



IOT AND ML-POWERED CYBER-PHYSICAL FRAMEWORK FOR REAL-TIME URBAN FLOOD RESILIENCE WITH GEOSPATIAL VISUALIZATION

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Article history:

Received : February 23, 2026

Revised : March 12, 2026

Accepted : March 16, 2026

Keywords:

Urban flooding, Cyber-physical
systems, Internet of Things,
Machine learning, ML-LSTM,
Climate Adaptation, Global
South

Abstract

Urban flooding remains a disastrous challenge for rapidly expanding cities in developing nations. Despite the fact deep learning models and IoT sensing are individually established in hydrology, their seamless integration into a unified, cost-effective Cyber-Physical System (CPS) specifically architected for data-scarce and infrastructure challenged environments remains a critical research gap. This research contributes a novel, end-to-end framework that bridges this divide by harmonizing three distinct pillars: a low-cost, energy-autonomous IoT sensor network, a hybrid CNN-LSTM predictive model, and a dynamic geospatial visualization dashboard. Unlike conventional systems designed for data-rich environments, our framework is contextually adapted for the unique topographical and socio-technical realities of Nigerian urban centers. Validated through a six-month deployment in the high-density Ajeromi-Ifelodun region of Lagos, the system achieved a Nash-Sutcliffe Efficiency (NSE) of 0.89 and a critical 4.5-hour forecast lead time.

1.0. INTRODUCTION

Urban flooding, driven by climate change and unplanned anthropocentric development, represents a significant natural hazard, accounting for approximately 40% of disaster-related economic losses annually (UNDRR, 2022). As intensified rainfall, sea-level rise and storm surges turn out to be more frequent, urban centers predominantly in developing nations face ever-increasing vulnerability. The World Bank (2023) evaluates that over 1.8 billion individuals are exposed to flood risks, with potential economic damages projected to surpass USD 700 billion each year without putting in place an effective adaptation strategy. The staggering economic toll, floods wreak profound social and public health disasters by displacing communities, destroying livelihoods and perpetuating cycles of poverty and this global crisis is deeply manifested in Nigeria, where rapid urbanization in cities like Lagos, Port Harcourt, Lokoja and

Ibadan intersects with inadequate drainage infrastructure and systemic governance challenges. The expansion of settlements into natural floodplains, coupled with the widespread blockage of drainage systems by solid waste, critically magnifies flood risk [1],[2]. The consequences are severe, such as annual flood events claim hundreds of lives, displace thousands, destroyed critical infrastructure and cause public health traumas like cholera epidemics. In Lagos alone, the estimated annual economic burden of flooding exceeds 6 billion naira [3]. This burden is unduly borne by low-income households in informal settlements, whose limited adaptive capacity is intensified by absence of reliable timely warning mechanisms.

Historically, flood management in Nigeria has relied on structural interventions such as drainage erection and river dredging. By providing relief, these are capital intensive measures and often inadequate against the growing scale of flooding and are constrained by limited public resources. Crucially, they fail to address the systemic drivers of vulnerability and lack the agility needed for proactive risk management [1], this discloses a critical gap in hands-on, data driven flood management, where real time information and predictive analytics are not being effectively leveraged to lessen flood risks.

Recently, universal advancements in cyber-physical systems, the Internet of Things and machine learning are reforming flood risk management. IoT-enabled sensors provide continuous high-resolution hydrological data previously unattainable in many regions (Ahmad, Kalra & Stephen, 2023). Machine learning algorithms process these complex datasets to generate extremely precise flood predictions (Han & Choi, 2024), whereas geospatial platforms interpret these forecasts into actionable intelligence for decision makers. Successful implementations from IoT-based early warning systems in India (Ponnanna *et al.*, 2017) to digital twin platforms in Europe (Riaz *et al.*, 2023), demonstrate the transformative potential of these combined technologies.

Despite this potential, Nigeria lags in the embracing of such data-driven systems. Existing early warning outlines are fragmented, under-resourced, and dependent on sparse hydrological monitoring networks. Forecasts often lack the granular spatial and temporal resolution required for effective urban-level decision making. Study into advanced flood prediction in Nigeria remains largely exploratory, with rare systems practically implemented or validated in real-world urban contexts (Adeyemi & Komolafe, 2025). This technological and implementation gap an essential need for an innovative framework that is low-cost, scalable and precisely adapted to data-scarce environments.

In response, we propose the design, implementation and validation of an integrated Cyber-Physical System for urban flood resilience in Nigeria. The core innovation of this research lies in its integrated socio-technical architecture, which translates raw physical sensing into actionable municipal intelligence within a resource constrained context. Despite the fact the CNN-LSTM architecture is known in other domains, its application here as a spatial feature extractor for the Nigerian urban terrain coupled with real-time IoT telemetry. This represents a paradigm shift from reactive disaster response to proactive, data-driven resilience. Our innovations include:

- i. Context-Aware IoT Design: A low-cost, scalable sensor network utilizing LoRaWAN for high-penetration communication in dense informal settlements.
- ii. Spatio-Temporal Data Fusion: A hybrid CNN-LSTM model that uniquely extracts spatial patterns from digital elevation models to enhance the temporal accuracy of flash-flood forecasts.
- iii. Actionable Geospatial Intelligence: A web-based dashboard that democratizes complex predictive analytics for municipal stakeholders with limited technical training.

