JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.7895

KALMAN FILTER APPLICATION IN WATER LEVEL FLOOD DETECTION

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Abstract*— Flooding is one of the most frequent natural disasters and often causes substantial damage to infrastructure and communities. Reliable flood monitoring and Early Warning Systems (FEWS) are therefore essential to mitigate risks and enable timely response. However, measurement noise caused by environmental disturbances such as water ripples can result in unstable sensor readings and false flood alerts. This study aims to improve measurement stability in an IoT-based FEWS by integrating a Kalman Filter (KF) into an ESP32-based embedded platform. The proposed system employs a resistive water-level sensor for real-time data acquisition, KF-based signal processing, web-based monitoring, and automated WhatsApp notifications via the Fonnte API. Experimental evaluation was conducted using 91 observations across three water-level scenarios representing conditions below, crossing, and above the flood-warning threshold. The KF improved measurement accuracy to 97.94%, 97.64%, and 97.75% across the three scenarios, while reducing measurement fluctuations caused by environmental disturbances. Furthermore, the proposed approach eliminated three false flood alerts generated by unfiltered measurements during the below-threshold scenario. These results demonstrate that integrating KF-based filtering into an IoT-based FEWS improves measurement reliability and supports a real-time flood monitoring and early warning.*

Keywords*: Accuracy, Early Warning System, Flood, Kalman Filter, Water Level.*

Intisari—Banjir merupakan salah satu bencana alam yang paling sering terjadi dan sering menyebabkan kerusakan yang signifikan terhadap infrastruktur dan masyarakat. Oleh karena itu, sistem pemantauan banjir dan peringatan dini (*Flood Monitoring and Early Warning System*/FEWS) yang andal sangat diperlukan untuk mengurangi risiko dan memungkinkan respons yang tepat waktu. Namun, noise pengukuran yang disebabkan oleh gangguan lingkungan, seperti riak air, dapat menyebabkan pembacaan sensor tidak stabil dan memicu peringatan banjir palsu. Penelitian ini bertujuan meningkatkan stabilitas pengukuran pada FEWS berbasis Internet of Things (IoT) dengan mengintegrasikan *Kalman Filter* (KF) pada platform tertanam berbasis ESP32. Sistem yang diusulkan menggunakan sensor ketinggian air resistif untuk akuisisi data secara real-time, pemrosesan sinyal berbasis KF, pemantauan berbasis web, serta notifikasi WhatsApp otomatis melalui Fonnte API. Evaluasi eksperimental dilakukan menggunakan 91 data pengamatan pada tiga skenario ketinggian air yang mewakili kondisi di bawah, melintasi, dan di atas ambang batas peringatan banjir. KF meningkatkan akurasi pengukuran menjadi 97,94%, 97,64%, dan 97,75% pada ketiga skenario, sekaligus mengurangi fluktuasi pengukuran akibat gangguan lingkungan. Selain itu, pendekatan yang diusulkan berhasil menghilangkan tiga peringatan banjir palsu yang dihasilkan oleh pengukuran tanpa penyaringan pada kondisi di bawah ambang batas. Hasil tersebut menunjukkan bahwa integrasi penyaringan berbasis KF pada FEWS berbasis IoT dapat meningkatkan keandalan pengukuran dan mendukung pemantauan serta peringatan banjir secara real-time.

Kata Kunci*: Akurasi, Sistem Peringatan Dini, Banjir, Filter Kalman, Ketinggian Air.*

INTRODUCTION

Flooding occurs when an area is inundated with a large volume of water[1], leading to water accumulation. It is one of the most frequent natural disasters worldwide, particularly in Indonesia[2]. Floods often result in severe infrastructure damage, economic losses, and casualties. Therefore, an effective flood monitoring and Early Warning System (FEWS) is essential for minimizing potential damage [3]and improving disaster preparedness [4]. Such systems provide early information before flooding occurs, enabling communities to take preventive actions and reduce potential losses [5]. In addition, FEWS help reduce risks associated with inadequate preparedness and delayed emergency responses[6].

