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Comprehensive Analysis of an Internet of Things-Based Rainfall Measurement Instrumentation System for Coastal Extreme Weather Mitigation in Padang

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Abstract

Coastal fishing operations are vulnerable to rapidly changing weather conditions, yet locally resolved rainfall observations are often insufficient to support timely operational decisions. This study evaluates the performance of an Internet of Things (IoT)-based rainfall measurement and warning system developed to support coastal extreme-weather mitigation in Padang. An engineering and experimental approach was employed to develop a prototype integrating a tipping bucket rain gauge (TBRG), ESP32 microcontroller, RTC DS3231 module, 20 × 4 LCD, local buzzer, Blynk IoT platform, and Telegram Bot. System performance was evaluated through comparisons with reference measurements to determine accuracy, repeated controlled-input tests to assess precision, and threshold-response tests to verify the warning function. The TBRG achieved an average measurement accuracy of 98.18%, with a mean relative error of 1.82%. Ten repeated measurements under controlled input yielded a precision of 95.789%. The warning subsystem responded correctly under all tested threshold conditions, producing a functional response rate of 100%. These findings demonstrate the prototype's capacity to measure localized rainfall quantitatively and translate the observations into local and remote warning signals. The study provides empirical evidence supporting the integration of rainfall instrumentation, microcontroller-based processing, and IoT communication for localized coastal monitoring. Further development should prioritize dynamic calibration across varying rainfall intensities, autonomous power supply, and resilient communication mechanisms.

Keywords: Coastal Monitoring; Early Warning System; Internet of Things; Rainfall Measurement; Tipping Bucket Rain Gauge

INTRODUCTION

Coastal weather information is a critical component of safety management for small-scale fisheries because fishing operations depend directly on atmospheric and oceanic conditions. Small-scale fishers face hazards from storms, high waves, and rapidly changing sea conditions, and recent international guidance continues to emphasize risk assessment and safety management for small fishing vessels (Nations, 2025).

Padang represents a particularly relevant setting for localized hydrometeorological monitoring. The city is directly exposed to the Indian Ocean and contains low-lying coastal areas that are vulnerable to intense rainfall and flooding. The waters off the west coast of Sumatra have been shown to be particularly prone to extreme weather anomalies and heightened wave activity—strongly influenced by tropical cyclone activity in the Indian Ocean and the Bay of Bengal—thereby increasing operational risks for fishing vessels (Ningsih et al., 2023). Spatial analysis of the Batang Kuranji watershed identified a vulnerable and flood-prone area of 166.25 ha, concentrated in the downstream region where lowlands, wetlands, and coastal conditions increase exposure to inundation (Hidayatullah et al., 2023). Atmospheric analysis of the 13 July 2023 flood event in Padang also identified unstable atmospheric conditions and convective cloud development associated with heavy rainfall (Badri et al., 2025). These findings indicate that rainfall variability is not only a climatological characteristic but also a relevant operational parameter for coastal risk management.

The measurement of rainfall at a local site is therefore important because regional forecasts and observations may not represent short-range variability at a specific coastal location. Local land-cover modifications have also been shown to significantly alter thermal parameters and meteorological dynamics—such as surface temperature and wind speed—underscoring why high-resolution weather observations at specific locations are crucial (Liao et al., 2014). IoT-based rainfall systems can reduce the delay between environmental observation, data processing, visualization, and user access. Recent systems have demonstrated the feasibility of combining tipping bucket sensors or digital rainfall sensors with ESP32-class microcontrollers and cloud platforms for continuous monitoring (Islam et al., 2024; Nofri Wandi Al-Hafiz et al., 2024; Putri et al., 2024). IoT-based rainfall systems can reduce the delay between environmental observation, data processing, visualization, and user access. The development of such systems relies on the broader foundation of physics and electronics instrumentation to produce devices that address human needs (Yulkifli et al., 2019).

