



# A Framework for a Geospatial Predictive Decision Support System for Hazard Risk Profiling

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**Abstract:** Natural hazards consistently pose significant challenges to urban communities, particularly in regions vulnerable to these threats, such as Catbalogan City, Samar, Philippines. Effective hazard risk profiling is essential for proactive disaster preparedness, resource allocation, and policy development. However, current approaches utilized by Catbalogan City and many Local Government Units (LGUs) in the Philippines continue to rely on static hazard maps and descriptive assessments, which limit predictive capability and decision-support effectiveness. This paper presents a conceptual, expert-validated framework for a Geospatial Predictive Decision Support System (GPDSS) to enhance hazard risk profiling and disaster preparedness. The study synthesizes findings from existing hazard-mapping, predictive modeling, and decision-support literature using a systematic review, a design science research approach, and a structured framework development process. The findings reveal persistent reliance on static data, regression-based analyses, and limited integration of decision-support mechanisms. These findings serve as the foundation for the proposed GPDSS framework, which integrates spatiotemporal geospatial datasets, GIS-based analysis, predictive modeling using machine learning techniques, and AI-assisted policy interpretation. Domain experts evaluated the framework, confirming its conceptual relevance, usability, scalability, and innovation for local disaster-risk governance. Rather than a deployed system, the proposed GPDSS is positioned as a governance-oriented framework that offers conceptual advantages over traditional hazard-mapping approaches by enabling predictive risk assessment, interactive visualization, and policy-oriented decision support. The study introduces a scalable, adaptive, and innovative framework intended to guide future system development and implementation for disaster-risk governance in hazard-prone localities in the Philippines.

**Keywords:** Disaster risk management; predictive analytics; information system framework; artificial intelligence; machine learning

## 1. Introduction

Natural hazards, including floods, typhoons, landslides, and earthquakes, continue to pose escalating risks to urban communities worldwide due to climate change, rapid urbanization, and environmental degradation [1–2]. These hazards exert increasing pressure on governments to strengthen disaster preparedness, mitigation, and recovery mechanisms, particularly in highly

vulnerable regions [3]. Consequently, there is a growing need to understand localized hazard dynamics and translate risk information into actionable, evidence-based governance strategies [4].

The Philippines is among the most hazard-prone countries globally, experiencing an average of 20 tropical cyclones annually, with 8 to 9 making landfall [5]. Situated along the Pacific Ring of Fire and within the Western Pacific typhoon belt, the country is exposed to multiple hazards, including earthquakes, volcanic eruptions, flooding, and storm surges [6–7]. Although the Philippine Disaster Risk Reduction and Management Act (RA 10121) institutionalized disaster risk governance frameworks [8], implementation at the local government level often remains reactive, constrained by fragmented datasets, static hazard assessments, and limited predictive risk-analysis capabilities. The Eastern Visayas region, particularly Samar Province, consistently ranks among the most disaster-affected areas in the Philippines [9]. As the provincial capital, Catbalogan City faces persistent exposure to typhoons, flooding, and landslides due to its coastal geography, complex terrain, and socio-economic vulnerabilities [10]. Despite these conditions, disaster preparedness efforts in Catbalogan City continue to rely heavily on static hazard maps and manual assessments, which provide limited foresight for anticipatory planning, scenario analysis, and timely resource allocation.

Geographic Information Systems (GIS) have been widely adopted to support hazard profiling and disaster management by integrating spatial datasets such as topography, land use, infrastructure, and hazard zones [11–13]. While GIS-based approaches are effective for spatial visualization and descriptive risk assessment, many existing applications remain focused on historical conditions and are largely map-centric, offering limited predictive and decision-support capabilities. [14–16]. Recent studies emphasize that integrating GIS with predictive analytics and machine-learning techniques substantially enhances hazard-risk forecasting capabilities. Machine-learning models, such as Random Forest, Support Vector Machines, and Neural Networks, have demonstrated significantly higher predictive accuracy than conventional interpolation and regression-based approaches, with reported accuracies reaching up to 96% in selected hazard-mapping applications [17–19]. These approaches enable spatio-temporal modeling and forward-looking risk estimation, shifting disaster management from reactive response toward proactive preparedness [20–25]. However, predictive accuracy alone is insufficient to support effective disaster governance. Decision Support Systems (DSS) are required to transform analytical outputs into actionable insights for planners and policymakers [26–29]. In disaster-risk contexts, Spatial Decision Support Systems (SDSS) integrate geospatial data, analytical models, and user interfaces to facilitate time-sensitive decision-making through dashboards, scenario simulations, and policy-support tools [27–28].