Despite significant advances in Internet of Things (IoT)-based FEWS, accurately measuring water levels remains a major challenge due to sensor measurement noise[7]. Noise refers to unwanted disturbances that reduce the accuracy and reliability of sensor data[8]. In water-level monitoring applications, one of the primary sources of noise is water surface ripples caused by wind, rainfall, flowing water, or other environmental disturbances [9]. These fluctuations introduce unstable sensor readings that may trigger false flood alerts or provide inaccurate information regarding actual water conditions.

Previous studies have reported the development of IoT-based flood monitoring and water-level monitoring systems [10], [11]. These systems have been developed to support real-time water-level observation and early flood detection, while recent low-cost IoT-based approaches have also incorporated intelligent data processing to improve flood monitoring capabilities [12]. However, measurement stability remains an important consideration, particularly when sensor readings are affected by environmental disturbances. Therefore, improving the reliability of water-level measurements is essential for the effective operation of flood early warning systems.

Among various filtering approaches, the Kalman Filter has been widely employed for sensor estimation and noise reduction in different monitoring applications. Recent studies have demonstrated the application of KF-based approaches for sensor estimation and data stabilization under varying operating conditions [13], [14]. In flood-related applications, a moving-update Kalman algorithm has also been investigated for estimating flood water levels in a low-cost IoT network [15]. These studies demonstrate the potential of KF-based estimation for improving the reliability of sensor measurements and supporting real-time monitoring applications.

Besides the KF, several signal filtering techniques have also been applied to reduce measurement noise, including Moving Average [16], Exponential Smoothing, Savitzky–Golay Filter, and Adaptive Filter[17]. Moving Average is computationally simple but introduces delays because each output depends on a fixed observation window, making it less responsive to rapid water-level changes. Exponential Smoothing provides faster responses by assigning greater weights to recent observations; however, its performance is highly dependent on the selection of the smoothing coefficient and remains sensitive to abrupt environmental fluctuations. Savitzky–Golay filtering effectively preserves signal characteristics through polynomial fitting but requires a fixed processing window, limiting its suitability for real-time embedded systems with limited computational resources. Adaptive filtering dynamically adjusts filter parameters according to signal variations and generally achieves good performance in non-stationary environments, although it requires higher computational complexity and additional adaptation mechanisms [18]. In contrast, the KF simultaneously considers process uncertainty and measurement uncertainty through recursive state estimation, providing reliable real-time filtering with relatively low computational cost. These characteristics make the KF particularly suitable for low-cost IoT-based FEWS that require both computational efficiency and accurate water-level estimation.

Recent studies have demonstrated continued developments in Kalman Filter-based estimation and IoT-based flood monitoring systems. Kruse et al. [19] proposed an adaptive Kalman filtering approach that estimates measurement and process noise covariance using Kalman smoothing, demonstrating the potential of adaptive parameter estimation to improve filtering performance under varying system uncertainties. ElMenshawy and Massoud [20] applied a forgetting-factor adaptive Extended Kalman Filter for short-term forecasting, showing the applicability of adaptive Kalman-based estimation to systems with changing operating conditions. In the context of flood monitoring, Hashemi-Beni et al. [12] developed a low-cost IoT-based deep learning approach for water gauge measurement, while Sanz et al. [21] proposed a cloud-based hydrological monitoring system using a dense sensor network and NB-IoT connectivity. Choosumrong et al. [22] further developed an IoT-based flood monitoring system integrated with GIS for lowland agricultural areas. These studies

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P-ISSN: 2685-8223 | E-ISSN: 2527-4864
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demonstrate that recent flood monitoring research increasingly combines intelligent estimation, IoT sensing, communication technologies, and data processing to improve monitoring and early warning capabilities. However, the application of KF directly on a low-cost embedded platform for stabilizing resistive water-level sensor measurements remains insufficiently explored.

Although these studies have demonstrated significant progress in flood monitoring and prediction, they address different aspects of the problem. Existing IoT-based flood monitoring systems primarily focus on real-time data acquisition and communication but generally rely on raw sensor measurements without effective noise suppression. Conversely, studies on KF mainly emphasize estimation accuracy or algorithm development, while their integration into practical, low-cost FEWS remains limited. In addition, intelligent prediction approaches such as Artificial Neural Networks (ANN) and other machine learning models are primarily designed to improve flood forecasting rather than stabilize real-time sensor measurements. Consequently, unstable water-level measurements caused by environmental disturbances, particularly water surface ripples, remain a practical challenge that may reduce the operational reliability of FEWS.

