

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

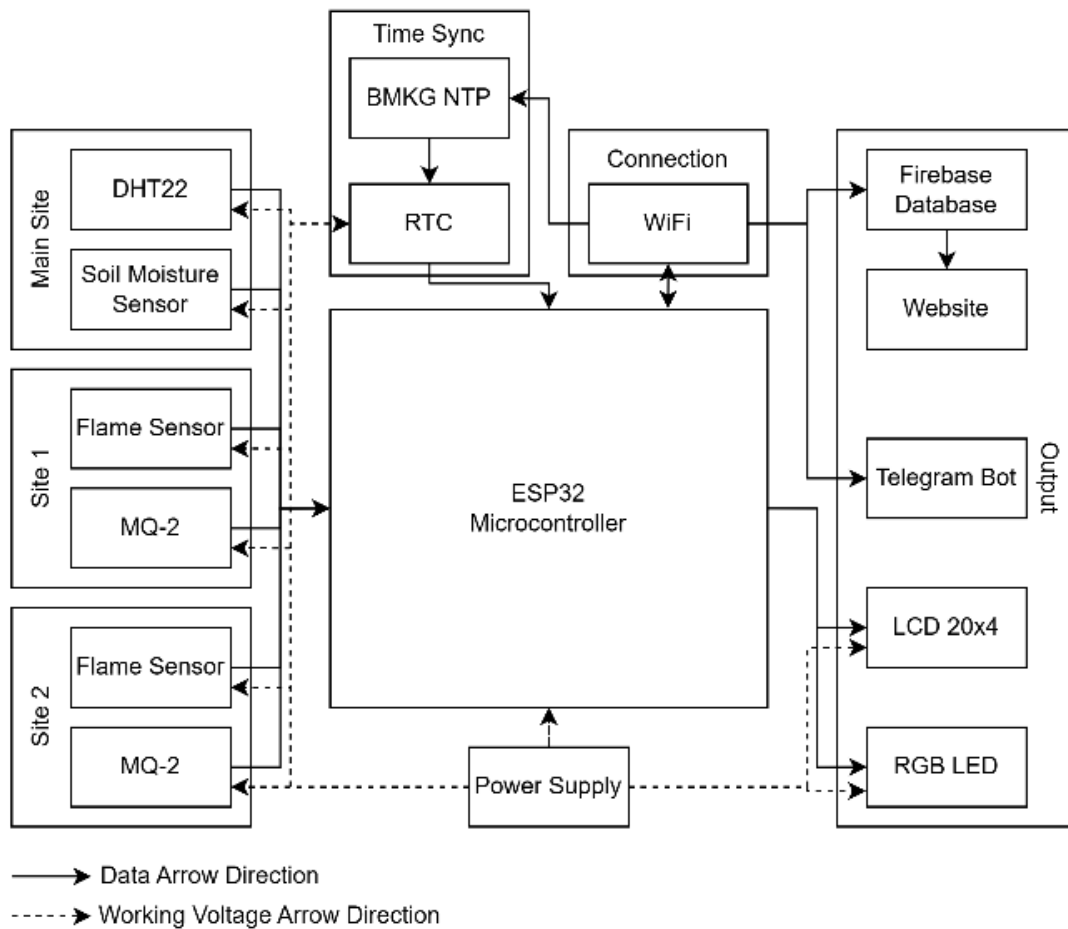


Fig. 1. System Block Diagram

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].