Recent advancements further highlight the role of Artificial Intelligence (AI), particularly Natural Language Interfaces and Conversational AI, in supporting evidence-based policymaking and governance. These AI-assisted tools can interpret analytical outputs, generate policy-relevant summaries, and provide context-aware recommendations to decision makers [30–33]. Embedding such AI-assisted policy modules into decision-support systems enhances transparency, adaptability, and responsiveness in local disaster risk governance. Despite these technological developments, many local government units (LGUs) in the Philippines, including Catbalogan City, continue to depend on fragmented systems and static hazard maps. National initiatives such as Project NOAH (Nationwide Operational Assessment of Hazards) and Project TANAW (Topographical Analysis and Angular Assessment of City Works) demonstrate the value of geospatial hazard mapping and visualization for disaster management [34–35]. However, these initiatives remain largely descriptive and centralized, offering limited integration of predictive machine-learning analytics, barangay-level socio-economic data, and interactive decision-support functionalities aligned with LGU decision-making workflows. These limitations underscore the need for a localized, governance-oriented Geospatial Predictive Decision Support System (GPDSS) that integrates dynamic geospatial datasets, predictive analytics, and AI-assisted policy support within a unified framework. Such a system is particularly relevant for Catbalogan City, where multi-hazard exposure requires anticipatory planning and data-driven decision-making at the barangay level.

Accordingly, this study aims to develop a conceptual framework for a Geospatial Predictive Decision Support System (GPDSS) for hazard risk profiling. The proposed framework integrates geospatial data, predictive modeling, and an AI-assisted decision interface to support barangay-level hazard-risk classification

and policy-relevant recommendations. Positioned explicitly as a framework proposal and expert-validated design, rather than a deployed system, the study contributes a scalable, governance-focused model intended to guide proactive disaster risk management in Catbalogan City and other hazard-prone localities in the Philippines.

## 2. Materials and Methods

### 2.1 Materials

#### 2.1.1 Research Design

This study employed a Design Science Research (DSR) approach, well-suited to the development and evaluation of innovative artifacts such as frameworks and decision support systems. The DSR cycle consisted of three iterative phases: (a) problem identification and requirements analysis, (b) framework design and development, and (c) evaluation and refinement [36-37]. This ensured that the proposed Geospatial Predictive Decision Support System (GPDSS) framework was both scientifically rigorous and contextually relevant to Catbalogan City's disaster preparedness needs.

#### 2.1.2 Data Sources

For the proposed GPDSS framework, relevant hazard, geospatial, and socio-economic datasets are identified from national and local data repositories commonly used for disaster risk assessment and governance in the Philippines. These datasets are intended to be requested and integrated during the system implementation phase, consistent with the conceptual scope of the present study. The primary data categories include meteorological, geological, topographic, and socio-economic information sourced from government agencies such as the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the Philippine Institute of Volcanology and Seismology (PHIVOLCS), the National Mapping and Resource Information Authority (NAMRIA), the Philippine Statistics Authority (PSA), and the Catbalogan City Disaster Risk Reduction and Management Council (CDRRMC). Table 1 summarizes the proposed data sources, including data type, temporal coverage, spatial resolution, and responsible agencies, to clarify data derivation and intended system integration.

**Table 1.** Proposed Data Sources for the GPDSS Framework

Data Type	Source Agency	Temporal Coverage	Spatial Resolution
Meteorological (rainfall, typhoon tracks)	PAGASA	Hourly / Daily	Station-based / Grid
Geological (fault lines, landslide records)	PHIVOLCS	Event-based	Municipal / Site-specific
Topographic (DEM, land use)	NAMRIA	Periodic updates	10–30 meters
Socio-economic (population, housing, vulnerability indicators)	PSA	Census-based	Barangay level
Disaster incident records	CDRRMC	Event-based	Barangay level

Although actual data acquisition and integration were beyond the scope of this framework proposal, data availability, interoperability, and quality considerations were incorporated into the framework design. The GPDSS conceptual architecture assumes standardized data formats, metadata documentation, and validation procedures to support reliable spatio-temporal analysis.