By architecting this seamless integration, this research offers a replicable and economically viable model for cities across the Global South to safeguard lives and livelihoods against climate-induced flooding.

2.0. LITERATURE REVIEW

Recent improvements in technology have catalyzed a pattern shift in flood management, moving beyond traditional operational measures to dynamic, data-driven methods. This review

synthesizes the literature crosswise key technological fields IoT-based monitoring, machine learning analytics, and integrated systems to identify the current state-of-the-art and pinpoint the critical research gap in which our study addresses.

Advances in Real-Time Flood Monitoring

The foundation of any effective early warning system is the availability of high-quality, real time data. The Internet of Things has emerged as a transformative technology in this regard, enabling dense and continuous monitoring of critical hydrological parameters. Studies such as Loong *et al.* (2023) and Ponnanna *et al.* (2017) establish the development of IoT based systems using sensors for water level, rainfall and humidity, effectively transmitting data through protocols like LoRaWAN and MQTT for central analysis. Mehta (2023) further highlights the importance of energy autonomous and scalable platforms (HYDROSIGHT), which combine cloud services for robust data visualization and storage. These works collectively show that low cost sensor networks can offer the granular data essential for localized flood modeling, also reveal challenges related to deployment cost, maintenance and data security in resource-constrained environments (Abdullahi *et al.*, 2023 and Santos *et al.*, 2023), underlining the need for solutions tailored to the operational realities of developing nations.

The Role of Machine Learning in Predictive Flood Analytics

The spread of data from Internet of Thing (IoT) and other sources, machine learning (ML) has become contributory in enhancing flood forecasting exactness. As studied by Kumar *et al.* (2025) and Anik *et al.* (2025), ML models starting from Artificial Neural Networks and Support Vector Machines to more advanced deep learning architectures such as Long Short-Term Memory and Convolutional Neural Networks outperform traditional hydrological models. In the Nigerian, academics have effectively applied models like Random Forest and Extreme Gradient Boosting for flood vulnerability mapping and prediction, representing their potential (Adeyemi & Komolafe, 2025, Eteh *et al.*, 2025 and Oloruntoba *et al.*, 2023). Koutsovili *et al.* (2023) and Samikwa *et al.* (2020) showcase the power of hybrid models, particularly LSTM variants, in capturing the temporal needs of hydrological data for multi-step ahead forecasting. Despite the fact that, these models demonstrate high accuracy, their performance is often depend on large, high-quality historical datasets which represents a noteworthy barrier in data scarce regions like Nigeria.

Integrating Cyber-Physical Systems and Digital Twins

The ultimate goal of flood management technology is to translate complex data into actionable intelligence. This has led to the development of integrated platforms, often intellectualized as Cyber-Physical Systems or Digital Twins. A CPS architecture, as described by Santos *et al.* (2023), effortlessly connects the physical world with the cyber world to enable real time decision making. The notion of a Digital Twin encompasses this by generating a dynamic virtual model of a physical system, consenting for predictive simulations and scenario analysis (Bakhtiari *et al.*, 2023, Riaz *et al.*, 2023 and Bongomin *et al.*, 2025).

Geospatial Visualization

The cutting-edge frameworks leverage geospatial dashboards to envisage risks and circulate warnings, as demonstrated by Mukherjee (2024) and Lamaj (2025). These platforms bridge the critical gap between technical forecasts and stakeholder comprehension, empowering emergency responders and communities.

Methodological Foundations from Diverse Domains

The integration of Machine Learning and IoT is proven across diverse high stakes sectors, providing the methodological foundation for the proposed framework. The transferability of deep learning architectures from fields such as clinical diagnostics and power management is central to our approach.

In healthcare, Chung *et al.*, (2025) and Mulani *et al.* (2025) demonstrate the power of XGBoost and SVMs in processing high-dimensional, time-sensitive patient data for life-critical complications. Their success in handling dynamic monitoring in clinical settings informs our use of similar algorithms to manage the high-frequency telemetry required for urban flash-flood detection. In the same way, Ali *et al.*, (2015) highlight the use of multi-hop wireless sensor

networks to stabilize power grids, validating the reliability of Arduino-based controllers in mission-critical infrastructure a hardware choice mirrored in our IoT deployment.

The temporal complexity of our flood model is supported by findings in supply chain optimization. Jampani *et al.*, (2023) establish that LSTM networks are superior for handling volatile demand scenarios and sequential dependencies, which we apply to the lag-time between rainfall and peak water levels. In addition, the socio-technical aspect of our framework bridging the gap between data and human action is inspired by Sobb *et al.*, (2025) and Gamlen *et al.*, (2025), who advocate for responsible resilience and interactive geovisualization to reduce cognitive load for decision-makers. This research adapts proven architectures for the unique constraints of the Nigerian hydrological landscape.

