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IoT-Based Instrumentation for Urban–Rural Thermal Comfort Assessment Using Temperature Humidity Index

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ABSTRACT

Urbanization alters land surface characteristics and may contribute to the Urban Heat Island (UHI) effect, affecting outdoor thermal comfort. This study presents an Internet of Things (IoT)-based instrumentation system for microclimate monitoring and thermal comfort assessment using the Temperature-Humidity Index (THI). The system integrates calibrated DHT22 sensors, an ESP32 microcontroller, a 20×4 LCD, Firebase Realtime Database, and a web dashboard. Sensor calibration against BMKG reference instruments produced maximum deviations of -0.116°C for air temperature and -0.87% for relative humidity. The system was deployed simultaneously for 24 hours at an urban site in Kelurahan Tanah Tinggi and a rural site in Desa Cibodas, with 10-minute sampling intervals. Tanah Tinggi recorded a higher mean air temperature (29.05°C) than Cibodas (26.63°C), lower mean relative humidity (75.77% and 81.93%), and higher mean THI (27.59 and 25.57). Based on Wati and Fatkhuroyan (2017), the mean THI at Tanah Tinggi was classified as “Uncomfortable,” while Cibodas was “Partly Comfortable.” The cumulative distribution showed 58.33% “Uncomfortable” observations at Tanah Tinggi and 65.28% “Comfortable” observations at Cibodas. These results indicate an urban–rural thermal contrast consistent with an urban heat island pattern. However, interpretation is limited by the 24-hour period, two sites, and differences in elevation and local environmental conditions. The proposed system provides a low-cost approach for high-temporal-resolution microclimate monitoring and thermal comfort assessment.

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1. INTRODUCTION

Rapid urbanization has significantly transformed urban land-surface characteristics by replacing natural vegetation and open areas with impervious surfaces such as asphalt, concrete, and rooftops. These changes can increase heat absorption and retention, contributing to the Urban Heat Island (UHI) phenomenon, in which urban areas tend to exhibit higher air temperatures than their surrounding rural areas [1]. A study of urbanization and surface urban heat islands (SUHIs) in western Java reported substantial urban expansion over the past two decades, accompanied by increasing land surface temperature and SUHI intensity. The study further identified anthropogenic heat flux and urbanization as positive contributors to SUHI intensity, while vegetation and water coverage contributed negatively [2]. Such thermal differences may affect outdoor human thermal comfort by increasing heat exposure and altering local microclimatic conditions [3].

Conventional microclimate monitoring commonly relies on Automatic Weather Stations (AWS) or standalone data loggers. Although these systems provide reliable measurements, their relatively high procurement and maintenance costs, limited spatial deployment, and operational requirements can constrain

their use for dense and real-time microclimate monitoring [4]. The development of Internet of Things (IoT) technology provides a cost-effective alternative by enabling automated data acquisition, wireless transmission, and remote monitoring [5]. However, low-cost sensors such as the DHT22 may be affected by measurement errors and environmental conditions. Therefore, laboratory calibration and appropriate correction procedures are important to improve measurement consistency and ensure the suitability of the sensor for field observations [22].

Previous studies have investigated the relationship between urban characteristics and microclimatic conditions. Reference [6] established the fundamental concept of UHI, explaining the role of urban materials and reduced vegetation in increasing heat retention, particularly during nighttime. Subsequent studies have reported that areas with greater vegetation coverage tend to exhibit cooler and more thermally comfortable conditions than densely built-up areas [7]–[10]. These findings highlight the importance of continuous measurements at the local scale to characterize thermal differences between urban and rural environments.

The Temperature-Humidity Index (THI) is a practical indicator for assessing thermal comfort because it incorporates air temperature and relative humidity into a single index [11]. Meanwhile, the availability of low-cost microcontroller platforms, such as the ESP32, and cloud-based services, such as Firebase, enables the development of IoT instrumentation for real-time environmental monitoring [12]. Previous research has demonstrated the application of DHT22 sensors and ESP32 microcontrollers for IoT-based temperature and humidity monitoring using platforms such as ThingSpeak [13]. An IoT wireless sensor network comprising 14 nodes was also used to monitor temperature and humidity differences between shaded green spaces and unshaded paved areas, demonstrating the feasibility of continuous and cost-effective microclimate monitoring [14]. In addition, Firebase-based IoT systems have been implemented for remote monitoring and smart-home applications [15].

Building upon these studies, this research develops and evaluates an IoT-based thermal monitoring instrument integrating a calibrated DHT22 sensor, ESP32 microcontroller, LCD display, Firebase database, and web dashboard. The system measures air temperature and relative humidity and calculates THI in real time for outdoor thermal comfort assessment. The instrument is deployed at an urban and a rural site to characterize their observed thermal contrast. Unlike studies focusing primarily on remote sensing or broader IoT sensor networks, this study emphasizes the instrumentation design, sensor calibration, real-time data transmission, and field implementation of a low-cost IoT system for localized thermal monitoring.

Accordingly, this study aims to design and implement an IoT-based instrumentation system for measuring air temperature and relative humidity, calculating THI, and assessing urban–rural thermal differences. The results are intended to demonstrate the applicability of low-cost IoT instrumentation for high-temporal-resolution microclimate and thermal comfort monitoring. Because the field comparison involves only two sites and a limited observation period, the observed thermal contrast is interpreted as consistent with an urban heat island pattern rather than as a definitive quantification of UHI intensity.

2. MATERIALS AND METHODS

2.1. System Flowchart

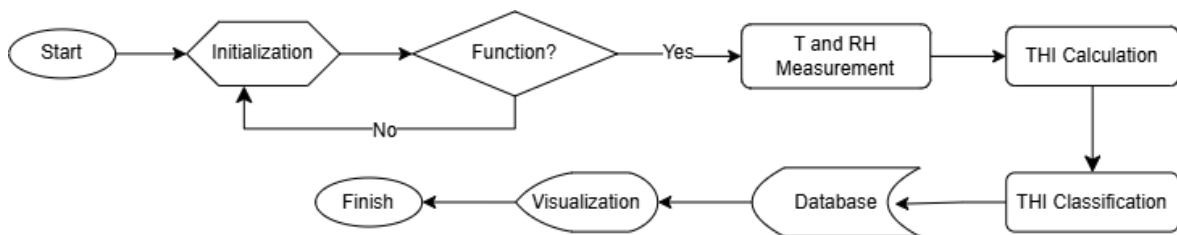


Fig. 1. System Flowchart

The developed IoT instrumentation system operates through a continuous sensing, processing, transmission, and visualization cycle, as illustrated in Fig. 1. The main operational stages are as follows:

1. **System Initialization:** The ESP32 microcontroller initializes hardware peripherals (DHT22 sensor, 20x4 I2C LCD) and establishes network connectivity via the Wi-Fi/MiFi module to configure the Firebase cloud environment.
2. **Connectivity & Diagnostic Verification:** The system continuously verifies network and sensor operational status; if a connection failure or hardware error occurs, an error alert is displayed on the local LCD, and the system attempts to re-initialize the link automatically.
3. **Data Acquisition:** The DHT22 measures ambient air temperature (T) and relative humidity (RH).

4. **THI Index Computation:** The measured temperature and relative humidity are corrected using the calibration parameters obtained from laboratory calibration. The corrected values are then used to calculate the Temperature-Humidity Index (THI).
5. **Thermal Comfort Classification:** The calculated THI value is classified according to the thermal comfort boundaries adopted in this study [20].
6. **Local Display:** The corrected temperature, relative humidity, THI, and thermal comfort classification are displayed on the 20×4 I2C LCD.
7. **Cloud Data Transmission:** The ESP32 packages the measurement parameters into a JSON payload and transmits the data to the Firebase Realtime Database.
8. **Web Visualization and Sampling Cycle:** The stored data are displayed on the web dashboard through real-time charts and tables. After the predefined sampling interval, the system repeats the measurement cycle.

2.2. Hardware Design

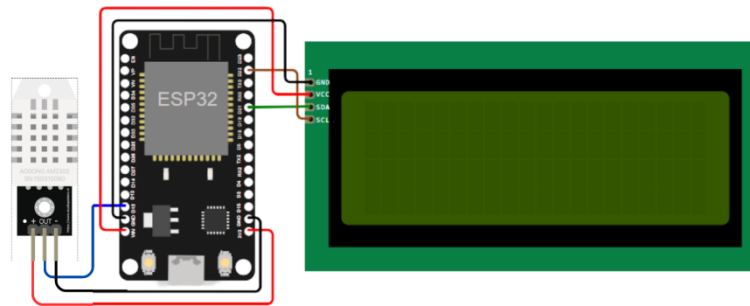


Fig. 2. Circuit Schematic

The hardware consists of an ESP32 microcontroller, DHT22 temperature and relative humidity sensor, and 20×4 I2C LCD. The DHT22 is connected to the ESP32 using 3.3 V for the supply, GND for the ground connection, and GPIO 13 (D13) for the data signal. The I2C LCD is connected to GND, VIN, GPIO 21 (SDA), and GPIO 22 (SCL), respectively, as shown in Fig. 2.

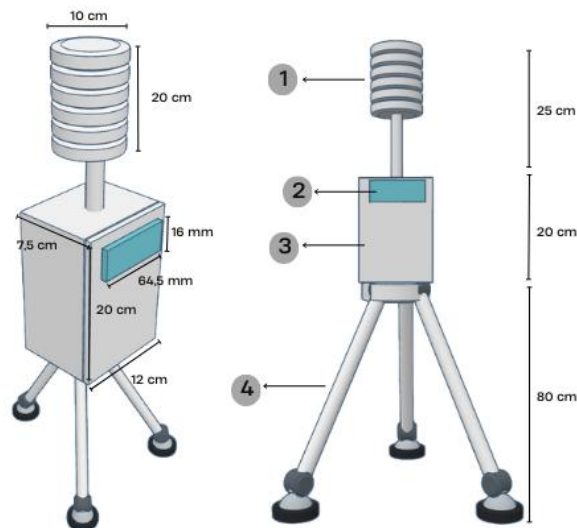


Fig. 3. Hardware Design

The physical instrument was designed to support outdoor measurements while protecting the sensing and electronic components from direct environmental exposure. As shown in Fig. 3, the system consists of four main components: (1) a Stevenson screen to reduce direct solar radiation exposure to the sensor, (2) an LCD frame for local data visualization, (3) an enclosure containing the ESP32 and electronic components, and (4) a tripod supporting the measurement assembly.

2.3. Software Design

The software system consists of the ESP32 firmware, Firebase Realtime Database, and web dashboard. The ESP32 performs sensor acquisition, data correction, THI calculation, thermal comfort classification, and data transmission. Firebase is used as the cloud-based data storage platform, while the web dashboard provides remote visualization of the measurement results.

Firebase Realtime Database is a NoSQL cloud database service that enables data storage and synchronization between connected devices and applications [16]. The database structure contains the following parameters: id as a unique data identifier, waktu as the measurement timestamp, tt_air as air temperature, rh as relative humidity, thi as the calculated THI, and status as the corresponding thermal comfort classification.

2.4. Sensor Calibration

Sensor calibration was conducted at the BMKG Central Calibration Laboratory by comparing DHT22 measurements with reference instruments. Temperature calibration was performed at set points of 20°C, 30°C, and 40°C using a Climatic Kambic Chamber and a Fluke Hart Scientific 5627A reference thermometer. Relative humidity calibration was conducted at 40%, 60%, and 80% using a Rotronic HG2S chamber and a Vaisala HMT 333 reference instrument. The calibration procedure was used to determine the measurement error and correction parameters of the DHT22 sensor [17].

The correction value was calculated as the difference between the reference measurement and the sensor reading:

$$C = X_{\text{standard}} - X_{\text{sensor}} \quad (1)$$

Where X_{standard} is the reference value and X_{sensor} is the uncorrected sensor reading. The correction parameter was subsequently applied to the corresponding sensor measurement:

$$X_{\text{corrected}} = X_{\text{sensor}} + C \quad (2)$$

Thus, the temperature and relative humidity values used for THI calculation and field analysis represent corrected measurements rather than raw DHT22 outputs.

2.5. Temperature Humidity Index

The Temperature Humidity Index (THI) is an indicator to assess thermal comfort levels based on environmental conditions by combining the effects of air temperature and relative humidity into a single index, without directly considering human physiological factors [15]. First proposed by Thom (1959), the THI was subsequently modified by Nieuwolt (1977) and Emmanuel (2005) for application in tropical regions by replacing the wet-bulb temperature parameter with relative humidity, as the latter more easily obtained from standard meteorological observations [18]. In this study, THI was calculated using the following modified empirical equation [19]:

$$THI = 0.8 \times T + \left(\frac{RH \times T}{500} \right) \quad (3)$$

Where T represents ambient air temperature in degrees Celsius (°C), RH represents relative humidity in percent (%), and THI is the resulting index value. The THI classification used in this study follows Wati and Fatkhuroyan (2017) [20], as presented in Table 1.

Table 1. Thermal Comfort Classification

THI Range	Classification	Thermal Perception
THI < 21	Cold	Cool / Cold condition
21 ≤ THI < 25	Comfortable	Optimal human thermal comfort
25 ≤ THI ≤ 27	Partly Comfortable	Mild thermal discomfort
> 27	Uncomfortable	High thermal discomfort / Heat stress

2.6. Urban–Rural Thermal Comparison

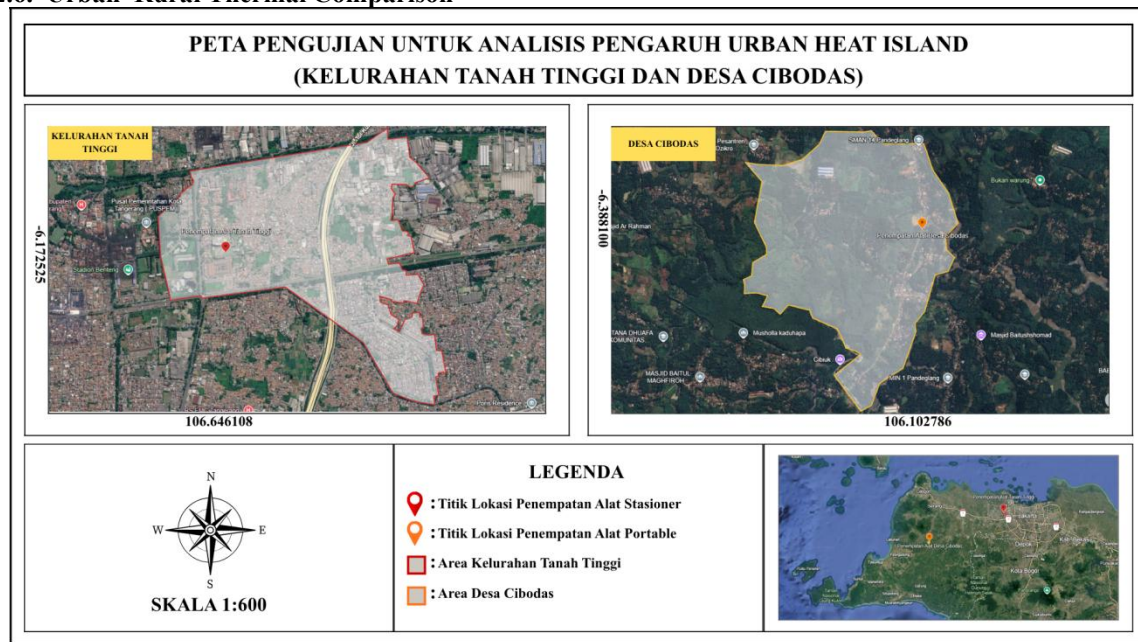


Fig. 4. Map of monitoring locations in Tangerang (Urban) and Serang (Rural)

To assess urban–rural thermal differences, two monitoring units were deployed simultaneously at two locations with contrasting urban characteristics. The urban site was located in Kelurahan Tanah Tinggi (−6.172525, 106.646108; elevation 12.53 m above sea level), while the rural comparison site was located in Desa Cibodas (−6.388100, 106.102786; elevation 99.63 m above sea level). Site classification was based on the Regulation of the Head of Statistics Indonesia (BPS) No. 120 of 2020 concerning the Classification of Urban and Rural Areas in Indonesia [21].

Field measurements were conducted continuously for 24 hours, from 18 July 2026 at 08:00 WIB to 19 July 2026 at 07:59 WIB. Both monitoring units were operated using the same measurement interval to enable temporal comparison between the two locations. Air temperature and relative humidity were measured simultaneously, and THI was calculated from the corrected sensor measurements.

The comparison was intended to characterize differences in air temperature, relative humidity, and thermal comfort between the urban and rural sites. The observed urban–rural differences were interpreted as thermal contrasts consistent with the UHI phenomenon, rather than as a definitive measurement of UHI intensity, because the observations were limited to two locations and a short monitoring period.

The two sites also differed in elevation and local environmental characteristics. The urban site was located at 12.53 m above sea level, whereas the rural site was located at 99.63 m above sea level. Therefore, differences in elevation, vegetation, land cover, shading, and other local environmental conditions may contribute to the observed thermal differences in addition to urbanization.

3. RESULTS AND DISCUSSION

3.1. Calibration Results

Calibration tests of the two DHT22 sensors were conducted at the BMKG Central Calibration Laboratory to determine their measurement errors and correction parameters. The results for temperature and relative humidity are presented in Tables 2 and 3.

Table 2. Temperature Sensor Calibration Results

Standard	DHT22-1	Correction	DHT22-2	Correction
20.241	20.200	0.041	20.300	-0.059
30.250	30.200	0.050	30.200	0.050
40.264	40.400	-0.136	40.200	0.064

As presented in Table 2, the calibration results reveal that the temperature measurement corrections for sensor DHT22-1 range between −0.136°C to 0.050°C. Meanwhile, sensor DHT22-2 exhibits narrower temperature corrections, ranging from −0.059°C to 0.064°C.

Table 3. Relative Humidity Sensor Calibration Results

Standard	DHT22-1	Correction	DHT22-2	Correction
39.95	40.00	-0.09	39.90	0.03
60.23	61.10	-0.87	60.30	-0.07
80.92	80.20	0.72	80.30	0.62

Table 3 illustrates the relative humidity calibration results. The humidity reading corrections for sensor DHT22-1 range from -0.87% to 0.72%, whereas sensor DHT22-2 demonstrates higher stability with corrections spanning from -0.07% to 0.62%. The calibration results show that the DHT22 sensors exhibited relatively small measurement deviations across the tested temperature and relative humidity ranges. The correction values were determined from the difference between the reference measurements and the corresponding sensor readings. These correction parameters were subsequently applied to the sensor measurements used during field observations.

3.2. Hardware and Software Implementation



Fig. 5. (a) Instrument at Cibodas; (b) instrument at Tanah Tinggi

The physical deployment of the monitoring instruments at the two observation sites is shown in Fig. 5. Each unit consisted of a DHT22 sensor housed in a Stevenson screen, an ESP32 DevKit V1, a MiFi router for wireless communication, a rechargeable battery pack, and a 20×4 I2C LCD. The Stevenson screen was used to reduce direct exposure of the sensor to solar radiation and precipitation, while the electronic components were placed inside a protective enclosure.

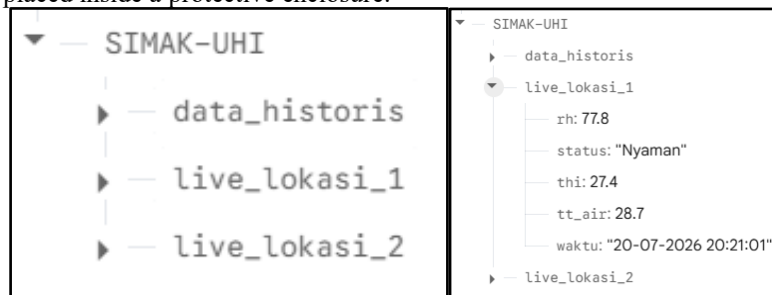


Fig. 6. Database Implementation

The Firebase Realtime Database implementation is shown in Fig. 6. Measurement data were organized under the SIMAK-UHI database into historical and site-specific nodes. The stored parameters included air temperature (tt_air), relative humidity (rh), THI (thi), thermal comfort classification (status), and measurement time (waktu). The database enabled the measurements from both monitoring units to be stored and accessed by the web application.

