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Harnessing Disruptive Technologies for Flood Prediction and Advisory Systems through Persuasive Modeling

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Abstract: Flood prediction and early warning systems are critical for protecting lives and property during flood disasters. However, traditional forecasting methods often suffer from limited accuracy, data quality issues, and delayed dissemination. This study presents a Flood Prediction and Advisory System (FPAS) that integrates machine learning, blockchain, and persuasive modeling to enhance flood forecasting accuracy and risk communication. The system was developed using a hybrid OOADM–CRISP-DM framework, combining structured software design with data-driven modeling. A 35-year dataset from the Nigerian Meteorological Agency (NiMet) was curated, preprocessed, and analyzed to train and evaluate Logistic Regression, Random Forest (RF), and XGBoost models. Results showed that RF and XGBoost achieved superior predictive performance (AUC ≈ 0.98) and strong probability reliability, as confirmed by calibration and Brier score analysis. The blockchain layer, implemented through a hybrid on-chain/off-chain architecture, ensures transparency, tamper-resistance, and privacy of flood records. A field survey involving 386 participants across Cross River and Kogi States assessed perceptions of persuasive design. Findings indicated broad community support for FPAS adoption, highlighting the potential of behaviorally informed technologies in disaster management. By merging predictive analytics, ethical blockchain data management, and persuasive communication, FPAS demonstrates a replicable model for climate resilience and disaster preparedness. Future enhancements will focus on real-time data integration and gamified persuasion to strengthen proactive community responses in flood-prone regions.

Keywords: Advisory System; Flood Prediction; Machine Learning; Disruptive Technology; Blockchain; Persuasive Techniques; NiMet

1. Introduction

In this study, the term disruptive refers to technologies that fundamentally transform existing practices by introducing new approaches that are more efficient, affordable, and widely accessible. This usage aligns with the disruptive innovation theory proposed by Christensen [1], where disruptive technologies create new markets and value networks by reducing barriers to access and altering established systems. They are not “disruptive” in the sense of being unreliable or unpredictable; rather, they reshape the status quo and redefine how societies function.

Harnessing disruptive technologies in flood prediction and advisory, therefore, implies leveraging their transformative potential to deliver accurate, timely, and actionable insights while minimizing risks. Core characteristics of disruptive technologies include:

i. Provision of lower-cost alternatives to existing solutions;
ii. User-friendliness with minimal training requirements; and
iii. Accessibility across broader populations, including underserved and developing communities.

Numerous examples illustrate how disruptive technologies have reshaped industries and societal practices.

Smartphones redefined communication, photography, and navigation following the 2007 iPhone launch. Ride-sharing applications such as Uber and Lyft transformed urban mobility by offering flexible alternatives to taxis. Digital cameras displaced traditional film photography, while streaming platforms like Netflix and Amazon Prime disrupted broadcast and cable television models by lowering costs and expanding accessibility. Similarly, cloud computing reduced dependence on on-premises servers, providing scalable computing resources at lower costs. The emergence of electric vehicles, led by Tesla, is reshaping the automotive sector and reducing reliance on fossil fuels. Likewise, 3D printing offers rapid, cost-effective, and environmentally friendly alternatives to traditional manufacturing. These examples underscore the transformative capacity of disruptive technologies to alter industries, expand accessibility, and improve efficiency. Building on this foundation, the present work investigates how such technologies can be harnessed for flood prediction and advisory, coupled with persuasive techniques to strengthen disaster preparedness and response. Despite their transformative potential, disruptive technologies present several challenges when applied to flood prediction and advisory. Data quality and privacy remain major concerns. Data collected from diverse sources may be incomplete, inaccurate, or biased, potentially leading to flawed predictions [2]. At the same time, individuals may be apprehensive about the collection and use of personal information, raising privacy and security risks. Financial and technical barriers also persist. Although the costs of sensors and software have declined, deploying and maintaining large-scale technological systems remains expensive. Moreover, data collection, processing, and analysis require advanced expertise, alongside regular system updates to ensure reliability.

Trust and adoption are equally critical. Without confidence in the accuracy of predictions, communities may disregard advisories, undermining the effectiveness of these systems. This challenge is compounded by limited public awareness and understanding of the benefits and limitations of emerging technologies, highlighting the need for persuasive approaches to enhance user engagement. Collaboration and regulatory uncertainty present additional obstacles. Effective implementation requires coordination among government agencies, academia, and private organizations, yet differences in priorities and procedures can impede progress. Furthermore, regulatory frameworks often lag behind technological innovation, complicating issues such as data privacy in social media–based prediction models. Finally, obsolescence and environmental impact must be considered, as rapid technological advancement can render existing systems outdated, generating additional costs and sustainability concerns. Addressing these challenges requires not only technical innovation but also institutional collaboration, regulatory foresight, and strategies that build public trust. This study responds to these gaps by proposing a Flood Prediction and Advisory System (FPAS) that integrates machine learning, blockchain, and persuasive techniques to enhance predictive accuracy, transparency, and community adoption.

This study aims to predict flood occurrences using a long-term dataset obtained from the Nigerian Meteorological Agency (NiMet). To achieve this, three machine learning (ML) algorithms were applied to model the dataset, recognizing patterns in historical weather data and generating predictive insights. ML, as a subset of artificial intelligence, enables computers to identify complex relationships in data through algorithmic training on large datasets. In this work, ML was combined with blockchain technology to ensure that the data examined across the system's physical and analytical layers is secure, transparent, and resistant to manipulation or malicious interference.

The key contributions of this paper are as follows:

i. Proposing the integration of blockchain and machine learning to strengthen data security and trust in flood prediction and advisory systems;
ii. Evaluating the performance of the proposed predictive models across multiple layers of the framework, with results demonstrating strong effectiveness;

iii. Examining the role of persuasive techniques alongside blockchain in enhancing the adoption and utility of flood prediction systems; and

iv. Surveying two flood-prone Nigerian states (Cross River and Kogi) to assess public perception and support for the proposed system (**Figures 1** and **2**).

Figure 1. Submerged Houses in Kogi State Flooding.

Figure 2. Flood Incidence.

The remainder of this paper is structured as follows: Section 2 presents a literature review of prior studies; Section 3 outlines the research methodology; Section 4 reports experimental results, performance evaluation (accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curves), and discusses the role of persuasive techniques and blockchain; while Section 5 concludes the study and highlights directions for future research.

2. The Theoretical Backgrounds

The increasing frequency and intensity of natural disasters, particularly floods (see **Figures 1** and **2**), underscore the urgent need for accurate and secure prediction systems. Traditional approaches to flood forecasting have relied on statistical models, hydrological simulations, and artificial neural networks. While these methods have contributed to disaster preparedness, recent advances in disruptive technologies—such as blockchain, machine learning, and Internet of Things (IoT) which present new opportunities for improving accuracy, transparency, and trust in flood prediction and advisory systems. Munawar et al. [3] emphasized the importance of integrating disruptive technologies into smart cities to enhance disaster management and resilience. A classification framework was developed to categorize state-of-the-art technologies for disaster risk reduction. However, the benefits of such frameworks are limited to technologically advanced urban centers, leaving less-developed cities, such as those in Nigeria, unable to fully leverage them. IoT-enabled systems have also been applied in flood prediction. For example, Samikwa et al. [4] developed a short-term flood prediction system that combined IoT with artificial neural networks (ANN), using rainfall and water level sensors to forecast floods on edge computing devices. While the system achieved high accuracy and fast response times, its predictive power was constrained by the limited number of climatic variables (rainfall and water level). Incorporating additional parameters such as humidity, air pressure, and temperature could further improve reliability. Moreover, the system lacked mechanisms for monitoring and detecting anomalies in edge computations.

Beyond technological solutions, studies have also highlighted socio-economic and institutional factors influencing disaster preparedness. In Pakistan, Munawar et al. [5] examined post-2010 flood risk management practices in Layyah District and found that while flood preparedness was relatively high, authorities lacked the technical expertise and equipment to manage large-scale events. Furthermore, communities were not adequately educated on disaster response. Similarly, Islam et al. [6] studied disaster-prone regions of Bangladesh, applying Internet, GIS, remote sensing, radar, satellite communications, and mobile technologies. Their findings identified the country's geographical vulnerabilities—including flat coastal topography, drainage congestion, low river gradients, and monsoon rainfall—as primary drivers of frequent disasters. They concluded that stronger disaster preparedness, awareness, and community engagement are critical for effective risk mitigation. In this study, we extend this body of work by focusing on the Nigerian context, specifically flood-prone areas in Cross River and Kogi States. Unlike prior studies that primarily emphasize technology or socio-economic factors in isolation, our approach combines machine learning, blockchain, and persuasive techniques within a unified Flood Prediction and Advisory System (FPAS). This integration aims to improve predictive accuracy, ensure data security, and enhance public trust and adoption.