Among automatic rainfall instruments, the tipping bucket rain gauge remains attractive because of its simple mechanical structure, low energy demand, digital pulse output, and suitability for remote data acquisition. A TBRG converts a calibrated water volume into a tipping event, and the resulting pulse can be counted by a microcontroller to estimate rainfall depth and intensity (Segovia-Cardozo et al., 2023). However, the simplicity of the mechanism does not remove measurement uncertainty. Wind-induced undercatch, wetting and evaporation losses, bucket imbalance, and mechanical response time can affect the relationship between actual and recorded rainfall. Furthermore, aggregated rainfall data recording often fails to accurately represent actual fluctuations in rainfall intensity over time; consequently, a high-resolution approach focusing on inter-tip times is crucial for minimizing measurement artifacts (Dunkerley, 2024).

The most important technical limitation concerns dynamic response. Their results also demonstrated that calibration parameters were sensitive to volumetric calibration and that dynamic correction could reduce, but not completely eliminate, measurement error. A broader review by (Segovia-Cardozo et al., 2023) similarly identified wind and mechanical effects as major uncertainty sources and distinguished static calibration from dynamic calibration. Recent work on portable calibration equipment further confirms the importance of traceable calibration for TBRG performance (Rohmah et al., 2024).

Previous IoT rainfall studies have primarily focused on automated data acquisition, visualization, or flood monitoring. (Nofri Wandi Al-Hafiz et al., 2024), for example, developed an IoT rainfall-intensity instrument using a tipping bucket sensor and ESP32/ESP8266 connectivity. (Putri et al., 2024) implemented a rainfall monitoring architecture for agricultural applications using a transmitter, receiver, ThingSpeak database, and mobile weather-station application. (Islam et al., 2024) developed a coastal rainfall monitoring system for rainy-flood detection. These studies establish the feasibility of IoT rainfall monitoring, but they do not fully address the combination of localized measurement performance, repeatability, and multi-channel warning response within a coastal fishing context.

The research gap addressed in this study is therefore methodological and contextual. Methodologically, the study evaluates the rainfall sensor using three linked performance dimensions: accuracy against a reference instrument, precision under repeated controlled input, and warning-response functionality. Contextually, the instrument is designed for a coastal environment in Padang where rainfall information is connected directly to a mitigation-oriented warning architecture. The novelty lies in integrating quantitative rainfall measurement and operational warning into one localized IoT system rather than treating data acquisition and risk notification as separate functions.

The theoretical foundation combines principles of precipitation measurement, measurement uncertainty, instrument calibration, embedded sensing, and IoT-based environmental monitoring. The study focuses on the performance of the developed TBRG and its warning architecture. Specifically, the objective is to determine the measurement accuracy, precision, and warning-response reliability of the system and to assess the extent to which the prototype can support localized coastal weather monitoring in Padang.

METHODS

Research Type and Design

This study employed an engineering research approach with an experimental design. The engineering approach was selected because the research involved the design, assembly, programming, testing, and performance evaluation of a functional instrumentation prototype. The experimental component was used to generate controlled measurement data and to compare the developed system with a reference instrument. The evaluation was organized into three stages: sensor accuracy testing, precision testing under repeated controlled input, and functional testing of the warning subsystem.

Research Location and System Architecture

The field-oriented system was developed for deployment in the coastal area of Cindakir, Bungus Teluk Kabung, Padang, West Sumatra. The prototype consists of a tipping bucket rain gauge, ESP32 microcontroller, RTC DS3231, LCD 20×4, local buzzer, and IoT communication services. The electronic components were housed in a weather-resistant enclosure to reduce exposure to moisture, dust, and coastal environmental conditions.

Figure 1. Original system configuration used in the study.

Figure 1 presents the authors' original system configuration. The TBRG and anemometer provide environmental inputs, the ESP32 performs signal acquisition and processing, and the IoT layer transfers information to the user interface. The architecture is consistent with the general structure of IoT environmental monitoring, in which sensing, local processing, communication, visualization, and notification form an integrated information chain (Islam et al., 2024; Nofri Wandi Al-Hafiz et al., 2024).