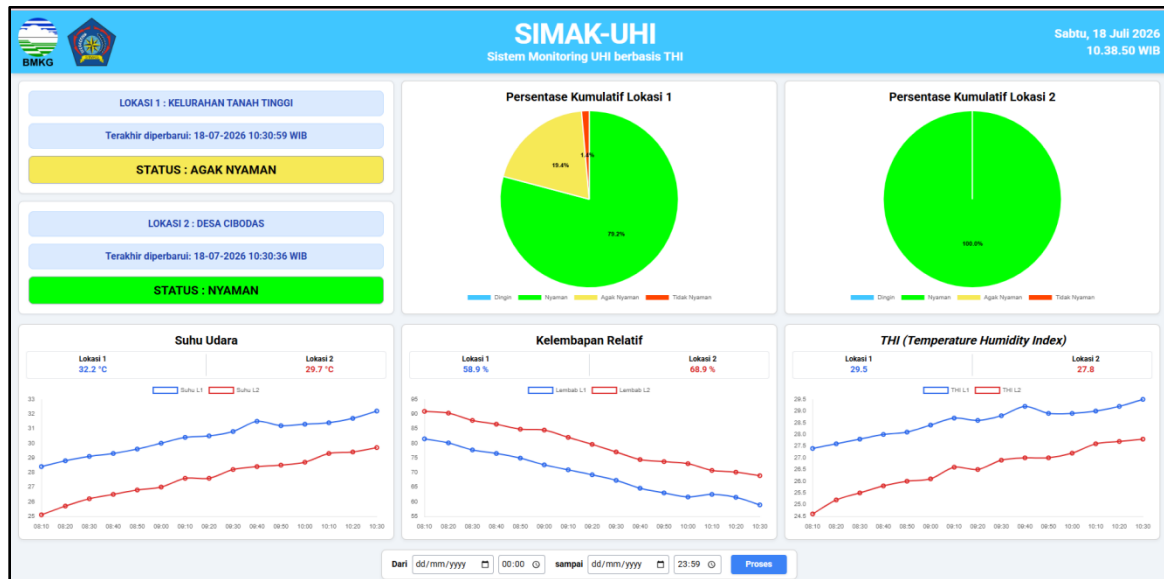


Fig. 7. Web Interface Implementation

The web interface developed for the system is presented in Fig. 7. The dashboard provides real-time visualization through time-series charts, status indicators, and historical data tables. This configuration enables remote observation of temperature, relative humidity, and THI from the two monitoring locations.

3.3. Air Temperature

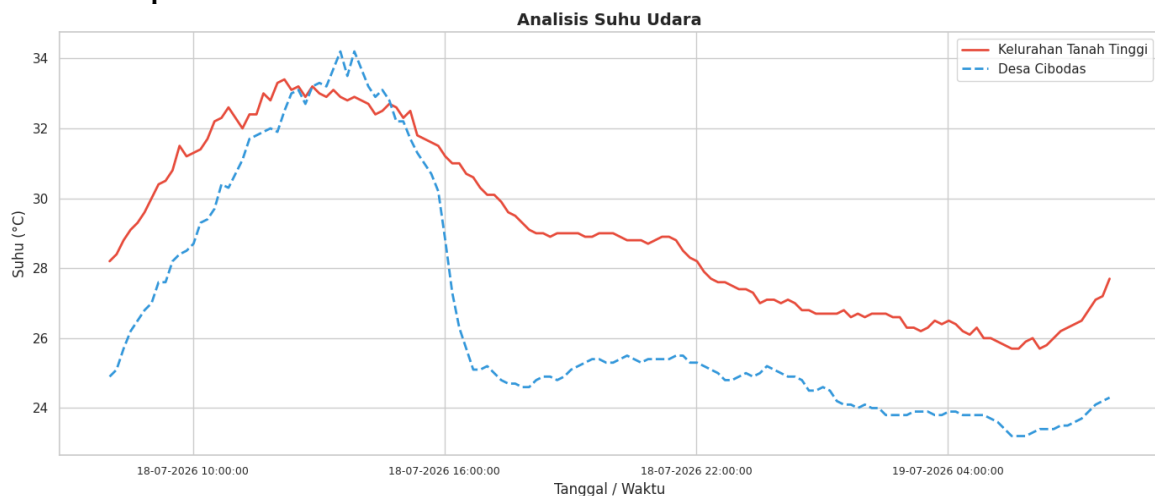


Fig. 8. Ambient Air Temperature Profile

The air temperature profiles at the two locations are shown in Fig. 8. Both sites exhibited a similar diurnal pattern, with temperature generally increasing from morning toward midday and decreasing during the afternoon and nighttime.

Kelurahan Tanah Tinggi recorded a maximum temperature of 33.4°C and a minimum of 25.7°C, while Desa Cibodas recorded a maximum of 34.2°C and a minimum of 23.2°C. The mean temperature was 29.05°C at Tanah Tinggi and 26.63°C at Cibodas, resulting in a difference of 2.42°C. Although the rural site recorded a slightly higher maximum temperature, the urban site maintained a higher minimum and mean temperature during the observation period. This pattern indicates greater persistence of warm conditions at the urban site.

The higher minimum and mean temperatures observed at Tanah Tinggi are consistent with an urban–rural thermal contrast. However, this difference may also be influenced by elevation, vegetation, land cover, shading, and other local environmental characteristics. Therefore, the observed temperature pattern should be interpreted as consistent with the UHI phenomenon rather than as definitive evidence of UHI intensity.

3.4. Relative Humidity

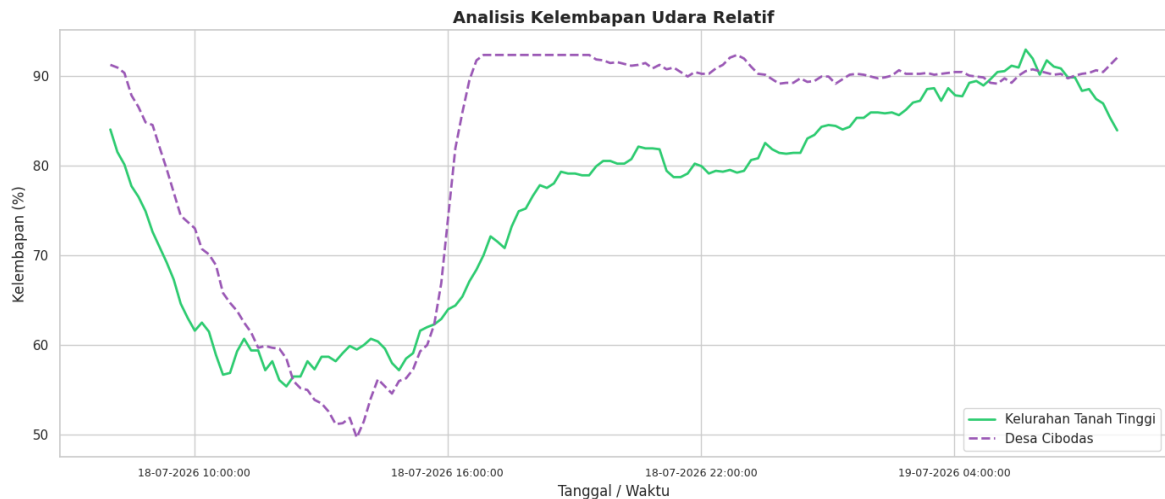


Fig. 9. Relative Humidity Profile

The relative humidity profiles are presented in Fig. 9. Both locations generally exhibited higher relative humidity during nighttime and early morning and lower values during periods of higher temperature. The maximum relative humidity was 92.9% at Tanah Tinggi and 92.3% at Cibodas, while the minimum values were 55.4% and 49.7%, respectively. The mean relative humidity at Tanah Tinggi was 75.77%, compared with 81.93% at Cibodas, representing a difference of 6.16 percentage points.

The lower mean relative humidity at the urban site occurred alongside its higher mean air temperature. Differences in vegetation, land cover, moisture availability, and local atmospheric conditions may contribute to the observed humidity contrast. Therefore, the difference should be considered as a site-specific microclimatic contrast rather than being attributed solely to urbanization.

3.5. Temperature Humidity Index

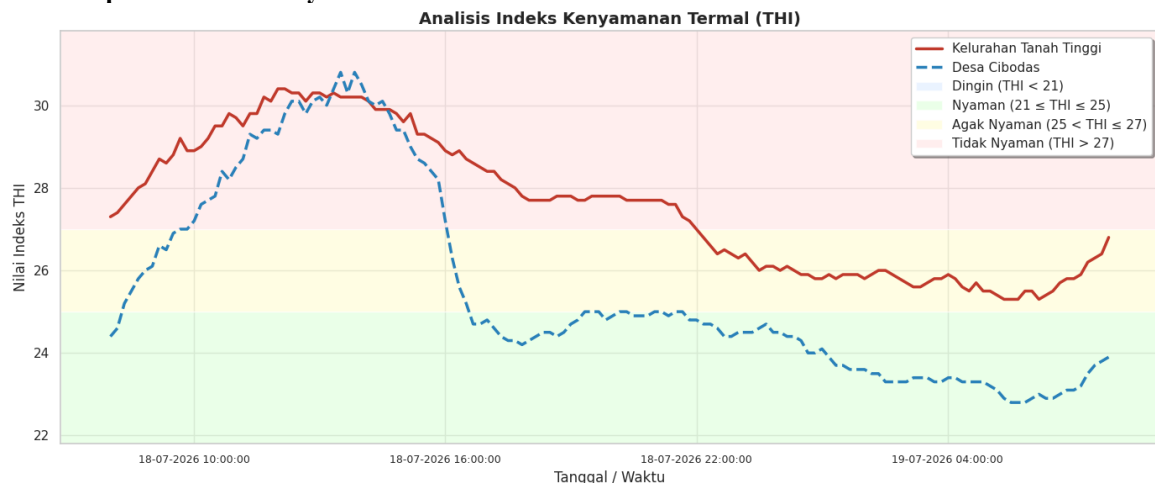


Fig. 10. Temperature Humidity Index (THI) Profile

The THI profiles for the two monitoring locations are presented in Fig. 10. The THI generally followed the temporal variation of air temperature, with higher values observed during warmer periods and lower values during nighttime and early morning. During the 24-hour observation period, the maximum THI values were 30.4 at Kelurahan Tanah Tinggi and 30.8 at Desa Cibodas, while the minimum values were 25.3 and 22.8, respectively. The mean THI was 27.59 at Tanah Tinggi and 25.57 at Cibodas, resulting in a mean difference of 2.02.

Based on the THI classification adopted from Wati and Fatkhuroyan (2017), the mean THI at Tanah Tinggi (27.59) was categorized as “Uncomfortable”, whereas the mean THI at Cibodas (25.57) was categorized as “Partly Comfortable.” The higher mean THI at Tanah Tinggi indicates warmer thermal conditions during the observation period compared with Cibodas. The difference in THI is associated with variations in air

temperature and relative humidity between the two locations. However, the observed thermal difference may also be influenced by differences in elevation, vegetation, land cover, and other local environmental characteristics.

3.6. Cumulative THI Distribution

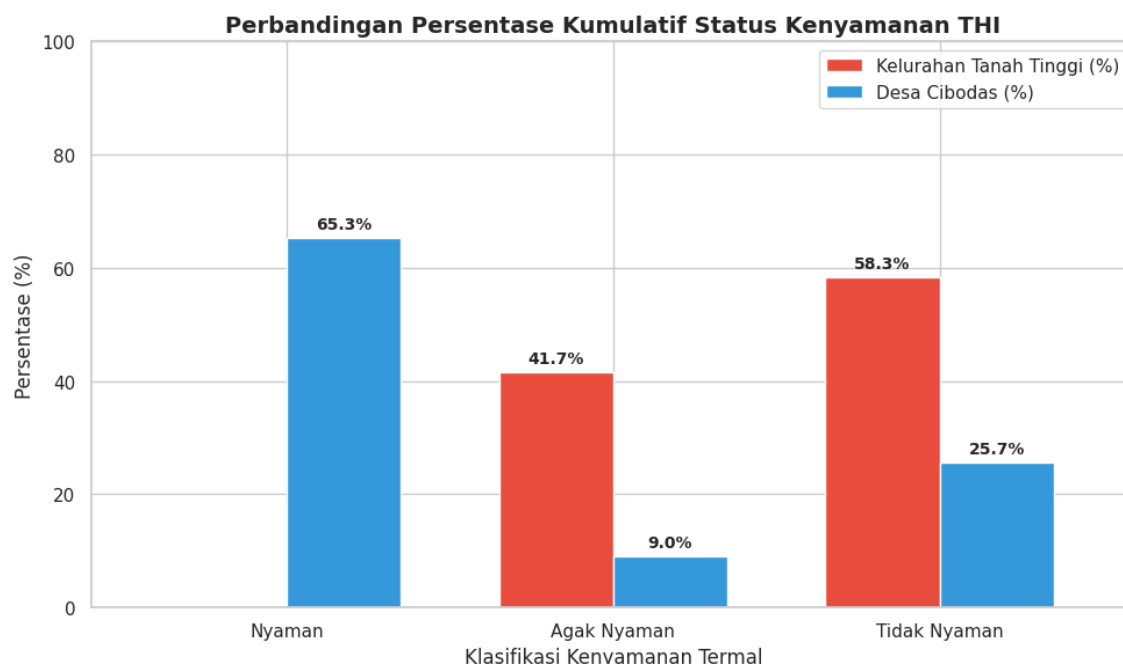


Fig. 11. Cumulative THI Percentage

The cumulative distribution of THI classifications is presented in Fig. 11. At Kelurahan Tanah Tinggi, 58.33% of the observations were classified as “Uncomfortable”, while 41.67% were classified as “Partly Comfortable.” No observations were classified as “Comfortable” during the monitoring period. At Desa Cibodas, 65.28% of the observations were classified as “Comfortable,” followed by 25.69% classified as “Uncomfortable” and 9.03% classified as “Partly Comfortable.” The “Cold” category was not observed at either location.

The distribution indicates that Tanah Tinggi experienced a greater proportion of thermally uncomfortable conditions than Cibodas during the 24-hour observation period. In contrast, Cibodas was predominantly within the “Comfortable” category. This difference is consistent with the higher mean air temperature and THI observed at Tanah Tinggi. Previous studies have reported that vegetation and natural land cover can contribute to the moderation of local thermal conditions [7]–[10]. Nevertheless, these factors were not independently measured in the present study, and therefore their specific contribution cannot be quantified.

Overall, the results demonstrate an urban–rural thermal contrast during the 24-hour monitoring period, with Tanah Tinggi exhibiting a higher mean air temperature and THI and a greater proportion of “Uncomfortable” conditions than Cibodas. This pattern is consistent with an urban heat island pattern; however, it should not be interpreted as a definitive quantification of UHI intensity because the comparison was based on only two monitoring locations with different elevations and local environmental characteristics. Longer observation periods and additional monitoring locations with comparable environmental conditions are required to better distinguish the influence of urbanization from other topographic and microclimatic factors.

3.7. Limitations

This study has several limitations that should be considered when interpreting the observed urban–rural thermal differences. First, the comparison was conducted at only two single-point monitoring sites over a limited 24-hour observation period. The monitored sites also differ in elevation and local environmental characteristics. Cibodas is located at 99.63 m above sea level (ASL), whereas Tanah Tinggi is located at 12.53 m ASL. Based on a standard environmental lapse rate of approximately 0.65°C per 100 m, the 87.10 m elevation difference could account for approximately 0.57°C of the observed 2.42°C difference in mean air temperature. Therefore, the observed temperature contrast cannot be attributed solely to urbanization, as topography, land cover, and vegetation may also influence the local microclimate.

Second, the 24-hour observation period provides only a short-term representation of the thermal conditions and does not capture diurnal patterns over multiple days, seasonal variability, or long-term UHI behavior. Third, the use of only two monitoring locations limits the spatial representativeness of the results. Consequently, the observed urban–rural thermal contrast should be interpreted as consistent with an urban heat island pattern rather than as a definitive quantification of UHI intensity. Future studies should employ longer observation periods and multiple monitoring sites with comparable elevation and systematically characterized environmental conditions to better isolate and quantify the contribution of urbanization to thermal differences.

4. CONCLUSION

This study designed, calibrated, and deployed a low-cost IoT-based instrumentation system for real-time microclimate monitoring and outdoor thermal comfort assessment using the Temperature-Humidity Index (THI). The system integrates a DHT22 sensor, ESP32 microcontroller, LCD, Firebase Realtime Database, and web dashboard to support local and remote monitoring. Laboratory calibration was conducted against BMKG reference instruments to determine sensor measurement deviations and correction parameters for air temperature and relative humidity. The corrected measurements were subsequently used for THI calculation and field observations.

During the 24-hour urban–rural comparison, with measurements recorded at 10-minute intervals, Tanah Tinggi recorded a higher mean air temperature (29.05°C) than Cibodas (26.63°C), with a difference of 2.42°C. Mean relative humidity was 75.77% at Tanah Tinggi and 81.93% at Cibodas, while mean THI values were 27.59 and 25.57, respectively. Based on the THI classification adopted from Wati and Fatkhuroyan (2017), the mean THI at Tanah Tinggi was categorized as “Uncomfortable,” whereas Cibodas was categorized as “Partly Comfortable.” The cumulative THI distribution showed that 58.33% of observations at Tanah Tinggi were classified as “Uncomfortable” and 41.67% as “Partly Comfortable.” At Cibodas, 65.28% were classified as “Comfortable,” 25.69% as “Uncomfortable,” and 9.03% as “Partly Comfortable.”

These results indicate an urban–rural thermal contrast consistent with an urban heat island pattern. However, the findings should not be interpreted as a definitive quantification of UHI intensity because the observation was limited to two sites over 24 hours, and the sites differed in elevation and local environmental characteristics. Future research should involve longer monitoring periods and multiple monitoring locations with comparable environmental conditions to improve the spatial and temporal representation of urban–rural thermal conditions and better isolate the influence of urbanization.

DECLARATIONS

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- **Author Contributions:** Muhammad Afif: Conceptualization, Methodology, Software, Data Acquisition, Investigation, and Writing – Original Draft. Dibyo Susanto, Muchamad Rizqy Nugraha, and Achmad Fahrudin Rais: Supervision, Validation, Review, and Editing.
- **Conflict of Interest:** The authors declare that they have no competing financial interests or personal relationships that could influence the work reported in this paper.
- **Data Availability:** The raw telemetry records generated during the field deployment are stored in the Firebase Realtime Database. The calibration datasets and analytical data used in this study are available from the corresponding author upon reasonable request, subject to applicable institutional restrictions.
- **Generative AI Use:** Generative AI tools (Google Gemini) were used solely for English-language grammar correction and translation refinement of author-generated text. All conceptualization, experimental design, data acquisition, calculations, data analysis, and interpretation were performed by the authors.
- **Ethics Approval and Informed Consent:** Not applicable.

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Experimental Evaluation of AMG8833 Thermal Sensor Performance for Hotspot Detection Under Different Distances and Lighting Conditions

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ABSTRACT

Early identification of abnormal temperature conditions is important for preventing overheating from developing into more serious thermal hazards. Thermal array sensors provide a non-contact approach for observing temperature distribution; however, their measurement behavior may vary with sensor-to-object distance and environmental conditions. This study experimentally evaluates the measurement performance of the AMG8833 thermal sensor for hotspot detection at different sensor-to-object distances and under different environmental lighting conditions. Measurements were conducted at distances of 5, 10, 15, 20, 30, 40, and 50 cm under bright, dim, and dark conditions. Each experimental combination was repeated five times, and one representative measurement was selected based on the relative stability of the temperature reading and hotspot pattern during the measurement process. The AMG8833 measurements were compared with a reference thermal gun to determine the measurement difference. The results showed that the mean measurement difference across the three conditions increased from 0.60°C at 5 cm to 2.73°C at 50 cm, with an R^2 of 0.956 for the linear fit of mean difference versus distance. The mean measurement differences across all tested distances were 1.59°C, 1.36°C, and 1.51°C under bright, dim, and dark conditions, respectively. Using a practical criterion of a mean measurement difference of $\leq 1^\circ\text{C}$ over the evaluated interval, the 5–20 cm interval was identified as the practical operating range for the tested hotspot measurement configuration. These results indicate that sensor-to-object distance produced a more pronounced variation in measurement difference than the tested environmental lighting conditions.