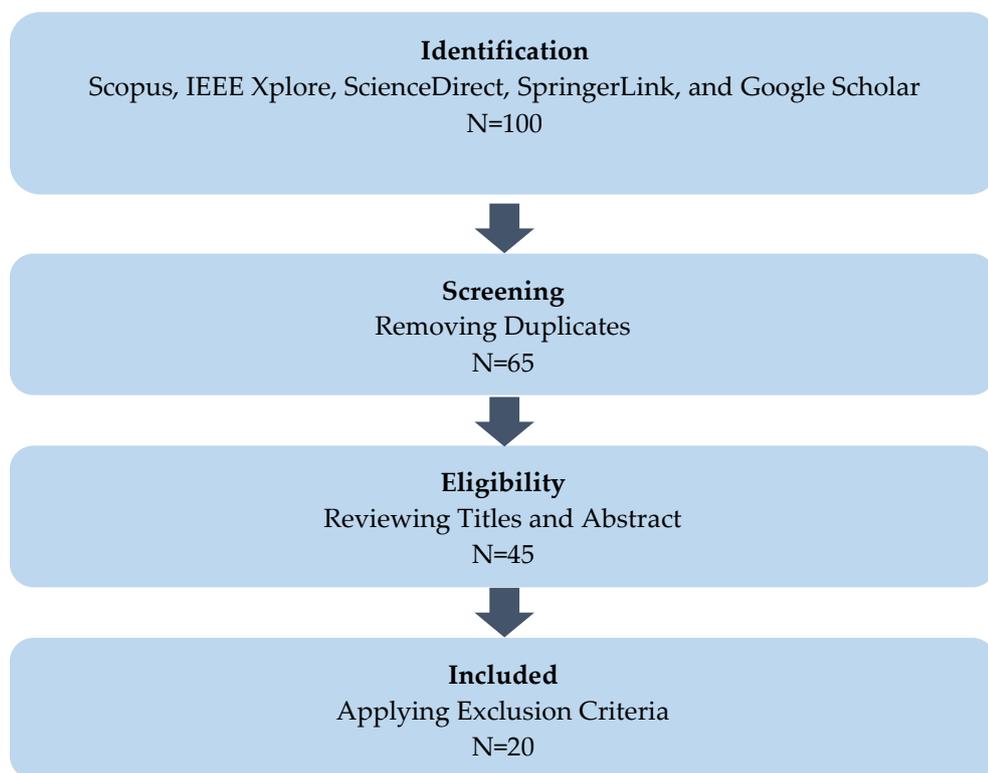
Data privacy and security are recognized as critical governance considerations, particularly for community-level socio-economic information. Any future implementation of the proposed framework shall comply with national data privacy regulations and local government data-sharing protocols to ensure ethical and responsible data use.

### 2.2 Methods

#### 2.2.1 Systematic Review of Literature

A systematic review [38] was conducted to examine existing approaches to hazard risk profiling, predictive modeling, geospatial decision support, and AI-assisted policymaking. The review adhered to a

structured process. Literature searches were conducted using Scopus, Web of Science, and Google Scholar. Search terms focused on hazard risk profiling, geospatial analysis, predictive modeling, machine learning, and decision-support systems. Broader concepts, including spatial decision support, early warning systems, and risk assessment frameworks, were also considered during the screening stage to capture relevant interdisciplinary studies. The initial search yielded approximately 100 records. Following title, abstract, and full-text screening, studies were excluded due to duplication, limited relevance to predictive hazard-risk profiling, absence of geospatial or analytical methods, insufficient methodological detail, or non-peer-reviewed status. A total of 20 studies were retained for synthesis, representing those most directly aligned with the objectives of framework design and gap identification. The relatively high exclusion rate reflects the review's focused emphasis on predictive and decision-support-oriented research rather than descriptive hazard mapping. The study selection process followed the core principles of the PRISMA guidelines. A PRISMA flow diagram illustrates the identification, screening, eligibility, and inclusion stages, with exclusion reasons described in the accompanying text. A formal PRISMA checklist was not included, as the review was intended to support conceptual framework development rather than comprehensive evidence synthesis. A formal quality appraisal using tools such as CASP or the Newcastle–Ottawa Scale was not conducted. This decision was intentional, as the review focused on identifying methodological trends and functional gaps rather than comparing study quality or empirical performance. This limitation is acknowledged in the discussion. Figure 1 presents the PRISMA flow diagram summarizing the identification, screening, eligibility, and inclusion process.



**Figure 1.** PRISMA Flow Diagram for the Systematic Review

Table 2. Summary of Included Studies

Author(s) & Year	Focus of Study	Methodology	Relevance to Hazard Risk Profiling
Farhadi & Najafzadeh, 2021 [39]	Flood risk mapping using remote sensing and Random Forest	Random Forest combined with remote-sensing inputs	Demonstrates the application of Random Forest for flood-risk mapping using satellite imagery
Mobley et al., 2021 [40]	Continuous flood-hazard quantification	Random Forest spatial classification	Example of a large-scale Random-Forest application for flood-probability mapping
De Vries et al., 2020 [41]	Rapid monitoring of flood events	Sentinel-1 synthetic-aperture-radar (SAR) time-series anomaly detection	Presents an algorithm for rapid flood detection using Sentinel-1 data
Yang et al., 2021 [42]	High-resolution flood-inundation archive	SAR-based inundation mapping (10 m resolution)	Provides a high-resolution inundation dataset for model validation
Islam et al., 2022 [43]	Urban flood mapping using Sentinel-1	Polarization analysis of vertical-horizonal and vertical-vertical bands	Evaluates Sentinel-1 polarizations for urban flood detection
Deng et al., 2022 [44]	Landslide susceptibility at the slope-unit scale	Information-Value analysis with Random Forest	Demonstrates slope-unit landslide susceptibility mapping using Information-Value-Random-Forest hybrid
Zhou et al., 2021 [45]	Hybrid models for landslide susceptibility	Hybrid machine-learning models combining Random Forest with other algorithms	Shows improved landslide-susceptibility prediction through hybrid modeling
Taalab, 2018 [46]	Landslide susceptibility mapping	Random Forest integrated with geographic information systems (GIS)	Demonstrates Random Forest application across heterogeneous regions for landslide susceptibility
Tehrany et al., 2019 [47]	Flood-susceptibility assessment	Evidential-belief approach combined with a machine-learning ensemble	Presents a robust ensemble approach for flood-susceptibility mapping
Althuwaynee et al., 2014 [48]	Landslide susceptibility mapping	Bivariate statistical analysis and Dempster-Shafer evidential-belief function	Provides a classic baseline method for landslide-susceptibility mapping
Luu et al., 2021 [49]	Flood susceptibility in Quang Binh, Vietnam	GIS combined with ensemble machine-learning models	Demonstrates a regional ensemble machine-learning plus GIS pipeline for flood mapping

