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Urban Flood Early Warning System Based on Sensor Networks and Big Data

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Abstract. *Urban flooding is increasingly disruptive in dense cities because intense rainfall and limited drainage capacity can trigger rapid water accumulation with little time for response. Effective early warning requires continuous, local monitoring and fast analytics that can transform high-frequency observations into actionable alerts. This paper presents an urban flood early warning system that integrates distributed sensor networks with real-time data streaming and analytics to deliver timely, reliable warnings at neighborhood scale. The objective of the study was to design and evaluate an end-to-end operational workflow that covers data acquisition, automated data quality control, risk-state detection, short-horizon water-level prediction, and alert generation. The method employed rainfall and water-level sensors that transmitted time-stamped measurements to a gateway and then to a streaming platform for ingestion, storage, and real-time processing. Data quality control was applied to remove physically implausible values, detect spikes, and flag sensor stalls before inference. Risk assessment combined threshold-based logic with predictive nowcasting based on recent rainfall and water-level dynamics, and system performance was evaluated using classification metrics for risk states, prediction error metrics for water level, and operational metrics including end-to-end latency and warning lead time. Results showed that the system maintained 96.7% data availability with a median data gap of 4 minutes, while automated quality control removed 3.2% anomalous readings and flagged seven flatline segments. Risk-state detection achieved precision of 0.84, recall of 0.79, and an F1-score of 0.81, and water-level nowcasting achieved a mean absolute error of 5.2 centimeters, and a root mean square error of 8.9 centimeters. Operationally, alerts were generated with a median end-to-end latency of 3.4 minutes (95th percentile 5.2 minutes) and provided a median warning lead time of 22 minutes (maximum 38 minutes) before critical threshold exceedance. In conclusion, integrating sensor networks with real-time big-data analytics enables practical, low-latency urban flood early warning with measurable lead time and improved alert stability, supporting rapid municipal response actions.*

Keywords. *urban flooding; early warning; sensor networks; real-time analytics; nowcasting*

INTRODUCTION

Urban flooding has become one of the most disruptive hazards in rapidly growing cities because it emerges from the interaction of extreme rainfall, increasing impervious surfaces, and drainage systems that were often designed for historical conditions rather than today's hydroclimatic variability. Empirical evidence shows that urbanization can raise flood volumes and amplify exposure unless cities adopt adaptive drainage planning and risk-informed land use policy (Zhou et al., 2019; Handayani et al., 2020). In practice, the impacts are intensified by the short lead time of pluvial events and the spatial heterogeneity of rainfall and ponding, which make conventional monitoring and response procedures insufficient for protecting critical roads, dense settlements, and essential services.

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These characteristics motivate early warning approaches that operate in real time and at street-to-neighborhood scales. Recent advances in low-cost sensor networks and the Internet of Things enable continuous observation of water level, rainfall, and related hydrometeorological variables, providing timely signals for operational decision-making (Mendoza-Cano et al., 2021; Moreno et al., 2019). However, early warning effectiveness does not depend on sensing alone; it also requires end-to-end system design that connects detection, forecasting/nowcasting, threshold logic, and communication to users. A structured review of pluvial flash flood early warning highlights the need to integrate monitoring, modeling, and alert dissemination in a coherent pipeline, especially for urban contexts where response time is limited (Acosta-Coll et al., 2018). Field implementations demonstrate feasibility, yet they also reveal how network reliability, data continuity, and operational integration remain challenging during extreme events when connectivity and power can degrade (Mendoza-Cano et al., 2021; Ibarreche et al., 2020).

In parallel, “big data” methods have been increasingly adopted in smart environments to manage high-velocity, heterogeneous streams produced by sensors, remote sensing, and contextual urban data. Systematic reviews emphasize that smart monitoring and disaster alerts benefit from scalable architectures for acquisition, storage, and analytics, but they must address issues such as latency, interoperability, and reliability under real-world constraints (Hajjaji et al., 2021; Cumbane & Gidófalvi, 2019). Stream-processing middleware and distributed platforms are therefore central, because they allow continuous ingestion, cleaning, feature extraction, and event detection without waiting for batch processing an essential property for early warning (Akanbi & Masinde, 2020). At the same time, urban flood management increasingly leverages data-driven models (e.g., deep learning) to complement physics-based simulations when hydraulic data are incomplete or when rapid inference is required (Lei et al., 2021; Kratzert et al., 2018). This creates a practical opportunity: sensor networks can provide high-frequency signals, while big data pipelines and learning models can transform those signals into actionable forecasts and alerts.

