

Developing Community-Based Early Warning Systems for Flood Disaster Management Using Mobile Technology

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DOI: <https://doi.org/10.51244/IJRSI.2026.130200156>

Received: 18 February 2026; Accepted: 23 February 2026; Published: 16 March 2026

ABSTRACT

Flooding has become increasingly frequent and severe in Akwa Ibom State, largely driven by rising rainfall variability, rapid urbanization, and limited early warning infrastructure. This study assessed long-term rainfall trends, flood incidence patterns, community risk perception, institutional capacity, and determinants of household preparedness between 2005 and 2026. Secondary data were obtained from NEMA and Akwa Ibom State Emergency Management Agency, while primary data were collected through structured questionnaires administered across selected Local Government Areas. The Mann–Kendall trend test revealed a statistically significant upward trend in annual rainfall ($\tau = 0.74$, $p < 0.001$), with Sen’s slope estimator indicating an average increase of 38 mm per year. Pearson correlation analysis showed a strong positive relationship ($r = 0.87$, $p < 0.001$) between annual rainfall and flood events. Logistic regression results identified access to early warning systems (OR = 4.14), mobile phone ownership (OR = 3.16), education level (OR = 2.09), prior flood experience (OR = 1.86), and income level (OR = 1.78) as significant predictors of household preparedness (Model accuracy = 76.3%; Nagelkerke $R^2 = 0.48$). Despite high levels of flood experience (87.4%) and growing risk perception (81.6%), more than half of respondents (54.3%) exhibited low preparedness, while institutional assessments revealed major gaps in real-time monitoring, last-mile communication, and mobile-based alert systems. The findings underscore the urgent need for integrated, technology-driven, and community-centered early warning systems to enhance resilience and reduce flood-related losses in the state.

Keywords: Early warning systems; Flood preparedness; Flood risk; Rainfall variability; Resilience.

INTRODUCTION

One of the most common and destructive natural hazards in the world today has become flood disasters that have been taking away millions of lives every year, causing significant socio-economic damage (IPCC, 2023; UNDRR, 2022). The risk of floods especially in low-lying coastal and riverine settlements in sub-Saharan Africa has been increased by rapid urbanization, climate variability, and lack of infrastructure (Adelekan, 2016; Olorunfemi et al., 2020). Flooding is very susceptible in Nigeria, and in the past decades, there has been recurrence, leading to loss of lives, displacement, property damage, and livelihood disruption (Nwokoro et al., 2021). The Akwa Ibom State, which is a part of the Niger Delta region, is especially prone to flood risks because of the low-lying terrain, elevated level of precipitation, large population, and ineffective drainage systems (Udoh and Akpan, 2019; Ekwere et al., 2021).

Flood effects in the Akwa Ibom State are not only physical, but socio-economic as well. In most cases, the devastation caused by flooding can take away homes, farmlands, and other important infrastructure, resulting into food insecurity, economic damage, and health problems (Udo and Etim, 2018). Although the government tries to address the consequences of floods, the repetitive character of the disaster implies a lack of disaster preparedness, dissemination of early warnings, and community involvement (NEMA, 2022; AKSEMA, 2023). The traditional early warning systems are usually centralized, slow and inaccessible to the vulnerable population especially in rural and peri-urban regions (Adelekan et al., 2015).

The emerging technologies in mobile technology, geospatial modeling, and real-time data collection create the prospects of creating community-based early warning systems (CBEWS) that can be used to bolster the

management of flood risks. The mobile-enabled systems have the potential to combine the sensors of rainfall and river level, satellite-based data, and community-sourced reports to provide people in danger with time-sensitive alerts (Shrestha et al., 2020). Such systems also allow the community to participate in disaster monitoring and response, which forms a feedback loop that enhances resilience and minimizes losses (Paul et al., 2021). Moreover, proactive disaster management can be achieved through the adoption of predictive algorithms and the risk scoring method into the mobile platforms (Musa et al., 2022). Since the occurrence and severity of floods in Akwa Ibom State have been on the rise, it is high time the community comes up with a mobile early warning system, which is context-specific and community-based so that it can help in strengthening the resilience of the area, provide timely response, and increase preparedness. This study, therefore, aims to address this gap by combining historical flood trend analysis, community preparedness assessment, institutional gap evaluation, and design science research for system development and validation. The specific objectives of the study are to:

- i. Examine the patterns, frequency, and impacts of flood disasters in Akwa Ibom State over the past two decades.
- ii. Assess community awareness, perceptions, and preparedness levels for flood disaster management.
- iii. Evaluate the current gaps and limitations in existing early warning systems for flood management in the study area.
- iv. Develop a mobile technology-based community early warning system framework for flood disaster management.
- v. Test and validate the effectiveness, accessibility, and sustainability of the proposed mobile-based community early warning system.

RESEARCH METHODOLOGY

The study adopted longitudinal, cross-sectional research design, the study also employed geospatial and hydrological modeling and pilot experimental validation to develop and evaluate a community-based mobile early warning system for flood disaster management in Akwa Ibom State, Nigeria. The methodology was implemented in interconnected phases aligned with the study objectives. A 20-year longitudinal assessment (2005-2025) was conducted to analyze flood patterns, frequency, and impacts across major flood-prone Local Government Areas including Uyo, Itu, Oron, Eket, Ikot Abasi, Ibeno, and Eastern Obolo. Secondary data were obtained from NiMet (rainfall), NIHSA (river discharge), NEMA and AKSEMA (flood records), alongside satellite datasets (Landsat, Sentinel-1 SAR and SRTM 30m DEM. Trend analysis was performed using the Mann-Kendall test, Sen's slope estimator, Rainfall Anomaly Index, and Standardized Precipitation Index. Flood frequency was modeled using Gumbel Extreme Value and Log-Pearson Type III distributions to estimate 10-, 25-, and 50-year return periods.

Community awareness and preparedness were assessed using a multi-stage sampling technique. High-risk LGAs were stratified, communities randomly selected, and households systematically sampled, yielding approximately 420 respondents determined using Cochran's formula. Data were collected through structured questionnaires, focus group discussions, and key informant interviews involving emergency officials and disaster coordinators. Statistical analyses included descriptive statistics, Likert-scale preparedness indexing, binary logistic regression to determine preparedness predictors, factor analysis to identify awareness drivers, and computation of a Community Resilience Index. An institutional and technical gap analysis of existing early warning systems was conducted through stakeholder consultations and SWOT analysis.

The system development phase followed a Design Science Research framework. A multi-layered architecture was designed comprising data acquisition (IoT rainfall and river sensors, satellite APIs, SMS reports), cloud-based processing and risk scoring, decision support classification (Green/Yellow/Red), multi-channel communication (SMS, USSD, mobile app, WhatsApp API, IVR in local languages), and a real-time feedback

module with geo-tagged reporting. The platform was developed using Python (Django/Flask), Flutter/React Native for mobile deployment, integrated SMS gateways, and cloud hosting services.

RESULTS

Table 3.1: Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	238	56.7
	Female	182	43.3
Education	No Formal	48	11.4
	Primary	112	26.7
	Secondary	186	44.3
	Tertiary	74	17.6
Mobile Phone Ownership	Yes	401	95.5
	No	19	4.5

Source: Field Survey, (2026)

The results show a slightly male-dominated sample (56.7%), though female participation is substantial (43.3%), ensuring gender inclusiveness. Educational attainment is relatively high, with 61.9% having at least secondary education, suggesting respondents possess adequate literacy to understand early

warning information. Notably, 95.5% of respondents own mobile phones, indicating strong feasibility for implementing a mobile-based early warning system. Limited phone ownership (4.5%) suggests the need for complementary communication channels.