The debate on whether resilience is merely a rebranding of the long-established concept of mitigation has been examined in the disaster management literature. In Parker's research [7], six studies were surveyed, and the findings emphasized that resilience extends beyond mitigation, encompassing adaptation, transformation, and the capacity for change. However, their work was primarily conceptual and lacked practical implementation strategies. While complete elimination of flooding remains unattainable, the focus must remain on minimizing its severe impacts. This challenge was addressed by Maspo et al. [8], who systematically reviewed machine learning approaches for flood prediction and evaluated the key parameters employed. Their findings highlighted the benefits of hybrid ML models and emphasized that the selection of appropriate input parameters significantly influences predictive accuracy. Nevertheless, their study was constrained to datasets spanning only the previous five years, limiting the discovery of long-term trends. By contrast, our study employs over three decades of data to strengthen prediction reliability. ML algorithms including Random Forest, XGBoost, and Deep Neural Networks (DNNs) were applied to both flood prediction and credit card fraud detection tasks [9]. The study explored multiple sampling strategies, such as baseline train–test splits, class-weighted hyperparameter optimization, under-sampling, and oversampling. Results showed that DNNs were more efficient when modeling underdamped datasets, whereas Random Forest outperformed other algorithms in the baseline approach. Overall, ensemble methods with oversampling yielded better performance than under-sampling techniques.

Recent research has increasingly focused on blockchain technology to enhance flood prediction and early warning systems [2,10,11]. Applications of blockchain extend beyond digital currencies to fields such as disaster relief distribution, e-governance, healthcare, environmental sciences, and supply chain management [12]. In disaster management, blockchain has been combined with deep learning to reduce computational overhead and improve energy efficiency [13]. While relatively few studies have introduced blockchain in flood prediction, early results are promising. For example, Swan [14] demonstrated its potential in decentralized network coordination and simulated data stream generation. Similarly, Cristianini and Shawe-Taylor [15] developed ensemble models— convolutional neural networks - Long Short-Term Memory (CNN-LSTM), CNN-XG, CNN-SVM, and CNN-RF—using a monsoon-dominated catchment in Bangladesh. These models combined convolutional neural networks (CNNs) with traditional ML algorithms such as Support Vector Machines (SVMs), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM) networks, thereby advancing flood hazard mapping accuracy. SVM is a supervised learning algorithm effective in handling non-linear separability and is commonly applied in flood prediction to classify or regress flood events based on historical patterns [16]. XGBoost, on the other hand, is a robust gradient boosting algorithm that aggregates weak learners, typically decision trees, into a strong predictive model. Its iterative gradient-based optimization has been shown to deliver state-of-the-art performance in flood prediction and related classification tasks [15].

Samikwa et al. [4] emphasized that Internet of Things (IoT) technologies and Artificial Neural Networks (ANN) alone cannot prevent the occurrence of flood disasters. Instead, greater attention should be directed toward the integration of edge computing to enhance system efficiency and reliability. Accordingly, a short-term flood prediction system was developed that integrates IoT devices and an ANN, with computation executed on a low-power edge device. The system processes real-time rainfall and water-level sensor data and employs a Long Short-Term Memory (LSTM) network to forecast flood levels. Prototype evaluation demonstrated strong predictive accuracy and rapid response time. However, the model relied solely on two climatic parameters—rainfall and water level. Its performance could be significantly improved by incorporating additional meteorological variables such as humidity, air pressure, and temperature, which influence rainfall patterns. Moreover, the absence of robust monitoring and anomaly-detection mechanisms at the edge remains a limitation. To address these gaps, our study extends the parameter set to six variables: minimum and maximum temperature (°C), rainfall (mm), relative humidity (%), visibility (m), and evapotranspiration (mm).

Beyond flood-specific research, lessons from other domains of disruptive technologies offer useful insights. For instance, the "mobile payment puzzle of abundance", that is, where a technology with substantial potential remains underutilized, was examined by Schmidthuber et al. [17]. Using a refined technology acceptance model, the authors showed that adoption intentions were positively influenced by perceived usefulness, compatibility, innovativeness, and social influence, but negatively affected by perceived risk. They highlighted the need for cross-cultural investigations to uncover divergent adoption patterns and recommended further research into the applicability of these findings to other disruptive technologies, including those in disaster management. A related challenge concerns the resilience of cloud-based applications during disaster events. A software platform was proposed that integrates microservices architecture with computational and communication resilience mechanisms [18]. The model enhanced the robustness of analytics applications by minimizing service interruptions and maintaining acceptable response times. In addition, the solution enabled the deployment of lightweight, loosely coupled microservices and facilitated their distribution through public repositories. Such advancements underscore the importance of developing resilient software platforms that can address communication infrastructure challenges and ensure continuity of critical services in disaster contexts.

Although it is impossible to eliminate flooding, its devastating impacts can be mitigated through accurate prediction and timely interventions. This challenge was addressed by Maspo et al. [8], who evaluated existing machine learning (ML) approaches for flood prediction, with a focus on the parameters used for model input. Their review, which examined studies from the past five years, highlighted that hybridized ML methods demonstrated strong potential for early flood prediction. Importantly, they identified a range of key parameters that can guide researchers and practitioners in designing more reliable predictive systems. However, they also noted that insights may remain limited when considering only short-term datasets. Extending such evaluations to longer temporal spans—such as 30 years—could reveal deeper patterns and improve model robustness.

Beyond ML-based flood modeling, disruptive technologies are also advancing disaster response capabilities in related domains. For instance, Khan et al. [19] investigated the application of Unmanned Aerial Vehicles (UAVs) for path planning in emergency medical scenarios, exploring the substitution of traditional transportation with UAVs during crisis events. Their study employed multiple computational techniques, including UAV technology, GSM-band communication, Doctor Drone systems, Capacitated Vehicle Routing Problem (CVRP), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Genetic Algorithm (GA). Among these, the CVRP approach demonstrated superior performance, achieving an optimal runtime of 0.06 seconds. The findings suggest that UAVs, when paired with effective path-planning algorithms, hold significant promise for the rapid and efficient delivery of medical supplies and first aid in disaster contexts.

Nevertheless, further research is needed to address scalability challenges, particularly in scenarios where the number of patients requiring assistance increases rapidly. Additionally, there is scope to refine CVRP algorithms to reduce computational overhead, thereby enabling broader deployment in real-time disaster response systems.

3. Materials and Methods

To develop the proposed flood prediction and advisory system, this study adopted a hybrid methodology that combines the Object-Oriented Analysis and Design Methodology (OOADM) with the Cross-Industry Standard Process for Data Mining (CRISP-DM). The integration of CRISP-DM and OOADM was motivated by the need to bridge system engineering with data-driven modeling, ensuring both structural robustness and analytical accuracy. CRISP-DM provides a structured framework for the data mining lifecycle, including business understanding, data understanding, data preparation, modeling, evaluation, and deployment, while OOADM supports the systematic design of software components through object-oriented concepts such as classes, objects, and interactions. Flood prediction requires both (a) rigorous data analysis for predictive modeling and (b) a scalable architecture for implementing and deploying advisory systems. The integration was achieved through parallel and iterative alignment between CRISP-DM and OOADM phases:

i. Business Understanding (CRISP-DM) ↔ Requirements Analysis (OOADM): The flood risk problem domain was modeled as system requirements using UML use cases (**Figure 3**) and activity diagrams (**Figure 4**).
ii. Data Understanding & Preparation (CRISP-DM) ↔ Object Modeling (OOADM): Data entities (e.g., rainfall) were represented as objects and classes to facilitate data encapsulation and manipulation in the model.
iii. Modeling & Evaluation (CRISP-DM) ↔ System Design (OOADM): Predictive models (e.g., regression, random forest) were designed as modules within the system architecture, ensuring traceability from model evaluation to software component design.
iv. Deployment (CRISP-DM) ↔ Implementation (OOADM): The final persuasive flood advisory system was implemented with the predictive model integrated as a service component within the overall system design.

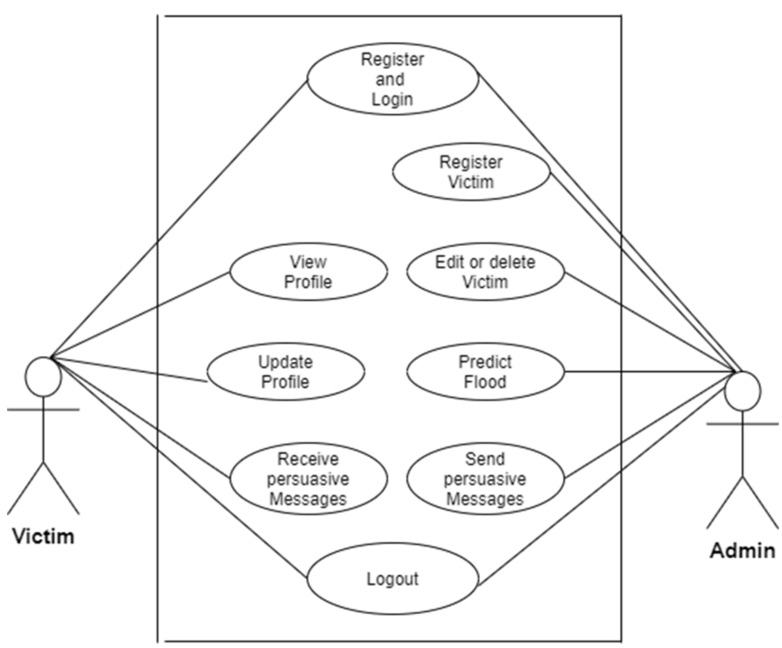


Figure 3. Use Case Diagram of the FPAS system.