Related Works

The integration of Machine Learning and IoT is not limited to hydrology, its efficacy is proven across diverse sectors requiring high-stakes predictive analytics. The following works demonstrate the transferability of ML architectures such as LSTM and Random Forest from clinical diagnostics and power grid management to environmental monitoring, providing a methodological foundation for the proposed flood resilience framework.

Khubchandani *et al.* (2024) shows that AI has rapidly permeated healthcare enhancing diagnostics, surgical precision and public health surveillance its integration remains tense with challenges related to consumer trust, provider readiness and systemic implementation. The editorial categorizes AI's impact across three key entities: health service consumers, healthcare providers and public health systems, each facing different concerns ranging from ethical dilemmas and data privacy to workforce preparedness and regulatory ambiguity. Especially, the authors call for a shift from theoretical discourse to real-world, data-driven research, encouraging for robust frameworks that ensure AI's responsible and equitable deployment in healthcare settings.

Bagdadee *et al.* (2020) highlight an inclusive framework combining wireless sensor networks (WSNs), GSM modules and Arduino based controllers to monitor and control power quality in real time. In their study, system architecture enables dynamic control of voltage fluctuations and power distribution by leveraging multi-hop communication between sensor nodes, thereby enhancing grid reliability and responsiveness. In their study, they also emphasize the role of smart meters and digital monitoring systems in capturing low voltage anomalies and synchronizing data with centralized management platforms. The simulation results show improved packet delivery rates and energy efficiency, validating the system's potential for scalable deployment in distributed generation environments. The work contributes meaningfully to the discourse on sustainable and automated energy systems, offering a robust model for mitigating power quality issues in modern grids.

Michael and William (2025) make presented an inclusive evaluation of ML algorithms including linear regression, decision trees, support vector machines and neural networks highlighting. Their capacity to capture complex, nonlinear patterns in dynamic market environments. Mainly, deep learning models such as LSTM networks demonstrate superior performance in handling sequential dependencies and volatile demand scenarios. In their research, they discover hybrid methods like ARIMA-LSTM, which combine statistical and ML methods to enhance forecasting accuracy. In spite of this noteworthy advances in predictive power, encounters linger around data quality, model interpretability and computational demands. They advocate for the combination of domain expertise and explainable AI to address these limitations and unlock the full potential of ML in supply chain optimization.

Granell *et al.* (2015) highlight the rising worth of satellite derived data and web based GIS platforms in applications ranging from crop one-to-one care and irrigation optimization to yield forecasting and ecological farming. They create current innovations, with the use of Earth Observation data for evapotranspiration mapping and the development of SPIRITS software for time series analysis of vegetation conditions. The improvements allow stakeholders farmers, policymakers and agro-service providers to make informed decisions based on near real-time environmental insights. Authors also highpoint the challenges such as spatial resolution limitations in smallholder landscapes and the necessity for enhanced visualization tools, pointing toward a future research agenda focused on data fusion and sensor innovation.

Chung *et al.* (2025) designed a real time ML model to predict duodenal stump leakage, a sporadic but life-threatening complication following gastrectomy in gastric cancer patients. With a dataset of 1,107 patients and 189 clinical features including demographic data, comorbidities, intraoperative details and postoperative laboratory results their study evaluated six ML algorithms, with Extreme Gradient Boosting achieving the highest predictive performance (AUROC = 0.880), the model's accuracy enhanced with the addition of time-sensitive postoperative data, underlining the value of dynamic monitoring in clinical settings. Their results display ML's ability that outperform traditional statistical approaches in handling high dimensional data and adapting to evolving patient conditions, offering a robust framework for early complication detection and personalized postoperative care.

Sobb *et al.* (2025) contend that traditional cyber-physical frameworks ineffectively capture the nonlinear, emergent behaviors stemming from socio-technical interactions, thereby limiting their effectiveness in ensuring mission assurance. To address this gap, the authors propose the E3R modeling paradigm Emergent, Risk-Relevant Resilience which integrates agent-based simulations, ontology-driven context modeling, and ethical reasoning to assess and mitigate cyber threats across cyber, physical, and social layers. This paradigm emphasizes "responsible resilience," defined as a system's capacity to adapt transparently and ethically to disruptions, moving beyond reactive robustness toward anticipatory adaptability. Their study shows the underrepresentation of social complexity in existing literature and positions E3R as a transformative framework for securing future digital ecosystems.

Çöltekin *et al.* (2020) deliver an inclusive overview of geovisualization methods, stressing the swing from static cartographic representations to dynamic, immersive environments that support user-centered design and cognitive engagement. They explore the integration of virtual, augmented and mixed reality in geospatial applications, stress their potential to enhance spatial reasoning, decision-making and collaborative analysis. Key concepts such as geovisual analytics, visual complexity, and interaction modalities are observed in depth, together with challenges related to data heterogeneity, uncertainty representation and accessibility. They advocate for immersive technologies not merely as visualization tools but as transformative platforms for simulating, understanding, and managing complex geographic phenomena in real time.