Table 3.2: The Annual Rainfall and Flood incidence in some selected LGAs in Akwa Ibom State (2005-2025)

Year	Annual Rainfall (mm)	SPI Value	Number of Flood events	Affected LGAs
2005	2,410	-0.12	3	Uyo, Itu
2006	2,530	0.45	1	Oron, Itu
2007	2,680	0.91	4	Uyo, Eket, Oron
2008	2,890	1.32	6	Oron,
2009	2,450	0.21	2	Itu, Eket
2010	2,710	0.98	5	Uyo, Eket
2011	2,820	1.18	6	Oron, Eket
2012	3,050	1.76	3	Statewide
2013	2,960	1.44	7	Uyo, Oron
2014	3,120	1.89	1	Statewide

2015	2,740	0.85	4	Eket, Itu
2016	2,880	1.22	6	Uyo, Eket
2017	2,610	0.54	4	Ikot Abasi
2018	3,180	2.01	10	Statewide
2019	3,090	1.68	8	Oron, Eket
2020	2,950	1.31	7	Uyo, Eket
2021	3,240	2.15	11	Statewide
2022	3,110	1.72	9	Eket, Oron
2023	3,290	2.28	13	Statewide
2024	3,180	2.05	10	Uyo, Itu

Source: NEMA and AKSEMA Flood Record (2026)

The data reveal an overall increasing rainfall trend, particularly after 2012, with SPI values consistently above 1.5 in several years (2012, 2014, 2018, 2021–2024), indicating very wet conditions. Flood events generally increase during high SPI years, with peak occurrences recorded in 2018 (10 events), 2021 (11 events), and 2023 (13 events). Statewide flooding becomes more frequent in later years, confirming intensifying hydro-climatic conditions and expanding flood exposure across LGAs.

Table 3.3 Discharge and Flood Return Period Analysis of Selected Rivers in Akwa Ibom State

River Basin	Mean Annual Discharge (m ³ /s)	Peak Discharge (m ³ /s)	Estimated Return Period	Flood Risk Level
Itu River Tributary	1,280	2,960	25 years	High
Qua Iboe River	950	2,140	10 years	Moderate-High
Ibeno River	1,120	2,520	20 years	High
Stubbs Creek	740	1,680	5 years	Moderate

Source: Analyze from the Field Data (2026)

Hydrological analysis indicates that Itu River Tributary and Ibeno River exhibit high flood risk with return periods of 25 and 20 years respectively, implying significant flood magnitude potential. Qua Iboe River shows moderate-high risk with a 10-year return period, suggesting more frequent flood occurrences. Stubbs Creek, with a 5-year return period, reflects recurrent moderate flooding. These results confirm river discharge as a critical contributor to flood hazards in the study area.

Table 3.4: Flood Experience and Risk Perception

Variable	Yes (%)	No (%)
Experienced Flood in Last 5 Years	87.4	12.6
Property Damaged Previously	72.1	27.9

Believe Flood Risk is Increasing	81.6	18.4
Have Emergency Plan	29.5	70.5
Received Early Warning Previously	34.8	65.2

Source: Field Survey, (2026)

Flood exposure is widespread, with 87.4% experiencing flooding within the last five years and 72.1% reporting property damage. A majority (81.6%) perceive increasing flood risk, indicating strong community awareness of climatic changes. However, only 29.5% have emergency plans and 34.8% previously received early warning alerts, revealing significant preparedness and communication gaps.

Table 3.5: Preparedness Index (Composite Score)

Preparedness Level	Frequency	Percentage (%)
High Preparedness	68	16.2
Moderate Preparedness	124	29.5
Low Preparedness	228	54.3

Source: Analyze from the Field Data (2026)

More than half of respondents (54.3%) fall within the low preparedness category, while only 16.2% demonstrate high preparedness. This indicates that despite high flood exposure and awareness, preparedness levels remain inadequate, reinforcing the need for structured early warning interventions.

Table 3.6: Preferred Early Warning Communication Channels

Channel	Frequency	Percentage (%)
SMS	332	79.0
WhatsApp	289	68.8
Radio	201	47.9
TV	138	32.9
Community Town Crier	167	39.8
USSD	241	57.4

Source: Field Survey, (2026)

SMS is the most preferred channel (79%), followed by WhatsApp (68.8%) and USSD (57.4%), confirming strong demand for mobile-based communication. Traditional channels such as radio (47.9%) and community town criers (39.8%) remain relevant, suggesting a multi-channel dissemination strategy is essential for inclusivity.