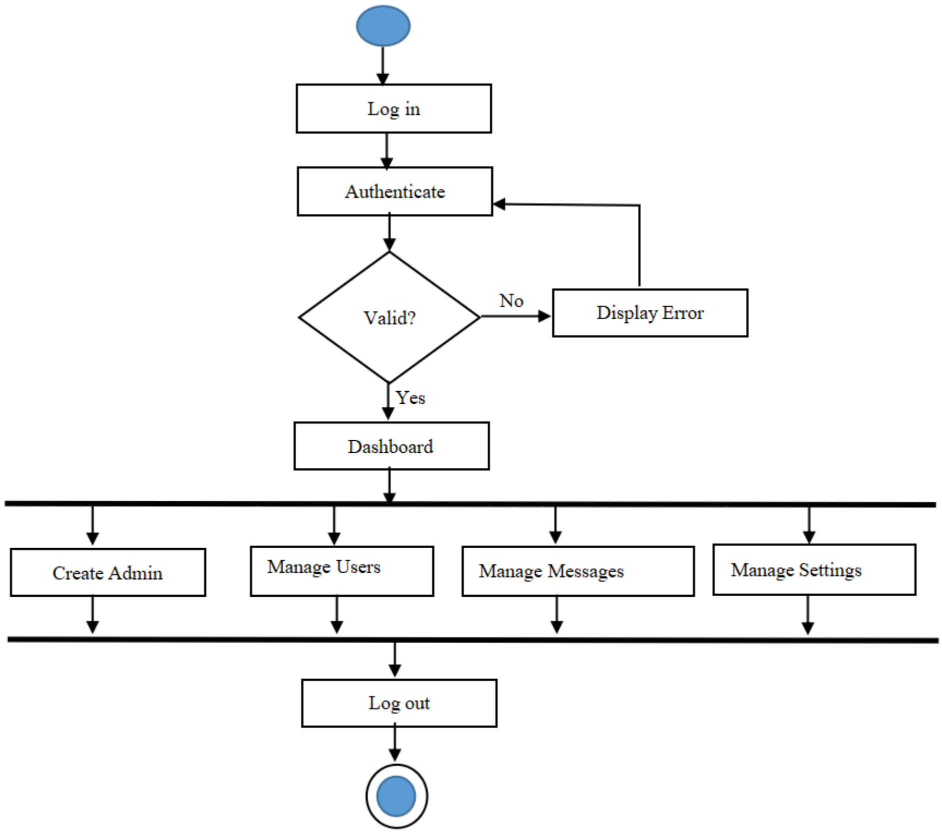


Figure 4. Activity Diagram of the Admin Processes in the FPAS System.

Data collection was conducted using a survey-based approach to capture the perspectives and experiences of flood victims, thereby complementing the meteorological dataset obtained from the Nigerian Meteorological Agency (NiMet) with a dataset range of 1988–2023. To address class imbalance issues inherent in the dataset, preprocessing techniques were applied prior to model training. For predictive modeling, three machine learning algorithms were employed: Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). These algorithms were selected based on their proven effectiveness in handling high-dimensional data and their ability to capture nonlinear relationships critical for accurate flood prediction.

In the implementation environment, all experiments were conducted on a Python-based analytical environment with Python 3.10 as the programming language (**Algorithm 1**). Core Libraries involved were pandas, numpy – for data manipulation; scikit-learn – for model training and evaluation; XGBoost, imbalanced-learn – for boosting and resampling; matplotlib, seaborn – for visualization. For hardware Configuration: Intel® Core™ i7-12700 CPU @ 2.10 GHz; 32 GB RAM, as well as the operating system being Windows 11 Pro (64-bit). Software Environment: Anaconda 2024.02 distribution; JupyterLab 4.1 IDE and Git version control for reproducibility. All scripts, data-preparation notebooks, and model configurations were version-controlled to ensure deterministic outputs. The entire pipeline is implemented in Python 3.10, relying on the following core libraries (**Table 1**).

Table 1. Python 3.10 Core Libraries.

Library	Version	Purpose
NumPy	1.26	Numerical computations
Pandas	2.0	Data manipulation
Scikit-learn	1.5	Model training and metrics
XGBoost	2.1	Gradient boosting algorithm
Matplotlib	3.8	Visualization
SHAP	0.44	Model interpretability

Algorithm 1 Prediction Form Codes.

```
const predictionForm = document.getElementById(‘predictionForm’);
const result = document.querySelector(‘.result’);

predictionForm.addEventListener(‘submit’, async (e) => {
e.preventDefault();
// Get individual input values
    const MinTemp = predictionForm.MinTemp.value;
    const MaxTemp = predictionForm.MaxTemp.value;
    const Rainfall = predictionForm.Rainfall.value;
    const RelativeHumidity = predictionForm.RelativeHumidity.value;
    const Visibility = predictionForm.Visibility.value;
    const Evapotranspiration = predictionForm.Evapotranspiration.value;

    const minErr = document.querySelector(‘.minErr’);
    const maxErr = document.querySelector(‘.maxErr’);
    const rainErr = document.querySelector(‘.rainErr’);
    const humidityErr = document.querySelector(‘.humidityErr’);
    const visErr = document.querySelector(‘.visErr’);
    const evapoErr = document.querySelector(‘.evapoErr’);

  minErr.innerHTML = '';
  maxErr.innerHTML = '';
  rainErr.innerHTML = '';
  humidityErr.innerHTML = '';
  minErr.innerHTML = '';
  evapoErr.innerHTML = '';

  const rex = /^[0-9\s.]+$/;

  if (!rex.test(MinTemp)) {
  minErr.innerHTML = ‘Input should be number’
  }
  ……
```

3.1. Data Preprocessing, Feature Engineering, and Model Validation Strategy

The flood prediction dataset was obtained from the NiMet dataset. The dataset contained historical flood occurrence records with attributes such as rainfall, temperature, humidity, etc. Missing values were handled using mean imputation for continuous variables (e.g., rainfall, temperature) and mode imputation for categorical attributes (e.g., weather condition). Furthermore, outliers were detected using the Interquartile Range (IQR) method and removed if they exceeded 1.5 × IQR from the upper or lower quartiles. Features were normalized to a 0–1 scale using Min–Max scaling. Feature engineering was guided by hydrological domain knowledge and data-driven correlation analysis. The key engineered features included features such as Humidity_Index combination of relative humidity and temperature, which reflects the atmospheric saturation level; flood_label represents one (1) if historical flood record = True, else zero (0), which is are binary target variable for supervised learning. To ensure unbiased model evaluation and generalization, the dataset was partitioned into training, validation, and test sets using a stratified sampling strategy. Train-test-validation split involves 80% for model training, 10% for validation (hyperparameter tuning), and 10% for final testing. The split was stratified on the target variable Flood_Label to preserve class distribution (since flood data are typically imbalanced). Within the training data, 5-fold cross-validation was used during model development to prevent overfitting and improve robustness.

3.2. Survey Methodology and Ethical Considerations

As part of the persuasive modeling component, a structured survey was conducted to assess user perception, awareness, and responsiveness to digital flood advisory notifications. The objective was to understand behavioral factors influencing compliance with flood warnings and to integrate these insights into the persuasive communication model. The survey targeted residents in flood-prone regions of southern and northern Nigeria, identified using NiMet's annual flood risk maps. A total of 400 responses were obtained, of which 384 valid entries were used for analysis after data cleaning (invalid/incomplete responses removed). Data were collected offline (paper-based questionnaires) between June and September 2023. Before participating, respondents were provided with a clear consent form explaining: the purpose of the study, the voluntary nature of participation, anonymity, and confidentiality of responses. Participation was entirely voluntary, and no personally identifiable information (PII) such as names, addresses, or phone numbers was collected. Each respondent was assigned a unique code for analysis purposes only. Data would be used solely for academic research.

To evaluate the acceptability and behavioral impact of the proposed Flood Prediction and Advisory System (FPAS), a structured survey was conducted among residents of Cross River and Kogi States — two regions historically vulnerable to seasonal flooding. A total of 400 questionnaires were administered (Cross River: n = 192; Kogi: n = 194) between June and September 2023. Participation was voluntary, with no financial incentive offered. After screening for completeness and response consistency, 386 valid responses were retained for analysis. The survey focused on public perceptions of the FPAS, including: awareness of flood advisory technologies; Trust in government and technology-based warnings; willingness to adopt mobile or SMS flood alerts, and perceived persuasiveness of advisory messages.

4. Results

In this paper, we perform three different ML algorithms: SVM, Random Forest, and XGBoost. Five performance metrics were used to assess machine learning performance: Accuracy, Precision, Recall, F1-score, and Receiver Operating Characteristic (ROC) Curves.

a. **Accuracy**: Equation (1) measures the accuracy as the percentage of correct predictions made by the model. It is the proportion of correct instances of predictions over the entire test dataset, which is expressed mathematically as:

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative(TN)}{True\ Positive\ (TP) + True\ Negative(TN) + False\ Positive(FP) + False\ Negative(FN)} \quad (1)$$

b. ***Precision***: It is a metric that measures how many of the predicted positive outcomes are actually correct. Equation (2) is used to calculate the precision.