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1. INTRODUCTION

Temperature monitoring plays an important role in identifying abnormal thermal conditions before they develop into more serious equipment failures or fire hazards. Excessive temperature increases in electronic devices may degrade component performance, damage electronic components, and increase the risk of fire [1], [2]. When an abnormal increase in temperature is not detected at an early stage, localized high-temperature areas or hotspots may develop and potentially lead to more serious thermal hazards [3]. This condition is

particularly relevant in enclosed environments containing continuously operating electronic equipment, such as laboratories, server rooms, and data centers [4]. Therefore, the ability to identify localized temperature variations without direct contact is important for supporting early thermal monitoring. Conventional temperature sensors generally provide temperature measurements at a specific sensing point and may not adequately represent the spatial distribution of temperature across an observed object. In contrast, thermal array sensors can acquire temperature information from multiple sensing elements simultaneously, allowing localized thermal variations to be represented as a thermal distribution. This characteristic makes thermal array sensors potentially useful for non-contact hotspot detection and monitoring applications. The application of thermal sensing for non-contact monitoring has previously been demonstrated for machine condition monitoring using a thermal camera and a web-based application [5].

One thermal array sensor that can be utilized for this purpose is the AMG8833. The sensor provides thermal information from multiple pixels, enabling the detection of localized temperature variations on the surface of an observed object. Previous research has evaluated the accuracy of the AMG8833 for temperature measurement and compared its performance with other non-contact temperature sensors [6], [7]. Studies using infrared thermal array sensors have also demonstrated their capability to acquire spatial temperature information for monitoring and positioning applications [8]. These studies demonstrate the potential of the AMG8833 for temperature measurement applications. However, the practical performance of a thermal array sensor may also depend on the measurement configuration. In hotspot monitoring applications, the distance between the sensor and the observed object is one factor that may influence the temperature measurement because changes in distance affect the spatial area represented by the sensor's field of view [9], [10].

In addition to measurement distance, environmental conditions may also influence the observed thermal measurement. This study considers three lighting conditions, namely bright, dim, and dark conditions, to evaluate whether the AMG8833 produces consistent temperature measurements under different experimental environments. Although visible lighting does not constitute the primary sensing mechanism of a thermal sensor, testing under different lighting conditions provides an additional evaluation of the sensor's measurement behavior within the experimental setup.

Previous research has demonstrated the use of sensor-based monitoring systems for fire and thermal conditions. Zaputra et al. developed a fire detection system capable of monitoring flame, gas, voltage, current, and power parameters, with the monitoring results displayed through a website and notifications delivered via WhatsApp [11]. Other research has developed fire monitoring systems by integrating flame, smoke, and temperature sensors with automatic response mechanisms [12], while smoke- and flame-based systems have also been implemented with SMS notification capabilities [13]. These studies demonstrate the application of multiple sensing technologies for fire monitoring. However, flame and gas sensors are generally more suitable for detecting fire-related conditions after the occurrence of flames or gas leakage, rather than characterizing localized temperature increases during the early overheating stage [14]. Thermal sensing therefore provides an alternative approach for observing temperature variations before a visible flame occurs. In contrast to conventional fire detection approaches that primarily rely on flame, smoke, or gas detection, thermal array sensing can provide information regarding the spatial distribution of temperature. Although previous studies have demonstrated the temperature measurement capability of the AMG8833 [6], [7], further experimental evaluation is required to investigate its measurement behavior for hotspot detection across different sensor-to-object distances and lighting conditions.

Previous studies on non-contact infrared thermometry have also reported that measurement results can vary with measurement distance and other measurement conditions, emphasizing the importance of controlling the measurement configuration when evaluating non-contact thermal sensors [15]. Therefore, this study focuses on the experimental evaluation of the AMG8833 thermal sensor for hotspot detection. Temperature measurements obtained from the AMG8833 are compared with measurements from a thermal gun as a reference to determine the measurement difference at several sensor-to-object distances. The evaluation is conducted under bright, dim, and dark lighting conditions. The analysis is intended to identify the measurement range in which the AMG8833 provides relatively small temperature differences and to determine an effective distance for hotspot measurement under the tested experimental conditions. The objective of this study is to evaluate the measurement performance of the AMG8833 thermal sensor for hotspot detection based on measurement distance and lighting condition, quantify the difference between AMG8833 and reference temperature measurements, and determine the effective sensor-to-object distance for hotspot measurement.

2. RESEARCH METHOD

2.1. Research Design

This study employed an experimental method to evaluate the measurement performance of the AMG8833 thermal array sensor for hotspot detection. The evaluation was performed by comparing the temperature measured by the AMG8833 with the temperature obtained from an industrial thermal gun as a

reference instrument. Two main experimental variables were considered: the sensor-to-object measurement distance and the surrounding lighting condition. The measurement distances were set at 5, 10, 15, 20, 30, 40, and 50 cm. The experiment was conducted under three lighting conditions, namely bright, dim, and dark. The bright condition was conducted between 09:00 and 10:00, the dim condition between 17:00 and 18:00, and the dark condition between 21:00 and 22:00.

Each combination of measurement distance and lighting condition was tested five times. From the five repeated measurements, one representative measurement result was recorded for each distance and subsequently used in the analysis. Therefore, the final analysis consisted of one representative measurement for each of the seven distances under each lighting condition.

2.2. Measurement Setup

The hardware of tools system consisted of an ESP32 microcontroller, AMG8833 thermal array sensor, flame sensor, TFT LCD, and microSD card. The AMG8833 served as the primary sensor evaluated in this study, while the ESP32 was used to acquire and process the thermal measurement data. The AMG8833 is an infrared thermal array sensor consisting of 64 sensing elements arranged in an 8×8 matrix. The sensor provides temperature information from multiple pixels, allowing the thermal distribution of an observed object to be represented. This characteristic enables the sensor to identify localized areas with higher temperatures, which are used as the hotspot information in this study. The flame sensor, TFT LCD, and microSD card functioned as supporting components of the overall monitoring prototype and were not used as the primary variables in the evaluation of AMG8833 measurement performance.

A Benetech GM320 infrared thermometer was used as the reference instrument for comparative temperature measurements. According to the manufacturer's specification, the GM320 has a temperature measurement range of -50°C to 400°C . Its stated accuracy is $\pm 1.5^{\circ}\text{C}$ or $\pm 1.5\%$ for measurements from 0°C to 400°C , and $\pm 5^{\circ}\text{C}$ for measurements from -50°C to 0°C . The instrument has a resolution of $0.1^{\circ}\text{C}/0.1^{\circ}\text{F}$, a stated repeatability of 1% of the reading or 1°C , and a response time of 500 ms (95%). The GM320 has a spectral response range of 5–14 μm , a preset emissivity of 0.95, and a distance-to-spot ratio (D:S) of 12:1. No additional calibration or adjustment was performed by the authors before the experiment.

During the comparative measurement, the GM320 was directed toward the same hotspot region of the smartphone that was observed by the AMG8833. The temperature reading from the GM320 was recorded at each sensor-to-object distance and subsequently compared with the maximum temperature obtained from the AMG8833. This procedure was applied consistently across the tested measurement distances and experimental conditions.



Fig. 1 Hardware Implementation

2.3. Test Object and Hotspot Simulation

The Poco F7 smartphone was used as the test object for hotspot simulation. To generate a consistent thermal workload, Mobile Legends was operated for approximately 25–30 minutes in each experimental session. The gameplay workload and device configuration were kept consistent across all experiments. All available game graphics and performance-related settings were configured to their highest available levels, including the ultra graphics mode, to impose a relatively high processing load on the smartphone and induce a measurable hotspot. The smartphone was operated under this workload before the measurement process was conducted. Because the hotspot temperature could fluctuate during operation, the thermal response was monitored during the measurement process using both the temperature readings and the thermal heatmap pattern. A measurement was considered representative when the temperature reading and the location and pattern of the hotspot appeared relatively stable, consistent with the representative-measurement procedure described in Section 2.6.



Fig. 2 Object of Simulation

2.4. Measurement Configuration

The effect of sensor-to-object distance was evaluated at seven measurement distances: 5, 10, 15, 20, 30, 40, and 50 cm. At each distance, the AMG8833 was positioned facing the hotspot area of the smartphone. The distance was measured between the sensing position of the AMG8833 and the surface of the smartphone. The same target area was subsequently measured using the industrial thermal gun as the reference instrument. The variation in measurement distance was intended to evaluate the ability of the AMG8833 to measure the hotspot temperature at different observation ranges. The results obtained at short distances were compared with those obtained at longer distances to determine the effective measurement range of the sensor.

2.5. Environmental Conditions

The experiment was conducted in an enclosed indoor room using natural sunlight entering through the room openings as the primary source of illumination. No additional artificial lighting was used during the measurements. Other environmental factors that could directly affect the thermal condition of the test object were also minimized; no air conditioning or additional fan was used during the experiment. Three environmental conditions were considered: bright, dim, and dark. The bright condition was conducted between 09:00 and 10:00, the dim condition between 17:00 and 18:00, and the dark condition between 21:00 and 22:00. Illumination was not quantitatively measured using a lux meter; therefore, the terms bright, dim, and dark refer to the naturally occurring illumination conditions observed during the specified measurement periods. Because the three conditions were tested at different times of day, differences in ambient temperature, environmental conditions, and the thermal state of the smartphone could not be completely separated from the lighting condition. Therefore, comparisons among the bright, dim, and dark conditions are interpreted as comparisons under the tested environmental conditions and measurement periods rather than as an isolated effect of illumination.



Fig. 3 Documentation of The Experiment in Each Condition

2.6. Experimental Procedure

The measurement procedure was conducted according to the following stages:

1. The Poco F7 smartphone was operated by running resource-heavy application to generate a localized hotspot.
2. The smartphone was operated until the hotspot temperature began to stabilize at approximately more than 30°C.
3. The experimental condition was established according to the specified lighting condition.
4. The AMG8833 was positioned at the predetermined distance of 5, 10, 15, 20, 30, 40, or 50 cm from the smartphone.
5. The thermal measurement from the AMG8833 was recorded.
6. The same hotspot area was measured using the industrial thermal gun.
7. The measurement distances were tested sequentially from 5 to 50 cm (5, 10, 15, 20, 30, 40, and 50 cm) without randomization. The same sequence was consistently applied across all experimental conditions and repeated measurements.

8. The measurement procedure was repeated five times for each distance and lighting condition. During each measurement, the temperature readings and thermal heatmap pattern were observed, as the smartphone hotspot could fluctuate during operation.
9. One representative measurement was selected from the five repetitions when the temperature reading and the location and pattern of the hotspot appeared relatively stable. The selection was performed during the measurement process and before comparison with the reference thermal gun. The procedure was repeated for all seven measurement distances and three environmental conditions.

The resulting data were then used to calculate the temperature difference between the AMG8833 and the industrial thermal gun.

2.7. Temperature Difference Analysis

The difference between the AMG8833 measurement and the reference thermal gun measurement was calculated using the absolute difference:

$$D = T_A - T_{Ref} \quad (1)$$

In equation (1) where D is the absolute temperature difference in $^{\circ}\text{C}$, T_A is the temperature measured by the AMG8833, and T_{Ref} is the temperature measured by the industrial thermal gun. The calculated difference was used to evaluate the agreement between the AMG8833 and the reference instrument at each measurement distance and lighting condition. A smaller value of (D) indicates that the AMG8833 measurement is closer to the reference measurement.

The average temperature difference for a specific measurement range was calculated from the representative measurement differences recorded at the corresponding distances:

$$Da = \frac{n \sum_{i=1}^n D_i}{n} \quad (2)$$

In equation (2) where Da is the average temperature difference, D_i is the temperature difference at the (i)-th measurement distance, and (n) is the number of measurement distances included in the evaluated range. The measurement differences obtained at 5–20 cm were subsequently compared with those obtained at longer distances to determine the effective measurement range of the AMG8833 under the tested experimental conditions.

3. RESULT AND DISCUSSION

3.1. Bright Condition

The measurement results under bright conditions are presented in Table 1. The experiment was conducted at seven sensor-to-object distances ranging from 5 cm to 50 cm. The temperature measured by the AMG8833 was compared with the temperature obtained from the industrial thermal gun.

Table 1. Temperature Measurement Results under Bright Conditions

Distance	AMG8833 ($^{\circ}\text{C}$)	Thermal Gun ($^{\circ}\text{C}$)	Difference ($^{\circ}\text{C}$)
5 cm	40.3	40.7	0.4
10 cm	39.8	40.1	0.3
15 cm	39.5	40.8	1.3
20 cm	39.3	40.5	1.2
30 cm	38.8	39.8	1.0
40 cm	37.0	39.7	2.7
50 cm	35.3	39.5	4.2

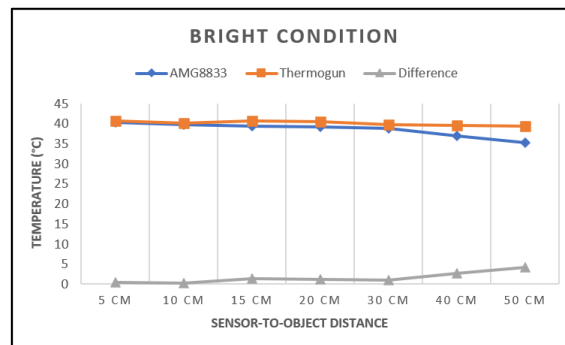


Fig. 4 Bright Condition Graph

Under bright conditions, the AMG8833 recorded a maximum temperature of 40.3°C and a minimum temperature of 35.3°C, while the thermal gun recorded a maximum of 40.8°C and a minimum of 39.5°C. The measurement difference was relatively small at distances of 5 and 10 cm, with values of 0.4°C and 0.3°C, respectively. At 15 and 20 cm, the differences increased to 1.3°C and 1.2°C.

A more pronounced difference was observed at longer distances. At 30 cm, the difference was 1.0°C, increasing to 2.7°C at 40 cm and 4.2°C at 50 cm. These results indicate that the AMG8833 measurement increasingly deviated from the thermal gun measurement as the sensor-to-object distance increased.

For the 5–20 cm measurement range, the average difference was 0.8°C. This indicates that the AMG8833 provided relatively close temperature measurements to the reference instrument within this range. In contrast, the increasing difference at distances above 20 cm indicates a reduction in measurement agreement at longer observation distances.

3.2. Dim Condition

The measurement results under dim conditions are presented in Table 2.

Table 2. Temperature Measurement Results under Dim Conditions

Distance	AMG8833 (°C)	Thermal Gun (°C)	Difference (°C)
5 cm	40.3	41.2	0.9
10 cm	40.3	41.1	0.8
15 cm	40.0	41.3	1.3
20 cm	39.8	40.8	1.0
30 cm	39.3	40.7	1.4
40 cm	38.0	40.3	2.3
50 cm	36.8	38.6	1.8

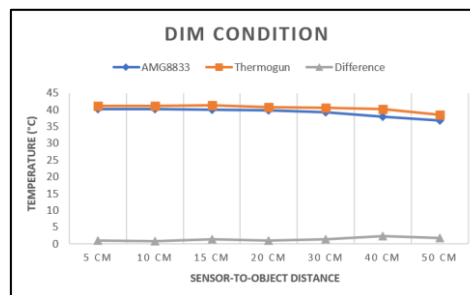


Fig. 5 Dim Condition Graph

Under dim conditions, the AMG8833 recorded a maximum temperature of 40.3°C and a minimum temperature of 36.8°C. The thermal gun recorded a maximum of 41.3°C and a minimum of 38.6°C. The measurement differences at 5, 10, 15, and 20 cm were 0.9°C, 0.8°C, 1.3°C, and 1.0°C, respectively.

Similar to the bright condition, the measurement difference generally increased at longer distances. The difference reached 2.3°C at 40 cm, while the difference at 50 cm was 1.8°C. The average difference within the 5–20 cm range was 1.0°C.

The results indicate that the AMG8833 maintained relatively close agreement with the reference measurement within the short-distance range. At distances beyond 20 cm, the difference generally became larger, indicating that the measurement distance had a more noticeable effect on the observed hotspot temperature.

3.3. Dark Condition

The measurement results under dark conditions are presented in Table 3.

Table 3. Temperature Measurement Results under Dark Conditions

Distance	AMG8833 (°C)	Thermal Gun (°C)	Difference (°C)
5 cm	41.5	42.0	0.5
10 cm	41.5	42.2	0.7
15 cm	41.0	42.2	1.2
20 cm	40.5	42.0	1.5
30 cm	39.0	41.2	2.2
40 cm	37.8	40.1	2.3

Distance	AMG8833 (°C)	Thermal Gun (°C)	Difference (°C)
50 cm	36.0	38.2	2.2

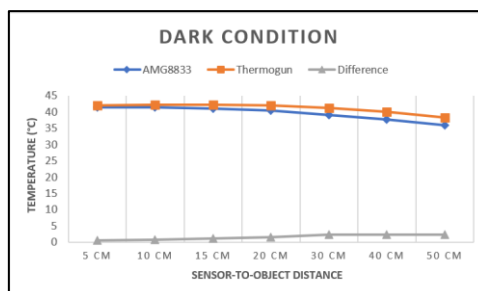


Fig. 6 Dark Condition Graph

Under dark conditions, the AMG8833 measured temperatures ranging from 36.0°C to 41.5°C, while the thermal gun measured temperatures ranging from 38.2°C to 42.2°C. The smallest measurement differences were obtained at 5 and 10 cm, with values of 0.5°C and 0.7°C, respectively.

At 15 and 20 cm, the differences increased to 1.2°C and 1.5°C. At longer distances, the differences were 2.2°C at 30 cm, 2.3°C at 40 cm, and 2.2°C at 50 cm. The average difference within the 5–20 cm range was approximately 1.0°C.

The results under dark conditions show a similar tendency to the bright and dim conditions, where the temperature difference between the AMG8833 and the reference instrument was generally smaller at shorter distances. The results also indicate that the AMG8833 remained capable of detecting the hotspot at longer distances, although the agreement with the reference measurement decreased.

3.4. Comparison of Measurement Differences Across Conditions

The measurement differences obtained under the three lighting conditions are summarized in Table 4.

Table 4. Comparison of Measurement Differences under Different Lighting Conditions

Distance	Bright (°C)	Dim (°C)	Dark (°C)
5 cm	0.4	0.9	0.5
10 cm	0.3	0.8	0.7
15 cm	1.3	1.3	1.2
20 cm	1.2	1.0	1.5
30 cm	1.0	1.4	2.2
40 cm	2.7	2.3	2.3
50 cm	4.2	1.8	2.2
Average (5-20cm)	0.8	1.0	1.0

The smallest measurement differences were generally observed at 5 and 10 cm, where all values remained below 1°C across the three tested lighting conditions. At 15 and 20 cm, some differences exceeded 1°C but remained relatively close to the reference values. The average measurement differences over the 5–20 cm range were 0.8°C, 1.0°C, and approximately 1.0°C under bright, dim, and dark conditions, respectively. Beyond 20 cm, the difference became more pronounced, with the largest value of 4.2°C observed under bright conditions at 50 cm.

A descriptive comparison was performed to examine the relative influence of measurement distance and lighting condition. The mean measurement difference across the three conditions increased from 0.60°C at 5 cm to 2.73°C at 50 cm. A linear fit of the mean measurement difference versus sensor-to-object distance produced a positive slope of approximately 0.049°C/cm with an R^2 of 0.956, indicating a strong increasing trend with distance. In comparison, the mean measurement differences across all tested distances were 1.59°C, 1.36°C, and 1.51°C for bright, dim, and dark conditions, respectively. These results indicate that measurement distance showed a more pronounced pattern of change in measurement difference than the tested lighting conditions.

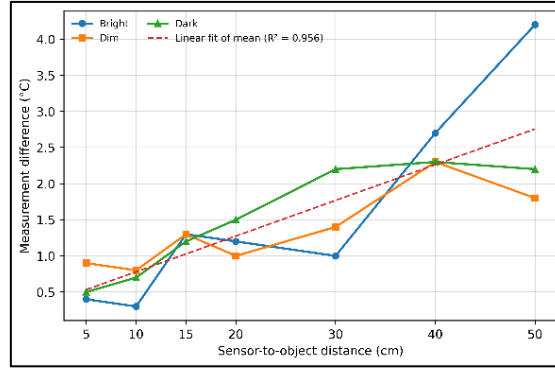


Fig. 7 Measurement Differences at Various Sensor-to-Object Distances

This behavior can be explained by the spatial characteristics of the AMG8833, which uses an 8×8 array consisting of 64 thermal sensing elements. As the sensor-to-object distance increases, the physical area represented within the field of view becomes larger, while the smartphone hotspot remains relatively localized. Consequently, the hotspot occupies a smaller portion of the sensing array, allowing surrounding lower-temperature areas to increasingly influence the detected maximum temperature. This spatial averaging effect provides a physical explanation for the increasing measurement difference observed at longer distances.