Table 2. Summary of Included Studies (Continue)

Author(s) & Year	Focus of Study	Methodology	Relevance to Hazard Risk Profiling
Li et al., 2024 [50]	Landslide susceptibility with space-ground data integration	Space-ground data integration with Random Forest	Demonstrates replicable methods for landslide assessment
Zhang et al., 2023 [51]	Landslide susceptibility comparison	Random Forest versus Extreme Gradient Boosting	Benchmark tree-based models for landslide susceptibility
Toma et al., 2024 [52]	Sentinel-1 flood mapping on Google Earth Engine	Sentinel-1 SAR processing with Google Earth Engine	Demonstrates scalable and rapid urban-flood mapping workflows
Albertini et al., 2024 [53]	Multi-source flooded-area mapping	Multi-source Random-Forest classification	Integrates varied geospatial inputs for flooded-area mapping
Saber, 2023 [54]	Ensemble gradient models for flood risk	Light Gradient Boosting Machine, CatBoost, and Random Forest	Supports gradient-boosting model selection for predictive flood mapping
Schoppa et al., 2020 [55]	Flood-prediction model comparison	Random Forest compared with physics-based hydrodynamic models	Validates Random Forest as a surrogate for computationally intensive hydrodynamic models
Lagmay et al., 2017 [34]	National hazard mapping and near-real-time dissemination (Philippines)	Multi-hazard GIS mapping, remote sensing, and web dissemination	Operational Philippine program for hazard mapping and public dissemination
Papadakis et al., 2024 [32]	Explainable and transparent artificial intelligence for public policymaking	Frameworks and real-world case studies applying explainable artificial intelligence methods	Guides the design of explainability and governance features for AI policy modules
Amarasinghe, 2023 [56]	Explainable machine-learning methods for public policy	Review of interpretability techniques such as SHAP and LIME	Provides approaches for integrating transparent AI tools into decision-support systems

**Table 2** presents the 20 studies included in the systematic review, detailing the authors, research focus, methodologies employed, and relevance to hazard risk profiling. The review shows that flood-related research predominates, with roughly 60% of the studies [39-53] [49][52-55] focusing on flood risk mapping, rapid inundation detection, or continuous flood hazard quantification. Landslide susceptibility represents the next most common hazard, accounting for about 30% of the studies [44-46][48][50-51]. Only one paper, or 20%, offered a broad, multi-hazard perspective at the national scale [34]. Methodologically, machine learning dominates hazard prediction and mapping. Random Forest is the most frequently implemented algorithm, either as a stand-alone classifier [39-40] or in hybrid and ensemble forms with techniques such as Extreme Gradient Boosting and Light Gradient Boosting Machine [51][54]. These models are commonly paired with remote sensing and Geographic Information Systems (GIS) for spatial analysis, as demonstrated by Sentinel-1 synthetic-aperture radar applications [41-42][52]. Classic statistical approaches, such as bivariate analysis and evidential-belief functions [51-52], appear less frequently but provide important baselines for model validation. The review also highlights the emerging integration of artificial intelligence for policy support. It presents frameworks for explainable and transparent AI in public policymaking, illustrating how machine-learning outputs can be translated into interpretable insights for governance [32][56]. These studies underscore the value of embedding explainable artificial intelligence and interactive decision-support features within hazard-risk systems. However, despite these advances, the review highlighted persistent gaps:

- a) continued reliance on static hazard maps rather than dynamic spatio-temporal models,
- b) limited integration of predictive analytics with GIS visualization, and
- c) inadequate incorporation of artificial-intelligence-driven policy tools and interactive decision-support features to translate analytical outputs into practical governance actions.

These findings directly inform the design of the proposed Geospatial Predictive Decision Support System (GPDSS) for hazard risk profiling in Catbalogan City, Samar. By integrating remote sensing, GIS, advanced machine-learning models, and AI-assisted policy guidance into a single platform, the GPDSS seeks to address documented gaps and enable anticipatory, evidence-based disaster risk governance at the local level.