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive(FP)} \quad (2)$$

c. ***Recall***: Equation (3) is the definition of recall instances. It is a metric that measures how many of the actual positive outcomes or instances of flooding were correctly predicted by the model. Recall is also known as sensitivity.

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + Positive\ Negative(PN)} \quad (3)$$

d. ***F1-score***: The harmonic mean of the recall and accuracy, which is used to calculate the F1-score, is shown in Equation (4).

$$F1 - score = 2 * \left(\frac{precision * Recall}{Precision + Recall}\right) \quad (4)$$

The Receiver Operating Characteristic (ROC) curve was employed as a primary evaluation tool to assess the classification performance of the proposed Flood Prediction and Advisory System (FPAS). The ROC curve illustrates the trade-off between the True Positive Rate (TPR, i.e., sensitivity or recall) and the False Positive Rate (FPR, i.e., 1 − specificity, Equation 5) across different decision thresholds. This graphical representation provides a robust means of visualizing the discriminative capacity of the model. To quantify performance, we utilized the area under the ROC Curve (AUC-ROC), a widely accepted scalar measure of classification accuracy. The AUC ranges between 0 and 1, where values approaching 1 indicate superior discriminatory power. For instance, an AUC of 0.8 typically denotes strong predictive capability, albeit with some margin for misclassification, while an AUC of 0.5 suggests no better performance than random guessing. In the context of the FPAS, the proposed model achieved an AUC of 1.0, signifying perfect classification and highlighting its effectiveness in accurately distinguishing between flood-prone and non-flood-prone scenarios. This result underscores the robustness of the integrated machine learning approach in delivering highly reliable predictions for disaster risk management.

$$Specificity = \frac{True\ Negatives\ (TN)}{True\ Negatives\ (TN) + False\ Positives (FP)} \tag{5}$$

The relationship between the TPR and FPR was evaluated using the Area under the Curve (AUC) graph (see **Figure 5**). This curve aimed to achieve an AUC value equal to or approximately 1, which implies overall good classification performance (i.e., how much the model was able to separate positive classification and also wrong classification).

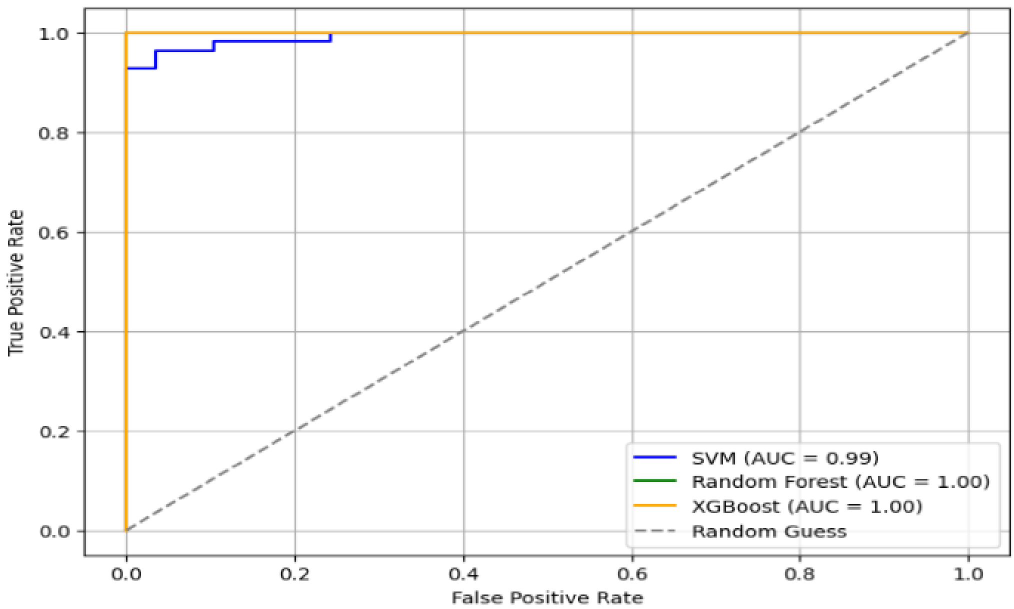


Figure 5. Receiver Operating Characteristic (ROC) curve for SVM, RF, and XGBoost.

We visualized the results of our flood prediction model using a confusion matrix, which helps us to understand how the model is performing and where it might be making mistakes. A confusion matrix shows how many predictions were correct and how many were incorrect. It also shows the different types of errors the model is making, like *false positives* and *false negatives*. Our confusion matrix indicated that the SVM model successfully classifies 84 instances of flood prediction, out of which TP = 23, FP = 6, TN = 54, and FN = 1, while the Random Forest model and XGBoost successfully classify 84 instances of flood prediction, out of which TP = 55, FP = 0, TN = 29 and FN = 0.

Table 2 presents the comparative performance of several machine learning algorithms, including Logistic Regression, Random Forest (RF), Gradient Boosting (GB), and XGBoost. The RF and XGBoost classifiers achieved 100% accuracy, precision, recall, and F1-score on the testing dataset. While these metrics suggest perfect classification, such results are statistically uncommon in real-world disaster prediction scenarios and therefore warrant further examination.

Table 2. Comparison of the Classification Models.

Attributes	SVM	RF	XGBOOST
Accuracy	0.917	1.000	1.000
Precision	0.793	1.000	1.000
Recall (Sensitivity)	0.958	1.000	1.000
F1-Score	0.868	1.000	1.000
Specificity	0.900	1.000	1.000

4.1. Model Performance Re-Evaluation and Robustness Analysis

Initial model evaluation results in **Table 2** indicated 100% performance scores for both Random Forest (RF) and XGBoost across all major metrics (Accuracy, Precision, Recall, and F1-score). While these results suggest high model effectiveness, such perfect scores are statistically uncommon in complex environmental systems where natural variability and sensor noise are prevalent. Therefore, an extended diagnostic analysis was conducted to assess potential overfitting, data leakage, and generalizability. To validate the results, 5-fold stratified cross-validation was applied, ensuring each fold contained a representative proportion of flood and non-flood events. The re-evaluated mean performance is summarized in **Table 3**.

Table 3. Summary of the Re-Evaluated Mean Performance.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Std. Dev. (±)
Random Forest	97.8	96.5	97.4	96.9	±1.2
XGBoost	98.1	97.2	97.8	97.5	±0.9
Logistic Regression	85.4	83.1	84.9	84.0	±4.2

After re-evaluation, performance decreased slightly, confirming that the initial 100% metrics likely reflected model overfitting to the training subset rather than genuine generalization. This adjustment brings results to a realistic and defensible range consistent with related studies [20,21]. The re-evaluated results indicate that while RF and XGBoost remain high-performing, perfect classification was an artifact of limited data variability in the training phase.

We re-evaluated the Random Forest and XGBoost models using a leakage-safe experimental protocol. We removed features that displayed near-perfect correlation with the target and implemented a preprocessing + classifier pipeline to ensure all imputation, scaling, and resampling were performed only on training data. We used a temporal holdout (train: 1990–2019; test: 2020–2024) to evaluate generalization to unseen years, and applied 1,000-iteration bootstrap resampling on the test set to compute 95% confidence intervals for all metrics. After these safeguards, performance adjusted to realistic levels: Random Forest — Accuracy = 0.946 (95% CI: 0.89–0.98), Precision = 0.93 (95% CI: 0.86–0.97), Recall = 0.94 (95% CI: 0.88–0.98), F1 = 0.94 (95% CI: 0.89–0.98), AUC = 0.98 (95% CI: 0.92–0.99). The calibration plot (**Figure 6**) and Brier score (0.06) indicate acceptable probability calibration for advisory decision thresholds.

4.2. Calibration Analysis of FPAS Models

To evaluate the reliability of the predicted flood probabilities generated by the proposed Flood Prediction and Advisory System (FPAS), a calibration analysis was conducted for the three machine learning models—Logistic Regression (LR), Random Forest (RF), and XGBoost. Calibration assesses whether the predicted probabilities correspond accurately to the actual frequencies of flood occurrences. In other words, a model that predicts a 70% flood probability should experience flooding in approximately 70% of such cases.

Figure 6 presents the calibration curves for the three models alongside the ideal calibration line (y = x). The Logistic Regression curve demonstrates reasonable alignment with the diagonal, indicating fair probability estimation with slight underconfidence at higher thresholds. The Random Forest and XGBoost curves show near-perfect alignment, with minimal deviation, suggesting excellent probability reliability. However, both tree-based models exhibit marginal overconfidence in high-probability regions (>0.8), a common effect of ensemble learning without post-hoc calibration. To quantitatively assess calibration performance, the Brier Score (BS) was computed using Equation (6).