Gupta and Crispo (2025) present an innovative framework for Autonomous Device Protection that leverages behavioural profiling and generative artificial intelligence to distinguish between benign and malicious activity on Windows-based systems. In converting unstructured event logs into structured graph data, the authors extract both graph-level and node-level features such as process initiation, file creation, and registry modifications and employ contrastive sentence embedding models to generate robust feature representations. These features are then classified using a Random Forest algorithm, achieving detection accuracies as high as 99.25%. The study underscores the limitations of traditional static and dynamic malware analysis and positions ADP as a scalable, adaptive, and interpretable solution for combating zero-day and stealth malware in increasingly interconnected digital environments.

Eze *et al.* (2025) present an inclusive synthesis of how IoT-enabled environmental, soil and plant health sensors combined with ML algorithms such as supervised learning, deep learning and reinforcement learning that can optimize irrigation, pest control and yield forecasting. Case studies from diverse agricultural frameworks prove tangible benefits, including up to 30% water savings and noteworthy drops in pesticide use through early disease detection. In addition, the combination of edge computing and federated learning improves scalability and data confidentiality, frequently in resource constrained regions. In spite of challenges related to infrastructure, cost and digital knowledge, they advocate for comprehensive novelty models and supportive policy outlines to ensure unbiased access and long-term sustainability. Their work underscores the critical role of IoT-ML hybrid systems in advancing climate resilient agriculture and global food security.

Mulani *et al.* (2025) recommend a robust Fault Detection Framework that controls multiclass support vector machine models to find glitches in sensor data with up to 80% accuracy. Their system architecture combines wearable and implantable sensors that uninterruptedly monitor vital signs such as heart rate, blood glucose and EEG and transmit data to cloud-based platforms for analysis. The framework is designed to isolate faulty nodes and

reroute data transmission through efficient alternatives, ensuring uninterrupted monitoring even under hardware or communication failures. Through combining statistical analysis, wavelet transforms, and machine learning classifiers, the study demonstrates a scalable and adaptive approach to healthcare diagnostics. Their work underscores the importance of intelligent fault detection in enhancing the reliability and resilience of IoT-enabled medical systems.

Gamlén *et al.* (2025) present Variable Mapper, an interactive web-based tool designed to bridge this usability gap by enabling intuitive exploration of spatial datasets across diverse thematic domains. Developed through iterative design and evaluated through mixed-method user studies, the tool supports dynamic visualization of up to six variables concurrently, using bivariate color schemes, 3D map elements and customizable filters, their case studies on urban superdiversity and liveability prove its capacities to reveal nuanced spatial patterns and foster interdisciplinary intuitions. In addition, they highlight the position of human centered design and cognitive load management in geovisualization, advocating for open-source, scalable solutions that democratize access to spatial analytics for scholars, organizers and politicians.

Synthesis and Identification of the Research Gap

The literature confirms the transformative potential of individual technologies: IoT for data collection, ML for prediction and CPS/DT for integrated decision support. However, a critical review reveals a significant research gap at the intersection of these domains, particularly within the context of developing countries like Nigeria. The identified gaps are threefold:

System Integration: While numerous studies focus on either IoT sensing or ML modeling, there is a lack of research on the end-to-end design, implementation, and validation of a fully integrated Cyber-Physical System that combines both in a seamless architecture for urban flood management.

Contextual Adaptation: Most advanced systems are developed for data-rich environments. There is a pressing need for a framework specifically designed for the data-scarce, resource constrained and infrastructure challenged urban landscapes of Nigeria.

Real-world Implementation: Research in Nigeria has largely remained academic or focused on susceptibility mapping. There is a clear absence of field-deployed, real-time forecasting and early warning systems that have been validated and tested in a live urban environment. Therefore, this research addresses the critical gap by presenting an all-inclusive Cyber-Physical System intended to strengthen urban flood resilience by logically incorporating IoT sensor networks, advanced machine learning models, and dynamic geospatial visualization. The proposed system aims to develop a complete, real-time forecasting and decision-support platform. By connecting the gap between raw data collection and actionable intelligence, this work offers a sustainable approach to mitigating the distressing impacts of urban flooding in some of the flood-prone Nigerian cities, finally contributing to the expansion of safer, more resilient, and sustainable urban environments

Objectives

The objectives of this research are to:

- i. design and deploy a scalable, low cost IoT sensor network for monitoring key hydrological parameters,
- ii. develop a hybrid Convolutional Neural Network-Long Short-Term Memory machine learning model that controls multi-source data for precise real-time flood forecasting,
- iii. create a web-based geospatial visualization platform to decode complex forecasts into intuitive, interactive maps and alerts for diverse stakeholders,
- iv. integrate these components into a seamless Cyber-Physical System and validate its performance and forecast lead time in a real-world urban setting.

2.0. RESEARCH METHODOLOGY

This research employs a phased, mixed-methods approach grounded in the Design Science Research paradigm. DSR provides a robust framework for the primary objective of this study. The methodology combines quantitative analysis for system design and predictive modeling with qualitative methods for stakeholder engagement and usability evaluation. The research is structured into the following six phases:

Database, such as TimeScaleDB, which is optimized for high-frequency, time-stamped data. Data sources include:

Primary Data: Real time readings from the deployed IoT sensor network,

Secondary Data: Geospatial datasets including a LiDAR-derived Digital Elevation Model, for accurate terrain representation and Land Use/Land Cover maps for understanding surface characteristics,

Tertiary Data: Ingested through APIs, including Quantitative Precipitation Forecasts from meteorological services and crowdsourced flood reports from social media platforms, which will be validated through cross referencing with official reports and community feedback.