Table 3.7: Institutional Early Warning Assessment

Indicator	Available (%)	Not Available (%)
Real-time Flood Monitoring	38	62

SMS-based Alerts	27	73
Community Feedback Mechanism	19	81
Local Language Alerts	21	79
Integrated GIS Mapping	42	58
Inter-agency Coordination Platform	36	64

Source: Field Survey, (2026)

Institutional capacity appears weak. Real-time flood monitoring (38%) and GIS integration (42%) are limited. SMS-based alerts (27%) and community feedback mechanisms (19%) are particularly low, indicating poor last-mile communication. Inter-agency coordination is also inadequate (36%), highlighting structural and technological deficiencies in existing systems.

Table 3.8: Identified Gaps (Stakeholder Rating on 5-Point Scale)

Limitation	Mean Score	Severity Level
Delayed Warning Dissemination	4.3	Very High
Poor Last-Mile Communication	4.5	Very High
Lack of Community Engagement	4.1	High
Inadequate Sensor Infrastructure	4.6	Critical
Weak Institutional Coordination	3.9	High
Absence of Mobile-Based Alert Platform	4.7	Critical

Source: Analyze from the Field Data (2026)

Stakeholders rated inadequate sensor infrastructure (4.6) and absence of a mobile-based alert platform (4.7) as critical gaps. Poor last-mile communication (4.5) and delayed warning dissemination (4.3) were also rated very high. Weak institutional coordination (3.9) and limited community engagement (4.1) further constrain system effectiveness. These findings strongly justify the development of a mobile-enabled, community-centered early warning framework.

Table 4.8: Analysis of the preparedness levels and impacts of flood disasters in Akwa Ibom State over the past two decades

Analysis Type	Variables Tested	Test Statistic	p-value	Significance ($\alpha=0.05$)
Mann–Kendall Trend Test	Annual Rainfall (2005–2024)	$S = +142; \tau = 0.74; Z = 3.89$	0.0001	Significant
Sen’s Slope Estimator	Annual Rainfall	+38 mm/year	—	—
Pearson Correlation	Rainfall vs Flood Events	$r = 0.87$	0.000	Significant

Chi-Square Test	Flood Experience vs Preparedness	$\chi^2 = 18.62; df = 2$	0.00009	Significant
Chi-Square Test	Early Warning Access vs Preparedness	$\chi^2 = 29.47; df = 2$	0.00001	Significant

Source: Computed from Meteorological Records (2005–2025), NEMA & AKSEMA Flood Records (2026), and Field Survey Data (2026)

Table 4.9: Logistic Regression Analysis of Determinants of Household Flood Preparedness

Variable	β Coefficient	Odds Ratio ($Exp\beta$)	p-value
Flood Experience	0.62	1.86	0.012
Education Level	0.74	2.09	0.003
Mobile Ownership	1.15	3.16	0.001
Access to Early Warning	1.42	4.14	0.000
Income Level	0.58	1.78	0.021
Model Statistics:	Nagelkerke $R^2 = 0.48$ Model Accuracy = 76.3% Hosmer–Lemeshow Test ($p = 0.62$) – Good Model Fit		

Source: Computed from Field Survey Data (2026).

The statistical analysis reveals a significant intensification of rainfall and flood risk in Akwa Ibom State over the past two decades. The Mann–Kendall test confirmed a strong upward rainfall trend ($\tau = 0.74, p < 0.001$), with Sen’s slope indicating an average annual increase of 38 mm. Additionally, rainfall showed a very strong positive correlation with flood events ($r = 0.87$), confirming rainfall as a major driver of flooding. Chi-square analyses further revealed significant associations between socio-environmental factors and preparedness. Flood experience was significantly related to preparedness level ($\chi^2 = 18.62, p < 0.001$), though many previously affected households still exhibited low preparedness. More importantly, access to early warning information showed a stronger association with preparedness ($\chi^2 = 29.47, p < 0.001$), demonstrating that early warning systems substantially improve disaster readiness.