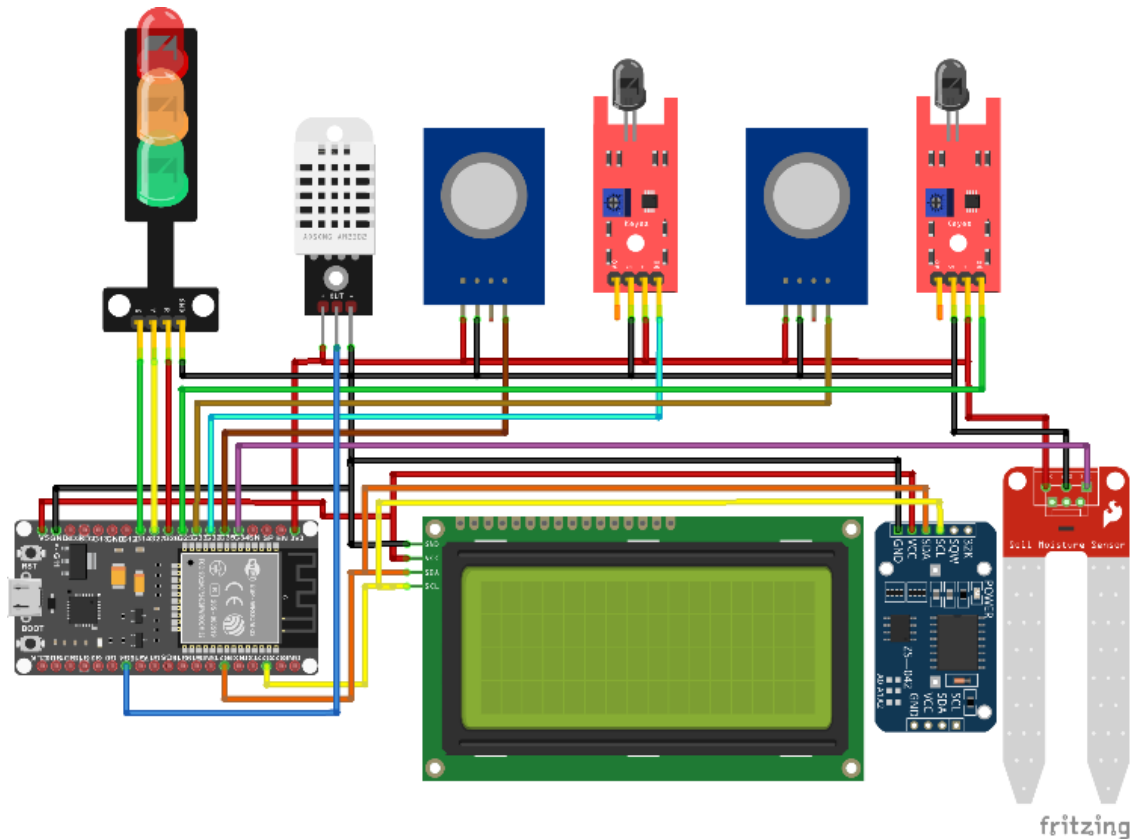


Fig. 2. Electronic Circuit

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].