Instrumentation

In this setup, the Tipping Bucket Rain Gauge (TBRG) served as the primary rainfall sensor, where each mechanical tip corresponded to a calibrated rainfall increment of 0.7 mm. These tipping events were converted into digital pulses and captured by the ESP32 microcontroller via an interrupt pin. To maintain precise data logging, an RTC DS3231 module provided accurate timestamps, while a 20×4 LCD facilitated real-time local monitoring. Although the comprehensive weather station architecture included a three-cup anemometer for wind-speed observation, this specific performance analysis is restricted to the rainfall measurement subsystem.

Table 1. The respective functions of the system components are summarized

Component	Function
Tipping Bucket Rain Gauge (TBRG)	Measures rainfall based on the number of bucket tipping events and converts the collected rainfall volume into rainfall depth.
ESP32 Development Board	Receives and counts tipping signals from the TBRG, processes rainfall data, controls the system logic, and manages data transmission.
RTC DS3231	Provides accurate time information for recording rainfall measurements according to the observation time.
LCD 20×4	Displays rainfall measurement results and system information locally in real time.
Power Supply and Supporting Circuit	Provides the required operating voltage and supports electrical connections between the sensor, microcontroller, display, and warning components.
Laptop and Arduino IDE	Used for ESP32 programming, system configuration, debugging, and serial monitoring during testing.
Reference Rainfall Measurement Instrument	Provides reference rainfall values used to evaluate the measurement accuracy of the developed TBRG system.

Rainfall Calculation

The rainfall depth was calculated from the number of tipping events and the calibrated rainfall volume per tip. The rainfall depth is calculated using the following equation:

$$R = N \times V_{tip} \quad (1)$$

where R is rainfall depth, N is the number of tipping events, and Vtip is the calibrated rainfall volume represented by one tip. Rainfall intensity was calculated from the rainfall depth and the observation interval:

$$I = \frac{(N \times V_{tip})}{\Delta t} \quad (2)$$

where I is rainfall intensity and Δt is the observation interval. These equations provide the computational link between the mechanical tipping mechanism and the numerical rainfall output displayed by the monitoring system.

Accuracy, Precision, and Warning Tests

Accuracy was evaluated by comparing the developed system with the reference measurement, which describes the closeness of a measurement result to its true value (Yulkifliet al., 2014). Measurement accuracy is evaluated using the following formulation:

$$A\% = \left(1 - \left|\frac{(Y_n - X_n)}{Y_n}\right|\right) \times 100\% \quad (3)$$

where A% is accuracy, Yn is the reference value, and Xn is the value measured by the developed systemPrecision was evaluated from repeated measurements under the same controlled input condition, typically by repeating the measurement of physical quantities 10 times (Yulkifli et al., 2018). Precision is evaluated using the following formulation

$$P\% = \left(1 - \left|\frac{(\bar{X} - X_n)}{X}\right|\right) \times 100\% \quad (4)$$

where P% represents the precision percentage, $\bar{X}$ is the mean of repeated measurements, and Xn is each observed measurement. The warning subsystem was tested by applying normal, advisory, and hazard conditions to the programmed threshold logic. A response was classified as successful when the system activated the intended local and remote warning outputs under the hazard condition and remained inactive under normal conditions.

Data Analysis and Quality Assurance

The analysis used descriptive quantitative statistics. Mean values were used to summarize repeated observations, relative error was used to quantify deviation from the reference, and precision was used to characterize repeatability. The system was also subjected to repeated functional checks to confirm the consistency of the warning logic. Because the study evaluates an instrumentation prototype rather than human participants, the experimental unit consisted of sensor measurements and system-response events. No personally identifiable information was collected.

RESULTS

System Implementation

The completed prototype successfully integrated rainfall sensing, local display, processing, and remote communication. The system recorded rainfall through the TBRG and transmitted processed observations to the IoT interface. Figure 2 presents the fieldinstalled configuration used to verify the operation of the monitoring station in a coastal setting.

Figure 2. Original field installation of the weather monitoring station.

Accuracy Performance

The accuracy evaluation produced an average reference rainfall value of 5.24 mm and an average system reading of 5.22 mm. The resulting mean relative error was 1.82%, corresponding to an average accuracy of 98.18%. Table 2 summarizes the principal accuracy indicators.