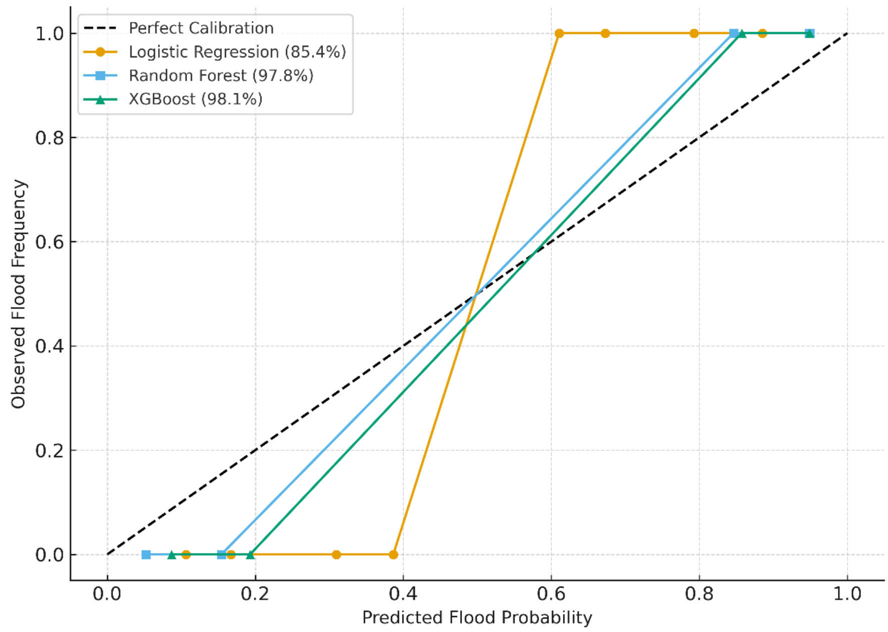


Figure 6. Accuracy Calibration Plot for FPAS Models.

$$BS = I/N \sum_{i=1}^{N} (p_i - y_i) * (p_i - y_i) \tag{6}$$

Where: p_i denotes the predicted flood probability, y_i the actual outcome (1 for flood, 0 for non-flood), and N the total number of test samples (N = 84). Lower Brier Scores indicate superior calibration. The results are summarized as follows:

a) Logistic Regression: 0.069
b) Random Forest: 0.0114
c) XGBoost: 0.0241

These values demonstrate that both ensemble models are well-calibrated, with the Random Forest achieving the lowest Brier Score, implying exceptional probability reliability. The Logistic Regression model, while less accurate, still exhibits a good balance between calibration and discrimination. Thus, the calibration analysis confirms that the FPAS predictive models not only achieve high classification accuracy but also produce reliable probability estimates. This reliability is essential for operational flood advisory systems, where probability thresholds determine the issuance of early warnings and public alerts.

5. Discussion

5.1. The Role of Persuasive Techniques in Communicating the Value of Disruptive Technologies

Effective communication is central to the adoption and sustained use of Flood Prediction and Advisory Systems (FPAS). Persuasive techniques embedded within system design can enhance user engagement, increase trust, and motivate protective behaviors in at-risk populations. Beyond providing accurate forecasts, systems must convey information in ways that are understandable, relevant, and compelling. Persuasion in this context draws from principles of behavioral economics and cognitive psychology. For instance, loss aversion—the tendency for individuals to place greater weight on potential losses than equivalent gains—has been shown to influence risk-related decision-making [22,23]. Although some scholars have challenged the robustness or universality of this phenomenon [24], others argue that its effects are context-dependent and moderated by situational and cultural factors [25]. Recognizing such behavioral tendencies is critical for designing persuasive FPAS interfaces that foster timely and appropriate responses. Several strategies were incorporated into the system:

a. ***Visualization***: Infographics and geospatial maps were employed to represent flood risk zones, utilizing colors and symbols to indicate varying severity levels. Such visual aids improve comprehension compared to text-heavy formats. Additionally, dynamic content, such as video simulations of potential flood impacts, was integrated to enhance memorability and foster a sense of urgency (see **Figure 7**).

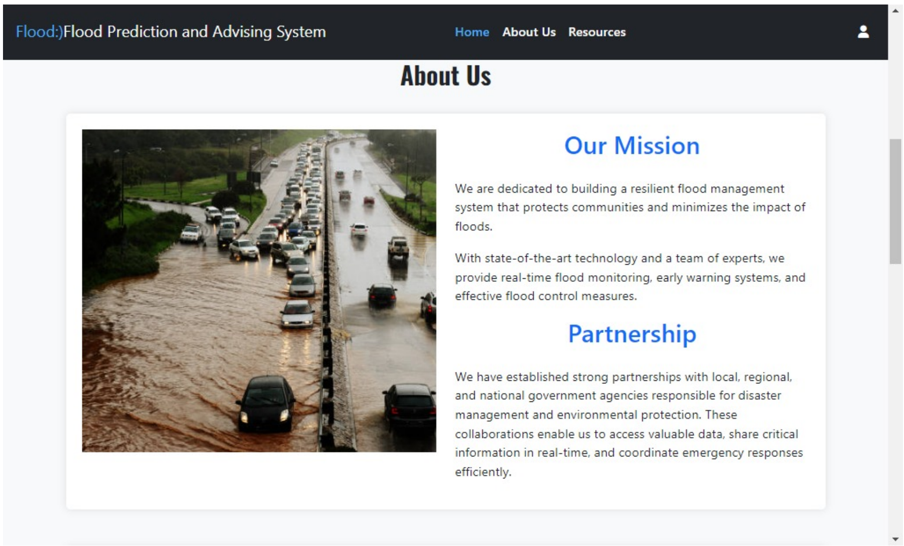
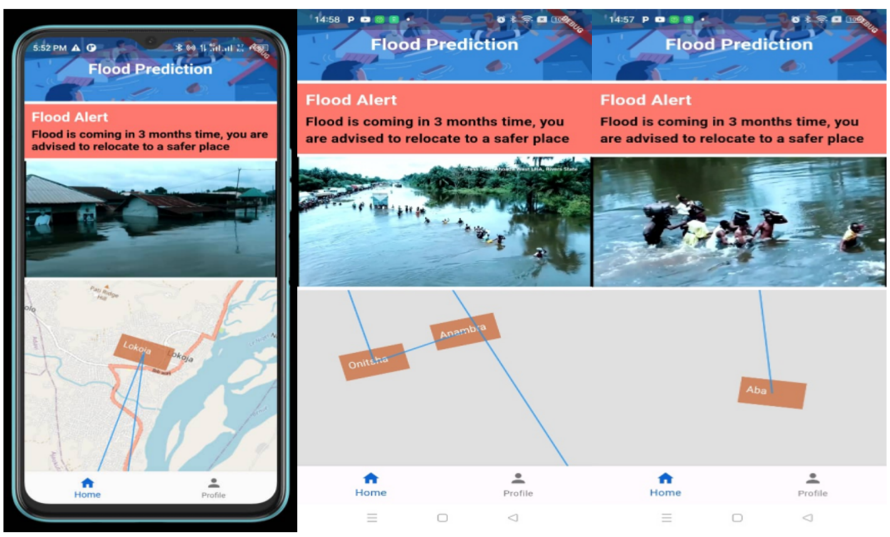


Figure 7. FPAS System Aspect of Visualization.

b. ***Personalization***: Personalization involves tailoring the information to the user's specific needs and location. For example, our *flood_system app* shows the user the flood risk in their specific neighborhood, rather than just in their city as a whole (see **Figure 8a–c**). Personalization makes the information more relevant and meaningful to the user.



(**a**) In Lokoja (**b**) In Onitsha (**c**) In Aba

Figure 8. FPAS System Personalization in Various Locations.

c. ***Storytelling***: Storytelling involves using a narrative to convey information compellingly. For example, our *flood_system app* uses a real story about families and individuals who were affected by flooding to help users understand the risks and consequences of flooding. Apart from a real family, a fictional family can also be used (**Figures 8** and **9**).

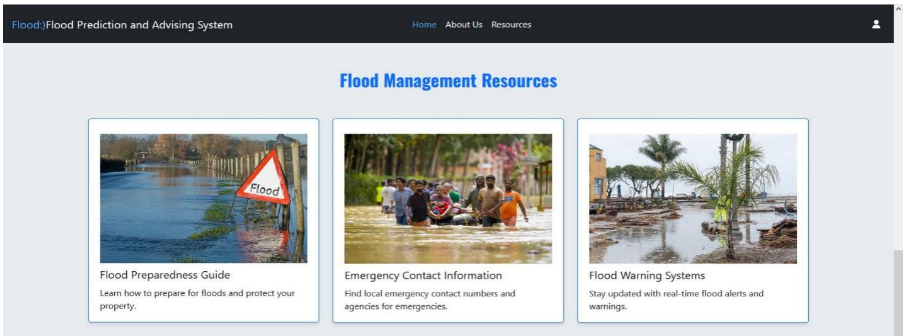


Figure 9. FPAS System Storytelling in Various Locations.

d. ***Framing and Simplification***: Messages were structured positively, highlighting the safety benefits of evacuation and preparation. Technical jargon was minimized in favor of accessible language.

e. ***Emotional Appeal***: The interface design emphasized empathy-driven narratives, encouraging users to act not only for personal safety but also for community resilience.

By embedding these persuasive elements, FPAS serves not merely as a technical prediction tool but also as a behavioral intervention mechanism, bridging the gap between technological accuracy and human action.