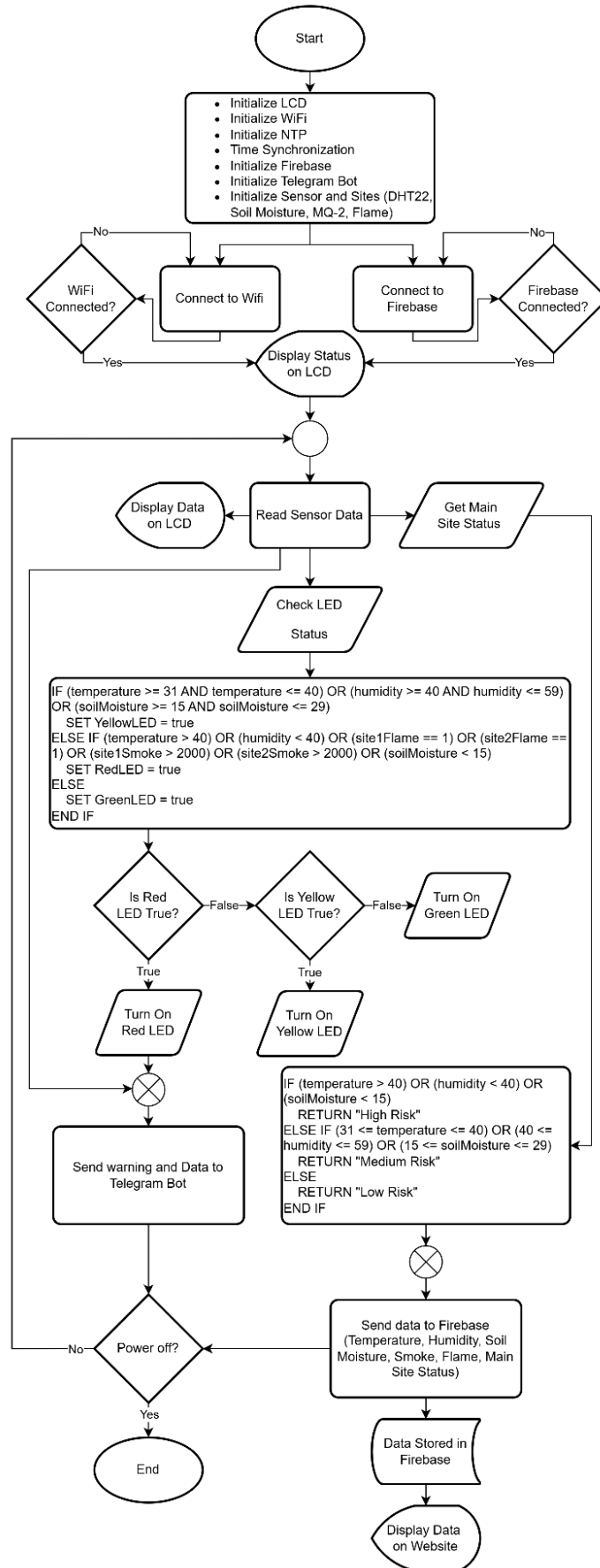


Fig. 3. Flowchart

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

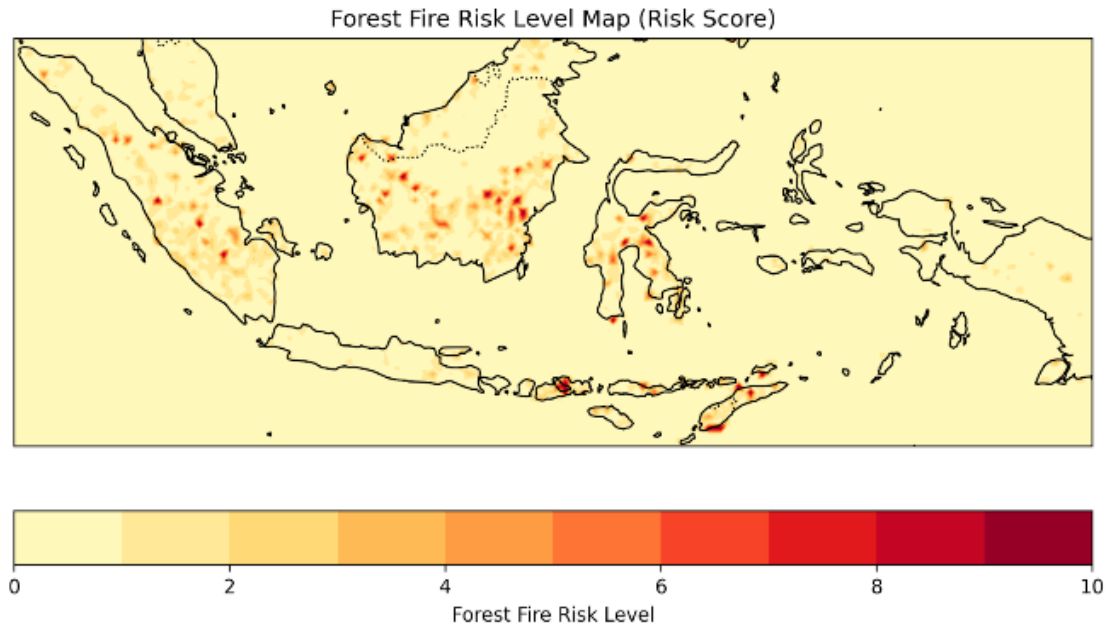


Fig. 5. Forest Fire Risk Level Map

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.

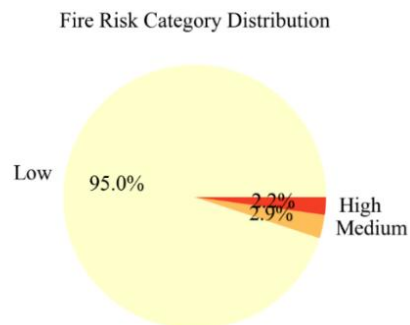


Fig. 6. Pie Chart of Fire Risk Category Distribution

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.