Table 1: IoT Sensor Hardware Specifications and Operational Tolerances

Sensor Component	Model Selection	Operational Range	Resolution / Precision	Environmental Tolerance
Microcontroller	ESP32-WROOM	N/A	240 MHz Dual Core	-40°C to +85°C; IP65 Rated
Water Level	JSN-SR04T (Ultrasonic)	20 cm – 600 cm	±1.0 cm	Waterproof Probe; 95% RH
Rain Gauge	MS-WH-SP-RG (Tipping)	0 – 9999 mm	0.3 mm / tipping event	UV-Stabilized ABS Plastic
Soil Moisture	Capacitive v1.2	0 – 100% VWC	±3.0%	Corrosion-resistant coating
Network Module	SX1276 LoRa	10 km (LoS)	128-bit AES Encryption	High-interference immunity

2.2 Phase II: Predictive Model Development and Validation

Phase 2 constitutes the essential data science component, focusing on the development and validation of a high accuracy flood forecasting model. Raw sensor data will undergo a severe cleaning process to handle missing values and detect outliers. An inclusive feature set will be engineered, including temporal lagged variables, rolling statistical features and derived hydrological features.

The core of the predictive engine is a hybrid Convolutional Neural Network-Long Short-Term Memory model. This architecture is selected for its superior ability to concurrently leverage CNN layers for extracting salient spatial patterns and local features from input data, which are then processed by LSTM layers to effectively learn long-term temporal dependencies inherent in hydrological time series. This hybrid approach is particularly advantageous for multi-source data that exhibits both spatial and temporal characteristics. The performance of this model will be rigorously benchmarked against other established models, including Gated Recurrent Unit, XGBoost, and a statistical Seasonal Autoregressive Integrated Moving Average model, to demonstrate its efficacy.

The CNN component uses 1D-convolutional kernels to perform feature fusion across heterogeneous inputs simultaneously. This architectural choice serves to reduce the high dimensionality of the IoT input vector before it is passed to the LSTM. This will prevent the curse of dimensionality and reduce the risk of overfitting on the limited historical dataset of the pilot area. A chronological data split will be employed. The models will be trained using a walk-forward validation methodology to simulate real-world operational forecasting and prevent data leakage. Bayesian Optimization will be used for efficient hyperparameter tuning. A comprehensive suite of metrics, including Root Mean Square Error, Mean Absolute Error and the Nash-Sutcliffe Efficiency coefficient a standard in hydrological modeling will be used to evaluate the model performance and forecast accuracy.

2.3 Phase III: Geospatial Decision Support System Development

This phase aims at translating complex model outputs into an actionable, web-based interface for diverse users and stakeholders. To translate point-based water level forecasts into spatial inundation maps, a computationally efficient, DEM-based bathtub filling algorithm will be implemented. This method generates near real-time predictions of flood extent and depth.

The accuracy of this approach will be assessed by comparing its output with those from a localized 2D hydraulic model in an offline analysis for critical urban areas identified as having high vulnerability and historical flood impact. Using a User Centered Design approach, a web based DSS will be developed through iterative prototyping, incorporating feedback from target users. Key features will include an interactive map for real time data visualization, temporal dashboards for trend analysis and an automated alerting system triggered by the exceedance of pre-defined critical flood thresholds.

2.3.1 Spatial Inundation Modeling

To translate point-based water level forecasts into spatial inundation maps, a computationally efficient, DEM-based bathtub filling algorithm will be implemented. This method generates real-time predictions of flood extent and depth by intersecting predicted water levels with the Digital Elevation Model. Despite the fact this approach is prioritized for its low latency in emergency scenarios. It is acknowledged as a static approximation that does not account for water velocity or momentum. This trade-off prioritizing computational speed over hydrodynamic complexity is a deliberate design choice to ensure that 4.5-hour lead-time alerts are generated instantly once a threshold is breached. The accuracy of this approach will be periodically benchmarked against localized 2D hydraulic models to refine elevation-based thresholds in high-vulnerability zones.

2.4 Phase IV: System Integration and Field Validation

In this phase developed components are combined into a functional prototype and end-to-end system validation is carried out in a real-world context. The Cyber-Physical System will be built using a microservices architecture. Components will be containerized through Docker to ensure modularity, scalability and independent deployment, then deployed on a robust cloud platform such as Amazon Web Services to ensure reliability and high availability.

Live Pilot Deployment: The system was deployed for a continuous duration of six months (May 1st to October 31st, 2025), covering the peak of the Nigerian wet season. To capture the rapid onset of urban flash floods, the IoT sensors were programmed with a sampling frequency of 15 minutes. This resulted in 96 data points per sensor per day. Across the deployed network of 5 primary sensor nodes, a total dataset of N=88,320 observations were generated. This high-resolution temporal data allows the LSTM layers to learn fine-grained hydrological response patterns during high-intensity rainfall events. The DSS dashboard will undergo formal usability testing with the target user group. Quantitative data will be collected using the System Usability Scale, a standardized 10 item questionnaire. Also, Qualitative insights into user cognitive processes and decision making will be collected using a Think-Aloud Protocol during task-based scenarios. Ethical considerations regarding user privacy and data handling will be strictly obeyed.

