Isabela State University Linker:
Journal of Engineering, Computing, and Technology
Volume 2, Issue 1
ISSN (Print): 3082-3676 ISSN (Online): 3082-3684
Publisher: Isabela State University, Desktop Publishing, Echague, Isabela

Development of an Integrated Natural and Socioeconomic Indicators Monitoring System for Bulacan Using Earth Intelligence Tools

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RESEARCH ARTICLE INFORMATION	ABSTRACT

Received: April 11, 2025
Reviewed: May 5, 2025
Accepted: June 16, 2025
Published: June 30, 2025

This study introduced an Integrated Natural and Socioeconomic Indicators Monitoring System for Bulacan aimed at strengthening local flood risk assessment and enhancing disaster resilience. It aligns with broader disaster risk reduction goals by integrating real-time Earth observation data, predictive analytics, and stakeholder-centered design to support proactive, community-level decision-making. The system adopted a Single Page Application (SPA) architecture using React.js for dynamic visualization and Django REST API for efficient backend data processing, chosen for their scalability, responsiveness, and suitability for real-time applications. Methodologically, the study follows a Design and Development Research (DDR) approach integrating satellite data, geospatial layers, socioeconomic indicators, and local dam telemetry. Stakeholder testing in Meycauayan City revealed substantial improvements in flood prediction accuracy, supporting timely response actions. Results also showed high satisfaction levels among users, with notable gains in usability and decision support. The key challenges included data integration and maintaining responsiveness during peak data loads. Overall, the study contributes a practical, replicable tool that addresses key limitations in fragmented disaster monitoring systems. Recommendations include expanding multi-hazard capabilities, stakeholder training, and continued system enhancement to advance resilience efforts in flood-prone regions.

Keywords: *Flood risk assessment, disaster preparedness, Geographic Information Systems (GIS), predictive analytics, earth intelligence tools*

Introduction

Flooding remains one of the most pervasive natural hazards in the Philippines, causing widespread damage to infrastructure, loss of livelihoods, and disruption to daily life. The country's vulnerability stems from its geographic exposure to typhoons, monsoon rains, and rising sea levels, making flood risk management a critical national concern. In recent years, national initiatives like Project NOAH and GeoRiskPH have improved centralized data availability, but many local government units (LGUs) still lack localized, real-time systems that translate raw data into actionable insights for barangay-level planning and response (Aspiras, 2022; Lagmay & Kerle, 2015).

Previous research has explored various methodologies for flood risk assessment and disaster preparedness, utilizing Geographic Information Systems (GIS), remote sensing data, and predictive analytics (Ahmed et al., 2024; Cepero et al., 2025; Saraswat & Choudhari, 2025). However, many existing platforms still exhibit limitations in integrating real-time environmental and socioeconomic data or lack user-centric design features that enable timely decision-making at the local level (Patel & Patel, 2024; Safaeian et al., 2024).

Bulacan, a flood-prone province in Central Luzon, was selected as the focal area for this study due to its strategic economic role and its repeated exposure to flood events triggered by dam releases, typhoons, and overflowing rivers. Municipalities such as Meycauayan, Marilao, and Malolos are frequently inundated, with limited access to live flood alerts tailored to local contexts. Despite improvements in forecasting accuracy at the national level, the gap remains in providing localized early warnings that incorporate both environmental and socioeconomic indicators.

This study responds to those specific challenges by introducing an integrated flood risk monitoring system tailored for Bulacan. The system goes beyond traditional GIS-based flood mapping by combining satellite data, predictive modeling, and real-time data processing using a web-based platform. Unlike existing systems used in countries like Malaysia or Indonesia, where regional flood dashboards often rely on generalized forecasts, this platform integrates barangay-level socioeconomic vulnerability indicators, dam telemetry, and remote sensing layers into one cohesive dashboard (Ahmed et al., 2024; Hadi et al., 2024).

To address this gap, the study introduced a localized Natural and Socioeconomic Indicators Monitoring System that delivers near real-time flood alerts and contextualized risk assessments. The platform is built using scalable technologies such as React.js and Django REST API, offering a novel combination of earth observation, machine learning, and local stakeholder engagement. This approach contributes a replicable, low-cost model suitable for other flood-prone regions and supports the operationalization of Sendai Framework priorities and Sustainable Development Goals 11 and 13 at the local level (Adu-Gyamfi et al., 2024; Group on Earth Observations [GEO], 2017, 2025).