Development Of A Mobile Technology-Based Community Early Warning System Framework For Flood Disaster Management In Akwa Ibom State



Figure 4.1 System Architecture Design

The proposed Community-Based Mobile Flood Early Warning System adopts a multi-layered, modular, and scalable architecture integrating hydrometeorological monitoring, geospatial analytics, community participation, and mobile communication technologies. The architecture is designed to ensure real-time data acquisition, automated flood risk computation, rapid multi-channel alert dissemination, and continuous feedback-driven system refinement. The system consists of six layers data acquisition layer, data integration and storage layer, processing and analytics layer, decision support layer, communication and alert dissemination layer, feedback and monitoring layer

Real-Time Data Acquisition

Table 5.1: IoT Rainfall Sensor Data Collected in Uyo LGA)

Date	Time	Rainfall Intensity (mm/hr)	24hr Cumulative (mm)	Soil Moisture (%)
12/02/2026	06:00	18	65	72
12/02/2026	12:00	35	112	81
12/02/2026	18:00	42	154	89
13/02/2026	06:00	28	178	91
13/02/2026	12:00	55	220	96
13/02/2026	18:00	61	248	98

The rainfall data show a progressive increase in both rainfall intensity and cumulative rainfall over the monitoring period. On 13/02/2026 at 12:00 and 18:00, rainfall intensity reached 55 mm/hr and 61 mm/hr respectively, exceeding the critical threshold of 50 mm/hr. Soil moisture levels also surpassed the saturation threshold of 90%, reaching up to 98%. These values indicate extreme hydrometeorological conditions with high runoff potential and elevated flood risk. The combination of intense rainfall and saturated soil significantly reduces infiltration capacity, increasing the likelihood of surface flooding.

Table 5.2: River Level Monitoring at Qua Iboe River)

Date	River Level (m)	Alert Threshold (m)	Status
12/02/2026	4.2	5.0	Safe
13/02/2026	4.8	5.0	Watch
14/02/2026	5.3	5.0	Exceeded
15/02/2026	5.8	5.0	Critical

Field Record (2026)

River levels show a steady upward trend from 4.2 m (Safe) to 5.8 m (Critical) within four days. The river exceeded the 5.0 m alert threshold on 14/02/2026 and reached critical status on 15/02/2026. This confirms that upstream rainfall translated into rising river discharge, validating the hydrological linkage between heavy rainfall and riverine flooding.

Table 5.3: SMS Flood Signal Reports

Report ID	Community	GPS Coordinates	Flood Depth (cm)	Road Passable (Yes/No)	Timestamp
SMS001	Itu	5.205N, 7.984E	15	Yes	13/02/2026 14:05
SMS002	Uyo	5.034N, 7.927E	45	No	13/02/2026 15:12
SMS003	Oron	4.810N, 8.240E	60	No	14/02/2026 08:21
SMS004	Eket	4.642N, 7.924E	30	Yes	14/02/2026 09:45

Field Record (2026)

Community-based SMS reports indicate varying flood depths across LGAs. Oron recorded the highest flood depth (60 cm), followed by Uyo (45 cm), both with roads reported as impassable. Itu (15 cm) and Eket (30 cm) experienced milder flooding with passable roads. The geo-tagged reports demonstrate effective last-mile data collection and confirm spatial variability in flood severity.

Table 5.4: Computed Flood Risk Score Dataset

Community	Rainfall Index	River Index	Soil Index	Community Index	FRS Score	Risk Level
Itu	65	55	72	40	58	Yellow
Uyo	82	70	88	65	77	Red
Oron	90	85	92	75	88	Red
Eket	60	50	68	45	55	Yellow

Field Record (2026)

The Flood Risk Score classification aligns with observed environmental conditions. Oron (FRS = 88) and Uyo (FRS = 77) fall within the Red (High Risk) category, reflecting high rainfall, river levels, soil saturation, and community-reported impacts. Itu (58) and Eket (55) fall under Yellow (Moderate Risk). The scoring system accurately integrates multi-source data into a coherent risk classification framework.

Table 5.5: Alert Dissemination Log

Alert ID	Community	Risk Level	Alert Channel	Time Sent	Delivery Success (%)
A001	Itu	Yellow	SMS + App	13/07/2025 15:30	96
A002	Uyo	Red	SMS + USSD + App	13/07/2025 16:00	94
A003	Oron	Red	SMS + IVR	14/07/2025 08:30	92
A004	Eket	Yellow	SMS	14/07/2025 10:00	97

Field Record (2026)

Alert delivery rates range from 92% to 97%, indicating high system reliability. Red-level communities (Uyo and Oron) received multi-channel alerts (SMS, USSD, App, IVR), demonstrating adaptive dissemination for high-risk situations. This confirms effective communication redundancy for critical warnings.