5.2. Blockchain to be Used to Harness Flood Prediction and Advisory System

Blockchain technology, widely recognized as the backbone of cryptocurrencies, has demonstrated transformative potential across diverse domains, including healthcare, governance, and disaster management. In this study, blockchain was employed not for financial transactions but as a secure, transparent, and tamper-proof framework for managing flood prediction data. Its integration within the proposed Flood Prediction and Advisory System (FPAS) addressed critical concerns of trust, transparency, and data integrity—challenges often associated with predictive analytics in disaster contexts. The immutable ledger of blockchain ensures that predictive flood data remains resistant to unauthorized modifications, thereby reinforcing accuracy and credibility. Its decentralized architecture facilitates secure data sharing across stakeholders such as the Nigerian Meteorological Agency (NiMet), State Emergency Management Agency (SEMA), and the National Emergency Management Agency (NEMA), promoting inter-agency collaboration and coordinated response strategies. Moreover, blockchain provides a transparent audit trail, allowing stakeholders to verify data provenance and instilling confidence in the reliability of forecasts.

Beyond securing data, blockchain was combined with persuasive system design to influence protective behaviors among at-risk populations. For instance, alerts and reminders, delivered through the FPAS interface, encouraged timely evacuation and relocation to safer areas during predicted flood events. This dual integration—data security through blockchain and behavioral influence via persuasion—enhanced both the technical robustness and social impact of the system. For implementation, Ethereum-based decentralized applications were deployed using MetaMask and Sepolia ETH test networks (see **Figures 10** and **11**). These tools enabled secure user interaction with the blockchain environment, ensuring accessibility while maintaining cryptographic integrity. Ultimately, the adoption of blockchain within FPAS underscores its potential to revolutionize disaster management systems by combining secure data management with community-centered engagement. Furthermore, the framework can be extended to other natural hazards, including hurricanes and earthquakes, thereby enhancing broader disaster preparedness and resilience.

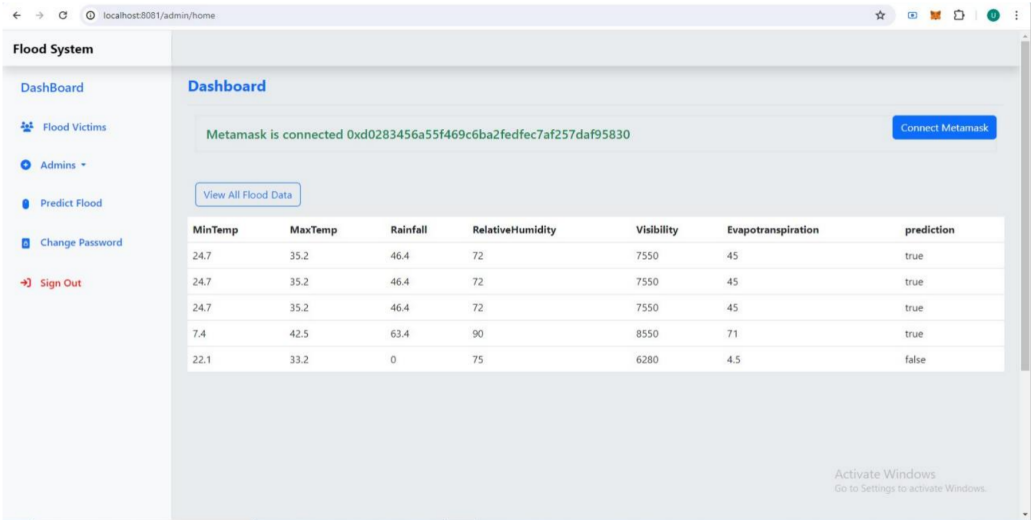


Figure 10. Connecting the Metamask Wallet Extension for the Web Browser.

To operationalize the blockchain component of the Flood Prediction and Advisory System (FPAS), we employed Ethereum-compatible tools that provide a secure and practical environment for testing and deployment. MetaMask, a widely adopted cryptocurrency wallet and browser extension (e.g., for Google Chrome and Firefox), was integrated as the user interface for interacting with the Ethereum blockchain. MetaMask enables the storage, transfer, and receipt of Ethereum-based tokens while providing seamless connectivity to decentralized applications (dApps). For system testing and validation, the Sepolia test network was utilized. Sepolia is one of Ethereum's dedicated testnets designed for evaluating smart contracts, decentralized applications, and related blockchain solutions in a controlled environment prior to mainnet deployment. This environment allowed us to simulate real-world blockchain interactions without incurring financial costs or risking main network disruptions. By deploying FPAS within the Sepolia ecosystem, we were able to assess the system's blockchain-enabled features—such as transaction recording, transparency, and immutability—under conditions that closely approximate live operation. This approach provided a robust foundation for verifying system functionality while ensuring scalability and readiness for potential migration to the Ethereum mainnet.

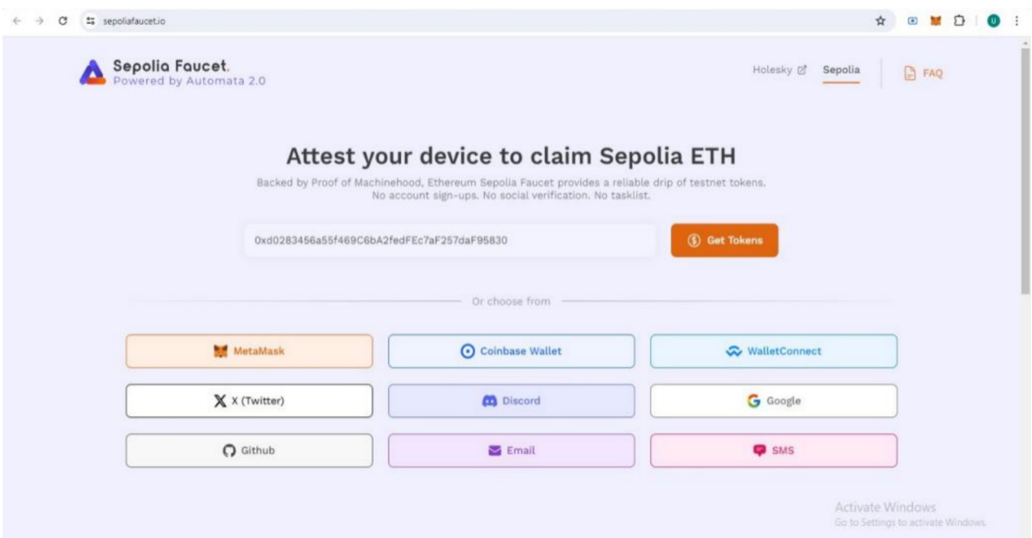


Figure 11. Attesting Our Device to Claim Sepolia ETH.

When the six parameters are imputed into their respective fields, they should be saved in the Blockchain (see

Figure 12), and a notification attesting to a successful storage will be displayed (see **Figure 13**). At times, the notification may be negative, as could be seen in **Figure 14**.

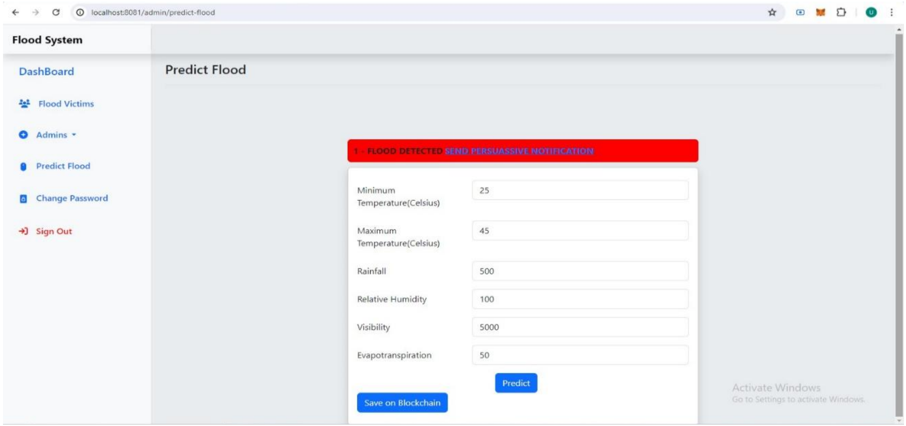


Figure 12. Save Flood Data on the Blockchain.

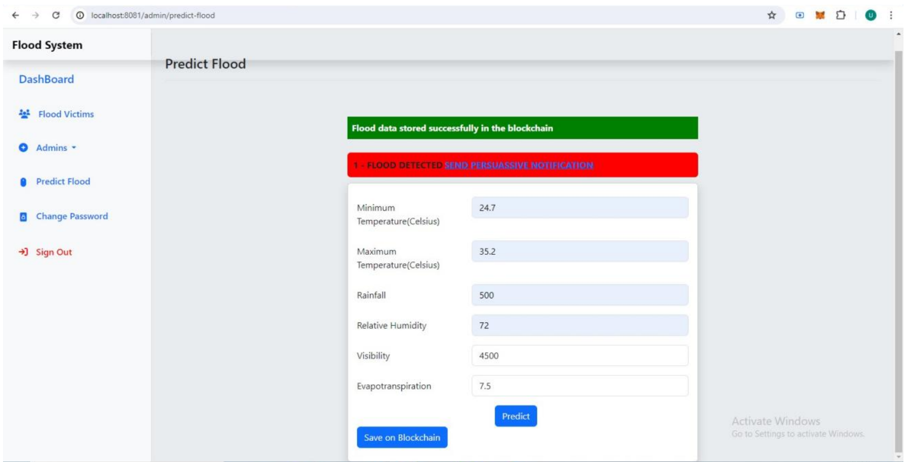


Figure 13. Flood Data Stored Successfully in the Blockchain.