Methods

This study adopted a Design and Development Research (DDR) approach for the creation of the Natural and Socioeconomic Indicators Monitoring System for Bulacan. DDR is well-suited for projects aiming to develop practical and innovative technological solutions. The methodology integrates both quantitative and qualitative components through data-driven modeling, geospatial integration, and iterative system design. This hybrid approach ensures that the system is grounded in empirical data while also responsive to stakeholders.

Development Methodology

The system was developed using the Agile Development Lifecycle, which encourages flexibility and ongoing improvement through iterative sprints. Each sprint included planning, development, testing, and evaluation. The major phases of development are outlined below and visually represented in Figure 1. The diagram illustrates the iterative phases involved in the system's Agile software development process.

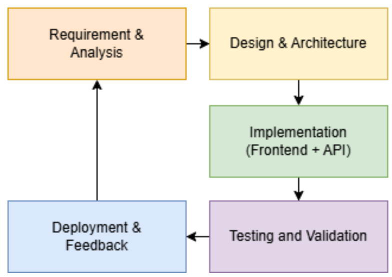

Figure 1. *Agile Development Workflow*

Data Collection and Sources

The monitoring system integrates a wide range of environmental and socioeconomic datasets. Table 1 summarizes the primary data sources, their providers, and applications within the monitoring system.

Table 1. Summary of Primary Data Sources

Data Category	Source/Provider	Application
Precipitation	NASA POWER/GPM IMERG (Sparks, 2018)	Real-time rainfall for model training
Dam Discharge	Angat, Bustos, Ipo Dams (Bulacan Provincial Disaster Risk Reduction and Management Office, n.d.)	Hydrological forecasting input
Satellite Imagery	Himawari-9 (MURATA et al., 2018), Sentinel-2 (Sentinel Hub by Planet Labs, n.d.)	Cloud and terrain analysis, flood context
Socioeconomic Data	SEDAC (GPWv4, GRDI, LECZ, GMIS, HBASE) (Brown de Colstoun, E. C., Huang, C., Wang, P., Tilton, J. C., Tan, B., Phillips, J., Niemczura, S., Ling, P.-Y., & Wolfe, 2017; Center For International Earth Science Information Network-CIESIN-Columbia University, 2021, 2022; Wang, P., Huang, C., Brown de Colstoun, E. C., Tilton, J. C., & Tan, 2017)	Exposure and vulnerability mapping
Hazard Maps	LIPAD & NOAH (Department of Science and Technology - Project NOAH, 2015b, 2015a; Lapidez et al., 2015; Tablazon et al., 2015),	Historical flood and landslide risk layers

Detailed descriptions of each dataset include:

- Meteorological Data: NASA POWER (GPM IMERG), Himawari-9 Bands 3, 8, 13
- Hydrological Data: Discharge from Angat, Bustos, and Ipo Dams
- Geospatial Data: LIPAD flood recurrence, Project NOAH maps, Sentinel-2 imagery
- Socioeconomic Data from SEDAC: GPWv4, GRDI, LECZ, GMIS, HBASE

Meteorological data, including NASA POWER's GPM IMERG, and Himawari-9 Bands 3, 8, and 13, were collected using RESTful APIs with temporal and geolocation query parameters. Dam discharge values were obtained from daily logs submitted by the Provincial Disaster Risk Reduction and Management Office (PDRRMO) through a Django-admin-secured form. Map layer from SEDAC was accessed through ArcGIS map service by NASA, and Satellite Imagery Sentinel Hub was accessed through standard WMS layers with preprocessing functions applied before integration.

Data Preprocessing and Harmonization

The system does not rely on bulk preprocessed datasets. Instead, it automatically processed the latest available raw data from satellite precipitation sources and current dam discharge values as they were submitted in real time. The model was trained using historical flood records and is already equipped to handle live values formatted to its expected structure. This eliminates the need for intensive preprocessing at runtime. Minimal validation routines checked for missing or out-of-bound values during submission. When minor gaps were detected (e.g., timestamp mismatches or nulls), fallback interpolation and temporal alignment scripts filled or skipped records based on model tolerance. The system was tested to ensure it could function robustly even with imperfect inputs, emphasizing operational reliability in live conditions.

System Design and Architecture

This section covers the conceptual and software design of the monitoring system, including the data flow, component interaction, and infrastructure layers, as illustrated in Figure 2. The diagram shows the interaction of APIs, data processing, and user interface components across the system layers.