Table 5.6: Community Response Monitoring

Community	Alert Received (%)	Took Protective Action (%)	Evacuated (%)	Response Time (Minutes)
Itu	91	74	35	18
Uyo	94	82	58	12
Oron	89	86	63	10
Eket	93	71	29	20

Field Record (2026)

Communities classified as Red risk (Uyo and Oron) show higher protective action (82–86%) and evacuation rates (58–63%) with shorter response times (10–12 minutes). Yellow-risk communities recorded lower evacuation rates and slightly longer response times. This suggests that higher perceived risk levels prompt faster and more decisive community action.

Table 5.7 System Performance Summary

Metric	Result
Prediction Accuracy	84.6%
False Positive Rate	8.2%
Alert Delivery Rate	94.8%
Average Latency	2.4 minutes
Community Adoption Rate	87%

Field Record (2026)

The system demonstrates strong operational performance with 84.6% prediction accuracy and a low false positive rate (8.2%), indicating reliable flood forecasting. The alert delivery rate of 94.8% and average latency of 2.4 minutes confirm rapid and effective communication. A community adoption rate of 87% reflects high usability and acceptance of the mobile-based early warning platform.

DISCUSSION OF FINDINGS

The study reveals a clear intensification of flood risk in Akwa Ibom State driven by both climatic and socio-environmental factors. The Mann–Kendall trend test and Sen’s slope estimator confirmed a statistically significant increase in annual rainfall over the past two decades, consistent with global patterns of climate variability. The very strong correlation ($r = 0.87$) between rainfall and flood events underscores rainfall intensity as a primary driver of flooding, confirming the urgency for predictive early warning mechanisms. Chi-square

analyses highlighted that flood experience alone does not guarantee preparedness, as many previously affected households remained poorly prepared. This suggests that economic constraints, limited access to information, and inadequate institutional support impede effective disaster readiness. Conversely, access to early warning alerts showed a strong positive association with preparedness levels, demonstrating the critical role of timely and inclusive communication channels in enhancing community resilience.

The development of a mobile-based early warning system demonstrated the feasibility of integrating real-time sensor data, satellite-derived precipitation information, and community-sourced reports to generate accurate and rapid alerts. Multi-channel dissemination (SMS, USSD, mobile app, IVR) ensured broad accessibility, while the feedback loop allowed communities to validate and respond to flood threats effectively. Prototype testing indicated high system accuracy and adoption potential, affirming the value of participatory, technology-driven approaches to flood disaster management.

RECOMMENDATIONS AND CONCLUSION

- i. Government and disaster management agencies should implement the developed mobile early warning system across all flood-prone LGAs in Akwa Ibom State to improve early detection and response.
- ii. Continuous training and awareness campaigns should be conducted to enhance community understanding of flood risks, proper response protocols, and effective use of mobile-based alert platforms.
- iii. Agencies such as NiMet, NEMA, and AKSEMA should integrate the mobile system with existing disaster management frameworks to ensure synchronized real-time data sharing, rapid decision-making, and coordinated emergency response.
- iv. Provision should be made for the long-term technical maintenance, sensor calibration, software updates, and community engagement to ensure the system remains operational, accurate, and widely adopted.

Flood disasters in Akwa Ibom State are increasing in frequency and intensity due to rising rainfall and changing climatic conditions. This study successfully developed a community-based mobile early warning system that integrates IoT sensor networks, satellite data, community reports, and predictive analytics to enhance preparedness and response. Statistical analyses demonstrated that access to timely flood alerts significantly improves community readiness, while experiential knowledge alone is insufficient. The mobile-based system proved effective in rapid alert dissemination and participatory feedback, highlighting the potential for scalable, technology-driven interventions in flood-prone regions. Implementing such systems, alongside capacity-building and institutional integration, offers a sustainable pathway to mitigate the adverse impacts of floods and strengthen community resilience.

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