### 2.2.2 Framework Development Process

The development of the proposed Geospatial Predictive Decision Support System (GPDSS) follows key principles of information systems development, emphasizing structured lifecycles, process models, and formal methodologies to guide system development [57]. This approach provides a systematic method for designing and evaluating public-sector information systems by combining rigorous data collection with iterative framework development, ensuring that the resulting platform is both robust and fit for local government use [58-59]. In particular, the development strategy highlights the importance of functional design and modular architecture to deliver a maintainable, web-based decision-support application that integrates geospatial analytics and AI-assisted policy reporting.



**Figure 2.** Framework Development Process

Figure 2 presents the framework development process, which served as the primary guide for creating the GPDSS. The process comprises three major phases [60]. **Application Modeling Phase** – requirements are gathered regarding the system’s objectives, core functions, data flows, and expected outputs for hazard risk profiling and policy support. From these requirements, the main components and data modules are identified. **Building-Block Tailoring Phase** – the essential building blocks of the system are customized to meet the specific needs of the GPDSS, including geospatial data integration, temporal predictive modeling, and AI-assisted report generation for policymaking. **Component Composition Phase** – all customized components are integrated

to form the complete decision-support platform, ensuring seamless interaction between the geospatial predictive analytics engine and the AI-based policy-reporting module. This structured development process ensures that the GPDSS is both technically sound and aligned with the decision-making requirements of the Catbalogan City local government.

### 3. Results and Discussion

This section presents the study's results in terms of the designed framework components, the synthesis of systematic review findings, and expert evaluation outcomes, focusing on the conceptual development and assessed feasibility of the proposed GPDSS framework. The systematic review of 20 selected studies identified three recurring patterns in hazard risk profiling research: (a) reliance on static datasets, (b) predominant use of conventional statistical or regression-based models, and (c) limited integration of decision-support functionality.

#### 3.1 Gap from Findings from the Systematic Review

The systematic review examined existing research on hazard-risk profiling and decision-support systems to identify limitations in current practices. The review highlighted key gaps, including reliance on static hazard maps, limited application of predictive analytics, and inadequate integration of multi-agency datasets, which guided the design of the proposed GPDSS framework.

**Table 3.** Summary of Findings from the Systematic Review

Theme	Key Observations from Literature	Implication for the Proposed Framework
Data Dependence	Hazard maps and census records dominate, with limited use of temporal satellite observations and other time-varying geospatial datasets.	Incorporate multi-source temporal data, such as satellite imagery and historical hazard records, to enable dynamic spatio-temporal analysis.
Analytical Approaches	Regression and other classical statistical methods remain common; machine-learning techniques are used mainly for hazard prediction but are not the focus of AI in this study.	Apply appropriate predictive models for temporal hazard forecasting.
Decision-Support Limitations	Most existing systems provide static visualization and lack mechanisms to translate analytical outputs into actionable governance.	Develop an AI-assisted Geospatial Predictive Decision Support System (GPDSS) that uses predictive results to automatically generate interpretive reports and policy options for local government decision makers.

Themes are derived from the systematic review of 20 studies on hazard risk profiling.

**Table 3** presents the gaps derived from the systematic literature review. It revealed three critical gaps that inform the conceptualization and design of the proposed GPDSS. First, the extant literature demonstrates a pronounced dependence on static data sources, with hazard maps and census records serving as the primary inputs for risk assessment. The limited adoption of temporal satellite observations and other time-varying geospatial datasets constrains the capacity to capture evolving hazard dynamics. Addressing this shortcoming requires incorporating multi-source temporal data, such as satellite imagery and historical hazard records, to enable dynamic spatio-temporal analysis within the GPDSS framework. Second, the review indicates that analytical approaches remain dominated by regression and other classical statistical techniques, while the application of machine-learning methods is largely confined to hazard prediction and does not extend to