3.5. Effective Measurement Range

Based on the measurement results, the AMG8833 demonstrated relatively close agreement with the industrial thermal gun at short sensor-to-object distances. Across the three lighting conditions, the average measurement differences within the 5–20 cm range were 0.8°C , 1.0°C , and approximately 1.0°C for bright, dim, and dark conditions, respectively. These average values were calculated from the measurement differences obtained at 5, 10, 15, and 20 cm for each lighting condition.

The measurement differences generally increased when the distance exceeded 20 cm. The largest deviation was observed under bright conditions at 50 cm, where the difference reached 4.2°C . Although the AMG8833 was still capable of detecting the hotspot at longer distances, the measured temperature became less comparable with the reference instrument.

In this study, a mean measurement difference of $\leq 1^\circ\text{C}$ across a distance interval was used as the practical criterion for identifying the short-range operating range. The 5–20 cm interval produced mean measurement differences of 0.8°C under bright conditions, 1.0°C under dim conditions, and approximately 1.0°C under dark conditions. Although an individual measurement beyond 20 cm could also produce a difference of $\leq 1^\circ\text{C}$, such as the 1.0°C difference observed at 30 cm under bright conditions, this result was not consistent across the other lighting conditions. Therefore, the 5–20 cm interval is considered the practical operating range for the tested hotspot measurement configuration based on its mean measurement difference across all three lighting conditions.

3.6. Discussion

The experimental results indicate that the measurement behavior of the AMG8833 was more strongly associated with sensor-to-object distance than with the tested lighting conditions. The descriptive analysis showed an increasing mean measurement difference from 0.60°C at 5 cm to 2.73°C at 50 cm, with a linear-fit R^2 of 0.956. In contrast, the mean measurement differences across all tested distances were 1.59°C , 1.36°C , and 1.51°C under bright, dim, and dark conditions, respectively. This suggests that changes in measurement distance produced a more pronounced variation in the measurement difference than the differences observed among the three experimental lighting conditions.

The distance-dependent behavior can be explained by the spatial characteristics of the AMG8833. The sensor uses an 8×8 thermal array with a 60° viewing angle. Based on a simple geometric approximation, the field-of-view width can be estimated as

$$W = 2d \tan(30^\circ) \quad (3)$$

resulting in coverage widths of approximately 5.77 cm at 5 cm and 57.74 cm at 50 cm. Thus, the estimated spatial coverage of each pixel increases from approximately 0.72 cm to 7.22 cm over this distance range, this calculation based on equation (4) below.

$$W_{\text{pixel}} = \frac{W}{8} \quad (4)$$

Considering that the POCO F7 has a width of 7.79 cm, the hotspot occupies a relatively smaller portion of the sensing area as the distance increases. This can cause the detected maximum temperature to be increasingly influenced by surrounding lower-temperature areas, which helps explain the larger measurement differences observed at longer distances.

The lighting comparison should, however, be interpreted with caution. The bright, dim, and dark conditions were conducted at different times of day, namely 09:00–10:00, 17:00–18:00, and 21:00–22:00, respectively. Therefore, the lighting condition was not independently controlled from other environmental factors such as ambient temperature and the thermal state of the smartphone. Illumination was also not quantitatively measured in lux. The comparison therefore represents different experimental environmental conditions rather than an isolated effect of visible illumination on the AMG8833. Nevertheless, the relatively similar measurement differences obtained across the three conditions within the 5–20 cm interval indicate that the sensor maintained comparable measurement behavior under the tested conditions.

The use of a smartphone operated with a consistent high workload also introduced a dynamic thermal condition. Five repeated measurements were performed for each experimental combination, and one representative measurement was selected during the measurement process based on the relative stability of the temperature reading and hotspot pattern. This approach was used because the smartphone temperature could fluctuate during continuous gameplay. Therefore, the reported results should be interpreted as representative measurement differences for the tested configuration rather than a statistical estimate of repeatability or absolute sensor accuracy. The reference thermal gun was used as a comparison instrument, and the observed absolute differences describe measurement agreement between the two instruments rather than establishing the absolute accuracy of the AMG8833. Non-contact infrared temperature measurements can be affected by measurement configuration and other sources of uncertainty; therefore, the observed difference should be interpreted within the context of the experimental setup [16].

4. CONCLUSION

This study evaluated the measurement performance of the AMG8833 thermal sensor for hotspot detection at different sensor-to-object distances under bright, dim, and dark environmental conditions. The results showed that measurement difference generally increased with distance, with the mean difference increasing from 0.60°C at 5 cm to 2.73°C at 50 cm ($R^2 = 0.956$). In comparison, the mean differences under bright, dim, and dark conditions were 1.59°C, 1.36°C, and 1.51°C, respectively, indicating that sensor-to-object distance produced a more pronounced variation than the tested environmental lighting conditions. Based on a practical criterion of a mean measurement difference of $\leq 1^\circ\text{C}$, the 5–20 cm interval was identified as the practical operating range for the tested configuration. The increasing difference at longer distances can be associated with the spatial characteristics of the AMG8833 8×8 thermal array, where the hotspot occupies a smaller portion of the sensing area as distance increases. However, the lighting results should be interpreted cautiously because the tested conditions were conducted at different times of day and illumination was not quantitatively measured. Further studies should use controlled lighting and more stable hotspot conditions to improve the evaluation of measurement variability and repeatability.

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6. AUTHOR CONTRIBUTIONS

- Rizky Ramadhani: Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, Visualization, Writing – Original Draft.
- Adi Widiatmoko Wastumirad: Supervision, Methodology, Validation, Writing – Review & Editing.
- Tri Istiana: Supervision, Validation, Writing – Review & Editing.
- Agustina Rachmawardani: Validation, Writing – Review & Editing.
- Anton Widodo: Validation, Writing – Review & Editing.

7. CONFLICT OF INTEREST

Conflict of interest: The authors declare no conflict of interest.

8. DATA AVAILABILITY STATEMENT

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

9. GENERATIVE AI USE STATEMENT

Generative AI Use Statement: Generative AI tools were used to assist with the translation of the manuscript from Indonesian to English. The authors reviewed and verified all AI-assisted text and take full responsibility for the final content.

10. ETHICS APPROVAL

Ethics approval: Not applicable.

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INA-FOREWS: An IoT-Based Multi-Site Indonesia Forest Fire Early Warning System with Real-Time Risk Assessment and Alert Capabilities

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ABSTRACT

Despite the limitations of existing forest fire detection solutions, this study proposes the development of an IoT-based INA-FOREWS system to enhance real-time monitoring and risk assessment capabilities in Indonesia's tropical forests. The system aims to mitigate the impacts of forest fires and support progress towards the Sustainable Development Goals (SDGs) by integrating local sensor data with global spatial datasets. The system utilizes a rule-based approach to analyze environmental variables such as temperature, humidity, precipitation, and vegetation index, generating interactive fire risk maps to inform more effective response strategies. The hardware components, including sensors for temperature, humidity, gas, flame, and soil moisture, are deployed across multiple strategic locations and connected to a central ESP32 microcontroller for data transmission to a cloud-based platform. The web-based interface provides visualizations of sensor data, fire risk assessments, and emergency notification features to support decision-making by policymakers, local communities, and emergency responders. The strategic placement of sensors, guided by the rule-based risk assessment model, helps to optimize coverage and enhance the system's capacity for early fire detection. The proposed INA-FOREWS system serves as a model for integrating technological innovation with sustainability-focused objectives, contributing to improved forest fire management practices and supporting ecosystem preservation and community well-being in Indonesia's tropical regions.

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1. INTRODUCTION

Forest fires are a persistent global issue, particularly pronounced in regions like Indonesia where tropical forests play a crucial role in global ecological balance. The escalation of forest fires has far-reaching impacts, contributing to biodiversity loss, extensive carbon emissions, and socioeconomic damages [1]. When burned, Indonesia's densely forested regions, release massive amounts of carbon dioxide and other greenhouse gases, exacerbating global warming and leading to significant regional air pollution crises, causing health problems for millions [2].

Forest fires have widespread impacts on human and ecological health, directly challenging several United Nations Sustainable Development Goals (SDGs) [3]. Specifically, SDG 13 (Climate Action) highlights the need to mitigate climate change, with forest fires being significant contributors to carbon emissions, altering climate patterns, and accelerating global warming [4]. SDG 15 (Life on Land) aims to protect terrestrial ecosystems severely affected by fire-induced habitat destruction and land degradation.

Additionally, SDG 3 (Good Health and Well-being) is relevant, as the smoke and particulate matter from forest fires degrade air quality and exacerbate respiratory diseases in affected populations [1] [5].

Conventional forest fire detection systems, including satellite imagery and manual ground patrols, face significant limitations that hinder timely response, such as high latency, periodic data updates, and interference from cloud cover, which delay fire detection and mitigation efforts [6][7]. While satellite-based systems offer broad coverage, they often lack real-time monitoring and integration, diminishing their effectiveness in addressing dynamic fire conditions. Recent technological advancements in IoT-based systems provide a promising alternative by enabling continuous monitoring, real-time alerts, and more efficient spatial coverage, yet conventional approaches remain inadequate in providing comprehensive, real-time data and risk assessments [8]. These limitations not only reduce system responsiveness but also exacerbate environmental degradation caused by forest fires, undermining progress toward SDG targets related to carbon emissions reduction and terrestrial ecosystem preservation [3][9].

This study introduces the INA-FOREWS (Indonesia Forest Fires Early Warning System), an IoT-based platform designed to address the challenges of forest fires in Indonesia by integrating real-time environmental monitoring, IoT data collection, and risk assessment. The system aims to mitigate the impacts of forest fires by providing early alerts and enabling proactive measures, thus supporting climate resilience and ecosystem preservation in alignment with the SDGs. Key objectives include enhancing fire risk assessments through rule-based methods and spatial modeling approaches, as well as developing an IoT framework for improved fire detection and mitigation [1][10][11][12].

Focusing on fire-prone tropical regions in Indonesia, where historical data shows high fire incidence, the system incorporates global environmental data from sources like ERA5, MODIS, and VIIRS to refine fire risk assessments[13][14]. The platform features a web-based interface, providing actionable insights for policymakers, local communities, and emergency responders [15]. By leveraging rule-based decision-making and spatial data integration, the INA-FOREWS system advances IoT-based solutions for forest fire detection, enhancing management practices and response strategies in Indonesia's tropical forests, while aligning with global sustainability goals [11].

1.1. IoT in Forest Fire Detection

The integration of the Internet of Things (IoT) into forest fire detection systems offers a promising approach for real-time monitoring and early warning. IoT systems use interconnected devices to monitor environmental parameters like temperature, humidity, gas concentrations, and flame presence, transmitting data for analysis to identify fire-prone conditions and enable rapid responses [1][16]. Successful implementations of IoT-based systems, such as temperature and gas sensors paired with microcontrollers, have been shown to monitor high-risk areas and detect fire indicators effectively [17].

1.2. Rule-Based Systems in Risk Assessment

Rule-based systems use "if-then" statements to compare environmental parameters against predefined thresholds, determining fire risk presence based on factors like temperature, humidity, wind speed, and rainfall [10][16]. These approaches have proven effective in forest fire detection, with multi-parameter inputs being used to calculate fire risk indices that enhance decision-making accuracy. Studies demonstrate that such indices provide reliable assessments of fire probability and severity, improving fire management strategies [18][19].

1.3. Environmental Data in Forest Fire Risk Modeling

Accurate modeling of forest fire risk requires comprehensive environmental data, including variables like 2-meter air temperature, relative humidity, precipitation, and vegetation indices [20]. Such data provides critical insights into the conditions that predispose an area to fire incidents [14][21]. The Magnus-Tetens formula, a widely used mathematical expression, calculates relative humidity based on air temperature and dew point, serving as a crucial component in fire risk assessment models [21] [22]. The use of these data-driven models has been shown to enhance the accuracy of fire risk assessment by capturing the interplay between climatic and environmental conditions [19].

1.4. Integration of IoT with Spatial Data

The integration of IoT-generated local data with global spatial datasets, such as ERA5 reanalysis and NASA's MODIS/VIIRS satellite observations, enhances fire risk mapping and management by providing critical insights into climate conditions, vegetation health, and land surface characteristics [4][23][24]. This combination improves the granularity of fire risk models and enhances the predictive capabilities of IoT systems, enabling the development of location-specific fire management strategies. For

example, combining ground-level sensor data with satellite-based temperature and vegetation indices has proven effective in identifying high-risk areas and implementing targeted mitigation measures [8][25].

1.5. Sustainable Development Goals and Forest Fire Monitoring

IoT-based forest fire detection systems contribute significantly to achieving the United Nations' SDGs [3]. Specifically, SDG 13 (Climate Action) is supported by reducing carbon emissions through early detection and rapid response to fires, while SDG 15 (Life on Land) is addressed by minimizing fire impacts on ecosystems and biodiversity. [1][26][27]. Additionally, these systems contribute to SDG 3 (Good Health and Well-being) by providing early warnings and reducing exposure to harmful smoke, thereby protecting public health [16][28]. Technological advancements in IoT and spatial data integration are essential for aligning fire mitigation efforts with SDG objectives, enhancing environmental and health outcomes, and promoting sustainable land and resource management for future generations [15][29].

1.6. Research Gap and Motivation

Despite the demonstrated benefits of IoT-based forest fire detection systems, several challenges and gaps remain. Many existing solutions rely solely on localized sensor networks without fully leveraging global spatial data, limiting their ability to model broader fire risk patterns accurately [3][16]. Furthermore, few studies have explored the integration of rule-based systems with IoT platforms to enhance fire risk assessment, particularly in alignment with the SDGs [10][30]. This gap underscores the need for comprehensive solutions that combine local and global data sources to create more robust and effective forest fire mitigation strategies.

Motivated by these limitations, this research aims to develop a multi-site IoT-based system that integrates real-time local sensor data with global spatial datasets[31]. By employing rule-based and data-driven approaches, this system seeks to enhance the accuracy and responsiveness of fire detection and risk assessment, ultimately supporting global efforts to mitigate the impacts of forest fires [32].

2. MATERIALS AND METHODS

2.1. Risk Assessment Model

The forest fire risk assessment model in this system is based on the integrated processing of environmental data from two main sources, namely ERA5 hourly data from the Copernicus Climate Data Store (CDS) and satellite fire data from NASA VIIRS and MODIS. The variables used in this model include 2-meter temperature, relative humidity (calculated from dewpoint temperature), total precipitation, tall vegetation index, number of fire pixels, and fire radiant power for Indonesia areas from 2020 to 2024. Relative humidity is calculated using the Magnus formula based on 2-meter dewpoint and 2-meter temperature, as it provides a more precise representation of atmospheric moisture conditions compared to dewpoint alone as the following equation [22]

$$RH = 100 \times \frac{e^{T_{dew}}}{e^{T_{air}}} \quad (1)$$

Where RH is the relative humidity in percentage, T_{dew} is the dew point temperature in degrees Celsius, T_{air} is the air temperature in degrees Celsius, $e^{T_{dew}}$ is the vapor pressure at the dew point temperature in hectopascals (hPa), and $e^{T_{air}}$ is the vapor pressure at the air temperature in hectopascals (hPa). These variables are all interrelated and used to describe the moisture content in the air, with RH indicating the extent of the air saturation with water vapor at a given temperature.

NASA fire data provides information on the location and intensity of satellite-detected fires, while ERA5 reanalysis data offers detailed meteorological conditions that influence fire risk, as outlined in previous studies [33]. The risk assessment model employs a rule-based artificial intelligence approach to calculate fire risk scores by comparing environmental variables such as temperature, humidity, rainfall, vegetation index, fire radiation power, and fire pixels with predefined thresholds [14]. When a variable exceeds its threshold, the system classifies the condition as high fire risk. For example, high temperatures, low humidity, and minimal rainfall increase the risk score, while changes in the vegetation index signal greater fire potential. This rule-based approach allows for the dynamic identification of high-risk areas, optimizing sensor placement for more accurate early warnings and faster response times.

2.2. Internet of Things System Design

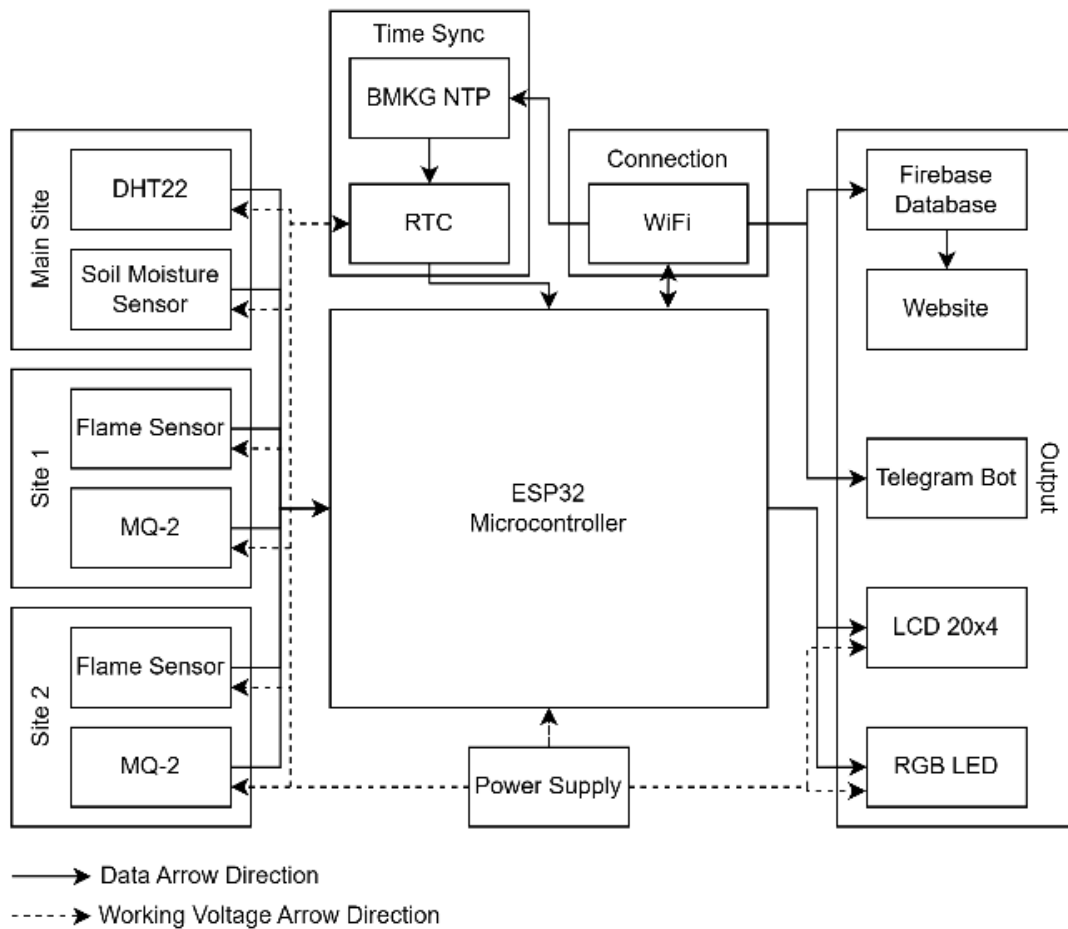


Fig. 1. System Block Diagram

The system block diagram is shown in Fig. 1, illustrating the integration of the main monitoring site with the ESP32 microcontroller and various environmental sensors. These include the DHT22 sensor for temperature and humidity, flame sensors for fire detection, and MQ2 sensors for monitoring harmful gases like carbon monoxide and methane. A soil moisture sensor is also used to assess moisture levels, which correlate with fire risk. The collected data is transmitted to the Firebase server via an internet connection managed by the ESP32 microcontroller [34][35]. Remote sites, labeled Site 1 and Site 2, are equipped with flame and smoke sensors connected to the main site via underground cables to reduce interference and improve system efficiency. Additionally, the system configures the Real-Time Clock (RTC) using the BMKG Network Time Protocol (NTP) to ensure accurate timestamping and data synchronization. The output will be sent to the Firebase Realtime Database, displayed on the website, sent to a Telegram bot, shown on an LCD, and indicated with an RGB LED. Similar ESP32-based environmental monitoring architectures have also demonstrated real-time multi-parameter sensing with web-based data delivery [36][37].