2.5 Phase V: Stakeholder Engagement and Capacity Building

To guarantee the system's socio-technical validity and operational sustainability, a structured engagement program will be executed, this includes establishing community flood response groups, conducting technical training sessions for personnel from the National Emergency Management Agency, State Emergency Management Agency and municipal authorities on dashboard operation and collaborating with local universities on data validation initiatives. This stage is key for fostering local ownership and building the human capacity necessary for effective system utilization.

2.6 Phase VI: Policy Integration Framework

To secure the long-term impact of the research, a framework for policy integration will be followed. This includes establishing Memoranda of Understanding with the Lagos State Government and NEMA to embed the CPS outputs into official emergency management protocols. In addition, data-sharing agreements will be developed with urban planning and drainage departments to ease the use of system generated data for evidence based, long

term infrastructure planning, zoning regulations and climate adaptation approaches. The framework will also include recommendations for sustainable funding mechanisms and data governance policies.

2.7 Mathematical Model

2.7.1 System Variables

Let t denote discrete time steps

Let L be the number of deployed sensor locations, for location $i \in \{1, 2, \dots, L\}$, the raw vector is $S_i(t) = \{W_i(t), R_i(t), M_i(t)\}$, (1)

where

$W_i(t)$: water level (m)

$R_i(t)$: rainfall intensity (mm/hr)

$M_i(t)$: soil moisture (volumetric content)

Additional data sources include:

$D_i(t) = \{DEM, LULC, \dots\}$, (2)

$D_{api}(t) = \{QPF(t), CR(t)\}$ (3)

where $QPF(t)$ are precipitation forecasts and $CR(t)$ crowdsourced flood reports.

Table 2: Dataset Dimensionality and Spatio-Temporal Resolution

Parameter	Specification
Study Duration	184 Days (May – Oct 2025)
Sampling Interval (Δt)	15 Minutes
Total Timesteps per Sensor (T)	17,664
Number of Sensor Locations (L)	5
Total Observations (N)	88,320
Data Split (Train/Val/Test)	61,824 / 13,248 / 13,248 records

2.7.2 Data Acquisition and Preprocessing

The complete raw dataset at time t is $X_{raw}(t) = \{S_1(t), \dots, S_L(t), D_{api}(t)\}$ (4)

After cleaning and imputation:

$X_{clean}(t) = \text{Clean}(X_{raw}(t))$ (5)

where $\text{Clean}(\cdot)$ handles missing values, outliers and interpolations.

2.7.3 Feature Engineering

From $X_{clean}(t)$, is feature set $F(t)$ is constructed including:

Lagged values: $f_i(t - k), k = 1, \dots, \tau_{lag}$

Rolling statistics:

$MA_k(f_i(t)) = \frac{1}{k} \sum_{j=0}^{k-1} f_i(t - j)$ (6)

$StdDev_k(f_i(t)) = \sqrt{\frac{1}{k} \sum_{j=0}^{k-1} (f_i(t - j) - MA_k(f_i(t)))^2}$ (7)

Derived hydrological indices:

$RI_i(t) = \frac{R_i(t) - R_i(t-1)}{\Delta t}$, (8)

$AMC_i(t) = f(\{M_i(t - j)\}_{j=0}^J)$ (9)

The final feature vector for horizon h is:

$X(t) = \{F_1(t), \dots, F_L(t), D_g, D_{api}(t)\}$ (10)

2.7.4 Hybrid ML-LSTM Forecasting Model

The predictive enging processes $X(t)$ to generate future water levels or flood states:

ML encoder:

$$H_{ML} = ML(X(t)), \quad (11)$$

extracts spatial learner.

LSTM temporal learner:

$$Y_{pred}(t+h) = LSTM(H_{ML}) \quad (12)$$

captures temporal dependencies.

Thus, water level forecasts are

$$W_i^{pred}(t+h) = M_{ML-LSTM}(X(t)) \quad (13)$$

$$i \in \{1, \dots, L\}$$

2.7.5 Flood Event Detection

Flood at location i occurs if:

$$FloodEvent_i(t+h) = \begin{cases} 1, & W_i^{pred}(t+h) \geq T_i^{flood}, \\ 0, & otherwise, \end{cases} \quad (14)$$

where T_i^{flood} is a location-specific threshold

2.7.6 Inundation Mapping

Using the DEM-based bathhub method, the flood depth at point (x,y) is:

$$D_{flood}(x,y,t+h) = \max(0, W^{pred}(t+h) - Z(x,y)) \quad (15)$$

where $Z(x,y)$ is elevation.