Table 1. Comparison of Previous Studies and the Proposed Method

Study	**Main Technology / Method**	**KF**	**Flood Monit**	**Real-Time Monitor**	**Auto Aler**
Mulyani et al. [6]	ESP32 + HC-SR04	✗	✓	✓	✓
Hashemi-Beni et al. [12]	IoT + deep learning water gauge	✗	✓	✓	✗
Zhong et al. [13]	Adaptive KF + Wi-Fi and vision	✓	✗	✓	✗
Sudarmadji and Rachmawati [14]	KF + IoT environmental monitoring	✓	✗	✓	✗
Nguyen et al. [15]	Moving-update KF + IoT water-level estimation	✓	✓	✓	✗
Proposed study	**Resistive water-level sensor + ESP32 + KF**	✓	✓	✓	✓

Source: (Research Results, 2025)

As shown in Table 1, previous studies mainly focus on water-level sensing, IoT-based monitoring, or Kalman Filter-based signal processing as separate components. However, limited attention has been given to the integration of Kalman Filter-based measurement stabilization with a low-cost resistive water-level sensor, embedded IoT processing, web-based monitoring, and automated alert notification within a single FEWS. Therefore, this study proposes an IoT-based FEWS that integrates a KF with a resistive water-level sensor and an ESP32 microcontroller for real-time data acquisition and processing. The proposed system is further integrated with a web-based monitoring platform and an automated WhatsApp notification service to provide timely flood warnings. The KF is employed to improve measurement stability, suppress ripple-induced noise, and reduce false flood alerts while maintaining the responsiveness required for real-time flood monitoring [15], [17]-[20].

The main contributions of this study are threefold. First, this study integrates KF-based signal processing directly into an ESP32-based embedded platform using a low-cost resistive water-level sensor for real-time flood monitoring. Second, it quantitatively evaluates the effectiveness of the KF in improving measurement stability and suppressing ripple-induced sensor noise under three experimental water-level scenarios. Third, it demonstrates that the proposed approach can reduce false flood alerts while integrating real-time web-based monitoring and automated WhatsApp notifications within a practical IoT-based FEWS. These contributions distinguish the proposed system from previous studies that primarily focus on sensing, communication, water-level estimation, or KF-based signal processing independently.

MATERIALS AND METHODS

Hardware and Software Components

This study utilized a combination of hardware and software to build a FEWS. The hardware components were responsible for sensing, data acquisition, and communication, while the software enabled filtering, visualization, and automated alert notifications. The system was tested in Singkawang, West Kalimantan, Indonesia, an area prone to frequent flooding. Table 2 summarizes the hardware and software specifications employed in this research.

Table 2. Hardware and Software Components of the System

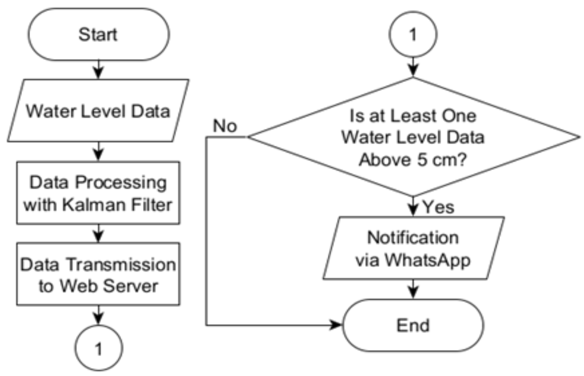
Component	Description / Specification
ESP32 microcontroller	Main controller for data acquisition, processing, and Wi-Fi communication
Resistive water level sensor	Measures water level changes in real time; sensitivity ±0.1 cm

Component	Description / Specification
Power supply	Portable power bank providing stable energy to the system
Connecting cables	Power and data transmission between devices
Arduino IDE	Programming environment and firmware upload to ESP32
Visual Studio Code + Laravel	Framework for web application development and data visualization
Laragon	Local server environment and database management
Fonnte API	Service for automated WhatsApp-based flood notifications

Source: (Research Results, 2025)

System Design

The system integrates sensing, processing, communication, and alert generation into a single workflow. A resistive water-level sensor detects water-level changes, while the ESP32 acquires and processes the analog signals using the embedded KF to reduce fluctuations caused by water ripples and other environmental disturbances. The raw and KF-filtered measurements are transmitted via the ESP32's built-in Wi-Fi to a web server for real-time visualization. The web interface provides filtered data, raw sensor data, and comparative measurements. When the water level exceeds the predefined threshold of 5 cm, the system sends an automated WhatsApp notification through the Fonnte API. The overall workflow of data acquisition, KF processing, monitoring, and alert dissemination is illustrated in Figure 1.