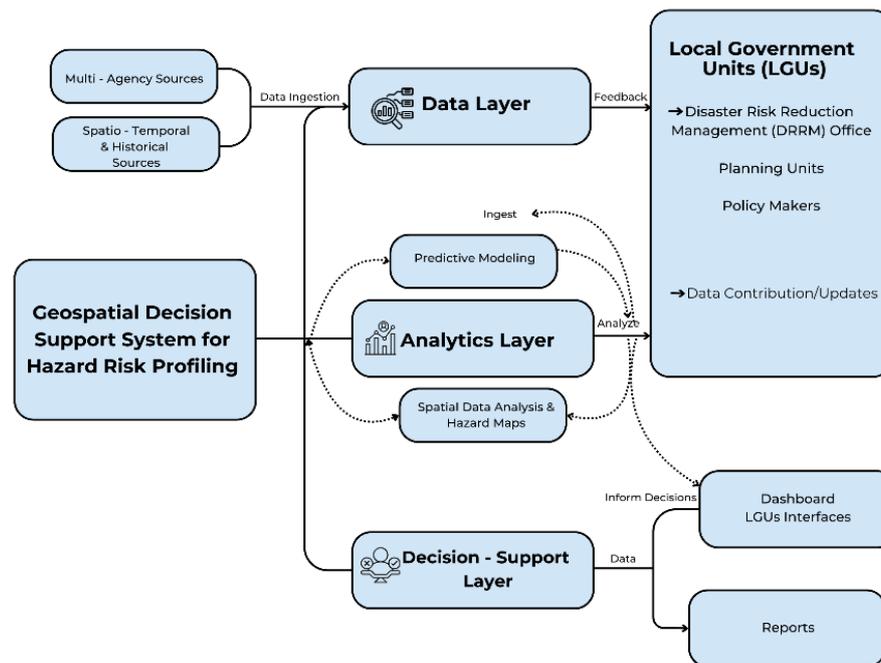
policy formulation. For the proposed system, this finding underscores the need to employ appropriate predictive models for temporal hazard forecasting, while clearly delimiting the role of artificial intelligence to post-analysis functions rather than predictive accuracy. Third, most existing platforms exhibit marked decision-support limitations. Current systems primarily provide static visualizations and lack mechanisms to translate analytical outputs into actionable governance strategies. To overcome this deficit, the GPDSS will incorporate an AI-assisted decision-support module that interprets predictive results and automatically generates policy-relevant reports and recommendations tailored to the needs of local government decision-makers. Collectively, these findings highlight the necessity for a comprehensive, responsive, and policy-oriented geospatial framework. By integrating diverse temporal datasets, employing robust predictive modeling, and embedding AI-driven policy guidance, the GPDSS aims to bridge the identified gaps and advance proactive, evidence-based disaster-risk governance at the local level.

### 3.2 Novel Contributions of the Proposed GPDSS Framework

While the proposed GPDSS adopts a three-layer architecture commonly found in decision support system (DSS) literature, comprising Data, Analytics, and Decision-Support layers, the novelty of the framework lies not in the architecture itself but in its governance-oriented integration and localized application. Existing Philippine disaster-management initiatives, such as Project NOAH and Project TANAW, primarily focus on hazard visualization, monitoring, and descriptive spatial analysis. Although these systems provide valuable geospatial insights, they remain largely centralized, map-centric, and focused on historical conditions, with limited integration into local government decision-making workflows. In contrast, the proposed GPDSS framework introduces several distinct contributions. First, it emphasizes barangay-level predictive hazard-risk profiling by integrating spatio-temporal environmental, geospatial, and socio-economic datasets. This shifts hazard assessment from static mapping toward anticipatory, data-driven risk estimation tailored to local governance needs. Second, the framework conceptually integrates predictive analytics with decision-support functionality. Rather than treating predictive models as standalone analytical tools, the GPDSS is designed to translate predictive outputs into policy-relevant insights through dashboards, scenario analysis, and structured decision-support mechanisms aligned with LGU planning and resource-allocation processes. Third, the framework incorporates an AI-assisted policy interpretation component using Natural Language Interfaces and Conversational AI. This feature is intended to support local officials by summarizing analytical results, generating context-aware recommendations, and enhancing the interpretability of complex predictive outputs, capabilities that are not explicitly addressed in existing Philippine hazard-management systems. Finally, the proposed GPDSS adopts a modular and scalable design philosophy. Although conceptual in nature, the framework is structured to facilitate future implementation across multiple local government units by allowing the integration of locality-specific datasets and retraining of predictive models. This scalability positions the framework as a transferable governance tool rather than a site-specific technical solution. Collectively, these contributions distinguish the proposed GPDSS framework from existing disaster-risk tools by foregrounding predictive capability, decision-support integration, and governance applicability at the local level, thereby addressing critical gaps identified in the systematic review and expert evaluation.

### 3.3 Proposed Framework for GPDSS

Based on the hazard and disaster challenges identified in Catbalogan City, Samar, insights synthesized from the systematic review of relevant literature, and framework development process, this section presents the proposed Geospatial Predictive Decision Support System (GPDSS) for the hazard risk profiling framework. The framework integrates multi-source geospatial data, predictive analytics, and interactive decision-support components to guide evidence-based hazard risk profiling and disaster-management planning.



**Figure 3.** Conceptual framework of the proposed Geospatial Predictive Decision Support System (GPDSS) for hazard risk profiling and local disaster-risk governance.