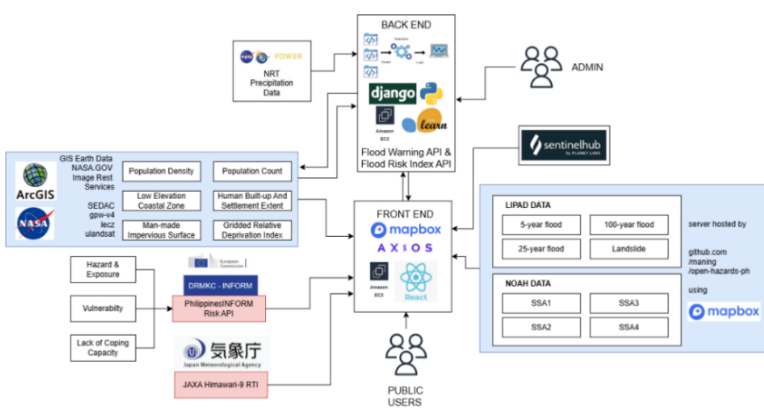

Figure 2. *System Architecture Overview*

The monitoring platform follows a modular, cloud-deployable architecture designed for scalability and ease of integration. The backend services were developed using Django REST Framework, which enabled a stateless architecture, allowing the system to scale horizontally by deploying multiple containerized instances using services like Docker and AWS Elastic Beanstalk. This ensures performance stability during periods of high data traffic, such as peak typhoon or flood seasons.

System interactions were exposed through RESTful API endpoints that support integration with third-party platforms and services. JSON-formatted data requests and responses enable future interoperability with weather APIs, government alert systems, or SMS-based dissemination platforms. This flexibility is critical for expanding the platform's role in multi-hazard early warning systems.

Analytical Models, Inputs, and Outputs

To process and interpret the collected data, analytical models were developed and integrated into the platform.

Flood Risk Index

The barangay-level Flood Risk Index was developed following the INFORM Risk Index framework, which classifies indicators across three core dimensions: exposure, vulnerability, and coping capacity. For this study, four key indicators were selected based on data availability, relevance to local conditions, and alignment with INFORM's structure:

- Population Density (PD) – representing the exposure of people to flood events.
- Gridded Relative Deprivation Index (GRDI) – serving as a proxy for socioeconomic vulnerability.
- Flood Index (FI) – derived from rasterized flood hazard data and historical recurrence maps.
- Land Cover Index (LC) – extracted from the uLandsat HBASE dataset, representing built-up area density and serving as an inverse proxy for coping capacity.

The Flood Risk Index (FRI) was computed using a normalized weighted aggregation formula:

$$FRI = \frac{(0.4 \times PD) + (0.3 \times GRDI) + (0.2 \times FI)}{0.1(LC + 1)}$$

Where:

- FRI is the computed flood risk index
- PD is the population density
- GRDI is the socioeconomic deprivation score
- FI is the flood index
- LC is the land cover index

Forecast Flood Warning Model

The forecast flood warning component of the system was developed using a Random Forest classifier, a supervised machine learning algorithm well-suited for handling classification tasks with imbalanced datasets. This algorithm was chosen for its robustness, interpretability, and capacity to manage nonlinear relationships across multiple predictors. The model uses two primary categories of input features:

- Precipitation values from the NASA POWER dataset; and
- Dam discharge records from Angat, Bustos, and Ipo Dams.

The output is a binary classification indicating flood alert status at the barangay level:

- 1 – Flood Watch
- 0 – Non-Flood Watch

To improve model sensitivity in low-frequency flood event conditions, a custom decision threshold of 0.35 was adopted during calibration. Data were split using an 80/20 train-test ratio, and the model was trained using Scikit-learn in Python. Evaluation metrics included accuracy, precision, recall, and F1-score.

The model was deployed as part of the system's backend infrastructure and is automatically triggered whenever new precipitation or dam discharge data are submitted through the Django administrative interface. This ensures that flood warnings remain responsive to near-real-time environmental updates and support timely decision-making by local disaster risk managers.

Validation and Evaluation

- **System Testing:** The system underwent unit testing, integration testing, and UI/UX walkthroughs to ensure frontend and backend functionality.
- **Model Evaluation:** The classification model was evaluated using standard performance metrics, including confusion matrix analysis, and threshold-based classification accuracy (accuracy: 95%, precision: 0.60, recall: 0.73, F1-score: 0.66).
- **Stakeholder Review:** A structured usability survey was administered to local DRRMO and LGU stakeholders in Meycauayan City, using a 5-point Likert scale to evaluate navigation, visual clarity, relevance of data, and decision-support usefulness. Responses were compiled into summary tables to quantify system satisfaction levels.