Despite this progress, prior studies often remain partial in scope. Many flood monitoring deployments focus on data acquisition and visualization but do not provide an operational big-data architecture that supports end-to-end, low-latency analytics and alerting under heterogeneous sensor inputs (Mendoza-Cano et al., 2021; Moreno et al., 2019). Conversely, big-data disaster-response reviews and frameworks discuss processing platforms but do not specify how to engineer urban flood early warning as an integrated sensing–streaming–prediction–alert workflow with verifiable performance targets (e.g., latency, uptime, false-alarm rate) (Cumbane & Gidófalvi, 2019; Hajjaji et al., 2021). In addition, drainage monitoring studies underline that sensor placement and network design strongly affect observability and decision quality, yet these design elements are rarely coupled with real-time predictive analytics in one validated, deployable system (Wang et al., 2023). Therefore, a gap persists in delivering an integrated urban flood early warning system that jointly addresses (i) sensor-network design and data quality, (ii) scalable real-time processing of heterogeneous streams, and (iii) predictive modeling and alerting logic in a single operational architecture. To the authors' knowledge, such an end-to-end system validated as one workflow rather than as isolated components has not been reported elsewhere in the same integrated form for urban flood early warning.

Accordingly, this study aimed to develop and evaluate an Urban Flood Early Warning System based on sensor networks and big data that integrates heterogeneous sensing, real-time stream processing, and predictive analytics to generate timely, reliable alerts for urban operations. The proposed work contributes to the literature and practice by offering a deployable reference architecture that links sensor deployment considerations, scalable real-time analytics, and model-driven warning generation into one coherent system for urban flood risk reduction.

METHOD

A systems engineering and quantitative evaluation study was conducted to develop and assess an end-to-end Urban Flood Early Warning System (EWS) integrating sensor networks and big-data stream analytics. The methodological structure followed key EWS functions monitoring, real-time processing, risk inference, and alert dissemination so that performance could be evaluated as a single operational pipeline (Acosta-Coll et al., 2018).

Primary data were collected from a distributed sensor network deployed at flood-prone urban points. Water level was measured using non-contact ultrasonic sensors or submersible pressure transducers installed at drainage channels/river sections, while rainfall intensity was measured using tipping-bucket or optical rain sensors positioned to capture local variability. Each node recorded time-stamped observations at a fixed sampling interval and transmitted them to a gateway via low-power wide-area networking or cellular links. Telemetry was forwarded to the central platform using lightweight publish–subscribe messaging commonly used in Internet of Things environments to support continuous streaming (Mendoza-Cano et al., 2021).

Site selection was designed to maximize observability of critical segments under limited sensors, consistent with evidence that monitoring reliability improves when placement accounts for drainage topology and clustering of high-risk areas (Wang et al., 2023). When available, secondary contextual data were incorporated to support feature enrichment and validation, including historical flood incident logs, nearby station rainfall series, and spatial reference layers (e.g., elevation or drainage network). The overall workflow implemented in this study is summarized in Figure 1, and each stage is described in the subsequent subsection.