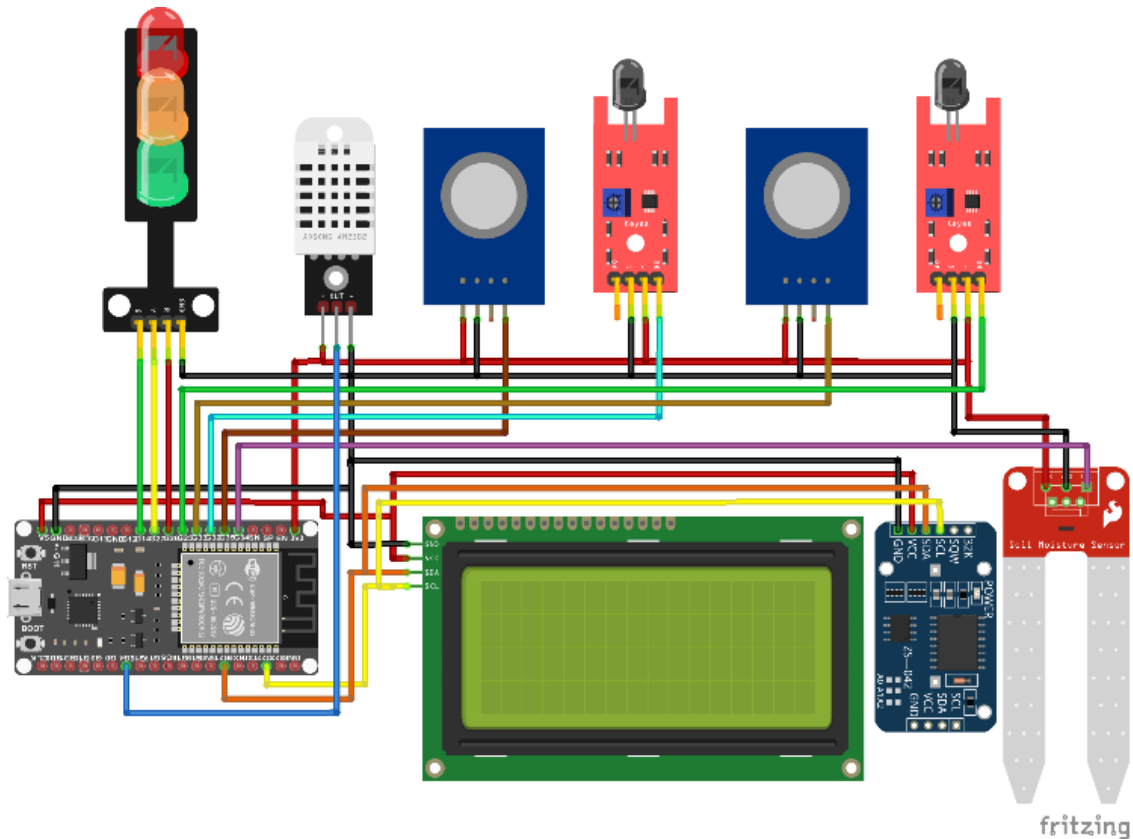


Fig. 2. Electronic Circuit

A web interface visualizes fire risk maps, sensor graphs, and status indicators, with an emergency button for direct fire service contact. AI-driven rule-based risk assessment analyzes environmental data and generates interactive fire risk maps across Indonesia. The system is programmed in C++ for hardware, Python for risk analysis, and HTML, JavaScript, and CSS for web development and Firebase integration. The hardware configuration, including sensor connections and the ESP32 microcontroller, is detailed in Fig. 2. Related work has likewise shown that real-time web interfaces can integrate live data processing, centralized storage, and browser-based visualization for remote monitoring [38].

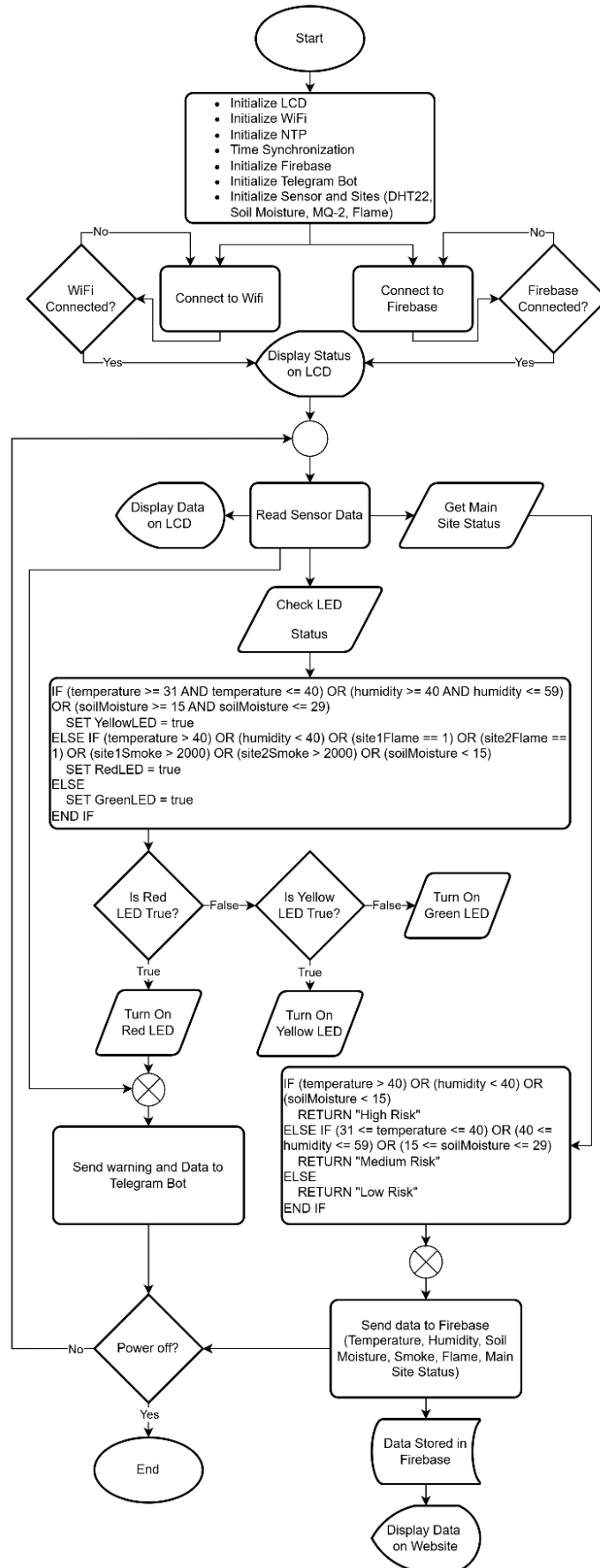


Fig. 3. Flowchart

The system flow diagram in Fig. 3 details the monitoring process for environmental parameters relevant to forest fire detection. Upon startup, the system initializes the hardware components, including the Wi-Fi module, sensors, and the LCD. The system then connects to Wi-Fi and synchronizes the RTC using the BMKG NTP protocol. Sensor data is collected continuously, with risk levels (low, moderate, high) assessed in real-time, triggering corresponding LED indicators. The data is sent to the Firebase Realtime Database for storage and analysis. The system operates continuously, collecting and processing data every 5 seconds. In the event of high-risk conditions, the system sends notifications via Telegram and displays the data on the LCD for on-site monitoring.

The components are strategically distributed across multiple sites for accurate real-time fire detection. The main site houses the ESP32, DHT22, and soil moisture sensors, while Sites 1 and 2 contain flame and smoke sensors. This configuration improves device efficiency and reduces costs by minimizing the need for microcontrollers at each site.

3. RESULTS AND DISCUSSION

3.1. Overview of the System Implementation



Fig. 4. System Implementation

The INA-FOREWS system is an IoT-based early warning solution designed to mitigate forest fires in Indonesia by enhancing real-time detection and risk assessment aligned with SDGs. IoT sensors are strategically placed in high-risk zones, leveraging a rule-based model that evaluates environmental factors like temperature, precipitation, and humidity. This optimized sensor deployment strengthens fire detection and supports effective prevention and mitigation strategies.

3.2. Evaluation of the Risk Assessment Model

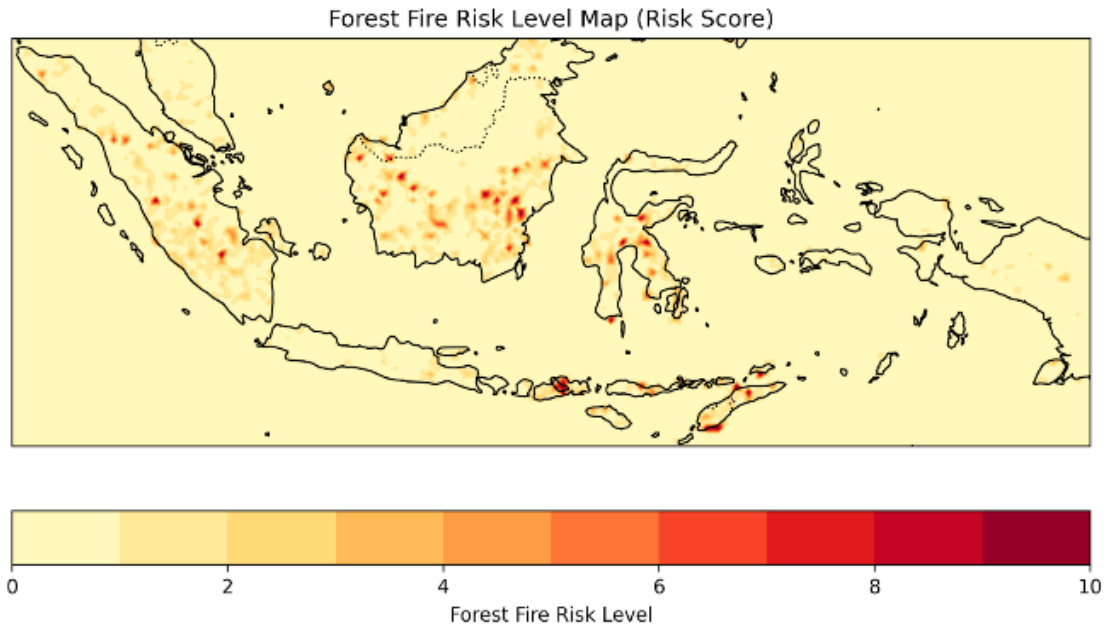


Fig. 5. Forest Fire Risk Level Map

The rule-based system evaluated fire risk scores (0–10) using environmental variables such as temperature, precipitation, humidity, vegetation index, fire pixels, and fire radiant power. Higher scores corresponded to greater fire risk, with low humidity identified as a critical factor, reflecting dry conditions conducive to fire ignition and spread. Although actual fire incident data was unavailable for validation, the results aligned with existing literature, indicating the system's effectiveness in identifying fire-prone areas.

Table 1. Threshold Values

Threshold Values	
Variable	Value
Mean Temperature	>35°C [21]
Mean Relative Humidity	<40% [20]
Total Precipitation	<2200 mm [39]
Mean Fire Radiation Power & Fire Pixel	1 [11]

The threshold values used in the rule-based system were derived from existing research and expert recommendations, as summarized in Table 1. These thresholds include mean temperature, relative humidity, total precipitation, fire radiation power, and the number of fire pixels. For instance, the threshold for mean temperature was set at >35°C, and areas with relative humidity below 40% and precipitation below 2200 mm were classified as high-risk. Fire radiation power and fire pixels were assigned a threshold value of 1, based on relevant studies.

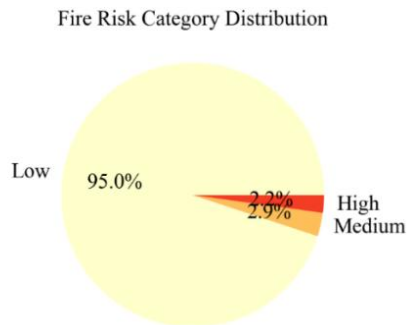


Fig. 6. Pie Chart of Fire Risk Category Distribution

A sensitivity analysis revealed that variations in thresholds for temperature, precipitation, relative humidity, fire radiation power, and fire pixels affected high-risk area identification. The model classified

2.16% of areas as high-risk (scores >7), 2.88% as medium-risk (scores 4–7), and 94.97% as low-risk (scores <4). Regular recalibration of thresholds using real-time data or future research is essential to maintain model accuracy and reliability.

3.3. Sensor Data and System Performance

This section presents real-time sensor graphs, offering insights into temperature, humidity, air quality, fire presence, smoke, and soil moisture across all sites.

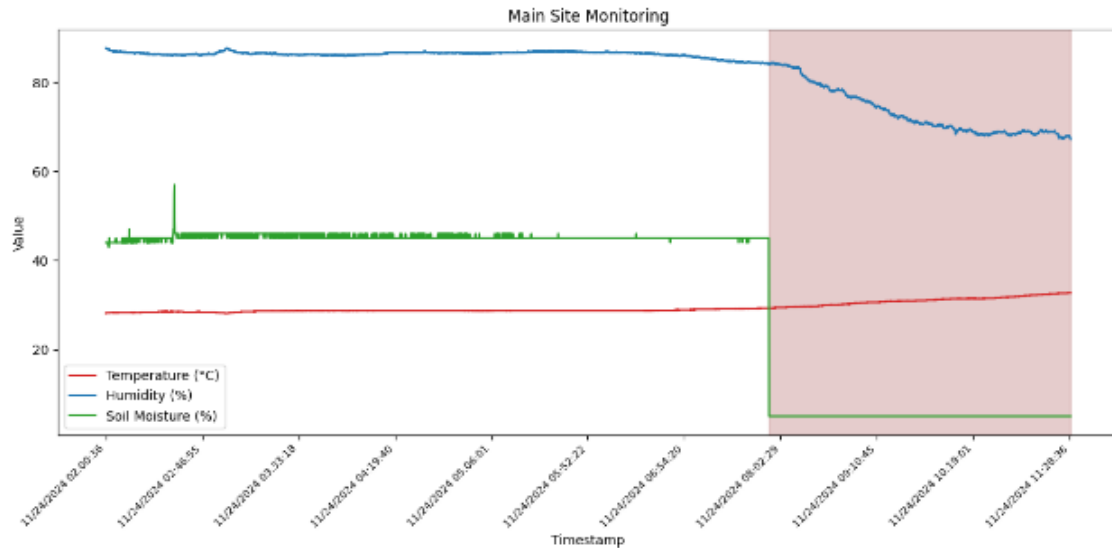


Fig. 7. Main Site Sensor Reading Graph

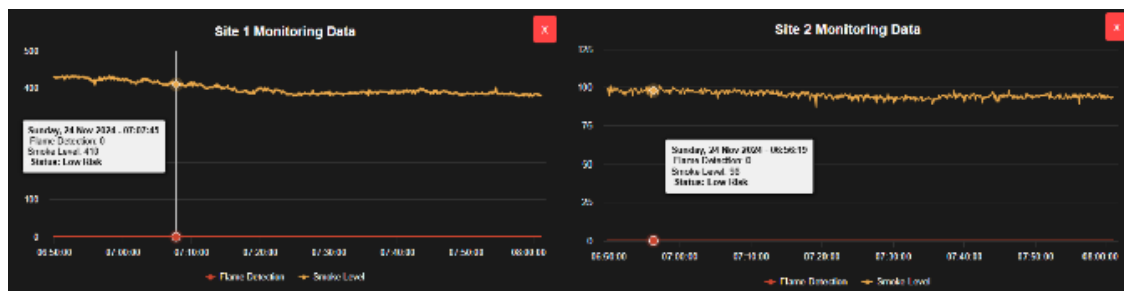


Fig. 8. Site 1 and Site 2 Sensor Reading Graph

Each graph is updated regularly at fixed intervals of 5 seconds to ensure the information displayed is accurate and relevant to current conditions. This data forms an important basis for detecting potential forest fires and taking appropriate mitigation measures. To evaluate stability, the time difference between successive data points is analyzed.

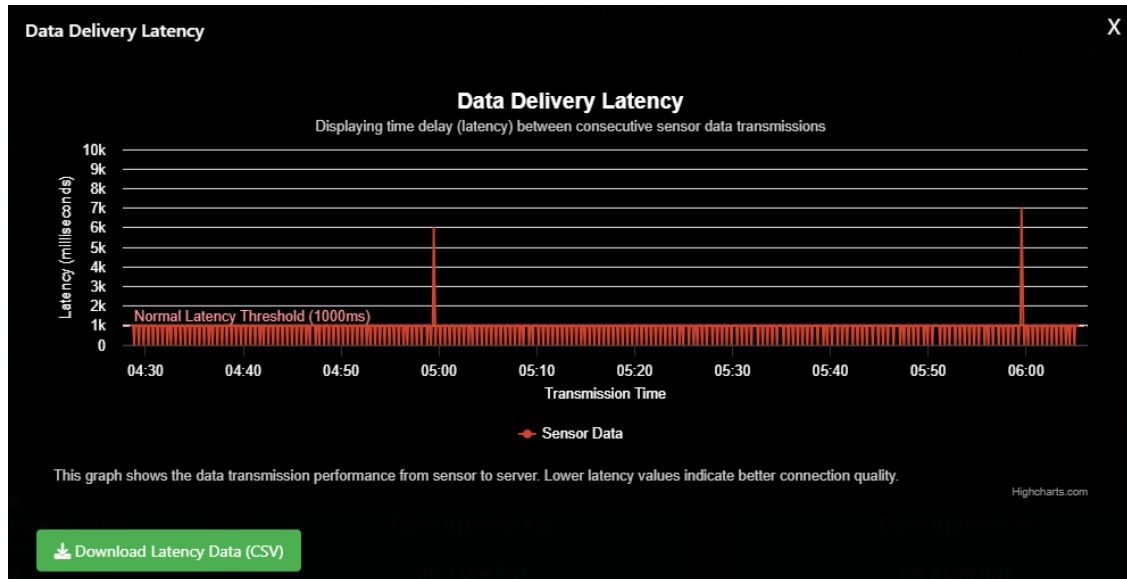


Fig. 9. Data Delivery Latency Graph

A stable transmission is characterized by minimal deviation within a threshold of ± 1000 ms of the expected interval. Observations showed consistent intervals of 5 seconds with negligible variation, indicating reliable network and hardware performance.

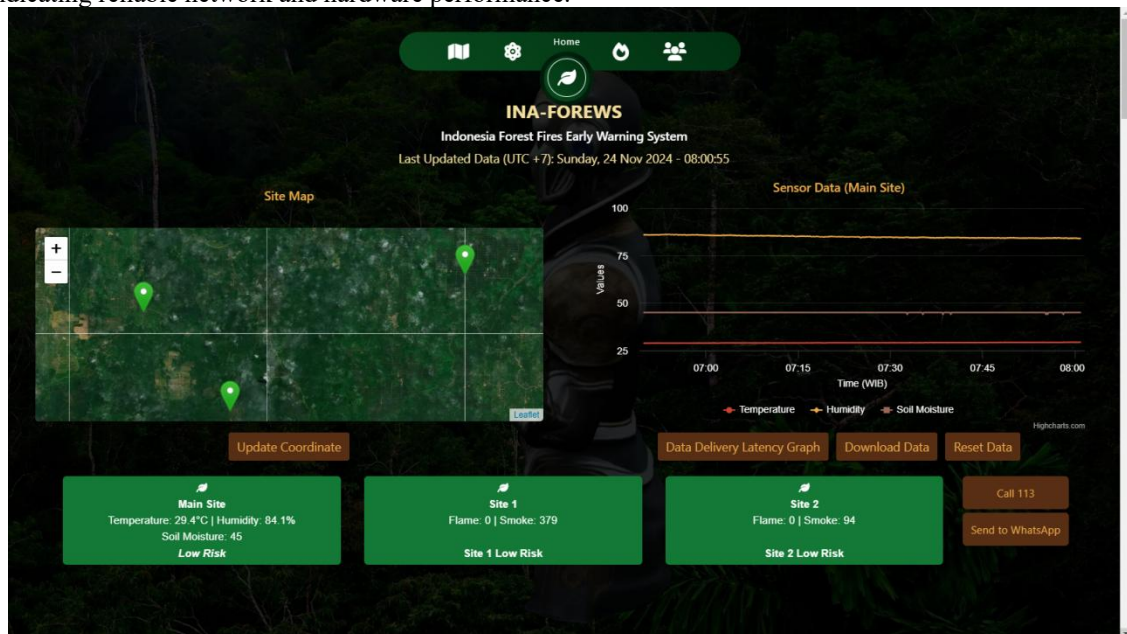


Fig. 10. Website Interface

A web-based interface was developed to visualize forest fire risk data in real time, enabling easy monitoring by users. The website also includes an emergency button feature that allows users to send quick warning notifications to relevant authorities via WhatsApp if dangerous conditions are detected to ensure that important information can be conveyed efficiently and quickly. In addition, an update coordinate button is provided to update the location of IoT sensors at the Main Site, Site 1, and Site 2.