Ethical Considerations

This study adheres to ethical research standards to ensure the integrity of the research process and the protection of all involved participants. Although the primary focus was on system development using publicly available datasets, the research also involved stakeholder participation through structured usability evaluations.

Prior to engagement, informed consent was obtained from all participants after providing a detailed briefing on the study's objectives, procedures, and their rights. Participants were assured of confidentiality and anonymity, and no personally identifiable information was collected or stored.

The study was approved through the academic research panel as part of the university's capstone project vetting process. Given its low-risk nature, a formal IRB review was not required. All data used in the system were sourced from reputable open-access repositories (e.g., NASA, JAXA, SEDAC, PDRRMO) and appropriately cited.

No conflicts of interest are declared. Participants retained the right to withdraw from the study at any stage without penalty. Their input was instrumental in refining the platform and validating its practical utility.

Limitations

While the system is designed for real-time data ingestion, it currently faces several constraints. These include gaps in data availability, particularly during periods of weak satellite coverage or inconsistent dam telemetry reporting. The system's real-time functionality is also dependent on reliable internet connectivity, which may be limited in some barangays. These conditions can affect the timeliness and accuracy of flood predictions and alert generation.

Sustainability

To ensure long-term adaptability, the platform was designed with a modular API structure that allowed integration of new datasets and expansion to additional hazard types, such as storm surges or typhoons. The machine learning model can be retrained periodically as new disaster event data becomes available, enhancing its predictive capacity over time. Future upgrades include the addition of offline-mode features to improve accessibility in low-connectivity areas and the implementation of adaptive threshold tuning to further optimize flood classification accuracy based on evolving field data and stakeholder feedback.

Results and Discussion

The results highlight system deployment outcomes, flood risk modeling accuracy, and stakeholder usability feedback, interpreted in relation to the study's aim of enhancing localized flood preparedness and data-driven decision-making.

System Deployment and Interface Overview

The system was deployed as a web-based platform using Django for backend services and React.js for frontend rendering. This approach mirrors recent efforts in LGU transparency and digital infrastructure using open-source tools for local governance (Albano, 2024). Hosted on AWS EC2 with NGINX for optimized request handling, the interface supports responsive design across desktop and mobile devices (Abante et al., 2023; Goh et al., 2023). Real-time geospatial layers are visualized using Mapbox and include flood status alerts, socioeconomic indicators (SEDAC), hazard maps, Sentinel Hub imagery, and data from JAXA Himawari-9.

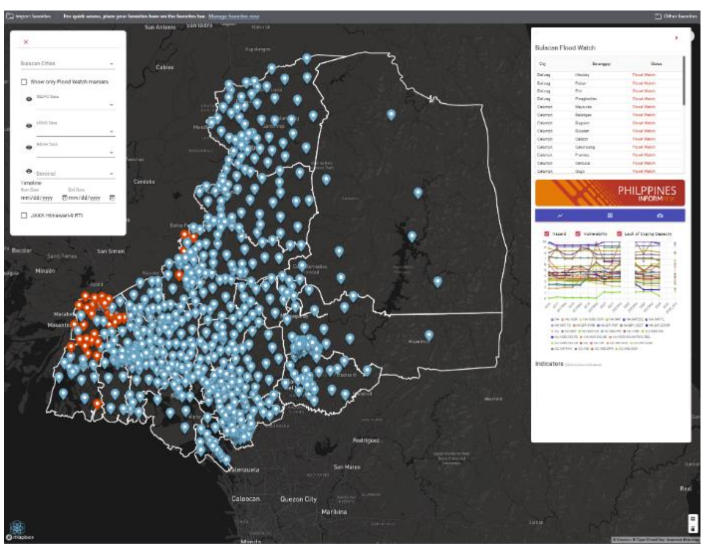

Figure 3. *Main System Dashboard Interface*

The system dashboard displays real-time flood alerts using binary color-coded markers: red for flood watch and blue for non-flood watch. This visual design was informed by user feedback requesting clearer differentiation between alert states. Accessibility was emphasized through mobile compatibility and login-free public access for field responders. Flood alerts were generated using a Random Forest model that processes dam discharge and real-time rainfall data. Administrative functions are accessible via a secure Django login, while the public frontend supports immediate community access.