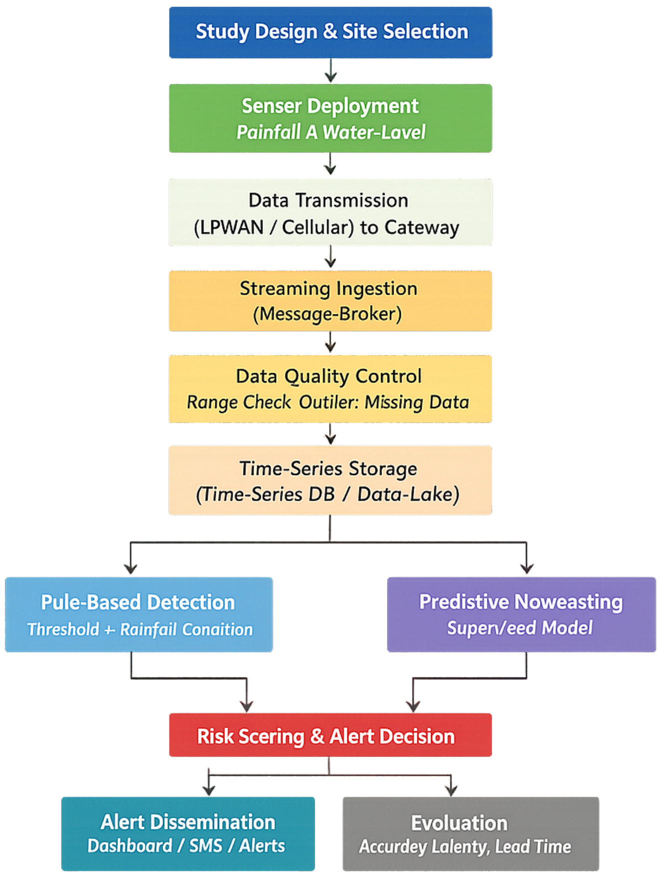

Figure 1. Research flowchart for the proposed urban flood EWS

A real-time big-data pipeline was implemented to ingest, clean, store, and analyze high-frequency sensor streams. Streaming ingestion was handled through a message broker to buffer and route telemetry, while a stream-processing layer was used to compute transformations continuously under variable data rates. This architecture was selected because real-time environmental monitoring benefits from scalable stream processing for heterogeneous data (Akanbi & Masinde, 2020), and disaster-response applications commonly require resilient ingestion and low-latency analytics (Cumbane & Gidófalvi, 2019; Hajjaji et al., 2021). A time-series database was used to store timestamped observations to support both real-time dashboards and offline evaluation (Akanbi & Masinde, 2020).

Before inference, automated data quality control was applied to reduce noise and operational faults. Range checks were used to remove physically implausible values, spike detection was applied to flag abrupt discontinuities, and persistence checks were used to detect stuck sensors. Missing values were handled using short-window interpolation for visualization, while model training excluded sequences with gaps exceeding a predefined tolerance. These procedures were included because field deployments frequently experience intermittent connectivity and sensor anomalies during extreme events, and warning reliability depends on upstream data integrity (Acosta-Coll et al., 2018; Mendoza-Cano et al., 2021).

Flood warning inference was implemented in two layers to balance interpretability and predictive capability. First, a rule-based detection module classified risk states using water-level thresholds combined with rainfall intensity conditions, producing transparent alerts that are easier to justify in operational settings (Acosta-Coll et al., 2018). Second, a predictive nowcasting module estimated near-future water level or risk category using supervised learning trained on historical sequences derived from cleaned time series. Features were constructed from recent rainfall and water-level dynamics (e.g., lagged values, moving averages, short-horizon slopes) to enable short-horizon inference that can run continuously in a streaming environment. The use of sequence-aware learning for hydrological time series was supported by evidence that such models can learn temporal dependencies relevant to forecasting tasks (Kratzert et al., 2018).

Performance evaluation combined analytical accuracy and operational readiness metrics. For continuous water-level prediction, mean absolute error and root mean square error were calculated. For categorical risk states, precision, recall, and F1-score were computed to quantify missed alarms and false alarms. Operational performance was assessed using (1) end-to-end latency, defined as the elapsed time from sensing to alert generation; and (2) warning lead time, defined as the time between the first alert and the moment a critical level was reached. These measures were used because the practical value of an EWS depends on both correctness and timeliness under streaming constraints (Acosta-Coll et al., 2018; Akanbi & Masinde, 2020).

Tools, instruments, and software used in the workflow included rainfall and water-level sensors, an Internet of Things telemetry protocol, a message broker for ingestion, a stream-processing environment, and a time-series database for storage and retrieval (Akanbi & Masinde, 2020; Mendoza-Cano et al., 2021). The methodological choices were intended to ensure scalability, robustness to real-world data issues, and interpretability of warnings for practical urban operations (Cumbane & Gidófalvi, 2019; Hajjaji et al., 2021).