Source: (Research results, 2025)

Figure 1. Flowchart of the FEWS with KF Integration

KF Configuration

The KF was implemented on the ESP32 microcontroller to reduce measurement noise generated by water surface disturbances while maintaining the ability to respond to actual water level changes. The KF employed a linear state-space model, where the state variable represented the water level measured by the sensor. The state transition and measurement models are expressed as:

$$xk = x_{k-1} + w_k \quad (1)$$

$$zk = x_k + v_k \quad (2)$$

Where x_k represents the estimated water level at time k, z_k is the measured water level, w_k denotes the process noise with covariance Q, and v_k denotes the measurement noise with covariance R. The measurement noise covariance (R) was determined through preliminary sensor calibration by comparing sensor measurements with manual ruler measurements under controlled conditions. The average calibration measurement error was 0.27 cm, which was adopted as the measurement noise covariance (R = 0.27). The process noise covariance (Q) was estimated based on field observations of natural water level variations during rainfall events. Several candidate values were evaluated during preliminary experiments, and Q = 0.10 provided the best balance between noise suppression and responsiveness to actual water level changes. Therefore, Q = 0.10 was used throughout the experiments.

Experimental Setup and Performance Evaluation

The proposed flood monitoring system was evaluated through three experimental scenarios representing different flood conditions. The first scenario simulated a stable water level below the flood warning threshold (4.5 cm). The second scenario represented a dynamic condition in which the water level gradually increased from 4.0 cm to 7.0 cm, crossing the flood warning threshold. The third scenario evaluated a stable water level above the warning threshold (5.5 cm). Each experimental scenario consisted of approximately 30 sensor observations collected at 10-second intervals, resulting in a total of 91 observations across all experiments. Manual water-level measurements using a ruler were used as the reference values (ground truth) for performance evaluation.

The effectiveness of the KF was evaluated by comparing the filtered measurements with the raw sensor readings using measurement accuracy, MAE, and standard deviation. Accuracy was calculated based on the agreement between sensor measurements and the manually measured reference values, while MAE quantified the average measurement error and standard deviation

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VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.7895

assessed the stability of the sensor readings before and after KF processing.

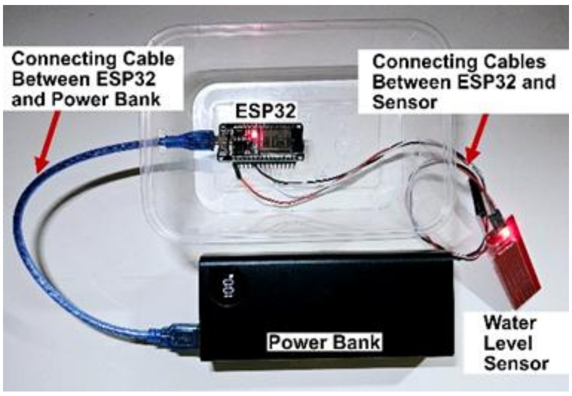
Table 3. Experimental Configuration

Parameter	Value
Sampling interval	10 s
Scenario 1	30 observations
Scenario 2	31 observations
Scenario 3	30 observations
Total observations	91
Process noise covariance (Q)	0.10
Measurement noise covariance (R)	0.27

Source: (Research Results, 2025)

RESULTS AND DISCUSSION

The flood monitoring system was successfully implemented using an ESP32 microcontroller integrated with a resistive water-level sensor, a KF algorithm, a web-based monitoring platform, and an automated WhatsApp notification system. The hardware configuration consists of the ESP32 connected to the resistive water-level sensor through an analog input for real-time water-level acquisition, while the embedded software performs sensor calibration, KF processing, and data transmission to the monitoring server. Figures 2 and 3 present the hardware configuration and the web-based monitoring interface used during the experimental evaluation. The monitoring application offers three visualization modes: filtered water-level data, raw sensor measurements, and a comparison between filtered and unfiltered measurements, allowing the real-time observation of the influence of KF processing on measurement stability. The experimental results obtained using this implementation are presented and discussed in the following subsections.