The proposed GPDSS framework addresses the limitations of static hazard mapping by integrating dynamic spatio-temporal datasets, advanced predictive analytics, and interactive decision-support tools, in contrast to conventional hazard maps, which are typically dependent on historical data and infrequent updates. The GPDSS framework illustrates a cyclical process of data integration, analytical processing, and stakeholder engagement. The workflow begins with the Data Ingestion phase, where information is aggregated from diverse streams, specifically Multi-Agency Sources and Spatio-Temporal & Historical Sources such as PAGASA, PHIVOLCS, NAMRIA, and PSA, as well as local records from the Catbalogan City CDRRMC. This raw data is funneled into the Data Layer, which serves as the primary repository and foundational structure for the system. By centralizing disparate datasets, the framework ensures that subsequent analyses are based on a comprehensive, unified information base. From the Data Layer, the framework transitions to the Analytics Layer, a sophisticated processing core that converts raw data into actionable intelligence. This layer utilizes two primary methodologies: Predictive Modeling, which forecasts future risks, and Spatial Data Analysis, which produces visualized Hazard Maps. These analytical outputs are then utilized by the Decision-Support Layer, which synthesizes the findings to provide clear, evidence-based guidance. The final delivery of this intelligence is facilitated through specialized LGU Dashboard Interfaces and comprehensive Reports, designed to "Inform Decisions" for end-users. The framework culminates in a dynamic interaction with Local Government Units (LGUs), specifically targeting Disaster Risk Reduction Management (DRRM) offices, Planning Units, and Policy Makers. This stage represents the practical application of the system's outputs in real-world governance and risk mitigation. Crucially, the model establishes a continuous feedback loop: LGUs provide feedback back to the Data Layer and offer Data Contributions or Updates based on localized observations. This iterative relationship ensures that the GDSS remains up to date, relevant, and highly responsive to the evolving needs of the communities it serves.

Applying the framework within the context of Catbalogan City underscores its practical applicability. The city's repeated exposure to typhoons, coastal flooding, and landslides, combined with notable socio-economic vulnerabilities, underscores the need for a data-driven decision-support mechanism. Although the framework emerges from a broad synthesis of international and local scholarship, the hazard profile and governance conditions of Catbalogan provide a realistic testbed and illustrate how the system can strengthen local disaster risk reduction and management (DRRM) strategies. Finally, the framework's modular

architecture promotes scalability and transferability. Its core design can be readily adapted to other Philippine cities or similarly hazard-prone localities by integrating site-specific datasets and refining predictive models. Such adaptability extends the framework’s relevance beyond Catbalogan and aligns with global imperatives for climate-resilient urban planning and evidence-based DRRM policy making.

### 3.4 Comparison of Traditional Approaches and the Proposed Framework

A comparative analysis between traditional hazard mapping practices in the Philippines, particularly in Catbalogan City, Samar, and the proposed Geospatial Predictive Decision Support System (GPDSS) framework was conducted.

**Table 4. Comparison of Traditional Approaches and the Proposed Framework**

Feature	Traditional Hazard Mapping	Proposed GPDSS Framework
Data Source	Static hazard maps, census data	Dynamic hazard maps, spatio-temporal datasets
Analytical Techniques	Descriptive statistics, regression	Predictive modeling, machine learning, scenario simulation
Decision-Support Features	Limited to static maps	Interactive dashboards, risk maps, and policy recommendation tools
Adaptability	Location-specific, non-scalable	Scalable and adaptable to multiple localities
End-Users	Planners, technical experts	LGUs, policymakers, and communities

The comparison highlights the advantages of the proposed GPDSS over traditional hazard-mapping practices.

Table 4 illustrates the comparative analysis of the traditional approaches and the proposed framework of the study. It highlights the substantive advantages of the proposed Geospatial Predictive Decision Support System (GPDSS) over conventional hazard-mapping practices currently used in the Philippines, particularly in Catbalogan City, Samar. Traditional approaches rely primarily on static hazard maps and census data, which provide only a static snapshot of risk conditions and are infrequently updated. In contrast, the GPDSS integrates dynamic hazard maps and spatiotemporal datasets, enabling continuous monitoring and incorporating evolving environmental and socio-demographic variables. Analytically, existing methods emphasize descriptive statistics and regression-based analyses, which are limited to retrospective or static evaluations. The proposed framework advances beyond these techniques by integrating predictive modeling, machine learning, and scenario simulation, thereby enabling forward-looking hazard forecasts and risk assessments. From a decision-support perspective, traditional systems offer limited functionality, typically confined to static map dissemination. The GPDSS introduces interactive dashboards, dynamic risk maps, and policy recommendation tools, providing local government units and policymakers with actionable insights for proactive planning and resource allocation.

In terms of adaptability, traditional hazard mapping tends to be location-specific and non-scalable, restricting its broader application. By contrast, the GPDSS is modular, scalable, and adaptable across multiple localities, ensuring relevance for diverse geographic and administrative contexts. Finally, while conventional methods are primarily designed for technical experts and planners, the GPDSS explicitly targets a broader user base, including local government units, policymakers, and community stakeholders, thereby fostering participatory and inclusive disaster risk governance. Overall, the proposed GPDSS framework addresses the limitations of traditional hazard mapping by combining dynamic data integration, advanced predictive analytics, and AI-assisted decision support, thereby enhancing the capacity for anticipatory, evidence-based disaster risk management.