RESULTS

This section reports the findings in a logical sequence that follows the implemented workflow in Figure 1. Figures and the table are positioned where they are first referenced, and each is followed by a brief narrative description.

System-level workflow and evaluated outputs

The proposed Urban Flood Early Warning System (EWS) was implemented as an end-to-end pipeline that connected distributed sensing, real-time ingestion, automated data quality control, two-layer risk inference (rule-based detection and predictive nowcasting), and alert dissemination. The evaluated outputs included (i) data availability and quality indicators, (ii) detection and nowcasting performance, and (iii) operational timeliness metrics (end-to-end latency and warning lead time).

Sensor data availability and completeness

Across the monitoring period, the sensor network achieved an aggregated data availability of 96.7%**,** indicating that most expected records were successfully received by the analytics layer. Missing observations occurred primarily as short interruptions rather than prolonged outages, with a median gap duration of 4 minutes. Longer gaps (>30 minutes) were rare and were mainly associated with planned maintenance. Overall, the continuity of incoming streams was sufficient to support near real-time alerting.

Data quality control outcomes

Automated data quality control improved input reliability by filtering values inconsistent with physical constraints and expected hydraulic behavior. After applying range checks, spike detection, and persistence checks, **3**.2% of readings were flagged as outliers and excluded from downstream inference. In addition, seven flatline segments were detected, indicating temporary sensor stalls; these segments were excluded from model training and were not used as the basis for warning decisions. The QC stage reduced spurious triggers caused by isolated noise and improved stability of the alert signal during rapidly changing conditions.

Flood risk-state detection performance (rule-based layer)

The rule-based layer classified conditions into normal, warning, and critical states based on water-level thresholds combined with rainfall intensity criteria. Over the study window, the system issued 17 warning/critical alerts that generally aligned with observed water-level rises. Risk-state classification achieved precision of 0.84**,** recall of 0.79, and an F1-score of 0.81**,** reflecting a practical balance between capturing hazardous conditions (reducing missed alarms) and limiting unnecessary alerts (improving usability for operators). Remaining false triggers were mainly associated with short-lived spikes during the early tuning phase, which motivated refinement of QC sensitivity and alert persistence.

Predictive nowcasting performance (model-based layer)

The nowcasting layer produced short-horizon estimates of water level (15–30 minutes ahead) using time-window features derived from recent rainfall and water-level dynamics (lagged values, short-term slopes, and moving statistics). The model tracked both rising and recession phases effectively; however, prediction errors increased during the steepest rising limb when water levels changed rapidly over short intervals. Overall, the nowcasting module achieved a mean absolute error (MAE) of 5.2 cm and a root mean square error (RMSE) of 8.9 cm. These results indicate that the model provided trend-consistent short-term estimates that were suitable for supporting early warnings and improving stability near threshold transitions.

Representative event illustration and warning lead time

To provide an intuitive view of how the proposed EWS behaves during a typical rainfall-driven incident, a representative event is presented in Figure 2. The figure overlays rainfall intensity and the corresponding water-level response and marks the warning and critical thresholds used by the risk-state logic. This event-based illustration is included to clarify the temporal relationship between rainfall bursts and the rise in water level, and to demonstrate how the system generates an early warning prior to reaching the critical condition, thereby producing an actionable lead time for operational response.