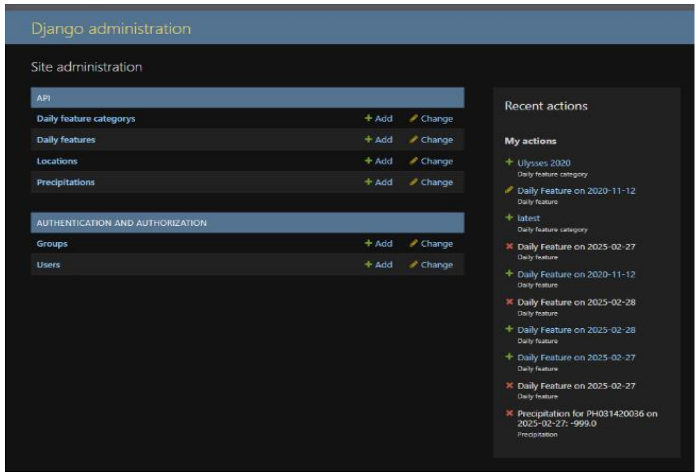

Figure 4. *Django Administrative Interface*

The admin panel allows for submitting dam discharge data and managing user access. This interface streamlines data curation by DRRM officers, ensuring the timely and accurate submission of critical inputs that directly influence the performance of the flood prediction engine. Its user-friendly design supports regular updates from local field personnel without requiring technical expertise.

Flood Risk Index Visualization

The platform synthesizes barangay-level flood risk using a localized version of the INFORM framework (European Commission (EU), 2024; Joint Research Centre, 2020). Users can filter by municipality to view a dynamically generated table of flood risk scores per barangay.

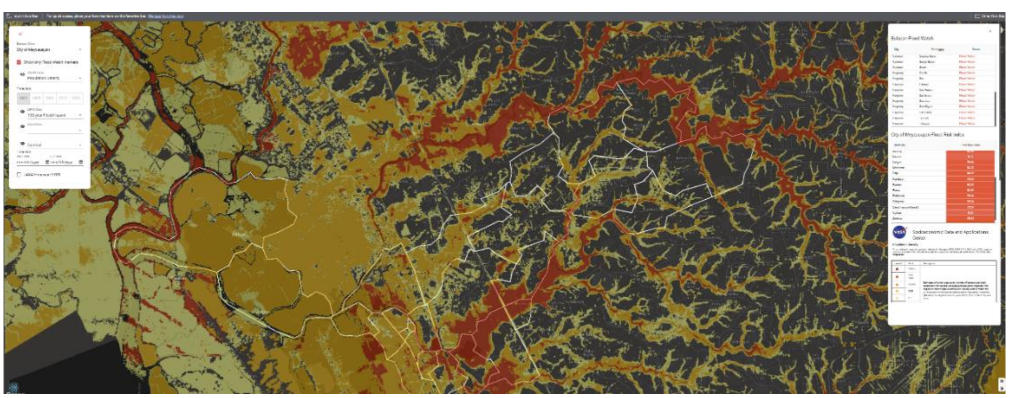

Figure 5. *Combined Flood Risk Index and 100-Year Flood Layer*

The red gradient is used to highlight high-risk areas, supporting LGUs in prioritizing interventions. This risk table is further enhanced by a map overlay of the 100-year flood hazard layer, providing spatial correlation between vulnerability and exposure.

Flood Forecast Model Results

The flood prediction component was developed using a Random Forest classifier (Hadi et al., 2024; Helen Joyice et al., 2024) trained on historical and real-time data from the Bulacan Provincial Disaster Risk Reduction and Management Office. Input features include precipitation data of each barangay in Bulacan and discharge data from Angat, Bustos, and Ipo Dams. The model was designed to balance performance between precision and recall, particularly in low-frequency flood events. Its architecture prioritizes generalizability across weather patterns and geographies. Recent applications in South and Southeast Asia have shown Random Forests to be effective in flood risk prediction (Ahmed et al., 2024; Hadi et al., 2024; Ogbuene et al., 2024).