Table 2. Accuracy performance of the tipping bucket rain gauge

Parameter	Reference	System	Error (%)	Accuracy (%)
Rainfall	5.24 mm	5.22 mm	1.82	98.18

The small difference between the reference and developed-system averages indicates close agreement within the tested range. The result provides empirical evidence that the sensor configuration was able to reproduce the reference rainfall measurement with a low average deviation.

Precision Performance

Precision testing used ten repeated measurements under the same controlled input condition. The original data produced a mean reading of 10.26 mm and a standard deviation of 0.147 mm, corresponding to a precision value of 95.789%. Figure 3 presents the original repeated-measurement graph.

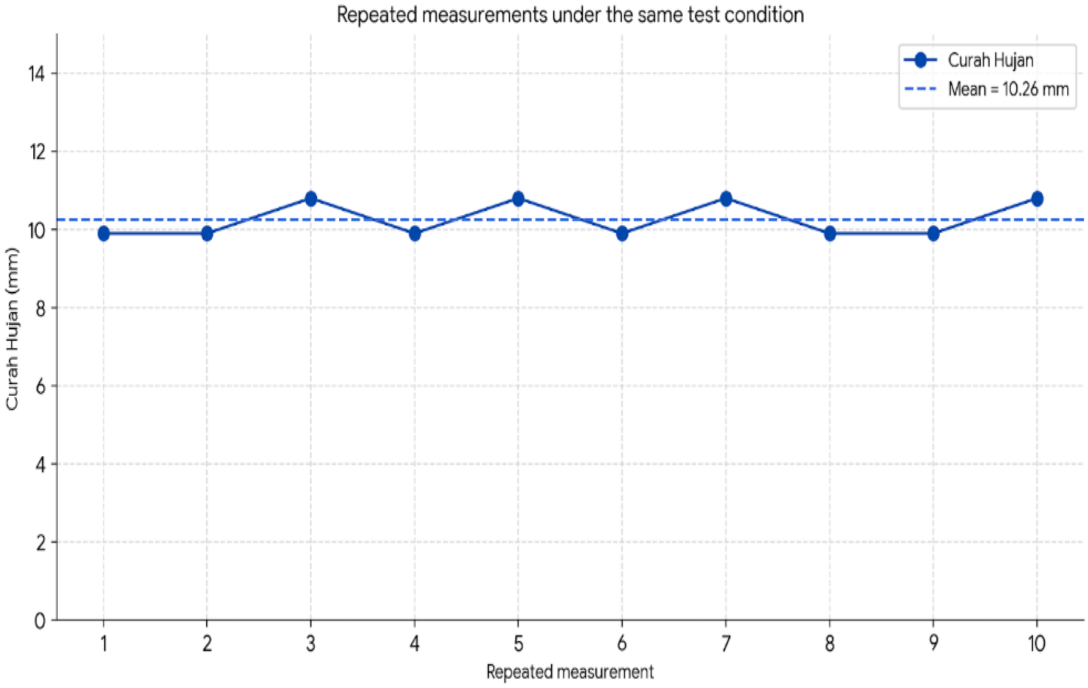

Figure 3. Original repeated-measurement graph for TBRG precision testing.

The repeated observations remained within a relatively narrow range around the mean. The observed dispersion indicates that the measurement mechanism and pulse-counting process produced consistent outputs under a controlled input condition. The result is relevant to threshold-based warning because unstable measurements near a decision boundary could cause repeated switching or false activation.

Warning-System Response

The warning subsystem was tested across normal and hazard conditions. The system remained inactive under normal conditions and activated the warning output when the programmed rainfall threshold was exceeded. The observed functional response rate was 100% across the tested cases. Figure 6 demonstrates the remote Telegram notification, while Figure 5 shows the corresponding Blynk monitoring interface.

The result confirms that the software logic correctly linked the measured rainfall condition to the warning actuator and remote communication services. The result is a functional test of the prototype. It should not be interpreted as evidence of 100% communication availability under all coastal weather conditions because the remote notification path remains dependent on network and power availability.