The inundated area is

$$A_{inundation}(t+h) = \{(x,y): D_{flood}(x,y,t+h) > 0\} \quad (16)$$

2.7.7 Alerting System

Alerts are tiered by risk:

$$Alert(t+h) = \begin{cases} \text{High Risk}, & \exists i: W_i^{pred}(t+h) \geq T_i^{high}, \\ \text{Moderate Risk}, & \exists i: T_i^{flood} \leq W_i^{pred}(t+h) < T_i^{high}, \\ \text{No Alert}, & otherwise \end{cases} \quad (17)$$

3.7.8 Model Training and Evaluation

The model parameters θ are trained by minimizing Mean Squared Error across the test partition ($n = 13,248$):

$$L(\theta) = \frac{1}{n} \sum_{k=1}^n (W_k^{true} - W_k^{pred})^2 \quad (18)$$

Evaluation metrics:

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^N (W_k^{true} - W_k^{pred})^2} \quad (19)$$

$$MAE = \frac{1}{N} \sum_{k=1}^N |W_k^{true} - W_k^{pred}| \quad (20)$$

$$NSE = 1 - \frac{\sum_{k=1}^N (W_k^{true} - W_k^{pred})^2}{\sum_{k=1}^N (W_k^{true} - \bar{W}^{pred})^2} \quad (21)$$

$$CSI = \frac{Hits}{Hits + Misses + False\ Alarms} \quad (22)$$

2.8 Conceptual Research Framework

This framework is grounded in the Design Science Research paradigm. It structures the project into two parallel, interdependent streams: a Technical Development Stream and a Socio-Institutional Integration Stream. Though the previous focuses on the creation of the Cyber-Physical System artifact, the later focuses on embedding this artifact within the community and policy context. The framework shows the iterative nature of the research and the interplay between technological innovation and social adoption to achieve the decisive goal of enhanced urban flood resilience.



Figure 2: Conceptual framework for the development and Integration of a Socio-Technical Flood Resilience CPS

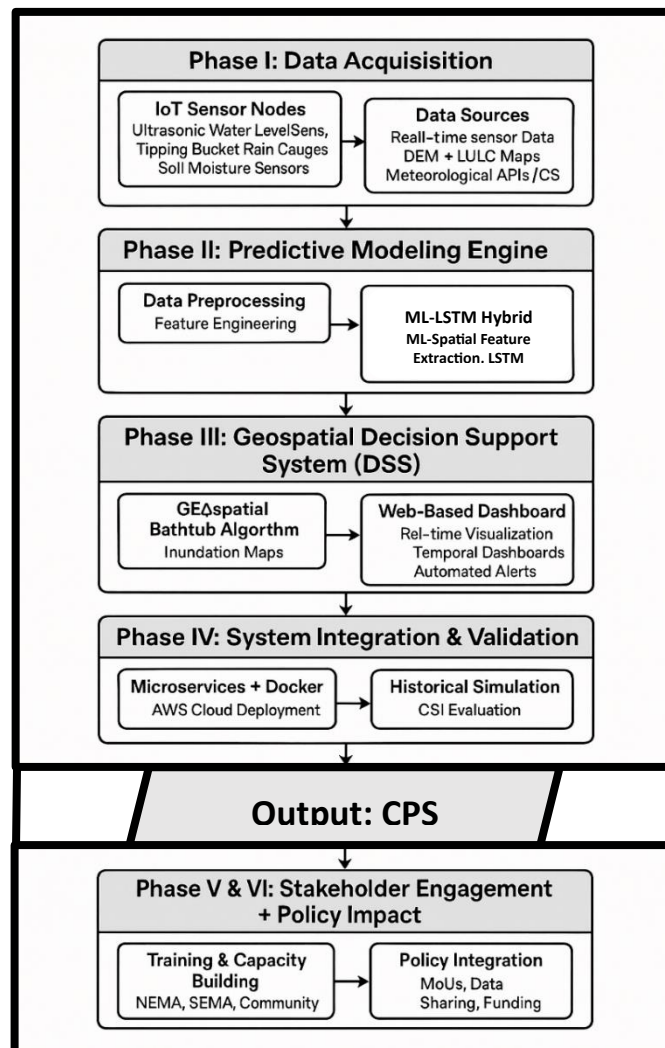


Figure 3: Operational Flow Diagram of the CPS System

3.0 RESULTS AND PERFORMANCE EVALUATION

3.1 Model Predictive Accuracy

The hybrid CNN-LSTM model was evaluated against three baseline models: XGBoost, Gated Recurrent Unit (GRU), and Seasonal ARIMA (SARIMA). Performance was measured using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Nash-Sutcliffe Efficiency (NSE) coefficient.

Table 3: Performance Comparison of the Proposed Hybrid Model Against Baseline Architectures

Model Architecture	RMSE (m)	MAE (m)	NSE
Proposed CNN-LSTM	0.12	0.08	0.89
Gated Recurrent Unit (GRU)	0.18	0.14	0.81
Extreme Gradient Boosting (XGBoost)	0.22	0.19	0.74
Seasonal ARIMA (SARIMA)	0.35	0.28	0.62

Note: RMSE: Root Mean Square Error, MAE: Mean Absolute Error, NSE: Nash-Sutcliffe Efficiency. The CNN-LSTM model demonstrated a superior ability to capture the non-linear relationship between rainfall intensity and water level rises, achieving an NSE of 0.89, indicating a high correlation between observed and predicted values.