The Random Forest classifier was evaluated on an 80/20 train-test split using real and historical data. This modeling approach is aligned with other recent AI-driven disaster response systems such as MOABC-based evacuation optimization (Jain & Vinluan, 2024). Results include:

- Accuracy: 95%
- Precision: 0.60
- Recall: 0.73
- F1-score: 0.66

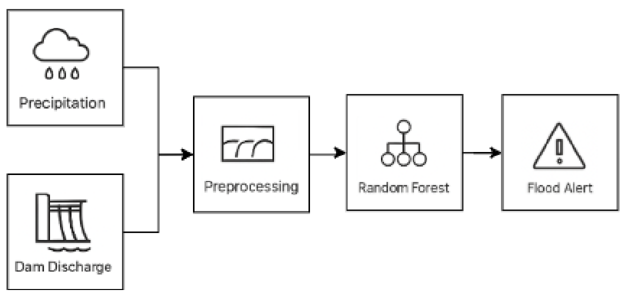

Figure 6. *Flood Forecast Model Workflow*

Figure 6 illustrates the automated machine learning pipeline used by the system. It begins with the submission of dam discharge data via the admin portal, while precipitation values are auto-fetched in real time. The Random Forest model then processes these inputs and generates barangay-level flood alerts. This end-to-end automation supports rapid risk communication for LGUs and DRRMOs.

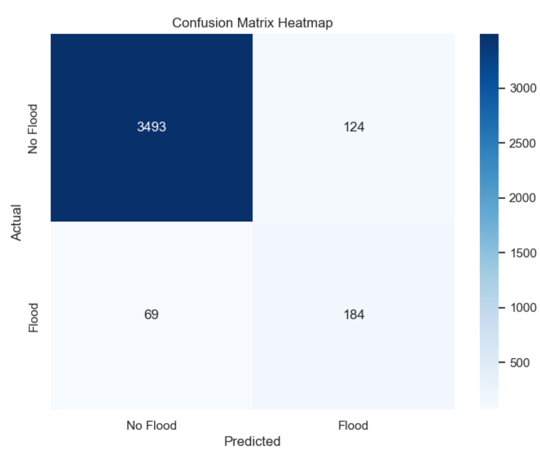

Figure 7. *Confusion Matrix of Flood Forecast Model*

Figure 7 displays the number of correct and incorrect flood predictions made at the 0.35 threshold. True positives represent correctly identified flood alerts, while false positives indicate alerts raised when flooding did not occur. This balance illustrates the system's trade-off favoring early warning over missed detection.

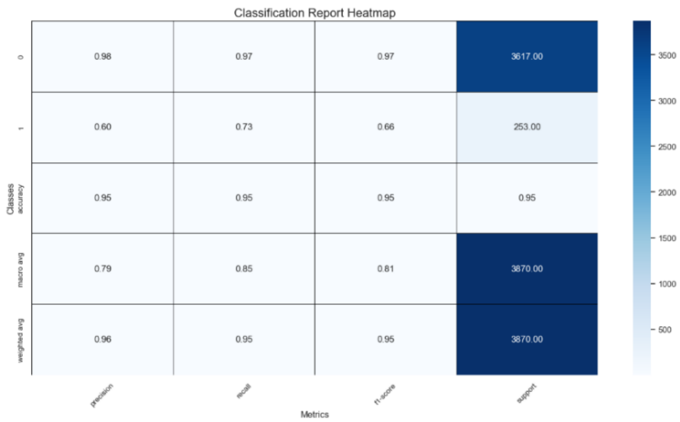

Figure 8. *Classification Report Heatmap*

Provides a visual breakdown of precision, recall, and support. A moderate precision of 0.60 implies the system may occasionally trigger false alerts; however, this is acceptable in disaster scenarios where recall (0.73) is prioritized to ensure that flood threats are not missed. This decision aligns with emergency management best practices that favor over-alerting over missed events (Adu-Gyamfi et al., 2024; Canlas, 2023)

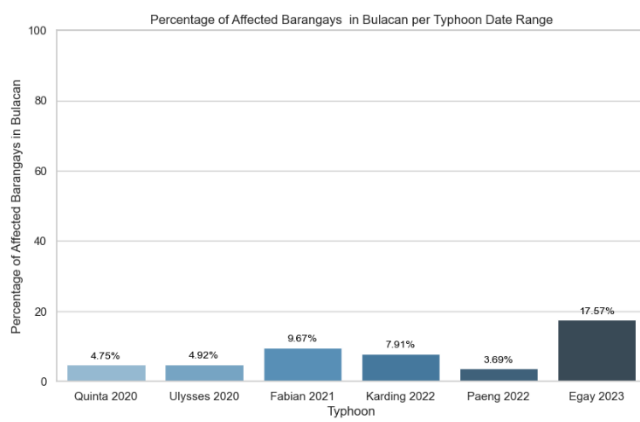

Figure 9. *Percentage of Affected Barangays per Typhoon*

Figure 9 visualizes the proportion of barangays affected by flooding during major typhoons in Bulacan. Events like Typhoon Quinta (2020), where fewer than 5% of barangays were impacted, illustrate the dataset's imbalance. This supports the system's use of a lowered threshold (0.35) to improve sensitivity in detecting rare but high-risk flood events, helping ensure timely alerts even when limited historical data is available.