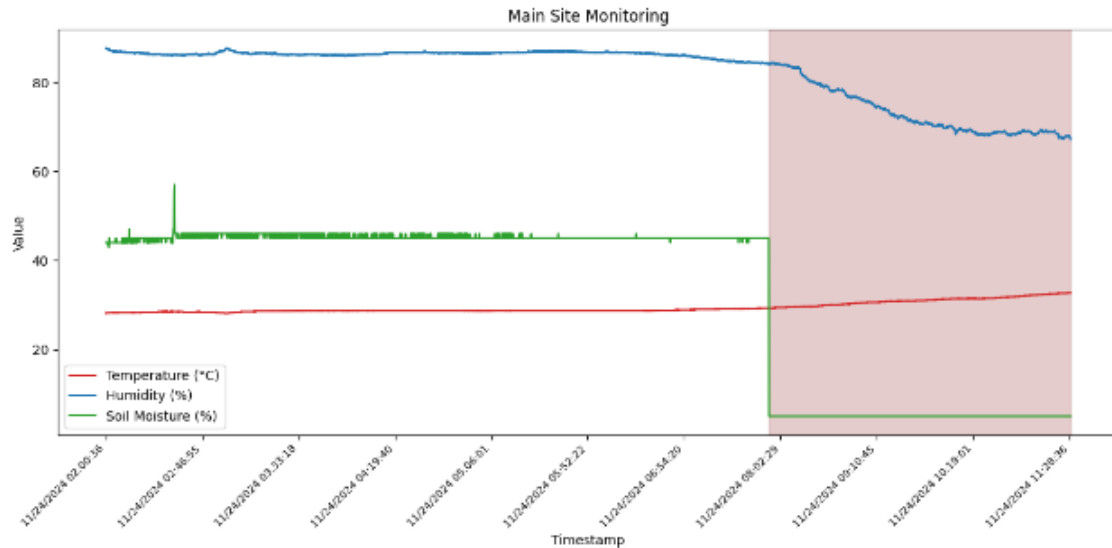


Fig. 7. Main Site Sensor Reading Graph

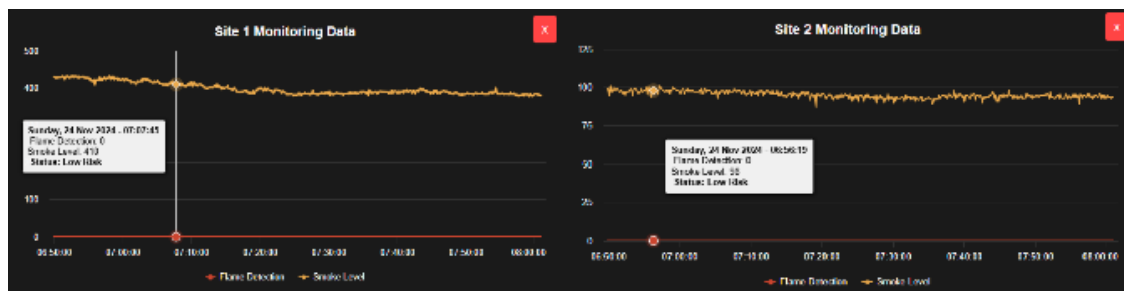


Fig. 8. Site 1 and Site 2 Sensor Reading Graph

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.

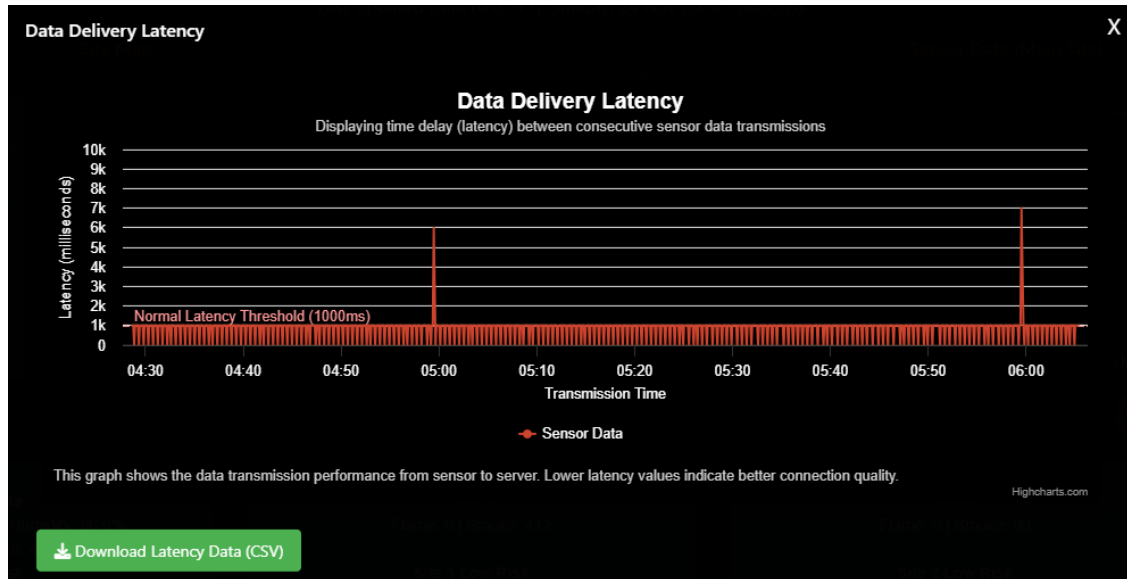


Fig. 9. Data Delivery Latency Graph

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.