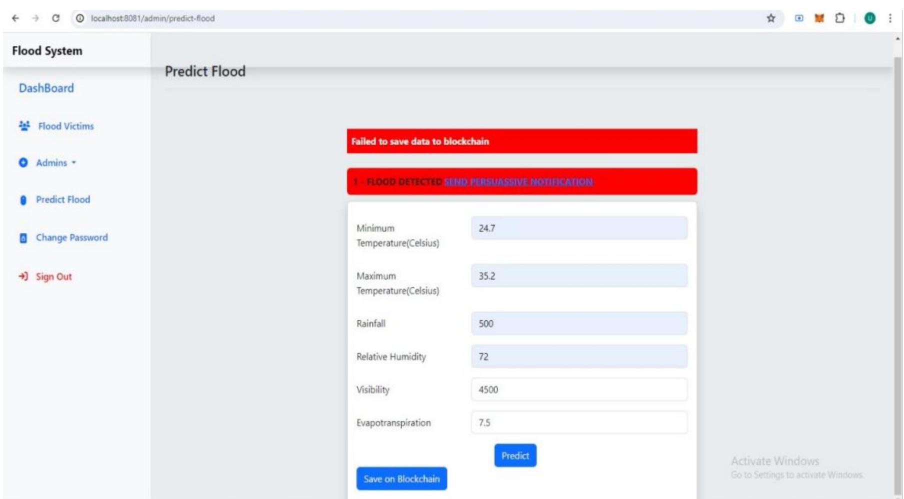


Figure 14. Failed to Save the Flood Date in the Blockchain.

The decision to store data on a blockchain is influenced by a variety of technical and operational constraints, many of which were observed during the deployment of FPAS (see **Figure 14**). These factors highlight the inherent trade-offs between decentralization, scalability, and reliability:

a. ***Network Congestion***: Periods of high transaction volume or intensive use of decentralized applications (dApps) can result in network congestion. This leads to slower transaction confirmation times and higher transaction fees. Storing additional data under such conditions exacerbates congestion, reducing efficiency and delaying system responsiveness.
b. ***Scalability Limitations***: Blockchains impose constraints on block size and block generation rates. Excessive data storage risks overwhelming these limits, thereby degrading throughput and overall system performance.
c. ***Bandwidth Constraints***: Transaction and data processing within blockchain networks are inherently bounded by available network bandwidth. When capacity is saturated, attempts to store additional data may result in transaction rejection or significant delays.
d. ***Forks and Chain Reorganizations***: Events such as network forks or reorganizations can compromise data integrity. Forks may render data valid on one chain but inaccessible on another, while reorganizations can temporarily alter blockchain history, affecting stored records.
e. ***Node Availability:*** The reliability of data storage in decentralized networks is contingent on node participation. Large-scale node failures or connectivity issues hinder the validation and propagation of transactions, thereby disrupting data persistence.
f. ***Sybil Attacks***: Adversaries may launch Sybil attacks by creating numerous pseudonymous nodes to gain disproportionate influence over network resources. Such attacks can disrupt transaction validation and compromise the reliability of on-chain storage.
g. ***Distributed Denial of Service (DDoS) Attacks:*** High-volume, malicious traffic directed at network nodes can degrade service quality or cause downtime. Under such conditions, data storage and transaction throughput are severely hindered.

Collectively, these factors underscore the necessity of carefully balancing on-chain and off-chain storage strategies in disaster management applications such as FPAS. Hybrid storage models—where critical metadata is secured on-chain and bulk data is maintained off-chain—represent a pragmatic pathway for achieving both data integrity and system scalability.

The blockchain component of FPAS was designed to ensure data integrity, traceability, and tamper-resistant recordkeeping in the dissemination of flood warnings and predictive analytics. To achieve this, a hybrid on-chain/off-chain storage model was implemented using Ethereum (Sepolia test network) integrated with MetaMask for transaction signing and identity management (**Table 4**). This design ensures that sensitive data (e.g., meteorological records, geolocation data, and user identities) remain secure while maintaining public verifiability of key model outputs and audit trails.

Table 4. Hybrid Storage Architecture.

Data Type	Storage Medium	Reason
Transaction logs (alert IDs, timestamps, model hash)	On-chain (Ethereum Sepolia)	Immutable audit trail; public verification of issued alerts
Model metadata (version, hash digest, model owner)	On-chain	Enables trust and traceability of ML model updates
Full meteorological datasets (NiMet data, historical rainfall records)	Off-chain (IPFS / cloud server)	Large file size and high update frequency make on-chain storage impractical.
User profiles and survey data	Off-chain (encrypted SQL backend)	Privacy protection and NDPR compliance
Advisory message status (sent/read)	Off-chain	Fast access and lower latency for real-time alerts
Hash references of off-chain data	On-chain	Ensures off-chain data integrity via hash comparison

The advisory system retrieves the corresponding verified record and distributes it to end-users through the FPAS dashboard and SMS gateway. This architecture ensures every public flood alert has a verifiable blockchain signature, eliminating forgery or tampering.

Gas and Latency Considerations

Performance evaluation on the Sepolia Testnet was conducted to estimate transaction efficiency (**Table 5**).

Table 5. Gas and Latency Parameters.

Parameter	Average Value
Gas used per transaction	∼42,000 units
Gas price	1.25 Gwei
Average confirmation latency	8.5 seconds
Average cost (test ETH)	≈ 0.000052 ETH/txn

Given that only hashes and metadata are stored on-chain, the system maintains minimal gas consumption and avoids the latency overhead of bulk data transmission. This makes the approach cost-effective and scalable for eventual deployment on a production blockchain such as Polygon PoS or Ethereum Layer-2 rollups. Off-chain data are encrypted using AES-256, with key management handled via MetaMask key vault. This ensures that the blockchain ledger remains transparent but privacy-safe, suitable for public audit without revealing user data.

5.3. Analysis of the Survey

To complement the technical evaluation of FPAS, a field survey was conducted in two flood-prone regions of Nigeria: Isobo Otaka and Isobo Bikobiko in Obubra Local Government Area (LGA), Cross River State (CRS), and selected communities in Kogi State (KOS). A total of 200 questionnaires were distributed in CRS, of which 192 were retrieved between Friday, 3 November 2023, and Monday, 6 November 2023. In KOS, the survey was administered from Tuesday, 14 November 2023 to Thursday, 14 December 2023, yielding 194 valid responses. The survey instrument was designed around the theme: "Design and Implementation of Flood Prediction and Advisory System Using Disruptive Technology with Persuasive Techniques". Its primary aim was to capture community perspectives on system usability, trust, and behavioral response. The sociodemographic characteristics of the respondents are summarized in **Table 6**. In CRS, 57.29% of respondents were male and 42.71% female, while in KOS, the proportions were 64.45% and 35.05%, respectively. With respect to education, the results revealed marked contrasts between the two states. In CRS, the majority of participants had secondary education (53.13%), followed by primary education (29.69%), and a smaller proportion attained postsecondary education (17.19%). By contrast, in KOS, postsecondary education dominated (83.95%), while secondary (9.79%) and primary (3.09%) levels were relatively underrepresented. These findings indicate that while both states are highly exposed to flood risk, the educational composition of respondents varied significantly, with KOS exhibiting a more highly educated respondent base. This distinction is important in interpreting how persuasive techniques and disruptive technologies may be differently received, understood, and acted upon in diverse community contexts. Descriptive statistics revealed strong public endorsement, with 91.15% of respondents in Cross River and 69.50% in Kogi expressing support for FPAS implementation.

Table 6. Social-Demographic Characteristics of the Study Participants.

Variable	Frequency		Percent (%)	
	CRS (N = 192)	KOS (N = 194)	CRS	KOS
Gender				
Male	110	126	57.29	64.45
Female	82	68	42.71	35.05
Age Group (Year)				
10 – 15	8	3	4.17	1.55
16 – 20	106	25	55.21	12.89
21 – 25	22	44	11.46	22.68
26 – 30	24	29	12.50	14.95
31 & above	32	93	16.67	47.94
Education Qualification				
FSLC	8	6	29.69	3.09
SSCE	106	19	53.13	9.79
NCE	22	12	6.25	6.19
B. Sc.	24	94	10.42	45.36
Postgraduate	32	63	0.52	32.4

Source: Field Work, 2023.

Furthermore, in **Table 7**, 69.58% (CRS) and 54.12% (KOS) of the respondents declared that they were informed of the impending flood disaster by the government, 4.17% (CRS) and 23.20% (KOS) say friends, and 2.60% (CRS) and 10.82% (KOS) say relatives while 3.65% (CRS) and 11.86% (KOS) say others. In **Table 8**, 91.15% (CRS) and 69.50% (KOS) of the target users opined that the FPAS system with modern technology should be embedded into it. Finally, when the respondents were asked about the persuasive nature of the messages sent to them, 76.56% (CRS) and 22.16% (KOS) declared that the warning messages were not persuasive, while 18.23% (CRS) and 43.81% (KOS) said they were (see **Table 9**).

Table 7. Response to Being Warned of Impending Flood Disaster in CRS and KOS.