Real-World Uncertainty Handling

The system is built for operational resilience during high-risk flood scenarios, with support for incomplete telemetry and sudden spikes in usage. Both the backend (Django REST API) and frontend (React SPA) are designed for horizontal scaling using cloud platforms and CDN-based delivery, ensuring responsiveness under heavy data or user loads.

Real-time dam discharge was submitted via a secure admin portal, while precipitation was auto-fetched from satellite APIs. To handle data inconsistencies, the system applied lightweight validation and interpolation to maintain model reliability without interrupting predictions. This scalable and fault-tolerant design enables uninterrupted flood alerting and dashboard access, even during peak disaster periods or degraded network conditions.

Dashboard Design and Features

The dashboard supports decision-making and situational awareness by presenting real-time data in an intuitive and accessible layout. Its key features include:

- Flood alert mapping
- Toggleable data layers (e.g., GRDI, elevation)
- Interactive summaries per barangay

These features help users assess flood risks quickly, navigate data intuitively, and make timely decisions. Similar to HealthSentry's municipal health forecasting system, this dashboard uses spatio-temporal indicators and user-centered design to empower local decision-makers (Bardiago at al., 2024). It also illustrates the dashboard in action, responding to feedback that emphasized clarity for non-technical municipal staff (Carrasco & Egbelakin, 2023; Cepero et al., 2025).

Usability Survey Results

System Usability and Functionality

The usability assessment focused on navigation, user interface, data processing, and visualization features.

Table 2. System Usability and Functionality

Criteria	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Clear and intuitive navigation	4	4	1	0	0
Visually appealing user interface	5	4	0	0	0
Effective interactive maps and charts	3	5	1	0	0
Customizable filters for risk analysis	4	4	1	0	0
Efficient data processing	4	4	1	0	0

These responses led to refinements such as adjusting font size, increasing contrast, and making charts collapsible. The balance of functionality and simplicity was enhanced following stakeholder walkthroughs.

Accuracy and Reliability of Data

This section evaluates the real-time flood monitoring, predictive modeling, and historical flood data integration.

Table 3. Accuracy and Reliability of Data

Criteria	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Accuracy of real-time flood monitoring	3	4	2	0	0
Reliability of predictive flood modeling	4	3	2	0	0
Historical flood data documentation	3	4	2	0	0
Integration of satellite imagery	3	5	1	0	0

Neutral feedback prompted a closer review of how flood predictions aligned with actual events. As a result, additional backend validation scripts were introduced to cross-check dam discharge data timestamps and precipitation data to improve model output reliability. Furthermore, multiple thresholds were tested during stakeholder walkthroughs to calibrate the model's sensitivity, resulting in the selection of a 0.35 threshold for optimized early detection in imbalanced datasets.

Impact on Decision-Making

This section assesses how the system supports stakeholder decision-making in disaster preparedness and risk mitigation.

Table 4. Impact on Decision-Making

Criteria	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Enhanced ability to assess flood risks	4	4	1	0	0
Support for flood preparedness planning	5	4	0	0	0
Data-driven decision-making support	4	4	1	0	0
Timely flood alerts and notifications	4	4	1	0	0
Improved collaboration among stakeholders	5	3	1	0	0

Users cited improved collaboration due to shared access to the same geospatial dashboard. This confirms the platform's potential as a cross-agency coordination tool.

Security and Accessibility

This section evaluates the system's security, accessibility, and cloud-based performance.

Table 5. Security and Accessibility

Criteria	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Secure data handling and system interactions	5	3	1	0	0
Accessibility across multiple devices	4	4	1	0	0
Cloud-based availability and reliability	3	5	1	0	0

Security settings were re-reviewed following survey completion, resulting in stronger password policies for admin accounts and a simplified mobile view based on early feedback.

Overall Satisfaction

Respondents were asked about their overall satisfaction and willingness to recommend the system.

Table 6. Overall Satisfaction

Criteria	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Overall system performance and functionality	4	4	1	0	0
Willingness to recommend the system	5	4	0	0	0

Stakeholder consensus validated the platform's practical value. The overwhelmingly positive reception justifies its expansion to other LGUs.