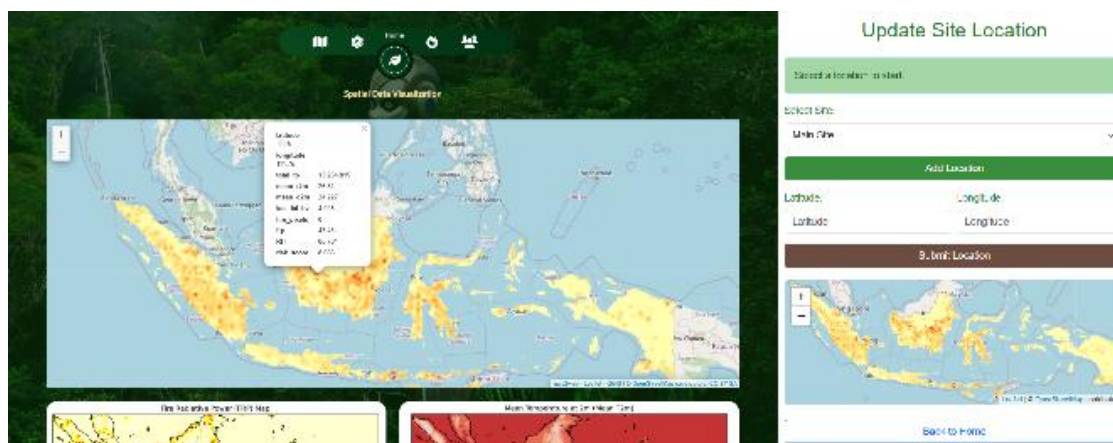


Fig. 11. Spatial Data Visualization and Update Coordinate Feature

The website incorporates data on high fire risk levels and spatial data visualization, facilitating user analysis and determining the optimal areas for IoT sensor installation. All visualizations are designed to be intuitive, responsive, and support accessibility on different devices, including desktop and mobile to maximize the system usability for stakeholders. These visualizations were created using QGIS, an open-source geographic information system that allows for detailed mapping and spatial analysis [40]. This web page can be accessed through <https://forest-fires-ews.web.app/>.

3.4. Discussion of Results

The INA-FOREWS system has several key strengths, including cost-efficiency, real-time monitoring capabilities, and ease of implementation. A user-friendly web interface and strategic sensor deployment enhance the system's practicality for Indonesia's forested regions. Some challenges, such as technical reliability and sensor accuracy in remote environments, need to be addressed. These technical hurdles need to be addressed to ensure the reliability and robustness of the system, particularly in remote forest environments. The INA-FOREWS system has the potential to significantly impact forest fire mitigation efforts in Indonesia by providing real-time risk assessment and early warning capabilities, supporting more effective resource allocation and response strategies, and helping to reduce the environmental and socioeconomic impacts of forest fires. This approach is adaptable to forest fire challenges in other tropical regions globally.

4. CONCLUSION

The INA-FOREWS system is an innovative IoT-based forest fire early warning solution designed to address the challenges of traditional fire detection methods in Indonesia. By integrating real-time sensor data with global spatial datasets like ERA5, MODIS, and VIIRS, the system provides enhanced fire risk assessment and early warning capabilities. Key innovations include the development of an IoT framework for improved fire detection and mitigation, leveraging rule-based models and spatial analysis to increase the accuracy and timeliness of fire risk assessments. The system deploys a range of sensors, including temperature, humidity, gas, flame, and soil moisture, at strategic locations, while its web-based interface allows for real-time visualization of fire risks, sensor data, and emergency notifications. A dynamic rule-based risk assessment model, guided by environmental variables such as temperature, humidity, and vegetation index, generates fire risk scores and identifies high-risk areas. This strategic deployment of sensors optimizes fire detection and enhances mitigation efforts.

Future developments will focus on field testing, integration with technologies like drones and satellites, and refining the risk prediction model. These improvements aim to strengthen the system's capabilities and guarantee its real-world effectiveness in managing forest fires.

DECLARATIONS

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Classification of Disaster Impact Severity in North Maluku Using Random Forest Based on Spatial-Temporal Characteristics

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ABSTRACT

Disaster impact severity is typically assessed only after casualty and damage data have been collected, even though the spatial-temporal characteristics of an event are known from the outset. This study aims to construct a disaster severity index using multi-component Principal Component Analysis (PCA) and to classify it using only spatial-temporal characteristics, deliberately excluding impact variables as predictors to avoid target leakage. The dataset comprises 239 disaster events in North Maluku Province (2021-2025) sourced from DIBI-BNPB. The severity index was built through log1p transformation, standardization, KMO (0.757) and Bartlett's Test (chi-square=1010.81; $p<0.001$), and Kaiser-criterion PCA yielding four principal components (cumulative variance 64.44%). The severity class was divided into four quartile-based classes and validated through a monotonic relationship with mean affected/displaced victims and a significant ANOVA test ($F=17.574$; $p<0.001$). Classification used five spatial-temporal features (year, month, week, regency/city, disaster type) under a temporal split scheme, comparing Random Forest, XGBoost, and a Dummy Classifier. Random Forest achieved the best performance with a Macro-F1 of 0.146 on the 2025 test set, outperforming the baseline (0.041) though the absolute value remains low. An ablation test revealed that a temporal-only feature scenario achieved the highest Macro-F1 (0.180), indicating limitations in the categorical encoding scheme. Sensitivity analysis confirmed the results are robust to changes in the class scheme (Macro-F1 difference of 0.047). The main contribution of this study is a validated severity-index construction methodology and early empirical evidence on the limitations of spatial-temporal features for early disaster severity classification.

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1. INTRODUCTION

North Maluku Province is an archipelagic region that is geographically and climatologically prone to various types of natural disasters. Based on the Indonesian Disaster Data and Information (DIBI) system managed by the National Disaster Management Authority (BNPB) [1], 239 disaster events were recorded across 10 regencies/cities in North Maluku Province during 2021-2025, with flooding as the dominant disaster type (164 events, 68.6%), followed by extreme weather, tidal waves/abrasion, landslides, earthquakes, and volcanic eruptions, as presented in Table 1 [2], [3].

Table 1. Distribution of Disaster Types in North Maluku, 2021-2025

Disaster Type	Count	Percentage
Flood	164	68.6%

Disaster Type	Count	Percentage
Extreme Weather	41	17.2%
Tidal Wave/Abrasion	14	5.9%
Landslide	10	4.2%
Earthquake	7	2.9%
Volcanic Eruption	3	1.3%
Total	239	100%

In disaster management practice, the severity of an event's impact is typically known only after casualty and damage data have been collected and verified, whereas spatial-temporal characteristics — location, disaster type, and time of occurrence — are already available from the moment an event is first reported [4], [5]. This gap raises the question of whether spatial-temporal characteristics alone are sufficiently informative to classify disaster impact severity.

Previous studies on disaster classification/prediction using Random Forest or XGBoost have generally included impact variables as predictor features [6]–[8], thereby risking target leakage — a condition in which information closely related to the target is used as input, rendering the estimated model performance unrealistic for an early-classification context [9]. This study avoids this issue by first constructing a severity index through multi-component PCA on casualty and damage indicators, then classifying the severity class using only spatial-temporal features.

The research problems addressed in this study are: (1) how to construct a valid severity index from casualty and damage indicators using multi-component PCA; and (2) how Random Forest and XGBoost perform in classifying the severity class based solely on spatial-temporal features, including the relative contribution of each feature group and the stability of the results across different class schemes. The objective of this study is to answer both research problems and to provide empirical evidence on the limits of spatial-temporal features for early classification of disaster severity. The novelty of this study lies in constructing a severity index based on a combination of principal components (multi-component PCA, Kaiser criterion [10]) used to classify severity based on spatial-temporal characteristics without involving impact variables as predictors.

2. RESEARCH METHOD

2.1. Data

This study uses secondary data on 239 disaster events in North Maluku Province during 2021–2025 sourced from DIBI-BNPB [1], covering 13 impact variables (casualty and damage indicators) as well as spatial-temporal attributes (regency/city, disaster type, year, month, week). Data quality testing showed no missing values, duplicate IDs, or negative values across all impact variables.

2.2. Severity Index Construction

All 13 impact variables were transformed using $\log_{1p}$ to reduce the effect of right-skewed distributions, then standardized using StandardScaler [11]. Data suitability for PCA was tested through KMO (0.757 obtained) and Bartlett's Test (chi-square=1010.81; $p < 0.001$). PCA with the Kaiser criterion [10] yielded 4 principal components with explained variance ratios of 30.28% (PC1), 13.63% (PC2), 10.99% (PC3), and 9.54% (PC4), cumulatively 64.44%, as shown in the scree plot in Figure 1.

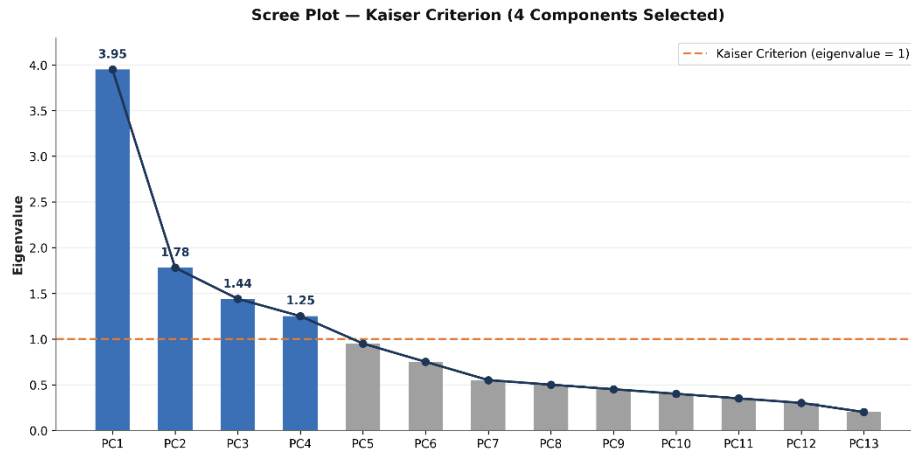


Fig. 1. PCA Scree Plot — Kaiser Criterion (4 Components Selected)

The severity index was calculated as a weighted sum of the four components, with weights normalized from the explained variance ratio: $w_1=0.4699$; $w_2=0.2115$; $w_3=0.1705$; $w_4=0.1481$. The multi-component approach was chosen because PC1 alone has a loading close to zero on the affected/displaced variable (correlation of only 0.015), whereas the 4-component weighted-sum approach increases the correlation to 0.204 with a perfect monotonic relationship.

2.3. Severity Class Determination

The severity index was converted into 4 quartile-based classes: Low (60 events), Moderate (61), High (58), and Very High (60), with cut-off points $Q1=-0.400$, $Q2=-0.209$, $Q3=0.064$. Construct validity was tested through the monotonic pattern of mean affected/displaced victims across classes ($25.6 \rightarrow 184.8 \rightarrow 670.4 \rightarrow 1,549.8$), as visualized in Figure 2, and a one-way ANOVA test against disaster type ($F=17.574$; $p<0.001$).

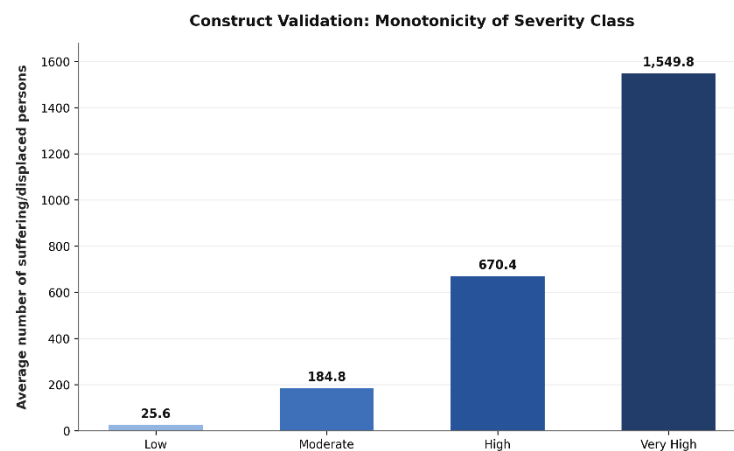


Fig. 2. Construct Validation — Monotonicity of Severity Class Against Mean Affected/Displaced Victims

2.4. Features, Data Split, and Models

Predictor features were restricted to five spatial-temporal features (year, month, week, regency/city, disaster type) without involving impact variables, in order to avoid target leakage [9]. The data were divided using a temporal split: training 2021-2023 (127 events), validation 2024 (56), and test 2025 (56); this scheme was chosen to prevent information leakage from future periods into past periods. Three models were compared: a Dummy Classifier (most_frequent) as baseline, Random Forest [12] (class_weight='balanced', n_estimators=300, random_state=42), and XGBoost [13] (n_estimators=300, max_depth=4, random_state=42), both implemented using scikit-learn [11].

2.5. Evaluation and Interpretation

Model performance was evaluated using Accuracy, macro Precision, macro Recall, and Macro-F1 as the primary metrics, given the imbalanced class distribution in the 2025 test set (the Low class has only 5 events, High has 19 events). The relative contribution of feature groups was analyzed through an ablation test with three nested scenarios (temporal only; +spatial; +disaster type), while model interpretation used native

feature importance and SHAP (TreeExplainer) [14], [15]. The stability of the results with respect to the class scheme was tested through a sensitivity analysis comparing the quartile scheme (4 classes) with the tertile scheme (3 classes).

3. RESULT AND DISCUSSION

3.1. Classification Model Performance

Table 2 presents the evaluation results of the three models on the 2025 test set. Random Forest achieved the best performance with a Macro-F1 of 0.146, outperforming the Dummy Classifier baseline (0.041) and XGBoost (0.103).

Table 2. Model Performance on the 2025 Test Set

Model	Accuracy	Precision (macro)	Recall (macro)	Macro-F1
Dummy Classifier	0.089	0.022	0.250	0.041
Random Forest	0.143	0.204	0.230	0.146
XGBoost	0.107	0.127	0.197	0.103

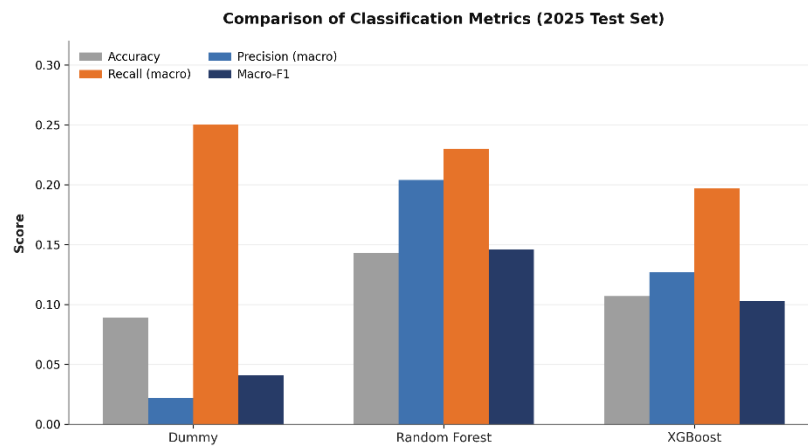


Fig. 3. Comparison of Classification Metrics Across Models (2025 Test Set)

Although Random Forest consistently outperformed the baseline across all metrics, the Macro-F1 value of 0.146 is still considered low in absolute terms. This is consistent with the study design, which deliberately excludes impact variables as predictors, so the model relies solely on spatial-temporal patterns that inherently have only an indirect relationship with actual impact severity. The confusion matrix in Figure 4 and Table 3 shows that the Random Forest model tends to over-predict the Low class, including for actual High-class events (13 out of 19 events) and Very High-class events (15 out of 17 events), which is the main source of the low recall for the higher-severity classes.

Table 3. Random Forest Confusion Matrix on the 2025 Test Set

Actual \ Predicted	Low	Moderate	High	Very High
Low	3	2	0	0
Moderate	7	4	3	1
High	13	1	1	4
Very High	15	0	2	0

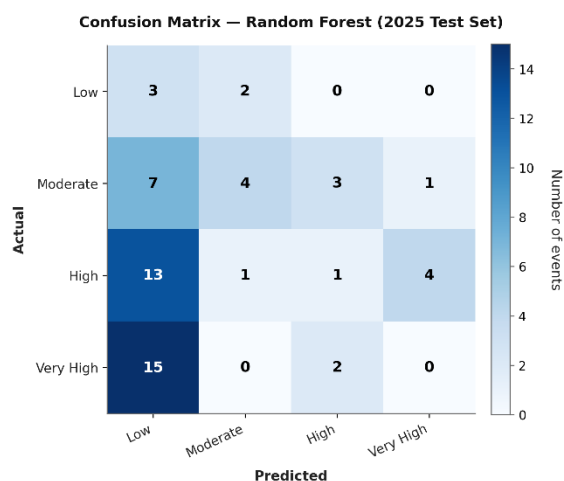


Fig. 4. Random Forest Confusion Matrix (2025 Test Set)

3.2. Ablation Test

Table 4 and Figure 5 show the results of the ablation test across three feature scenarios for both models. For Random Forest, Scenario A (temporal features only) achieved the highest Macro-F1 (0.180). Interestingly, adding the regency spatial feature in Scenario B actually decreased the Macro-F1 to 0.092, before slightly improving again to 0.146 in Scenario C with the addition of the disaster type feature — this non-monotonic pattern was not observed for XGBoost, which instead increased slightly from Scenario A (0.118) to B (0.122) before decreasing in Scenario C (0.103).

This pattern indicates that, given the small test sample size (56 events) and the simple categorical encoding scheme (label encoding), the regency and disaster type features do not yet provide a stable predictive signal for Random Forest — likely because label encoding fails to represent a meaningful ordinal relationship between categories. This finding is openly discussed as a limitation of the encoding scheme used, not as evidence that the spatial and disaster type features are substantively irrelevant.

Table 4. Ablation Test Results (Random Forest and XGBoost)

Scenario	Features	RF Macro-F1	RF Accuracy	XGB Macro-F1	XGB Accuracy
A	Temporal (year, month, week)	0.180	0.179	0.118	0.125
B	A + spatial (regency)	0.092	0.107	0.122	0.125
C	B + disaster type (complete)	0.146	0.143	0.103	0.107

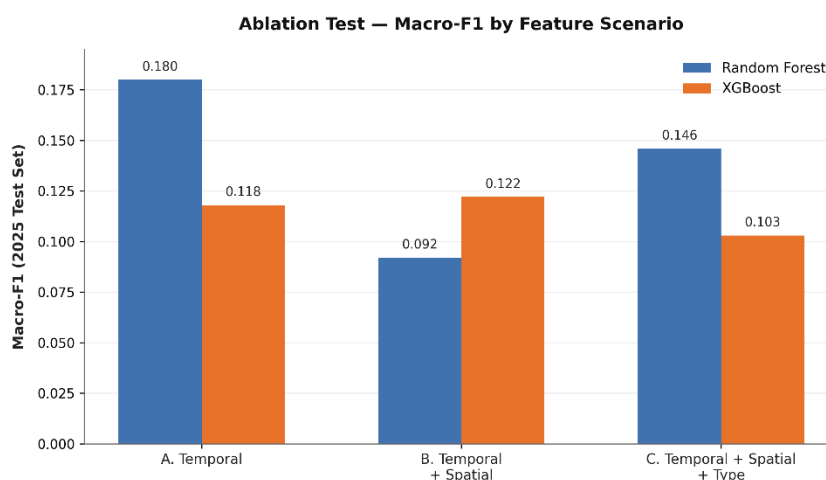


Fig. 5. Macro-F1 by Feature Scenario in the Ablation Test

3.3. Model Interpretation

Table 5 and Figure 6 compare native feature importance from Random Forest with the mean absolute SHAP value [14], [15]. Native feature importance shows the following order of feature importance: Week (0.2977) > Regency (0.2899) > Month (0.1618) > Disaster Type (0.1307) > Year (0.1199). In contrast, the SHAP analysis (TreeExplainer) shows Year (0.0865) as the most dominant feature, well above the other features, which have SHAP values of 0.04-0.06.