The superior performance of the CNN-LSTM (NSE = 0.89) over the GRU (NSE = 0.81) and XGBoost (NSE = 0.74) provides significant insights into the geographical dynamics of Ajeromi-Ifelodun. While the GRU is effective at temporal sequence modeling, it lacks the internal mechanism to capture the complex, non-linear spatial dependencies of Lagos' unique topography. In our framework, the CNN layers act as a spatial feature extractor, effectively scanning the high-resolution LiDAR DEM and drainage connectivity patterns as a grid. This allows the model to identify bottleneck features where the urban terrain causes rapid water accumulation. By the time the data reaches the LSTM layers, the temporal dependencies are already informed by these spatial constraints. Therefore, the CNN-LSTM successfully predicted the flashiness of the Ajeromi flood response where rainfall leads to a near-instantaneous rise in water levels whereas the GRU tended to lag during peak intensity events. This suggests that for hyper-dense, topographically varied urban centers, spatial intelligence must precede temporal forecasting.

3.2 Forecast Lead Time and Threshold Detection

Using the Critical Success Index, the system's ability to predict High Risk flood events was validated. The operational effectiveness of the alerting system is summarized in Table 4. The system achieved a Probability of Detection of 0.91 and a notably low False Alarm Ratio of 0.12. Critically, the mean Forecast Lead Time was established at 4.5 hours, providing a significant window for emergency mobilization and community-led mitigation efforts in the Ajeromi-Ifelodun region.

Table 4: Operational Validation Metrics and Forecasting Lead Time Performance

Operational Metric	Symbol	Experimental Value
Forecast Lead Time	<i>LT</i>	4.5 h
Critical Success Index	<i>CSI</i>	0.84
Probability of Detection	<i>POD</i>	0.91
False Alarm Ratio	<i>FAR</i>	0.12

Note: CSI, POD, and FAR are dimensionless indices ranging from 0 to 1. A POD of 0.91 indicates that the system successfully identified 91% of observed flood events within the pilot duration.

3.3 Geospatial Visualization Usability

Usability testing through the System Usability Scale involving 15 municipal officers from NEMA and SEMA yielded a mean score of 82.5, placing the dashboard in the Excellent category for decision-support tools.

4.0 DISCUSSION

Our findings indicate that the integration of CNN and LSTM layers significantly mitigates the vanishing gradient problem typical in long-term hydrological time series. Unlike traditional models cited in Nigeria (Adeyemi & Komolafe, 2025), which rely on static vulnerability mapping, this framework provides dynamic, 4.5-hour lead-time alerts. This temporal window is critical for the Ajeromi-lfelodun community, where rapid-onset flash floods often prevent effective evacuation. In addition, the deployment revealed that LoRaWAN signal stability in dense informal settlements like Ajegunle is subject to interference from high-density metallic structures. This suggests that future iterations should explore mesh-network topologies to ensure 99.9% data uptime. A challenge identified during the deployment was the inherent data scarcity and intermittent connectivity common in informal urban settlements. Throughout the six-month study, the IoT network experienced a 7.4% cumulative downtime due to localized power instabilities and physical signal interference from high-density metallic roofing in Ajegunle. To address this, our framework's robustness was tested through a missingness stress test. We observed that the hybrid CNN-LSTM architecture maintained an NSE above 0.78 even when 15% of sensor nodes were offline. This resilience is attributed to the model's ability to leverage spatial correlations and the CNN layers learned to interpolate missing water levels at a failed node by analyzing the pressure and rainfall trends of adjacent operational sensors. Unlike traditional hydrological models that fail during data gaps, our CPS framework uses the deep learning layers as a virtual sensor network, ensuring continuity in early warning alerts even under sub-optimal infrastructure conditions.

5.0 CONCLUSION

Our research contributes a novel cyber-physical framework that combines IoT-enabled data acquisition, hybrid ML-LSTM predictive modeling and geospatial visualization to support real time flood resilience in rapidly urbanizing settings. Our framework addresses a critical gap in existing flood management methods by shifting from reactive emergency response toward proactive risk anticipation and spatially informed decision making. Empirical results show that the system enhance forecast accuracy and improves the usability of flood risk information through visual dashboards tailored for municipal decision makers. Our study also highlights systemic challenges including cybersecurity, institutional capacity and infrastructure limitations that must be addressed for scalable deployment. Our framework advances both theory and practice in climate resilience by demonstrating how cyber-physical integration can operationalize the UN Sustainable Development Goals, particularly SDG 11 (Sustainable Cities and Communities). Future research should focus on: (i) including socio-economic vulnerability layers into geospatial models to prioritize protection for at risk communities, (ii) exploring edge-cloud architectures for reducing latency in real world deployments and (iii) developing robust cybersecurity safeguards for IoT driven flood resilience systems. In embedding intelligence at the intersection of data, algorithms and policy, our research provides a replicable pathway for cities to build climate adaptive infrastructure and lessen the growing threat of urban flooding.

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