### 3.5 Expert Validation Result

To ensure methodological robustness and contextual applicability, the proposed Geospatial Predictive Decision Support System (GPDSS) conceptual framework was subjected to expert validation using a structured evaluation matrix. Expert-based assessment is a recognized and widely employed method for

establishing the quality, feasibility, and potential utility of decision-support frameworks [61-62]. Using the adapted evaluation matrix, 12 domain experts, including disaster-risk management officials, geographic information systems (GIS) analysts, and information-technology practitioners, independently evaluated the framework across four key dimensions: relevance, usability, scalability, and innovation.

**Table 5.** Expert Validation Results of the GPDSS Framework

Validation Dimension	Indicators for a Conceptual Framework	Mean	Representative Expert Feedback	Interpretation
Relevance	Alignment with local DRRM priorities; potential to inform LGU policy and planning once implemented	4.6	“Directly addresses Catbalogan’s hazard risks; highly relevant for future DRRM initiatives.”	Extremely Acceptable
Conceptual Usability	Clarity and logical coherence of the proposed structure; feasibility of eventual interface design	4.5	“The framework is clearly organized and would be intuitive to translate into an operational system.”	Highly Acceptable
Scalability	Transferability of the framework to other municipalities or hazard-prone areas	4.5	“Design can be readily adapted to other municipalities with appropriate local data inputs.”	Highly Acceptable
Innovation	Novel integration of predictive analytics and geospatial modeling at the conceptual level	4.7	“Combines machine-learning forecasting with GIS-based risk profiling in an original way for local governance.”	Extremely Acceptable

Experts rated each criterion using a five-point Likert scale with the following interpretation: 4.51–5.00 = Extremely Acceptable, 3.31–4.50 = Highly Acceptable, 2.51–3.30 = Acceptable, 1.51–2.50 = Needs Improvement, and 1.00–1.50 = Not Acceptable. Mean scores represent the average of twelve independent expert evaluations of the proposed GPDSS framework.

**Table 5** presents the results of the expert evaluation of the GPDSS framework. The findings show that the expert panel assigned ratings of 4.5-4.7 across all evaluation criteria, indicating strong support for the framework’s theoretical robustness and future implementation potential. Reviewers emphasized its relevance to Catbalogan City’s disaster-risk reduction requirements and noted the framework’s logical coherence and conceptual feasibility. Experts further affirmed its scalability, highlighting its capacity to be adapted to other hazard-prone municipalities through the integration of local datasets and retraining of predictive models. The strong rating for innovation reflects how original this framework is in combining machine-learning predictive analytics with GIS-based spatio-temporal analysis for municipal disaster management. This finding aligns with the study by [63], which stresses the importance of user-centred design approaches in disaster risk visualisation. The acknowledgment of scalability in the expert feedback is also supported by recent systematic reviews of disaster management systems, which highlight the need for adaptable, technology-enabled frameworks across diverse localities [64]. It should be noted that the results presented in this section pertain to framework design and expert-based assessment, and do not represent operational system performance or predictive accuracy metrics. These aspects are identified as directions for future work, including prototype development, empirical testing, and pilot implementation in Catbalogan City, Samar, Philippines.

## 4. Conclusions

The increasing frequency and complexity of natural hazards in the Philippines underscore the need for more proactive, data-driven approaches to local disaster risk governance. This study presented a Geospatial Predictive Decision Support System (GPDSS) framework designed to address identified gaps in existing hazard risk profiling practices, particularly the reliance on static datasets, conventional analytical methods, and limited decision-support integration. By synthesizing findings from a systematic review and expert evaluation, the study contributes a governance-oriented framework that integrates geospatial analysis, predictive modeling, and AI-assisted decision support for barangay-level hazard risk profiling. The primary contribution of this study lies in the conceptual design and expert validation of a localized, predictive, and decision-support-oriented framework rather than in the development of an operational system. The proposed GPDSS framework emphasizes anticipatory planning, policy relevance, and alignment with local government unit (LGU) workflows, distinguishing it from existing hazard mapping initiatives that remain largely descriptive and centralized. This study is subject to several limitations. First, the framework was evaluated through expert-based assessment rather than empirical system implementation or performance testing. Second, actual data acquisition, model training, and system deployment were beyond the scope of the present work. As such, predictive accuracy metrics, system responsiveness, and operational effectiveness were not assessed. Future research will focus on translating the proposed framework into a functional prototype by integrating real-time and historical hazard data from relevant national and local agencies. Subsequent phases include model training and validation, pilot testing in Catbalogan City, Samar, and evaluation of system performance under multi-hazard scenarios involving floods, landslides, and typhoons. Further work will also examine system sustainability, maintenance requirements, capacity-building for LGU personnel, and ethical considerations related to data privacy and algorithmic transparency. Generally, the proposed GPDSS framework provides a structured foundation for advancing predictive, data-driven disaster risk governance at the local level. It offers a scalable reference model for future geospatial decision-support system development in hazard-prone communities in the Philippines.

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