Table 5. Comparison of Native and SHAP Feature Importance

Feature	Native Importance (RF)	Mean SHAP value
Week	0.2977	0.0552
Regency	0.2899	0.0527
Month	0.1618	0.0445
Disaster Type	0.1307	0.0398
Year	0.1199	0.0865

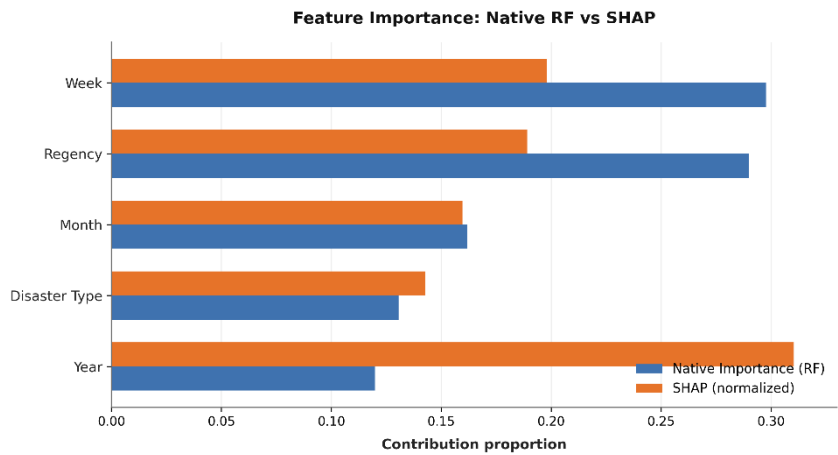


Fig. 6. Feature Importance: Native Random Forest vs SHAP

3.4. Sensitivity Analysis

As a comparison, a tertile scheme was also tested (3 classes: Low/Moderate/High, cut-off points $t1=-0.315$ and $t2=-0.054$). The quartile scheme yielded a Macro-F1 of 0.1458, while the tertile scheme yielded 0.0988, an absolute difference of 0.047 — below the 0.10 threshold set, so the classification results are declared robust to the choice of severity class-division scheme, as shown in Figure 7. The Random Forest feature-importance ranking under the tertile scheme (Week, Regency, Month, Year, Disaster Type) is also consistent with the ranking under the quartile scheme, further reinforcing the stability of this study's findings.

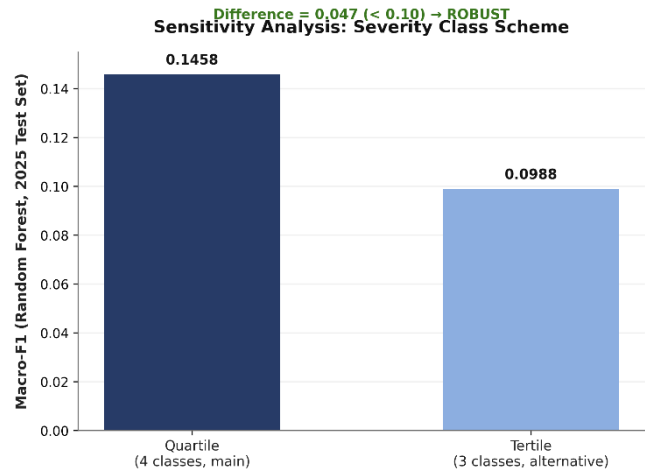


Fig. 7. Sensitivity Analysis — Quartile vs Tertile Scheme

4. CONCLUSION

A statistically valid severity index was successfully constructed through multi-component PCA based on the Kaiser criterion ($KMO=0.757$; Bartlett's chi-square=1010.81, $p<0.001$; cumulative variance 64.44%), with construct validity demonstrated through a monotonic relationship with mean affected/displaced victims and a significant ANOVA test ($F=17.574$; $p<0.001$). The Random Forest model [12] achieved the best classification performance (Macro-F1=0.146) based on spatial-temporal features, outperforming the baseline but still low in absolute terms, indicating the limitations of spatial-temporal characteristics alone in accurately predicting disaster impact severity. The ablation test revealed that temporal features alone actually yielded the highest performance (Macro-F1=0.180), indicating limitations in the categorical encoding scheme, while the classification results proved robust to changes in the class scheme (Macro-F1 difference=0.047). The low absolute performance is not a research failure but rather a logical consequence of a design that avoids target leakage [9]; the main contribution of this study is a validated methodology for constructing a severity index, along with early empirical evidence on the limitations of spatial-temporal features for early disaster classification. Future research is recommended to test alternative categorical encoding schemes (one-hot/target encoding), expand the scope of historical data, explore derived temporal features (rainy/dry season), and test ordinal classification models given the hierarchical nature of the severity class.

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Multi-Hazard Risk Typology and Temporal Trends of Disaster Events in East Nusa Tenggara Province (2008–2025)

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ABSTRACT

East Nusa Tenggara (NTT) Province faces complex multi-hazard threats from hydrometeorological and geological disasters. This study developed a multi-hazard risk typology for 22 regencies/cities in NTT and examined temporal trends in disaster frequency over 2008–2025 (complete years; partial 2026 data excluded). The dataset comprised 1,158 records, adjusted to 1,128.5 real events using fractional weights across eight disaster types. Clustering was evaluated across three feature schemes and two algorithms (K-Means and Agglomerative Ward), with the number of clusters validated through a consensus of Silhouette, Davies-Bouldin, and Calinski-Harabasz indices while avoiding degenerate solutions. Temporal trends and change points were evaluated using the Mann-Kendall and Pettitt tests, preceded by lag-1 autocorrelation (ACF) screening. The selected hazard-only Agglomerative Ward model ($k = 6$; Silhouette = 0.2105, DBI = 1.205, CHI = 5.28) categorized regions into six distinct typologies, from low-risk to high-frequency flood/extreme-weather clusters, with Sabu Raijua identified as an impact-severity outlier. Auto correlation checks confirmed the validity of test assumptions. The Mann-Kendall and Pettitt tests consistently revealed no statistically significant monotonic trend or change point ($p > 0.05$) across the province, dominant disaster types, and all clusters. This meaningful null result demonstrates that disaster occurrences in NTT are driven by sharp inter-annual fluctuations rather than long-term trends, emphasizing the necessity of continuous preparedness and differentiated, typology-based mitigation strategies.

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1. INTRODUCTION

East Nusa Tenggara (NTT) Province is located at the junction of tectonic plates and an active volcanic arc, and its climate is influenced by strong seasonal rainfall variability; consequently, the region faces complex multi-hazard threats, ranging from hydrometeorological disasters such as floods, landslides, and extreme weather, to geological disasters such as earthquakes and volcanic eruptions [1], [2].

Most disaster studies conducted in Indonesia, including in NTT, tend to be single-hazard, focusing on one particular disaster type in one study area. Such an approach has rarely accommodated the simultaneous multi-hazard character of a region or linked it to long-term temporal trend patterns, even though combining a multi-hazard profile with temporal trend analysis is highly relevant for differentiated mitigation planning across regions [3].

This study aimed to (1) build a multi-hazard risk typology for the 22 regencies/cities in NTT Province based on hazard profiles (real frequency) and impact severity from eight disaster types, using a clustering method selected systematically among several feature schemes and algorithms and validated across three cluster indices, and (2) test the significance of the temporal trend and possible change points in disaster

event frequency over the 2008–2025 period using the Mann-Kendall test and the Pettitt test, both preceded by an autocorrelation-assumption check, including a comparison of trend patterns among the resulting risk-typology clusters. The contribution/novelty of this study lies in integrating multi-hazard typology analysis with temporal trend and change-point analysis for the context of NTT Province, accompanied by a number of data- and method-validity assurance steps rarely found together in similar studies: (a) correction of the event-frequency definition for data containing fractional weights arising from cross-regency events, (b) exclusion of the current, not-yet-complete year from the trend test, (c) validation of the number of clusters across three indices rather than a single index, and (d) an autocorrelation check prior to the non-parametric trend test.

2. LITERATURE REVIEW

A comprehensive disaster risk science perspective emphasizes the importance of characterizing multiple hazard types and their interactions within a region simultaneously, rather than treating each hazard in isolation [4].

2.1. Disaster Characteristics of East Nusa Tenggara

The geographical and geological characteristics of NTT, which lies along the Pacific Ring of Fire and experiences a long dry season, make the region vulnerable to a wide range of disasters, both hydrometeorological and geological [2], [5].

2.2. Clustering and Cluster-Number Validation for Disaster-Prone Area Typology

Non-hierarchical clustering methods such as K-Means and hierarchical methods such as Agglomerative Clustering are commonly used to group regions based on the similarity of their disaster-risk characteristics. Selecting the optimal number of clusters should not rely on a single validity index; the Silhouette Score, Davies-Bouldin Index, and Calinski-Harabasz Index each capture slightly different aspects of cluster compactness and separation, so using more than one index simultaneously strengthens the reliability of the choice of k . The data-mining literature also emphasizes the importance of avoiding degenerate or trivial cluster solutions (clusters consisting of a single observation unit caused by an extreme outlier) [6], [7].

2.3. Mann-Kendall Trend Test, Autocorrelation, and Change-Point Test

The Mann-Kendall test is a widely used non-parametric statistical test for detecting monotonic trends in climate and disaster time series, with Sen's slope used as an estimate of the rate of change. The test theoretically assumes the data are independent and identically distributed (free of serial autocorrelation); if a series has strong positive autocorrelation, the Mann-Kendall p -value can become overly optimistic (prone to detecting spurious trends), so checking the autocorrelation function (ACF) and, where necessary, using an autocorrelation-corrected test (e.g., the Hamed & Rao modification) is recommended as a screening step before interpreting the results. As a complement to the monotonic trend test, the Pettitt test is commonly used to detect a single change point in a time series [8], [9].

3. RESEARCH METHOD

3.1. Data

The data used in this study consisted of disaster event records for East Nusa Tenggara Province, comprising 1,158 recorded rows over 2008–2026, covering 22 regencies/cities and 8 disaster types. Initial screening found no duplicate rows or missing values in the columns used in the analysis.

Important data note: the 'Number of Events' column in the source data was not uniformly valued at 1, but rather carried a FRACTIONAL WEIGHT (e.g., 0.5; 0.333; 0.25; 0.0909) for events recorded across multiple regencies or split into several impact sub-rows, such that the sum of the weights for one physical event equaled 1. Calculating event FREQUENCY from the ROW COUNT would double-count these multi-regency/multi-row events. Therefore, every frequency calculation in this study (Table 1, hazard features for clustering, and annual series for the trend test) used SUM('Number of Events') rather than row count, so the actual total number of events in this dataset was approximately 1,128.5 events from 1,158 recorded rows. In contrast, the IMPACT variables (deaths, injuries/illness, displaced/affected persons, damaged houses) did not suffer from the same issue because their values were already specific and real per row/regency (not the result of a proportional split of a total impact figure), and were therefore summed as recorded.

Second data note: 2026 data were recorded only through the eighth month (36 event rows) and thus did not represent a complete year. Including an incomplete year at the end of the series risks biasing the Mann-Kendall test, Sen's slope, and the Pettitt test (an apparently 'low' event count in 2026 would simply reflect a shorter time coverage, not an actual decline). Accordingly, all TEMPORAL TREND ANALYSIS (Sections 3.4 and 4.2–4.3) in this study was restricted to the COMPLETE years 2008–2025; the 2026 data are still reported descriptively but

were excluded from the statistical trend tests. The typology clustering (Sections 3.2–3.3, 4.1) was not affected by the same issue because it is cross-sectional (an accumulation over the entire period) rather than a time series.

A summary of the real number of events per disaster type together with the total impact (entire data period, including partial 2026) is presented in Table 1.

Table 1. Summary of Real Number of Events and Total Impact per Disaster Type in NTT, 2008–2026

Disaster Type	Number of Events (real)	Total Deaths (persons)	Total Damaged Houses (units)	Total Displaced/Affected (persons)
Extreme weather	429.0	62	16,185	58,397
Flood	365.0	297	77,138	868,081
Landslide	150.0	44	1,299	9,043
Drought	60.0	2	0	2,999,936
Tidal wave / Abrasion	53.0	9	1,735	11,370
Forest and land fire	40.0	0	15	111
Earthquake	18.5	70	14,700	142,625
Volcanic eruption	13.0	20	2,384	121,877

As shown in Table 1, extreme weather was the disaster type with the highest number of real events (429.0 events), followed by flood (365.0 events), which recorded the highest number of deaths and displaced/affected persons among all disaster types, at 297 persons and 868,081 persons, respectively.

3.2. Data Preprocessing and Feature Engineering

Event data were aggregated to the regency $\times$ disaster-type level by summing the 'Number of Events' weights (not row counts, see the data note in Section 3.1) to compute the REAL frequency of events for each combination, producing 8 HAZARD feature columns.

For impact features, this study formed 4 SEVERITY feature columns as average-impact-PER-REAL-EVENT indices — namely the number of deaths, the number of displaced/affected persons, total damaged houses, and the number of injured/ill persons — each summed as recorded and then divided by the real event frequency (SUM 'Number of Events') for that regency, rather than a raw total that would be dominated by a single extreme event.

Three feature schemes were formed and compared at the clustering stage: (a) Hazard-only (8 real-frequency features), (b) Severity-only (4 per-event impact-index features), and (c) Combined Hazard+Severity (12 features). All features were standardized using a StandardScaler prior to clustering.

3.3. Feature Scheme, Method, and Cluster-Number Selection

This study compared 2 clustering algorithms — K-Means (k-means++, n_init=20) and Agglomerative/Hierarchical Clustering (Ward linkage) — across the three feature schemes above, each for k=2 to k=6 (3 schemes $\times$ 2 methods $\times$ 5 values of k = 30 combinations), evaluated with 3 indices: Silhouette Score (higher is better), Davies-Bouldin Index/DBI (lower is better), and Calinski-Harabasz Index/CHI (higher is better).

Methodological note (degenerate solution): the highest raw silhouette score was found in the Severity-only scheme with the K-Means method at k=2 (silhouette=0.6137), but this was degenerate (smallest cluster size=1) due to Sabu Raijua Regency separating out as an extreme outlier on the severity indices (see Table 4 and the robustness discussion in Section 4.1). Model selection was therefore restricted to non-degenerate solutions (smallest cluster size ≥ 2).

Among the non-degenerate solutions, the highest silhouette score was obtained with the Hazard-only scheme using the Agglomerative (Ward) method (see Table 2a). For this scheme-method combination, the number of clusters was further validated across the 3 indices for k=2 to k=6 (Table 2b, Fig. 1).

Table 2a. Ten Non-Degenerate Feature-Scheme $\times$ Clustering-Method Combinations with the Highest Silhouette Score

Feature Scheme	Method	k	Silhouette	DBI	CHI	Min. Cluster Size
Hazard-only	Agglomerative (Ward)	5	0.2340	1.227	5.24	2

Feature Scheme	Method	k	Silhouette	DBI	CHI	Min. Cluster Size
Hazard-only	K-Means	5	0.2235	1.267	5.12	2
Hazard-only	K-Means	4	0.2219	1.334	4.97	2
Hazard-only	Agglomerative (Ward)	4	0.2142	1.357	5.00	2
Hazard-only	Agglomerative (Ward)	6	0.2105	1.205	5.28	2
Hazard-only	Agglomerative (Ward)	3	0.1996	1.482	4.86	2
Hazard-only	K-Means	3	0.1993	1.499	4.99	3
Hazard-only	K-Means	2	0.1829	1.783	5.51	11
Hazard-only	Agglomerative (Ward)	2	0.1688	1.880	4.97	11
Combined Hazard+Severity	K-Means	3	0.1471	1.661	4.02	4

Methodological note (k selection via 3-index consensus): for the Hazard-only + Agglomerative (Ward) combination, the highest Silhouette Score was at $k=5$ (0.2340), whereas the Davies-Bouldin Index and Calinski-Harabasz Index BOTH showed (marginally) better performance at $k=6$ (DBI=1.2048; CHI=5.278) than at $k=5$ (DBI=1.2265; CHI=5.244). Because the majority of indices (2 of 3) favored $k=6$ and that solution remained non-degenerate, $k=6$ was selected as the final decision through a majority-consensus/voting principle across indices, rather than relying on the Silhouette Score alone — following the methodological recommendation to validate the number of clusters with more than one index.

Table 2b. Cluster-Number Validation with 3 Indices for the Selected Scheme (Hazard-only, Agglomerative (Ward))

k	Silhouette (higher better)	Davies-Bouldin (lower better)	Calinski-Harabasz (higher better)
2	0.1688	1.8796	4.966
3	0.1996	1.4820	4.861
4	0.2142	1.3568	4.999
5	0.2340	1.2265	5.244
6	0.2105	1.2048	5.278

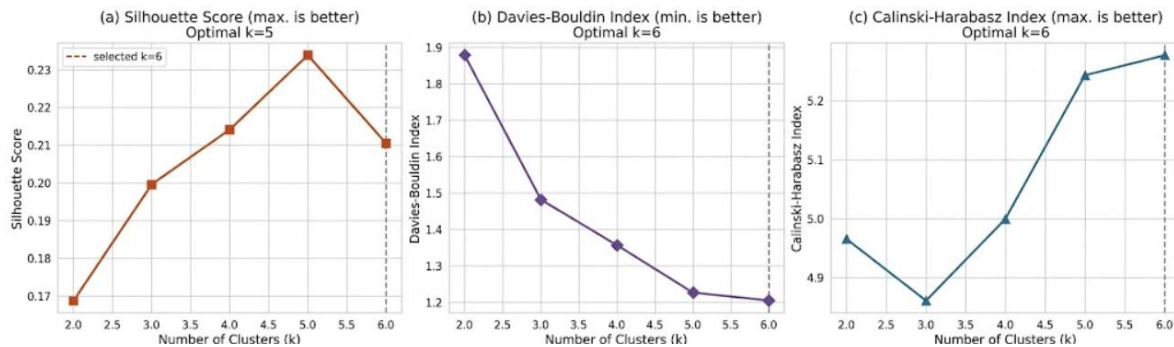


Fig. 1. Cluster-Number Validation with 3 Indices (Hazard-only Scheme, Agglomerative (Ward))

A comparison of the silhouette curves for all 30 feature-scheme and method combinations is shown in Fig. 2, clarifying the position of the degenerate solution (Severity-only scheme) relative to the selected non-degenerate solution.

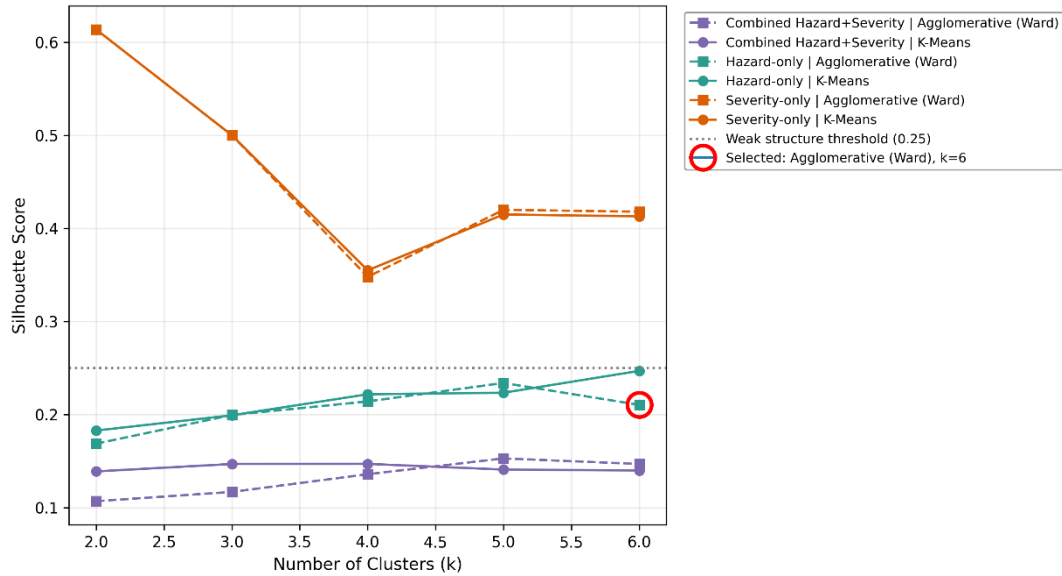


Fig. 2. Comparison of Silhouette Scores across Feature Schemes and Clustering Methods

The final clustering result (Hazard-only scheme, Agglomerative (Ward) method, $k=6$) was then projected into two-dimensional space using Principal Component Analysis (PCA) for visualization purposes.

3.4. Trend and Temporal Change-Point Analysis

Trend analysis was performed on the annual REAL disaster-event series (SUM 'Number of Events') at the provincial level and for the three most frequent disaster types, restricted to the COMPLETE years 2008–2025 (see the note in Section 3.1 regarding the exclusion of the partial 2026 data). Before applying the Mann-Kendall test, the lag-1 autocorrelation (ACF) of each series was checked against the significance threshold of $\pm 1.96/\sqrt{n}$; where autocorrelation was significant, the Hamed-Rao modified Mann-Kendall test (robust to autocorrelation) was to be reported as a sensitivity check. The (original) Mann-Kendall test was used to detect monotonic trends at the 5% significance level, with Sen's slope as the rate-of-change estimate, and the Pettitt test was used to detect a possible single change point. The same analysis was also applied to the annual series of each risk-typology cluster.