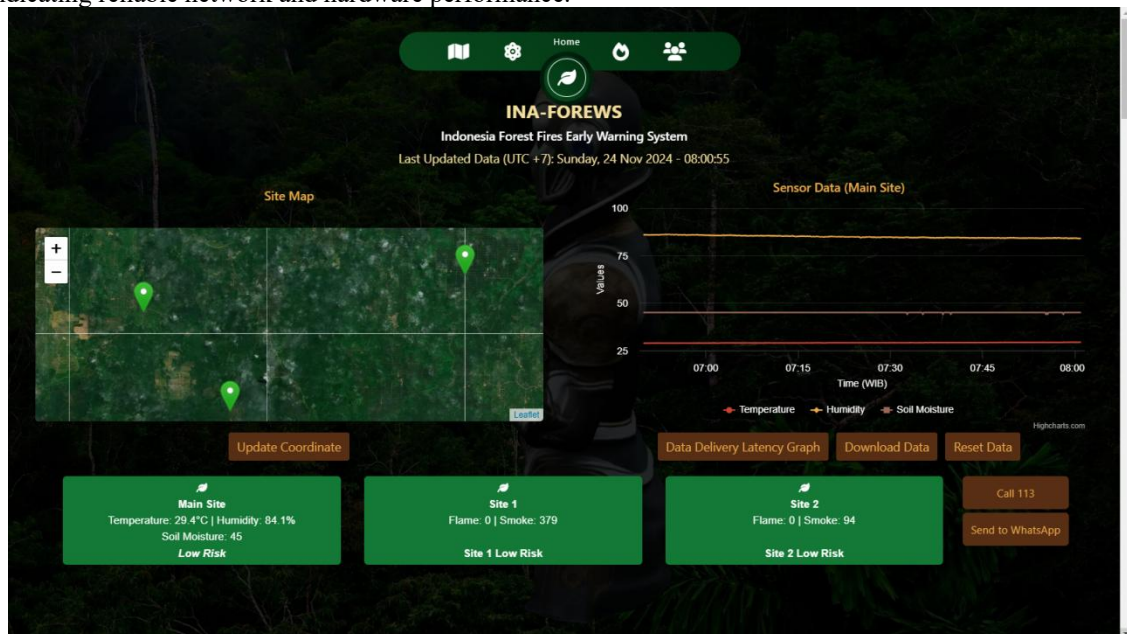


Fig. 10. Website Interface

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.

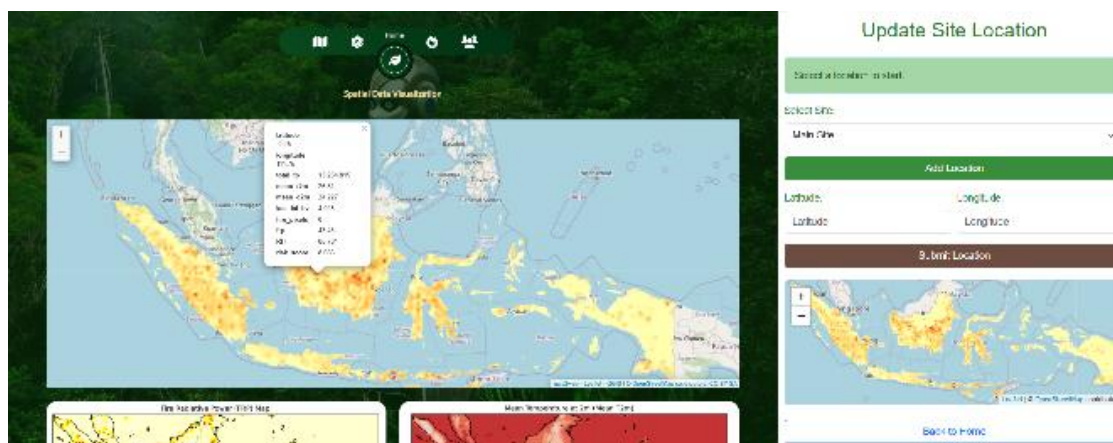


Fig. 11. Spatial Data Visualization and Update Coordinate Feature

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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