The system successfully achieved its goals: real-time flood alerting, local risk visualization, and intuitive dashboards for stakeholders. Survey feedback directly influenced interface improvements and validated technical assumptions. Compared to similar systems in Southeast Asia, this platform aligns with benchmarks and best practices (Hadi et al., 2024; Ogbuene et al., 2024).

Moderate precision was an intentional trade-off to ensure high recall and reduce the chance of missed floods. The system's recall score confirms its suitability for proactive disaster response, particularly in resource-constrained settings.

System limitations such as internet dependency and gaps in dam telemetry were acknowledged by users and have been addressed through modular architecture, adaptive design, and future retraining plans. Annotated visuals and figure captions were added throughout to better engage non-technical readers. Overall, this project contributes a replicable and responsive model to support LGU disaster preparedness and localized risk assessment.

Conclusion and Future Works

This study presented the development and evaluation of an Integrated Natural and Socioeconomic Indicators Monitoring System tailored for flood-prone areas in Bulacan. The platform successfully delivered on its goals: enabling near real-time flood alerting, predictive analytics through machine learning, and responsive geospatial dashboards for LGU and DRRM stakeholders. The Flood Risk Index and Forecast Warning Model achieved notable performance, with survey validation confirming its clarity, usability, and potential for inter-agency coordination.

Key limitations such as data imbalance, dependency on connectivity, and lack of high-resolution dam telemetry were acknowledged and addressed through system modularity, backend validation, and stakeholder-informed thresholds. The system's architecture and real-world adaptability allow for sustained performance under uncertainty.

Future enhancements may focus on improving the precision of the flood prediction model by introducing feature enrichment techniques, experimenting with ensemble and deep learning approaches, and incorporating temporal rainfall patterns. Additional improvements may involve expanding the system to monitor other hazard types such as typhoons, storm surges, and landslides to increase its relevance across broader disaster scenarios. Offline-access modules, finer geospatial overlays, and localized alert customization are also envisioned to make the system more accessible to LGUs with limited resources.

Ultimately, this work offers a practical, scalable, and human-centered model that LGUs can adopt, adapt, and build upon to advance local disaster preparedness efforts.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgements

The researcher dedicates this work to his loving wife, Lady Danlene Pascual, and his daughter, Matthea Daine Pascual, whose unwavering love, patience, and support have been a constant source of inspiration and strength throughout this journey. He gives praise and appreciation to the Lord Almighty, who has blessed him with courage, wisdom, and perseverance to complete this work.

He also extends his sincere gratitude to the Provincial Disaster Risk Reduction and Management Office (PDRRMO) of Bulacan, especially Mr. Raul D. Agustin, Team Leader and Local DRRM Officer II, for providing essential dam discharge data for model development and validation. Likewise, he wishes to thank the City Disaster Risk Reduction and Management Office (CDRRMO) of Meycauayan City, particularly Mr. Cirilo O. Delos Santos, City Government Department Head I – LDRRM, for his coordination and support.

Special thanks go to the local government officials, DRRMOs, and barangay representatives who participated in the system evaluation and usability survey, contributing valuable insights that guided improvements to the platform.

In addition, he sincerely acknowledges the guidance of his thesis adviser, Engr. Jeffrey T. Leonen, and the collaborative support of his co-author. He is also grateful to the College of Graduate Studies of AMA University for their academic leadership and mentorship.

Lastly, he extends his appreciation to the committee's chairman and critic, and the members of the panel of examiners—Dr. Reagan Ricafort, Dr. Maksuda Sultana, Dr. Carmencita G. Rabano, Dr. Richard N. Monreal, and Dr. Shaine J. Maglapuz—for their valuable feedback and encouragement throughout the research review process.

Artificial Intelligence (AI) Declaration Statement

This study employed artificial intelligence (AI) tools during the manuscript preparation stage only. Specifically, OpenAI's ChatGPT was used to assist in refining grammar, improving sentence structure, and suggesting academic phrasing in accordance with scholarly writing standards. Additionally, Perplexity.ai was consulted during the early stages of literature review to aid in identifying relevant research themes and enhancing contextual understanding.

No AI tools were involved in hypothesis formulation, data analysis, or the interpretation of results. All AI-assisted content was thoroughly reviewed, verified, and edited by the author to ensure factual accuracy, proper citation, and adherence to academic integrity. The author bears full responsibility for the content and interpretation of the work presented. No AI-generated material was used without manual validation and oversight.