DISCUSSION

Measurement Accuracy and the Meaning of the 98.18% Result

The measured accuracy of 98.18% indicates a low average deviation between the developed TBRG and the reference instrument within the tested measurement range. This finding supports the feasibility of the prototype for localized rainfall observation. However, the accuracy value should be interpreted as an empirical result for the tested configuration and conditions rather than as a universal specification for all rainfall intensities. Such a distinction is important because TBRG performance is known to vary with rainfall intensity, mechanical characteristics, and environmental exposure.

The result is consistent with the established behavior of tipping bucket instruments. (Segovia-Cardozo et al., 2023) identified mechanical and wind-related biases as major sources of uncertainty and emphasized the need for calibration to improve data reliability. (Shedekar et al, 2016) found that three TBRG models systematically underestimated rainfall and that underestimation generally increased with rainfall intensity. Therefore, the high accuracy observed in the present test is encouraging, but it should not be extrapolated to extreme rainfall conditions without additional dynamic testing..

The accuracy result also demonstrates the value of comparing a low-cost field-oriented instrument with a reference rather than relying only on nominal sensor specifications. A sensor can produce a digital pulse reliably while still representing rainfall inaccurately if the tipping volume or mechanical response is not correctly calibrated. The present comparison provides an empirical check of the complete sensing chain, including the mechanical bucket, pulse detection, microcontroller counting, and rainfall conversion.

Precision and Repeatability

The precision value of 95.789% indicates that repeated measurements under a controlled input were relatively consistent. This result complements the accuracy assessment. Accuracy describes agreement with a reference, whereas precision describes the stability of repeated observations. The distinction is essential for an automated warning system because a highly variable sensor output can generate unstable warning decisions even when the mean value is close to the reference.

The present result is consistent with the engineering rationale for controlled calibration. (Rohmah et al., 2024) emphasized that TBRG calibration requires control of both water volume and time so that the applied flow can be related to rainfall intensity. The ten repeated trials in the present study provide evidence of short-term repeatability, but they do not replace a dynamic calibration curve across multiple rainfall intensities.

Calibration as a Metrological Requirement

TBRG calibration should be understood as a continuing metrological requirement rather than a one-time adjustment. Static calibration verifies the nominal tipping volume by applying water slowly until the bucket tips. Dynamic calibration evaluates the instrument while the bucket is moving and is therefore more capable of revealing intensity-dependent mechanical error.(Segovia-Cardozo et al., 2023) distinguish these two procedures and note that dynamic calibration is particularly relevant when the measurement rate changes substantially.

This issue is directly relevant to the present system because the intended application includes extreme-weather mitigation. A sensor that performs well at moderate input rates may underestimate intense rainfall because water continues to enter the mechanism while the bucket is moving. (Shedekar et al, 2016) experimentally demonstrated this intensity dependence and reported successful statistical correction models after calibration. Consequently, future validation should include several controlled flow rates rather than a single controlled input volume.

IoT Integration and Operational Value

The integration of the TBRG with ESP32, Blynk, and Telegram converts a conventional rainfall measurement into an operational information service. Previous studies have shown that ESP32-based rainfall systems can provide real-time monitoring through cloud or mobile platforms(Nofri Wandi Al-Hafiz et al., 2024; Putri et al., 2024) . The present system extends this concept by linking measurement to an explicit warning decision and by providing both local and remote outputs. The integration of weather parameter sensors controlled by an ESP32 microcontroller as a server facilitates real-time data transmission, allowing users to obtain actual weather information without being physically present at the monitored area (Alifia Sekar Ratri et al., 2021).

The multi-channel architecture has practical value. The local buzzer can provide an immediate signal at the station, while Blynk and Telegram extend access to users who are not physically present at the instrument. This design reduces dependence on a single visualization channel. It also follows the broader logic of weather-information services for fishers, in which timely and accessible environmental information can strengthen decision-making and resilience(Okeke-Ogbuafor et al., 2022).