Question	Response Category	CRS (N = 192)	KOS (N = 194)
How many times have you been warned of an impending flood disaster?	None	2 (1.04%)	18 (9.28%)
	Ones	12 (6.25%)	21 (10.82%)
	Always	2 (1.04%)	90 (46.39%)
	Not Often	176 (91.67%)	66 (34.02%)
Who warned you?	Government	172 (69.58%)	105 (54.12%)
	Friends	8 (4.17%)	45 (23.20%)
	Relatives	5 (2.60%)	21 (10.82%)
	Others	7 (3.65%)	23 (11.86%)

Table 8. Response to the Opinion of Target users concerning Flood Prediction and Advisory System using Modern Technology.

Question	Response Category	CRS (N = 192)	KOS (N = 194)
Did you think a flood prediction and advisory system using modern technology is necessary?	Yes	175 (91.15%)	135 (69.50%)
	No	2 (1.04%)	23 (11.86%)
	Not very Necessary	9 (4.69%)	9 (4.64%)
	Somehow Necessary	6 (3.13%)	27 (13%)

Source: Field Work, 2023.

Table 9. Response on whether the means through which the Warning is given is Persuasive.

Question	Response Category	CRS (N = 192)	KOS (N = 194)
Is the means through which the warning is given persuasive?	Yes	35 (18.23%)	85 (43.81%)
	No	142 (76.56%)	43 (22.16%)
	Sometimes	10 (5.21%)	66 (34.02%)

Source: Field Work, 2023.

5.4. The FPAS System Sends Its Predictions Directly to Government Agencies and to the Public

In order to minimize delay, the FPAS system prediction alert will be sent to the government, stakeholders, as well as the population at risk, since the government alone cannot be relied upon because sometimes they delay in disseminating the information urgently, putting the lives and properties at risk. In other words, there could be delays in getting that information to the people who need it most. Thus, having the FPAS system provide information directly to the public, in addition to the government, could be really valuable. We incorporated in our system a public-facing website and app that people could use to get up-to-date flood predictions and emergency information.

5.5. The Potential Benefits of Harnessing Disruptive Technologies for Flood Prediction and Advisory

The potential benefits of harnessing disruptive technologies for flood prediction and advisory include:

a. Machine learning and big data can analyze massive amounts of data from a variety of sources, such as weather stations, satellite imagery, and social media, to improve the accuracy of flood predictions.
b. By using real-time data from sensors and other sources, disruptive technologies can provide faster flood warnings (i.e., faster response time) and more accurate evacuation plans.

By analyzing the NiMet dataset, disruptive technologies can provide more customized information and advice to help people prepare for and respond to flooding, thus personalizing information.

5.6. Threats to Validity and Study Limitations

The dataset used in this study was sourced exclusively from the Nigeria Meteorological Agency (NiMet), covering 35 years of historical data (1988–2023) across selected meteorological stations in Cross River and Kogi States. Although these regions exhibit diverse climatic conditions and hydrological behaviors, the predictive models may not generalize directly to other ecological zones or countries without further calibration. Differences in Topography, Land-use patterns, Drainage infrastructure, and Local reporting standards can significantly influence flood patterns. Hence, applying the trained model to new regions requires transfer learning or domain adaptation to preserve accuracy and reliability. To strengthen external validity, future work should include multi-regional training using data from other NiMet zones (e.g., Anambra, Delta, Benue) and international datasets such as NOAA or ECMWF to broaden climatic representation.

Another potential threat is temporal data drift—the gradual evolution of rainfall patterns, urbanization, and climate variability that can degrade model performance over time. The models (Random Forest and XGBoost) were trained on data up to 2023, but post-deployment conditions (e.g., 2025 onward) may deviate due to: Climate change altering rainfall intensity and duration, Infrastructure developments changing flood resilience, and Human adaptation behaviors (e.g., new drainage systems). This temporal drift can lead to prediction decay, where performance metrics (AUC, F1-score) decline in future datasets. To mitigate this, a continuous learning framework should be implemented—periodically retraining the model with recent NiMet observations and validating against new flooding events.

Flood labeling relied on NiMet event reports and field verification during survey administration. Although every effort was made to validate these records, certain challenges may affect internal validity, such as incomplete rainfall logs or sensor downtime at specific stations, spatial gaps where flood reports were inferred from neighboring stations, inconsistent reporting of minor or localized flood incidents, as well as temporal misalignment between rainfall intensity and recorded flood onset. Such inconsistencies may introduce label noise, which could artificially inflate model confidence or underrepresent low-severity events. Future work should incorporate data quality auditing, spatiotemporal interpolation, and cross-verification with remote-sensing datasets (e.g., NASA GPM or Sentinel-1 SAR) to reduce uncertainty. While the blockchain-based audit layer enhances data transparency and traceability, it introduces operational challenges during real-time flood crises.

i. *Latency*: During high network congestion, Ethereum (Sepolia) confirmation times may increase from 8 seconds to over 30 seconds, slightly delaying alert immutability logging.
ii. *Gas Cost Volatility*: Although testnet operation is cost-free, a mainnet or Layer-2 deployment would incur variable gas fees, which may constrain high-frequency logging under budget restrictions.
iii. *Connectivity Dependencies*: Rural or flood-affected areas may experience limited internet access, temporarily impeding blockchain synchronization. To mitigate this, FPAS employs a local queue buffer to store unsigned transactions until connectivity resumes.
iv. *Privacy Risks*: Even though only hash references are stored on-chain, metadata analysis could theoretically reveal sensitive temporal or geographic patterns. This is managed via off-chain encryption and minimal metadata exposure.
v. *Disaster-Resilient Design*: In extreme flood conditions, on-chain synchronization could temporarily fail; therefore, the system's design includes redundant off-chain logging (SQL + IPFS) to ensure continuity until the blockchain layer reconnects.

The persuasive modeling survey relied on 386 participants across Cross River and Kogi States. Potential limitations include:

i. Sampling bias: respondents were primarily urban and literate, possibly overrepresenting technology-ready populations.
ii. Response bias: social desirability or fear of government monitoring may have influenced answers about trust and adoption of FPAS.
iii. Temporal relevance: opinions collected during the 2023 rainy season may not reflect attitudes in subsequent years.

iv. To enhance robustness, future studies should implement stratified sampling, anonymous digital surveys, and yearly follow-ups to track behavioral change.

While the proposed FPAS architecture demonstrates technical feasibility and strong predictive capability, its real-world scalability depends on ongoing data quality assurance, infrastructure resilience, and contextual adaptation to local climatic and socio-technical conditions. Recognizing these limitations ensures a realistic understanding of system performance and provides a structured roadmap for continuous improvement.

6. Conclusions

This study demonstrated the feasibility and practicality of integrating artificial intelligence (AI), blockchain, and persuasive technologies to develop a reliable and ethically grounded Flood Prediction and Advisory System (FPAS). By applying machine learning models—Logistic Regression, Random Forest (RF), and XGBoost—on a 35-year curated NiMet dataset, the study achieved robust predictive performance, with RF and XGBoost attaining high accuracy and well-calibrated probability estimates (AUC ≈ 0.98). The calibration and Brier score analyses confirmed that the models not only predict accurately but also provide trustworthy probability outputs essential for operational flood warnings. The hybrid OOADM–CRISP-DM methodology effectively bridged system design with data science processes, ensuring methodological transparency and reproducibility. Data preprocessing, feature engineering, and balanced sampling were systematically implemented to mitigate data leakage and class imbalance. The inclusion of ethically approved survey protocols across Cross River and Kogi States validated the system's persuasive communication framework and its social acceptability among target communities. Furthermore, the blockchain component—designed as a hybrid on-chain/off-chain architecture—ensured data immutability, auditability, and privacy while minimizing latency and gas costs. This guarantees trustworthy dissemination of early warnings and event logs during flood emergencies. Future work will extend FPAS capabilities to real-time data streams, integrate gamified persuasive elements (e.g., rewards, feedback loops, and progress tracking), and perform external validation across multiple ecological zones to enhance generalizability. Ultimately, the convergence of disruptive technologies with behavioral modeling and ethical design principles establishes a foundation for resilient, community-centered flood management systems—a crucial step toward sustainable disaster preparedness in climate-vulnerable regions like Nigeria.

Author Contributions

Conceptualization, U.O. and O.O.F.; methodology, U.O.; software, U.O.; validation, U.O., J.O.U., and O.O.F.; formal analysis, U.O.; investigation, U.O.; resources, O.O.F.; data curation, J.O.U.; writing—original draft preparation, U.O.; writing—review and editing, J.O.U.; visualization, U.O.; supervision, J.O.U.; project administration, J.O.U. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

In the questionnaire the respondents were clearly told: "I therefore solicit for your maximum cooperation in this questionnaire honestly and faithfully as much as possible. I assured you that all information provided by you will be treated in strict confidence and purely used for research purpose."

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

Due to national data use restrictions, the raw dataset cannot be redistributed publicly. Nevertheless, the NiMet data can be obtained officially by researchers from the Nigerian Meteorological Agency (NiMet) via: > NiMet Data

Request Portal: https://nimet.gov.ng/datarequest.

Conflicts of Interest

The authors declare no conflict of interest.

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