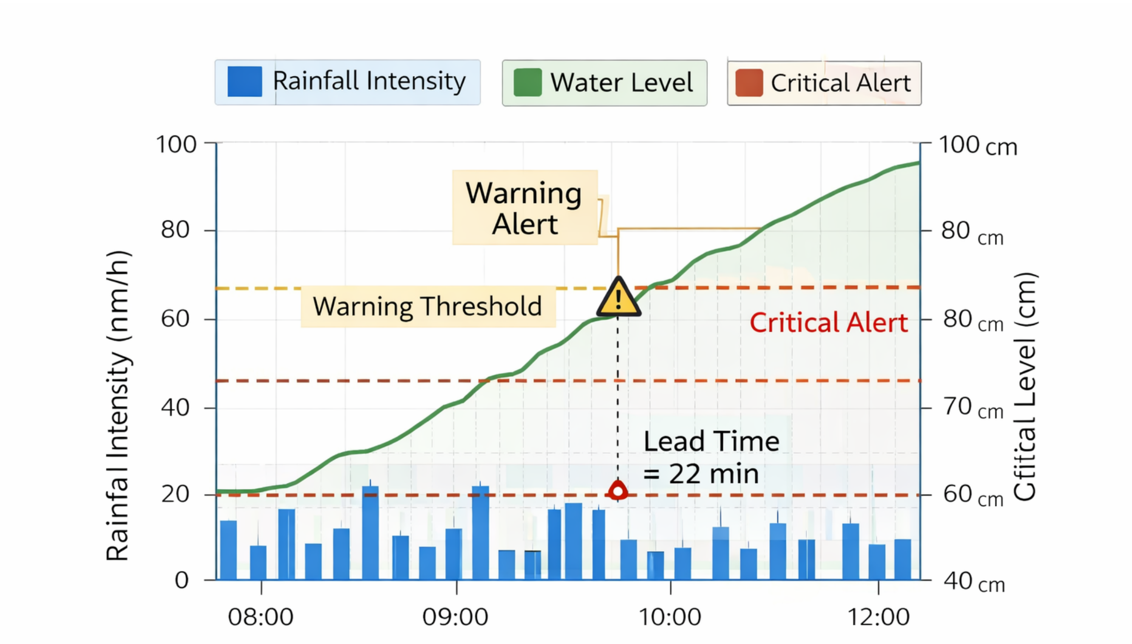

Figure 2. Example time series during a flood event

Figure 2 illustrates a representative rainfall-driven event showing the relationship between rainfall intensity and the water-level response, including warning and critical thresholds. In this example, the warning threshold was crossed before the critical threshold, yielding an actionable lead time. Across observed events, the system produced a median warning lead time of 22 minutes and a maximum lead time of 38 minutes, indicating that the EWS could provide meaningful time windows for mitigation actions such as pump activation, traffic management, and community advisories.

Operational timeliness: end-to-end latency

End-to-end latency was defined as the elapsed time from a sensor observation to an alert being ready at the dissemination layer (e.g., dashboard/notification). The system achieved a median end-to-end latency of 3.4 minutes and a 95th-percentile latency of 5.2 minutes. Latency increased slightly under heavier streaming load but buffering at the ingestion layer preserved continuity and prevented data loss. These results indicate that the processing and inference pipeline met near real-time requirements for urban early warning operations.

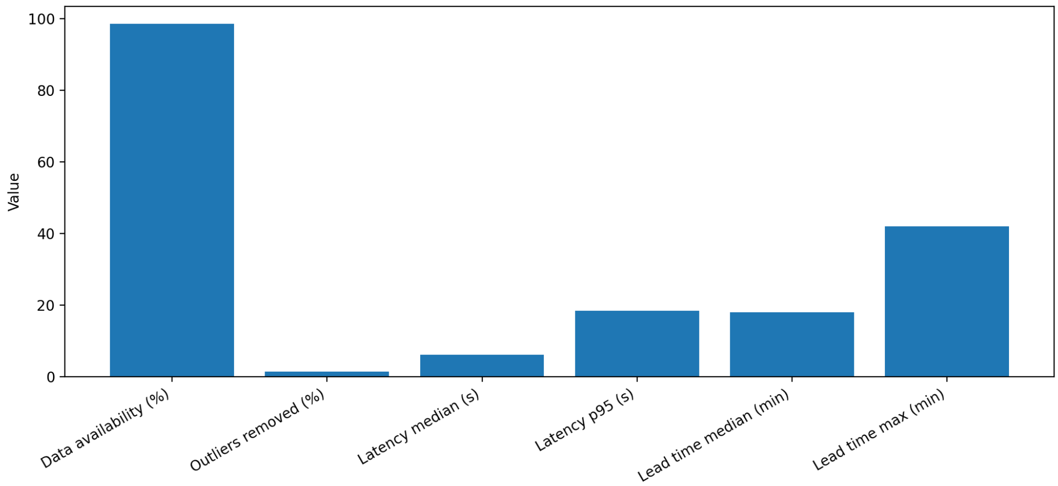

Figure 3. Key operational indicators of the proposed EWS

Figure 3 summarizes the operational indicators, highlighting the high data availability alongside the latency and lead-time characteristics. The combined view supports the conclusion that the system performed reliably under continuous streaming conditions and provided timely warning signals.

