajehei et al. (2020) caution that overreliance on structural solutions without integrating non-structural measures (like zoning and early warning systems) can create a false sense of security.

Topography, though weighted lower than other physical indicators, remains vital. Elevation and slope influence flood propagation and inundation depth, affecting both hazard severity and evacuation logistics.

Methodological Strengths and Policy Relevance

The combination of FDM and AHP not only provided quantitative rigor but also incorporated expert judgment, making the results both technically valid and locally relevant. The selection of FDM experts from Nabunturan and Davao de Oro LGUs ensured contextual sensitivity, while the inclusion of regional experts for AHP introduced technical diversity and minimized bias—a practice recommended by Saaty (2008) and Habibi et al. (2015).

Moreover, the participatory, multi-criteria approach aligns with Sendai Framework priorities and global best practices in disaster risk reduction (UNDRR, 2022), which advocate for stakeholder engagement and the use of empirical data to inform policy and planning.

CONCLUSION

The study results demonstrated the varying influence of the indicators, highlighting the critical role of socio-economic exposure, infrastructural capacity, and environmental degradation in shaping flood vulnerability. The prioritization process revealed strong correlations between demographic pressures, past disaster experiences, and heightened flood risks. Areas with limited infrastructure and degraded environmental conditions were consistently identified as more vulnerable.

Integrating FDM and AHP ensured a robust, evidence-based framework for indicator selection and weighting, culminating in a localized Flood Vulnerability Index (FVI). This FVI provides a practical tool for differentiating flood risks across barangays and components, supporting targeted disaster risk reduction and climate adaptation strategies.

The study's findings affirm the theoretical frameworks proposed by UNESCO-IHE and the IPCC, which conceptualize vulnerability as a function of exposure, susceptibility, and resilience. By operationalizing these dimensions through validated local indicators, the research advances proactive vulnerability assessment practices and offers valuable insights for integrating empirical risk data into municipal planning and resilience-building initiatives.

RECOMMENDATION

Based on the findings, the following practical and actionable recommendations are proposed:

1. Institutionalize the validated flood vulnerability indicators within Nabunturan's Climate and Disaster Risk Assessment (CDRA) and Barangay DRRM Plans (BDRRMPs) to support intervention prioritization and resource allocation.
2. Refine and adopt the developed FVI for continuous monitoring and evaluation of flood vulnerability, guiding investment decisions and progress tracking.
3. Design programs focusing on infrastructure improvement, environmental restoration, and enhancing community adaptive capacities. Use results to update the CLUP and LCCAP, and other related plans.
4. Strengthen the technical capacity of the MDRRMO and barangay DRRM committees for indicator application. Institutionalize regular data collection and indicator updates.
5. Encourage the application of the study's FDM and AHP methodology in other municipalities within Davao de Oro and the region to standardize localized flood vulnerability assessments.

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CONFLICT OF INTEREST

The author declares no conflict of interest regarding the conduct and publication of this research.

AUTHOR CONTRIBUTIONS

Conceptualization: F. J. C.; methodology: F. J. C.; validation: F. J. C.; analysis: F. J. C.; data curation: F. J. C.; resources: F. J. C.; writing-original draft preparation: F. J. C.; writing-review and editing: F. J. C. and A. S. O.; visualization: F. J. C.; supervision: F. J. C. and A. S. O.; presentation: F. J. C..

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