Source: (Research results, 2025)
Figure 2. Hardware Configuration of the Proposed Flood Monitoring System

Source: (Research results, 2025)
Figure 3. Testing Equipment and the Web-Based Monitoring Interface

Experimental testing was conducted to evaluate the performance of the proposed KF–based flood monitoring system. Testing in this study was conducted to evaluate the effectiveness of the KF in filtering sensor data noise and reducing inaccurate warnings. The testing process includes sensor calibration, testing sensor measurement error, determining process uncertainty parameter and data collection interval, testing under non-rain condition with a water level of 4.5 cm, testing under rainy condition with a water level crossing 5 cm, and testing under non-rain condition with a water level of 5.5 cm. The KF equations used in this study are presented in Equations 3 to 7.

$$\hat{x}_k^- = \hat{x}_{k-1} \quad (3)$$

Equation 3 states that the predicted value ($\hat{x}_k^-$) at the current time step is equal to the previous estimated value ($\hat{x}_{k-1}$). This assumption is made because, in phenomena where changes do not follow a continuous pattern over time, the variations in data may not always be significant unless a major event occurs.

$$P_k^- = P_{k-1} + Q \quad (4)$$

According to Equation 4, the covariance error (P_k^-) slightly increases compared to the previous error (P_{k-1}) due to the additional uncertainty introduced by external environmental factors, represented by Q, in each iteration.

$$K_k = \frac{P_k^-}{P_k^- + R} \quad (5)$$

Equation 5 shows the Kalman Gain (K_k). Kalman Gain determines the weighting between the sensor measurement and the predicted value. Its value ranges between 0 and 1. When the Kalman Gain approaches 1, it indicates that the covariance error (P_k^-) is significantly larger than the measurement error (R), meaning that the system relies more on the latest sensor data for correction. Conversely, when the Kalman Gain is closer to 0, it implies that the sensor measurement is less reliable, causing the system to trust the previous prediction more than the new measurement.

$$\hat{x}_k = \hat{x}_k^- + K_k \cdot (z_k - \hat{x}_k^-) \quad (6)$$

According to Equation 6, the corrected prediction ($\hat{x}_k$) is obtained by combining the initial predicted value ($\hat{x}_k^-$) with the latest sensor measurement (z_k). A higher Kalman Gain results in a corrected value that is more influenced by the recent measurement, whereas a lower Kalman Gain makes the corrected value closer to the initial prediction.

$$P_k = (1 - K_k) \cdot P_k^- \quad (7)$$

After incorporating the latest measurement to refine the prediction, the covariance error is updated (P_k) using Equation 7 to reflect the accuracy of the latest estimation. The reduction in error corresponds to the extent to which the Kalman Gain has adjusted the initial prediction value. To quantitatively evaluate the performance of the filtering method, statistical error metrics were used to compare the raw sensor measurements and the KF–processed data. In this study, Mean Absolute Error (MAE) and standard deviation (σ) were used as evaluation indicators. The MAE represents the average magnitude of the difference between the measured water level and the actual reference value. A lower MAE indicates higher measurement accuracy. The MAE is calculated using Equation (8):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |zi - xi| \quad (8)$$

where zi represents the sensor measurement, xi represents the actual water level measured using a ruler, and n is the number of observations. In addition, the standard deviation (σ) was calculated to measure the stability of the sensor readings. A lower standard deviation indicates more stable measurements with less fluctuation caused by environmental disturbances. The standard deviation is calculated using Equation (9):

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(xi - \bar{x})^2} \quad (9)$$

Where $\bar{x}$ represents the average value of the measurements.

System testing was conducted to evaluate the KF's performance in the Flood monitoring and EWS. This testing phase involved measuring sensor error, determining the process uncertainty parameter and data collection interval, and analyzing the KF's performance under various conditions.