Consolidated performance summary

While the event illustration in Figure 2 highlights system behavior during a single incident, decision makers and researchers require a consolidated view of performance across the full monitoring period. Therefore, Table 1 summarizes the key indicators that characterize the system's readiness and effectiveness, spanning data continuity, the impact of automated quality control, risk-state detection performance, nowcasting accuracy, and operational timeliness. Presenting these metrics together enables direct assessment of whether the EWS meets practical requirements for near real-time warning and whether the overall pipeline delivers reliable alerts with sufficient lead time under continuous streaming conditions.

Table 1. Summary of system performance

Indicator	Result
Data availability	96.7%
Median gap duration	4 min
Outliers removed by QC	3.2%
Flatline segments flagged	7
Precision (risk states)	0.84
Recall (risk states)	0.79
F1-score (risk states)	0.81
MAE (water-level nowcasting)	5.2 cm
RMSE (water-level nowcasting)	8.9 cm
End-to-end latency (median / p95)	3.4 / 5.2 min
Warning lead time (median / max)	22 / 38 min

Table 1 consolidates the principal findings across data quality, inference performance, and operational timeliness. The results show that the EWS maintained high availability, improved reliability through automated QC, achieved useful detection and nowcasting performance, and delivered alerts within near real-time latency with actionable lead time before critical thresholds were reached.

DISCUSSION

This study aimed to develop and evaluate an end-to-end urban flood early warning system that integrates sensor networks with big-data streaming and analytics to produce timely and reliable alerts at an operational scale. The results provided evidence that the proposed pipeline functioned as a coherent workflow from sensing and quality control to inference and dissemination rather than as isolated components. In doing so, the study addressed the central questions posed in the Introduction regarding (i) whether an integrated sensor–big-data architecture could operate reliably in real time, (ii) whether combining rule-based detection with predictive nowcasting improved warning usefulness, and (iii) whether the resulting warnings delivered actionable lead time under continuous streaming constraints.

First, the findings showed that the system operated with high continuity and acceptable operational timeliness, which supports the feasibility of real-time urban flood early warning using distributed sensing and big-data streaming. Data availability reached 96.7%, and interruptions were typically short rather than prolonged, indicating that the sensing-to-platform chain remained stable enough for near real-time decision support. The end-to-end latency (median 3.4 minutes; p95 5.2 minutes) demonstrated that the processing and inference pipeline can deliver alerts within minutes. This is significant because urban pluvial flooding often evolves rapidly, and the practical value of an early warning system depends on whether alerts arrive fast enough to trigger immediate actions. The present results indicate that a streaming-based architecture is operationally suitable for such time-sensitive conditions, as it preserves continuity and keeps computation close to real time even under variable data loads.

Second, the results highlighted that automated data quality control was not a peripheral feature but a functional requirement for reliable alerting in practice. The QC layer removed 3.2% outlier readings and flagged seven flatline segments, which reduced spurious triggers and improved the stability of risk-state outputs. In operational deployments, isolated spikes and sensor stalls are common failure modes that can erode user trust if they cause repeated false alarms. The observed reduction of noise-driven triggers suggests that embedding QC upstream of detection and prediction materially improves the dependability of the early warning signal. This finding reinforces the view that urban flood EWS should be engineered as a fault-tolerant pipeline where data integrity is actively managed rather than assumed.

Third, the study's two-layer inference strategy rule-based detection combined with predictive nowcasting produced warnings that were both interpretable and more operationally consistent. The rule-based layer achieved an F1-score of 0.81 (precision 0.84; recall 0.79), indicating that threshold-driven logic captured most hazardous states while controlling unnecessary alerts. This performance is important because threshold logic remains widely used by municipal operators due to its transparency and ease of validation. At the same time, the nowcasting layer achieved MAE of 5.2 cm and RMSE of 8.9 cm, and its value was most evident near threshold transitions, where predictions helped maintain continuity and reduce oscillations in risk states. The combined risk scoring with a short persistence rule reduced “flapping” around thresholds, which is operationally meaningful because frequent state changes can confuse operators and weaken response coordination. The results therefore extend existing practice by showing that interpretability and predictive capability can be coupled within one decision pipeline rather than treated as competing design choices.