4. RESULT AND DISCUSSION

4.1. Regency Typology Based on Multi-Hazard Profile

The final clustering result (Hazard-only scheme, Agglomerative (Ward), $k=6$) produced clusters of varying size with no single-member cluster (silhouette=0.2105; DBI=1.205; CHI=5.28). The two-dimensional PCA projection (Fig. 3) explained 27.5% of variance on PC1 and 18.5% on PC2 (46.0% total).

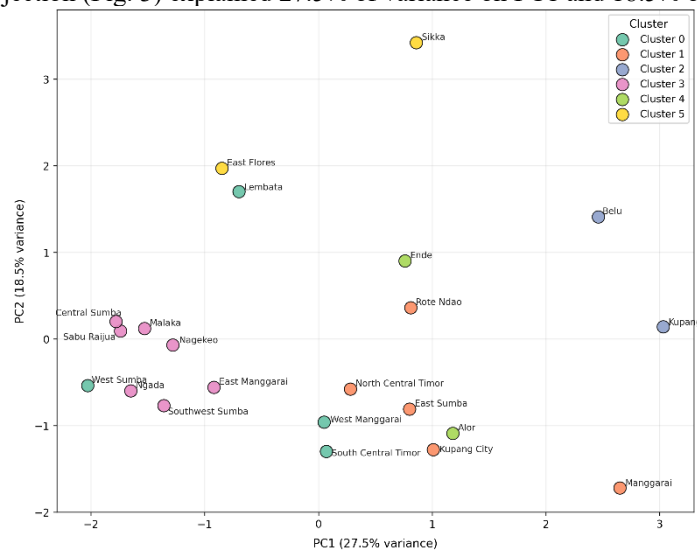


Fig. 3. Agglomerative (Ward) Clustering Result ($k=6$) for NTT Regencies/Cities Based on Multi-Hazard

Profile (2D PCA Projection)

The average real-frequency profile of each disaster type per cluster is shown in Table 3 and Fig. 4.

Table 3. Membership Profile and Dominant Disasters of Each Risk-Typology Cluster

Cluster	Descriptive Name	No. of Reg./City	Member Regencies/Cities	Dominant Disaster (avg. freq.)
K0	Moderate Extreme Weather–Flood Cluster with Forest/Land Fire	4	Lembata, Manggarai Barat, Sumba Barat, Timor Tengah Selatan	Extreme weather (11.0); Flood (9.8)
K1	Extreme Weather and Landslide–Prone Cluster	5	Kota Kupang, Manggarai, Rote Ndao, Sumba Timur, Timor Tengah Utara	Extreme weather (35.0); Flood (19.3)
K2	Highest-Frequency Flood and Extreme Weather–Prone Cluster	2	Belu, Kupang	Flood (40.7); Extreme weather (28.0)
K3	Low Multi-Hazard Risk Cluster	7	Malaka, Manggarai Timur, Nagekeo, Ngada, Sabu Raijua, Sumba Barat Daya, Sumba Tengah	Flood (7.7); Extreme weather (7.1)
K4	Extreme Weather and Coastal Abrasion–Prone Cluster	2	Alor, Ende	Extreme weather (37.0); Flood (23.5)
K5	Volcanic and Coastal Abrasion–Prone Cluster	2	Flores Timur, Sikka	Flood (23.5); Extreme weather (15.0)

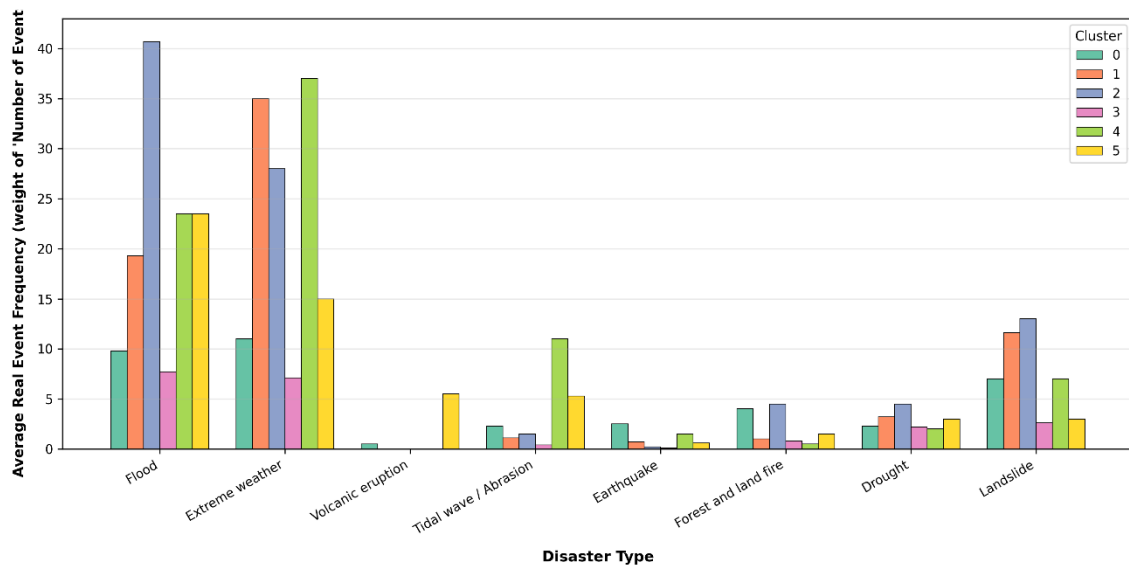


Fig. 4. Average Real-Event-Frequency Profile per Cluster

Based on Table 3 and Fig. 4, the six clusters show distinct hazard profiles. Cluster 0 (Lembata, Manggarai Barat, Sumba Barat, Timor Tengah Selatan) shows the highest forest and land fire frequency among all clusters (4.0 events) alongside moderate extreme weather and flood, hence named the “Moderate Extreme Weather–Flood Cluster with Forest/Land Fire.” Cluster 1 (Kota Kupang, Manggarai, Rote Ndao, Sumba Timur, Timor Tengah Utara) has a high extreme-weather frequency (35.0 events) together with the second-highest landslide frequency (11.6 events), named the “Extreme Weather and Landslide–Prone Cluster.” Cluster 2 (Belu, Kupang) records the highest flood frequency among all clusters (40.7 events) together with high extreme weather (28.0 events) and the highest landslide frequency (13.0 events), named the “Highest-Frequency Flood and Extreme Weather–Prone Cluster.” Cluster 3 (Malaka, Manggarai Timur, Nagekeo, Ngada, Sabu Raijua, Sumba Barat Daya, Sumba Tengah), with 7 members — the largest cluster — shows the lowest frequency across almost all disaster types, named the “Low Multi-Hazard Risk Cluster.” Cluster 4 (Alor, Ende) stands out with the highest extreme-weather frequency (37.0 events) and the highest tidal-wave/abrasion frequency (11.0 events) among all clusters, named the “Extreme Weather and Coastal

Abrasion-Prone Cluster.” Cluster 5 (Flores Timur, Sikka) stands out with the highest volcanic-eruption frequency (5.5 events), named the “Volcanic and Coastal Abrasion-Prone Cluster.”

Robustness Analysis: Additional Findings from the Severity-Only Scheme

As a robustness check, the Severity-only scheme ($k=2$), which had briefly produced the highest silhouette score (though degenerate, Section 3.3), still provided substantive information: this scheme consistently separated Sabu Raijua Regency as the sole outlier in impact severity. The average number of displaced/affected persons per event in Sabu Raijua reached 20,067 persons/event and the average damaged houses per event reached 1,037.5 units/event, far exceeding the average of the other 21 regencies/cities (4,648 persons/event and 86.4 units/event). Sabu Raijua Regency did not stand out in terms of hazard frequency (it was grouped in Cluster 3, the low-risk cluster) but showed a very high per-event impact vulnerability and deserves separate attention in mitigation planning.

Table 4. Per-Event Impact-Severity Index: Sabu Raijua (Outlier) vs. the Average of Other Regencies/Cities

Regency	Sev. Deaths (persons/event)	Sev. Displaced (persons/event)	Sev. Damaged Houses (units/event)	Sev. Injured (persons/event)
Sabu Raijua (outlier)	0.80	20,067	1,037.5	0.90
Average of other 21 regencies/cities	0.49	4,648	86.4	3.11

4.2. Temporal Trend and Change-Point of Disaster Events 2008–2025 (Complete Years)

Trend analysis was performed on the annual real disaster-event series at the provincial level and for the three most frequent disaster types, restricted to the complete years 2008–2025 (2026 data, recorded only through month 8, were excluded; see Section 3.1). The annual fluctuation pattern, Sen's slope trend line, Pettitt change-point indication, and lag-1 ACF value for each series are shown in Fig. 5.

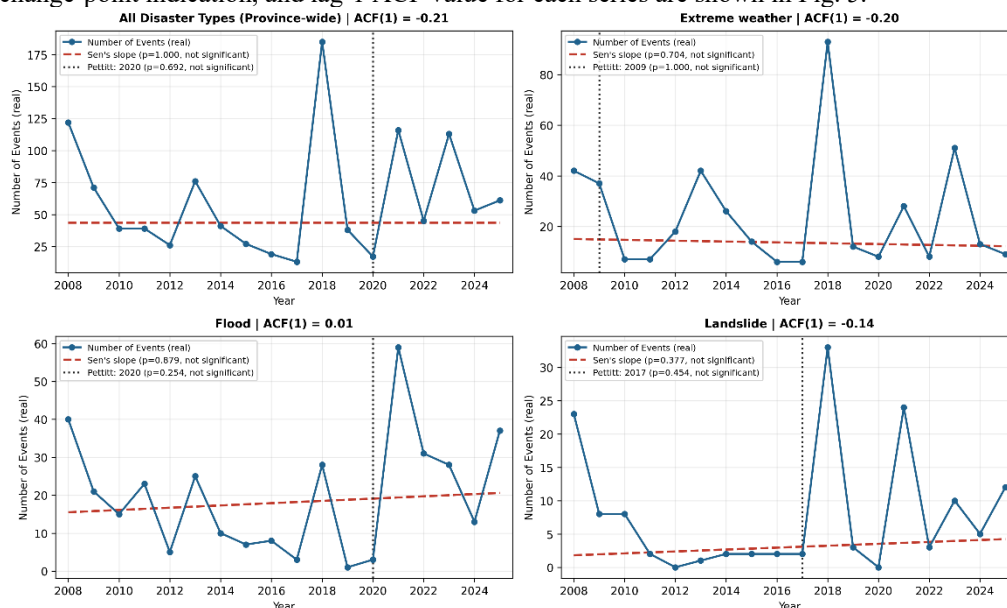


Fig. 5. Temporal Trend and Change-Point Indication for Disaster Events in NTT, Complete Years 2008–2025

Table 5a. Mann-Kendall Test, Sen's Slope, and Lag-1 Autocorrelation (ACF) Check Results

Data Series	Trend Direction	Significant ($p < 0.05$)	p-value	Sen's Slope	ACF Lag-1	Autocorr. Sig.?
Province (all disasters)	No trend	No	1.0000	0.0000	-0.206	No
Extreme weather	No trend	No	0.7040	-0.1667	-0.202	No
Flood	No trend	No	0.8794	0.3000	0.007	No
Landslide	No trend	No	0.3768	0.1429	-0.144	No

As shown in Table 5a, the lag-1 autocorrelation (ACF) check found NO significant autocorrelation in any tested series (all $|ACF(1)|$ values were below the $\pm 1.96/\sqrt{n}$ threshold), so the independence assumption of the original Mann-Kendall test was satisfied and the Hamed-Rao correction was not required for these series (the Hamed-Rao sensitivity-check results were therefore empty across all series). The Mann-Kendall test on the province-wide series found no statistically significant monotonic trend ($p=1.0000$; Sen's slope=0.0000 events/year). Similar results were found for extreme weather ($p=0.7040$), flood ($p=0.8794$), and landslide ($p=0.3768$).

Table 5b. Pettitt Test Results (Change-Point Detection)

Data Series	Indicated Change Year	K Statistic	p-value	Significant ($p<0.05$)
Province (all disasters)	2020	33.0	0.6919	No
Extreme weather	2009	21.0	1.0000	No
Flood	2020	46.0	0.2543	No
Landslide	2017	39.0	0.4542	No

The Pettitt test in Table 5b likewise found no statistically significant change point at the 5% level in any tested series. The peak Pettitt statistic for the province-wide and flood series both occurred in 2020 (though not significant), while the landslide series peaked in 2017 and extreme weather in 2009.

Overall, the absence of a significant monotonic trend, change point, or serial autocorrelation in the series above is a meaningful finding in itself (a meaningful null result): disaster-event frequency in NTT over 2008–2025 appears to be dominated by sharp year-to-year fluctuation that is relatively uncorrelated between consecutive years, rather than by a consistent long-term trend (see the spikes in 2018 and 2021–2023 in Fig. 5) [3]. This pattern is consistent with a disaster character strongly influenced by inter-annual climate variability (e.g., El Niño/La Niña) and sporadic large-scale extreme events such as tropical cyclones, rather than a gradually unidirectional climate/environmental shift from one year to the next [10].

4.3. Relationship between Risk Typology and Temporal Trend

The Mann-Kendall test was also applied to the annual (complete-year) real disaster-event series of each cluster, to examine whether regencies of a particular risk type showed trend patterns different from the provincial aggregate pattern. The per-cluster temporal patterns are shown in Fig. 6, and a summary of the test results (including lag-1 ACF) is shown in Table 6.

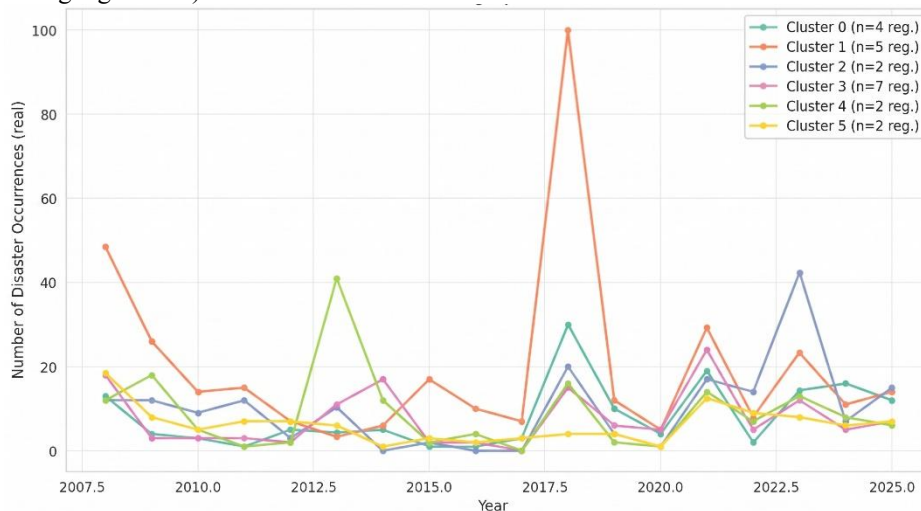


Fig. 6. Temporal Trend of Real Disaster-Event Frequency per Risk-Typology Cluster, Complete Years 2008–2025

Table 6. Mann-Kendall Test Results per Risk-Typology Cluster

Cluster	No. of Reg.	Trend Direction	Significant ($p<0.05$)	p-value	Sen's Slope	ACF Lag-1
K0	4	No trend	No	0.1956	0.4615	0.043
K1	5	No trend	No	0.7615	-0.2000	-0.107
K2	2	No trend	No	0.5424	0.1818	0.065

Cluster	No. of Reg.	Trend Direction	Significant ($p < 0.05$)	p-value	Sen's Slope	ACF Lag-1
K3	7	No trend	No	0.5668	0.1538	-0.146
K4	2	No trend	No	0.8492	-0.1250	-0.065
K5	2	No trend	No	0.7604	-0.0625	0.248

As shown in Table 6, NONE of the 6 clusters showed a statistically significant trend at the 5% level, consistent with the province-wide and per-disaster-type results (Section 4.2). Lag-1 autocorrelation was also non-significant across all clusters, so the original Mann-Kendall test remained valid without requiring the Hamed-Rao correction. Descriptively (not statistically significant), Cluster 0 (the “Moderate Extreme Weather–Flood Cluster with Forest/Land Fire,” comprising Lembata, Manggarai Barat, Sumba Barat, and Timor Tengah Selatan) showed the largest positive Sen's slope among all clusters (0.4615 events/year; $p=0.1956$); however, this p-value remained far from the 5% significance threshold, so it cannot be concluded as a genuinely increasing trend — this pattern warrants further monitoring as the data series lengthens in future years, but CANNOT be claimed as a significant finding based on current data. This finding differs from an earlier exploratory stage of the study which, before the frequency-definition correction (Section 3.1) and before the exclusion of the partial-year data (Section 3.1), had briefly shown one cluster with a significant trend — after both methodological corrections were applied, no cluster showed a statistically significant trend, underscoring the importance of both data corrections to the study's final conclusions [7].

4.4. Implications for Disaster Mitigation

The absence of a statistically significant long-term trend, change point, or per-cluster trend does not mean that disaster risk in NTT can be ignored; on the contrary, the sharp and unpredictable year-to-year fluctuation (low lag-1 autocorrelation, Fig. 5) indicates that preparedness needs to be CONSISTENT over time, rather than reactive to trends perceived as “declining” in certain years. The risk typology produced by this study can serve as a basis for Regional Disaster Management Agencies (BPBD) and local governments to design differentiated mitigation strategies: regions in the “Extreme Weather and Landslide–Prone Cluster” and the “Highest-Frequency Flood and Extreme Weather–Prone Cluster” require strengthened extreme-weather early-warning systems and flood/landslide preparedness given their high event frequency; regions in the “Extreme Weather and Coastal Abrasion–Prone Cluster” and the “Volcanic and Coastal Abrasion–Prone Cluster” require coastal-abrasion mitigation, with additional volcanic-specific mitigation for the latter; regions in the “Moderate Extreme Weather–Flood Cluster with Forest/Land Fire” require strengthened forest- and land-fire prevention alongside extreme-weather/flood preparedness; while Cluster 3, as the relatively low-risk group, still requires basic preparedness. Special attention should also be given to Sabu Raijua Regency, given its per-event impact-severity index far exceeding that of other regencies/cities (Section 4.1), despite its relatively low hazard frequency [1], [5].

5. CONCLUSION

This study produced two main findings, both obtained after applying a number of important methodological corrections to the event-frequency definition and the data's temporal coverage. First, through a model-selection procedure comparing 3 feature schemes, 2 clustering algorithms, and a consensus of 3 cluster-validity indices (Silhouette, Davies-Bouldin, Calinski-Harabasz), clustering of the REAL frequency profile of 8 disaster types across 22 regencies/cities in NTT produced 6 risk-typology clusters (silhouette=0.2105; DBI=1.205; CHI=5.28), ranging from a low-risk cluster, an extreme-weather/landslide-prone cluster, a highest-frequency flood/extreme-weather-prone cluster, an extreme-weather/coastal-abrasion-prone cluster, and a volcanic/coastal-abrasion-prone cluster, to a cluster distinguished by forest/land fire. Robustness analysis further identified Sabu Raijua Regency as an outlier in impact severity. Second, after correcting the event-frequency definition (using the 'Number of Events' weight rather than row count) and excluding the not-yet-complete 2026 data from the trend test, the Mann-Kendall and Pettitt tests on the annual province-wide series, the three most frequent disaster types, AND all risk-typology clusters CONSISTENTLY found no statistically significant trend or change point ($p > 0.05$) over 2008–2025, with lag-1 autocorrelation also non-significant across all series (confirming the validity of the original Mann-Kendall assumption). The contribution/novelty of this study lies in the integrated analysis of multi-hazard typology and temporal trend/change-point analysis for the context of NTT Province, accompanied by a series of data- and method-validity assurance steps (correction of fractional event weights, exclusion of partial-year data, multi-index validation of k , and an autocorrelation check) rarely applied together in similar disaster studies, while also illustrating how methodological correction can change a study's substantive conclusions (from one cluster briefly showing a significant trend in an early exploratory stage, to no significant trend in the final,

corrected analysis). Further research is recommended to extend the historical data coverage to increase the statistical power of trend detection, to consider socio-economic exposure and vulnerability variables as additional clustering features, and to explore the relationship between NTT's annual disaster fluctuations and large-scale climate indicators (e.g., El Niño/La Niña indices).

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