The sensor measurement error obtained from this test will be used as the R parameter (measurement noise covariance) in the KF. To determine this value, a preliminary calibration experiment was conducted by collecting 30 measurements at three fixed reference water levels (4 cm, 5 cm, and 6 cm). The actual water levels were measured using a ruler and compared with the sensor readings to calculate the measurement error. Based on the calibration results, the average measurement error of the resistive water level sensor was approximately 0.27 cm. Therefore, this value was used as the measurement noise covariance (R = 0.27) in the KF model.

The process noise covariance (Q) represents the uncertainty associated with natural variations in water level over time. In this study, the process uncertainty was estimated by observing the smallest measurable increase in water level during heavy rainfall conditions. Field observations showed that the water level could increase by approximately 0.1 cm within a 10-second interval. Consequently, a process noise value of Q = 0.1 was selected to represent environmental variability in the KF model. In addition, preliminary tests were performed using several Q values ranging from 0.05 to 0.2 to observe their effect on filtering performance. The results indicated that Q = 0.1 provided the best balance between responsiveness to actual water level changes and suppression of noise caused by water ripples.

The data collection interval in this study was determined by measuring the time required for the water level to increase by 0.1 cm during heavy rain, accounting for possible process uncertainties caused by natural phenomena. The results of this measurement indicate that in heavy rain conditions, it takes 10 seconds for the water level to increase by 0.1 cm. The assignment of these values in the KF calculation establishes that for each prediction made (every 10 seconds), there is an additional process uncertainty of 0.1 cm.

First Testing Scenario

First, the system was evaluated under a stable water-level condition below the predefined flood-warning threshold. This test was conducted under conditions with minimal process uncertainty, with the water level remaining consistently below the predefined flood-warning threshold. The

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
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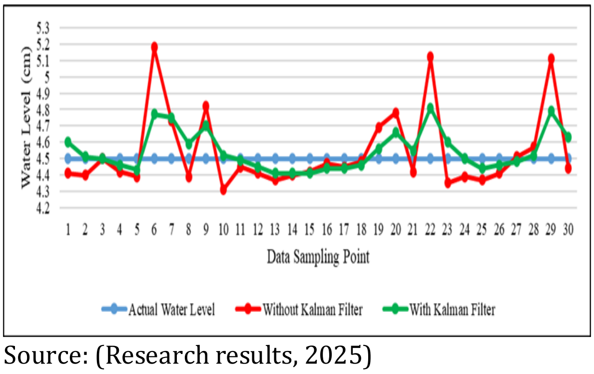
primary objective was to evaluate the effectiveness of the KF in enhancing measurement accuracy and minimizing the occurrence of false or unnecessary flood alerts under non-critical conditions. Throughout the testing period, minor environmental disturbances, such as water ripples, were observed. These disturbances were attributed to human and vehicular movement in the vicinity of the puddle area. Despite these minor fluctuations, the actual water level did not exceed the predefined flood-warning threshold at any point during the experiment.

The sensor measurements without KF processing exhibited an average error rate of 3.60%, corresponding to a measurement accuracy of 96.40%. In contrast, when the KF was applied, the average error decreased to 2.06%, improving the overall accuracy to 97.94%. These results are consistent with the statistical evaluation using MAE and standard deviation, which showed that the filtered data produced lower error magnitudes and reduced measurement variability compared with the raw sensor data. Notably, the system using raw sensor data without filtering triggered false flood warnings at three specific sampling points: the 6th, 22nd, and 29th observations.

Since the actual water level remained safely below the threshold throughout the test, these alerts were erroneous and did not reflect the actual water condition. In contrast, the KF effectively suppressed these false alarms, with no warnings issued throughout the entire sampling period, which was consistent with the expected behavior under non-flooding conditions. These results confirm the ability of the KF to refine sensor measurements, mitigate transient disturbances, and improve the reliability of the flood alert system. A comparative plot illustrating the actual water level, unfiltered sensor data, and KF-filtered data under the first testing scenario is presented in Figure 4.