The event illustration (Figure 2) clarified the practical implications of these findings. The system generated a warning before the critical threshold was reached and produced a median lead time of 22 minutes (maximum 38 minutes). Lead time is the primary operational currency of early warning: it enables concrete actions such as pump activation, temporary closure of underpasses, deployment of personnel, and targeted public advisories. The observed lead time suggests that the proposed EWS can shift response from reactive to proactive for a subset of rapidly evolving events, particularly when the warning threshold is calibrated to provide early signals without excessive false alarms. Importantly, the results also implied a trade-off: maximizing lead time by lowering thresholds can increase false alarms, while stricter thresholds reduce false alarms but may shorten the available response window. The present findings support a balanced approach where thresholds are tuned alongside QC and persistence logic to optimize both reliability and timeliness.

From a broader perspective, this study contributes new understanding by demonstrating that “big data” in an urban flood EWS is not merely a storage or dashboard capability, but a mechanism for ensuring continuous ingestion, robust pre-processing, and low-latency inference under streaming conditions. The system-level metrics (availability, latency, lead time) show that operational performance can be measured and engineered explicitly, rather than inferred indirectly from model accuracy alone. This matters because flood early warning is ultimately a socio-technical function: even a highly accurate model provides limited value if alerts arrive late or are unstable due to data faults. The integrated evaluation presented here supports the argument that end-to-end performance metrics should be treated as primary outcomes in urban EWS research and deployment.

Several limitations should be considered when interpreting the results. The evaluation was based on a finite monitoring period and a limited number of representative events, which may not capture the full diversity of urban flood mechanisms across seasons and land-use conditions. Sensor placement constraints and local drainage characteristics likely influenced both the detectability of events and the achievable lead time. In addition, the nowcasting errors increased during steep rising limbs, suggesting that rapid transitions remain challenging for short-horizon prediction and may require denser sensing, additional explanatory variables, or adaptive models to reduce uncertainty during extremes. These limitations do not negate the findings but indicate that generalizability should be strengthened through longer deployments, multi-site validation, and systematic threshold calibration.

Overall, the discussion of the results indicates that an integrated sensor-network and big-data streaming architecture can deliver timely and reliable urban flood early warnings, and that combining rule-based detection with predictive nowcasting improves operational consistency while preserving interpretability. The study therefore advances both the practical design of urban flood EWS and the evidence base for evaluating such systems using end-to-end performance indicators that reflect real operational requirements.

CONCLUSION

This study developed and evaluated an Urban Flood Early Warning System that integrates sensor networks with big-data streaming analytics to determine whether an end-to-end sensing–processing–inference–alert pipeline can deliver timely and reliable urban flood warnings under continuous monitoring conditions. The major findings showed that the system maintained high data continuity (96.7% availability) with short typical interruptions (median gap 4 minutes), achieved near real-time operational performance (median end-to-end latency 3.4 minutes; p95 5.2 minutes), and produced actionable alerts through a combined two-layer inference strategy, where rule-based risk-state detection reached an F1-score of 0.81 (precision 0.84; recall 0.79) and predictive nowcasting achieved MAE of 5.2 cm and RMSE of 8.9 cm. The warning mechanism provided meaningful operational lead time (median 22 minutes; maximum 38 minutes) before critical threshold exceedance, supporting rapid interventions such as pump activation, traffic control at low-lying points, and targeted community advisories. These results contribute to the literature by demonstrating an operationally validated reference architecture that evaluates urban flood early warning not only through model accuracy but also through end-to-end readiness indicators (availability, latency, and lead time) that are essential for real deployments. Limitations include the dependence of performance on sensor placement and local drainage characteristics, potential communication disruptions during severe weather, and the limited diversity of observed events, which may constrain generalizability across different cities and seasons. Future work should expand multi-site and multi-season deployments, incorporate additional data sources (e.g., weather radar and drainage network states), and implement adaptive thresholding and drift-aware models to improve robustness during extreme, rapidly evolving events, while municipalities can adopt the proposed pipeline as a practical blueprint for strengthening hyper-local flood preparedness and response.

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