Nevertheless, the 100% warning-response rate should be interpreted narrowly. It demonstrates correct software and actuator behavior during the tested conditions. It does not establish end-to-end reliability during network interruption, power loss, sensor blockage, or prolonged heavy rainfall. This distinction is important because the most severe weather conditions are also the conditions most likely to challenge communication and power infrastructure.

Coastal Deployment and Future Resilience

Coastal deployment introduces environmental constraints that are less pronounced in laboratory testing. Salt aerosols, high humidity, wind, and rainfall can affect mechanical and electrical components. The use of an enclosure is therefore appropriate, but enclosure protection alone does not guarantee long-term reliability. Preventive maintenance should include cleaning the collector and bucket mechanism, checking the leveling of the instrument, inspecting the pulse switch, and verifying calibration periodically.

The energy and communication architecture should also be strengthened. The current prototype relies on electrical power and Wi-Fi for remote communication. A resilient field station would benefit from solar-battery power and a communication layer that can operate over longer distances with lower energy consumption. Such development is particularly relevant for coastal monitoring because local weather stations may need to remain operational when conventional infrastructure is disrupted. Furthermore, designing the IoT architecture with independent components facilitates easier system modifications and functional upgrades without disrupting other existing monitoring parts . Long-term field monitoring also benefits from standardized observation practices and instrument maintenance, as emphasized in meteorological observation guidance(World Meteorological Organization., 2018, 2021).

Implications, Limitations, and Research Direction

Scientifically, the study contributes an integrated evaluation framework in which rainfall measurement quality and warning functionality are assessed within the same instrumentation system. Methodologically, the separation of accuracy, precision, and warning response avoids treating a single performance indicator as evidence of complete system reliability. Practically, the prototype provides a pathway for localized rainfall information to be delivered to coastal users in a form that supports rapid interpretation.

The study has several limitations. First, precision was evaluated using ten repeated controlled measurements, which limits the ability to infer long-term repeatability. Second, the accuracy test did not cover the full range of rainfall intensities expected during extreme events. Third, the physical deployment on a 200cm pole with a 70cm sensor mount at the coast introduces mechanical vibration risks; high coastal winds may induce false tipping events in the TBRG mechanism. Fourth, while the 40x40cm enclosure provides general weather resistance, long-term degradation from corrosive coastal salt aerosols on the electronic components was not evaluated. Finally, although the broader station architecture integrates a cup anemometer and an immediate warning siren, this study isolated the rainfall subsystem. Consequently, the evaluated warning response relies on a single hazard variable, which does not fully capture the multi-parameter nature of extreme coastal weather.

Future research should therefore implement dynamic calibration at multiple flow rates, conduct long-duration field observations, quantify wind-related undercatch, and evaluate sensor performance during high-intensity rainfall. The communication subsystem should be tested under intermittent connectivity, while the power system should be redesigned for autonomous operation. A further research direction is to combine rainfall with wind speed, wave conditions, and other meteorological variables to produce a multi-parameter coastal risk indicator rather than relying on rainfall as a single hazard variable. Comparative measurement using weighing or optical precipitation instruments may also strengthen validation because different gauge technologies have different uncertainty characteristics (Ro et al., 2024).

CONCLUSION

The developed IoT-based rainfall measurement instrumentation demonstrated high short-term measurement performance under the tested conditions. The TBRG achieved an average accuracy of 98.18% with a mean relative error of 1.82%, while repeated controlled measurements produced a precision value of 95.789%. The warning subsystem correctly responded to all tested threshold conditions, yielding a functional response rate of 100%.

The study contributes to the field by integrating quantitative rainfall measurement, embedded processing, local visualization, and remote warning into a localized coastal monitoring architecture. The findings support the use of the prototype as a supplementary rainfall-monitoring and warning instrument for coastal applications in Padang. The results should not, however, be interpreted as a replacement for official meteorological services or as a complete maritime risk assessment system.

Further research should focus on dynamic calibration across a wider rainfall-intensity range, long-term field reliability, wind-induced measurement error, autonomous power, and resilient communication. These developments would strengthen the scientific validity and operational reliability of the system for deployment in coastal communities.

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