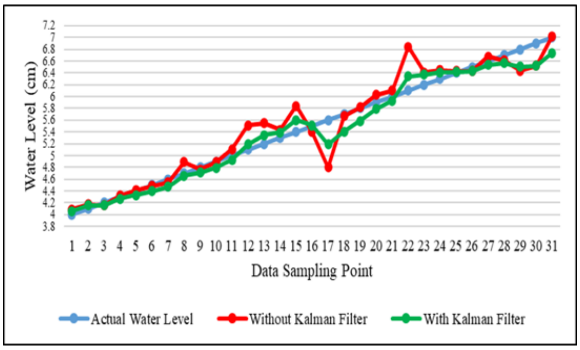


Source: (Research results, 2025)
Figure 4. Data Comparison Graph for the First Condition

Second Testing Scenario

Following the first testing scenario, the second testing scenario was conducted to evaluate the performance of the KF under conditions representing a gradual increase in water level during heavy rainfall. This test was conducted to represent a process uncertainty of 0.1 cm caused by heavy rainfall. The tested water level ranged from 4 cm to 7 cm, with an interval of 0.1 cm for each data collection point. During the test, the water level crossed the 5 cm flood-warning threshold once. The test was performed under conditions where environmental disturbances, such as water ripples caused by people walking and vehicles passing through the water puddle, were present.

The results of this second testing scenario showed that sensor measurements without the KF had an average error of 3.02% (accuracy of 96.98%). Meanwhile, the results with the KF had an average error of 2.36% (accuracy of 97.64%). During this test, flood warnings generated by data without the KF appeared at the 11th and 18th data collection points, whereas flood warnings generated by data with the KF appeared at the 12th data collection point. A comparative plot illustrating the actual water level, unfiltered sensor data, and KF-filtered data under the second testing scenario is presented in Figure 5.

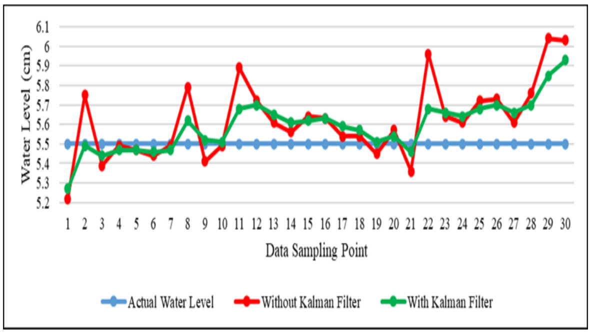


Source: (Research results, 2025)
Figure 5. Data Comparison Graph for the Second Condition

Third Testing Scenario

Following the second testing scenario, the third testing scenario was conducted to evaluate the performance of the KF under a stable water-level condition above the predefined flood-warning threshold. This test was conducted to represent the absence of process uncertainty, with the water level remaining consistently above the predefined flood-warning threshold. The purpose of this test was to analyze the performance of the KF in improving measurement accuracy and reducing incorrect or unnecessary warnings under this condition. During the test, environmental disturbances occurred in the form of water ripples caused by people walking and vehicles passing through the water puddle.

The results of this third testing scenario showed that sensor measurements without the KF had an average error of 3.11% (accuracy of 96.89%). Meanwhile, the results with the KF had an average error of 2.25% (accuracy of 97.75%). During this test, both the unfiltered and KF-filtered data triggered a flood warning once, precisely at the first data collection point. This result was consistent with the expected behavior for this testing condition, as the actual water level was already above the predefined flood-warning threshold from the beginning of the experiment. A comparative plot illustrating the actual water level, unfiltered sensor data, and KF-filtered data under the third testing scenario is presented in Figure 6.



Source: (Research results, 2025)
Figure 6. Data Comparison Graph for the Third Condition

To further validate the performance improvement statistically, the percentage reduction in measurement error was analyzed across all three testing scenarios. In the first testing scenario the KF reduced the average error from 3.60% to 2.06%, corresponding to an error reduction of approximately 42.78%. In the second testing scenario, the average error decreased from 3.02% to 2.36%, representing an error reduction of approximately 21.85%. Similarly, in the third testing scenario, the average error decreased from 3.11% to 2.25%, resulting in an error reduction of approximately 27.65%. These consistent improvements across the three testing scenarios indicate that the KF effectively enhanced measurement accuracy and measurement stability under varying environmental disturbances.

Beyond improvements in numerical accuracy, these results also have practical significance for FEWS. Small fluctuations in water-level measurements near the predefined threshold can produce false warning signals and unnecessary emergency responses. During the first testing scenario, the system without KF generated three false flood warnings despite the actual water level remaining below the warning threshold. In contrast, the KF successfully eliminated all false warnings. These findings indicate that the filtering process not only improves numerical accuracy but also enhances the operational reliability of the FEWS.

The improved measurement stability observed in the filtered data can be explained by the KF's ability to combine prediction and measurement information. In this system, the KF continuously estimates the current water-level state by combining the previous estimate with the latest sensor measurement. This mechanism allows the filter to suppress short-term fluctuations caused by environmental disturbances, such as water ripples, while still responding to actual changes in water level. As a result, the filtered measurements exhibit lower variability and fewer abrupt spikes than the raw sensor data.

Another factor contributing to the improved performance is the Kalman Gain, which dynamically adjusts the weighting between the predicted state and the incoming sensor measurement. When measurement uncertainty increases, the Kalman Gain determines the relative influence of the new sensor measurement and the predicted state, thereby helping stabilize the output signal. Compared with other filtering approaches, such as Moving Average, Exponential Smoothing, and Adaptive Filtering, the KF provides recursive state estimation while simultaneously considering process uncertainty and measurement uncertainty. Moving Average filters smooth data using a fixed window size and may introduce delays in detecting actual changes, whereas the KF adjusts its response based on the estimated system uncertainty. This adaptive behavior makes the KF particularly suitable for FEWS that require both responsiveness and noise suppression.

Limitations of the Study

Despite the promising results obtained in this study, several limitations should be acknowledged. First, the experimental evaluation was conducted using 91 observations collected under three representative water-level scenarios at a single testing location in Singkawang, West Kalimantan. Although these observations were sufficient to evaluate the proposed system under controlled conditions, larger datasets collected over longer monitoring periods and across multiple flood-prone locations are required to further validate the robustness and generalizability of the proposed approach. Second, the KF parameters ($Q = 0.1$ and $R = 0.27$) were determined through preliminary

VOL. 12. NO. 1 AUGUST 2026
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experimental evaluation rather than a systematic optimization procedure. Future studies should investigate parameter optimization techniques and perform comprehensive sensitivity analyses to evaluate the influence of different Q and R values on filtering performance. Third, this study focused exclusively on evaluating the KF. Quantitative comparisons with other signal filtering techniques, such as Moving Average, Exponential Smoothing, Savitzky–Golay, and Adaptive Filtering, were beyond the scope of this work and should be investigated in future research. Finally, the proposed system was evaluated under representative experimental conditions, but additional validation under more diverse environmental conditions, including different rainfall intensities, river characteristics, and water-flow conditions, is necessary to further assess its practical applicability.

CONCLUSION

This study developed an Internet of Things (IoT)-based Flood Monitoring and Early Warning System (FEWS) that integrates a resistive water-level sensor, an ESP32 microcontroller, a KF, a web-based monitoring platform, and automated WhatsApp notifications. The experimental results demonstrate that the KF effectively improves measurement stability by suppressing ripple-induced fluctuations while maintaining real-time responsiveness. Across the three experimental scenarios, the proposed system achieved measurement accuracies of 97.94%, 97.64%, and 97.75%, while reducing false flood alerts caused by temporary environmental disturbances around the flood-warning threshold. From a scientific perspective, this study demonstrates that integrating KF-based signal processing into an embedded IoT platform improves the reliability of resistive water-level measurements under dynamic environmental conditions. Unlike previous studies that primarily focus on sensing, communication, or flood prediction independently, the proposed approach integrates embedded signal filtering, real-time monitoring, and automated alert notification within a unified low-cost FEWS. These findings contribute to the practical implementation of recursive state estimation for enhancing the reliability of IoT-based flood monitoring systems.

From a practical perspective, the proposed system offers a cost-effective solution for flood-prone areas with limited monitoring infrastructure. Real-time web-based visualization and automated WhatsApp notifications support timely dissemination of flood warnings, thereby improving disaster preparedness and emergency response. Furthermore, the modular architecture facilitates future expansion through multiple sensing nodes to support wider river monitoring networks. Future research should focus on validating the proposed system using larger and more diverse datasets, evaluating its performance under broader environmental conditions, investigating systematic optimization of KF parameters, and comparing its performance with other signal filtering techniques to further enhance the robustness and scalability of IoT-based flood monitoring systems.

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