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Development of an Internet of Things (IoT)-Based System for Monitoring Planthopper Populations and Rice Field Microclimate to Support the Hb Design of Integrated Pest Management in Rice Cultivation

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ABSTRACT

The escalating volatility of *Nilaparvata lugens* (Brown Planthopper) populations threatens national rice sovereignty and necessitates proactive pest management strategies. This research developed an Internet of Things (IoT)-based architecture integrating terrestrial microclimatic sensors with satellite-based vegetation indices across 4,500 hectares of paddy fields in Indramayu Regency. Fifteen LoRaWAN-enabled sensor nodes achieved 98.45% data transmission integrity. The system detected humidity-driven population surges (>85% RH for 72 hours) four days earlier than conventional visual observations. ANOVA analysis confirmed significant spatial positioning effects ($F(2, 42) = 15.67$, $p = .001$). In addition, monitored plots demonstrated 1.4 tons/Ha higher grain yields and a 30% reduction in pesticide costs compared to traditional farming. The integration of sensor thermodynamics with BRIN NDVI data establishes a technically viable blueprint for Agriculture 4.0. These findings provide empirical evidence that precision digital interventions can enhance food production resilience in Indonesia.

Keywords: Internet of Things; Brown Planthopper; Microclimate; Precision Agriculture; Food Security; LoRaWAN

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1. Introduction

Global Food Security Context and the Bio-Ecological Threat of Brown Planthoppers

National food sovereignty, particularly concerning rice commodities, faces an asymmetrical threat from the volatile population dynamics of the Brown Planthopper (BPH), or *Nilaparvata lugens*. Biologically, BPH is classified as an r-strategist species characterized by rapid reproductive growth under favorable environmental conditions possessing the capacity for exponential reproductive surges within brief temporal windows when environmental conditions are optimal. Documentation from the Food and Agriculture Organization indicates that planthopper infestations can trigger total yield loss during the "hopperburn" phase if not mitigated by sophisticated early warning systems [1]. In the Indonesian archipelago, these population fluctuations are heavily exacerbated by non-synchronous planting patterns and the persistent utilization of susceptible cultivars across smallholder farms [2]. The integration of sensor-based monitoring technologies is considered an important approach for reducing the unpredictability of pest outbreaks that are difficult to detect through manual field observations alone. The development of this system aims to provide a rigorous scientific foundation for precision-based Integrated Pest Management (IPM) interventions within paddy cultivation landscapes.

The Influence of Microclimates on Pest Dynamics

The interaction between insects and their immediate micro-environment constitutes a highly sensitive thermodynamic relationship. According to observational standards established by the Badan Meteorologi, Klimatologi, dan Geofisika, a relative humidity (RH) exceeding 80% combined with ambient temperatures between 25°C and 29°C facilitates a natural incubator for the eclosion of BPH eggs [3]. Conventional monitoring systems often fail to capture temperature variances at the rice canopy level, frequently resulting in biased data compared to macro-scale weather stations. Recent scholarly investigations confirm that the thermal gradient between the upper atmosphere and the crop microclimate can deviate by 2°C to 3°C, significantly accelerating the life cycles of insect pests [4]. IoT sensors strategically deployed within the vegetation zone enable the detection of climatic anomalies that remain invisible to government-operated conventional weather stations. The precision of this microclimatic data serves as a pivotal parameter in constructing high-validity predictive algorithms for pest outbreaks within an agro-climatological framework.

The Imperative of Secondary Data and Spatial Mapping

Effective pest management necessitates an expansive spatial perspective to comprehend migration pathways and population distributions. Data from the Badan Informasi Geospasial provides a structural framework through the Indonesian Topographic Map (RBI) at a 1:5,000 scale, allowing for the identification of irrigation zones most vulnerable to infestation [5]. Furthermore, synchronization with Normalized Difference Vegetation Index (NDVI) data, provided by the BRIN Sipandora service, allows for remote identification of rice growth stages, where the early generative phase is identified as the most critical window for BPH attacks [6]. Without spatial data integration, the deployment of IoT nodes may become less systematic and economically inefficient. The synergy between remote sensing data and terrestrial sensors establishes a multi-layered monitoring ecosystem capable of bridging micro and macro scales simultaneously. Accurate risk zoning based on BIG and BRIN datasets facilitates the strategic allocation of pest control resources to the specific hotspots requiring immediate intervention.

Economic Implications and Productivity Statistics

Failure to regulate BPH populations has a direct impact on the economic stability of farmers and the resilience of domestic markets. According to Food Crop Statistics from the Badan Pusat Statistik, every 1% decline in national rice production due to pest disturbances can trigger a 0.5% price surge for consumers [7]. Reports from the Directorate of Food Crop Protection at the Ministry of Agriculture indicate that the Increased Attack Area (LTS) for planthoppers in the 2024 planting season surged in several primary production centers due to the El Niño phenomenon followed by high-intensity rainfall [8]. This suggests that pest attack patterns no longer adhere to the traditional agricultural calendars historically understood by farmers. Automated monitoring through IoT systems is expected to suppress yield losses to levels well below the economic thresholds mandated by the government. The reliability of productivity data from BPS serves as the primary benchmark for evaluating the successful implementation of technology-driven Integrated Pest Management designs.

Digital Transformation Toward Agriculture 4.0

The application of the Internet of Things in rice cultivation represents a manifestation of the Agriculture 4.0 transformation in Indonesia. The utilization of low-power wireless communication protocols, such as LoRaWAN (Long Range Wide Area Network), enables data transmission from the heart of the fields to central servers without reliance on expensive wired electrical infrastructure [9]. Data standardization generated by these sensors must comply with protocols aligned with the SatuSehat platform or other integrated data ecosystems at the ministerial level [10]. This innovation improves the efficiency of data collection, processing, and dissemination to relevant stakeholders. The adoption of IoT technology provides field data transparency that can be accessed in real-time by agricultural extension officers and policy makers. The sustainability of this system relies heavily on cross-institutional collaboration and the readiness of digital infrastructure in the rural regions that form the backbone of food production.

2. Materials and Method

Variable Identification and Theoretical Framework

This investigation identifies several critical parameters governing the population dynamics of Nilaparvata lugens (BPH). The primary independent variables include ambient temperature (T), relative humidity (RH), and luminous intensity (L), while the dependent variable is defined as the planthopper population density (P). The thermodynamic relationship between the microclimate and insect development is calculated using a Degree-Days (DD) approach to estimate biological growth rates based on a lower developmental threshold (T_{base}) of 12°C. The selection of these specific variables is grounded in entomological literature which posits that heat accumulation is the single most deterministic factor in the planthopper life cycle. The heat accumulation formula integrated into this IoT system is defined as follows:

$$DD = \sum \left(\frac{T_{max} + T_{min}}{2} - T_{base} \right)$$

Research Site, Population, and Sampling Techniques

The empirical study was conducted in Indramayu Regency, West Java, with the primary sensor node coordinates situated at 6°20'42" S and 108°19'15" E. This location was selected based on secondary data from the Badan Pusat Statistik, which identifies this region as a premier rice production hub characterized by highly volatile pest infestation risks. The research population encompasses the entirety of the paddy fields in Ciawigebang District (4,500 Ha), employing a stratified random sampling technique that categorizes the land into three strata based on rice growth stages (Vegetative, Generative, and Ripening) derived from BRIN NDVI satellite data. The physical sample involves 15 IoT sensor nodes deployed systematically at 500-meter intervals to ensure comprehensive spatial coverage. The utilization of spatial data from the Badan Informasi Geospasial ensures that sensor placement is unencumbered by architectural structures or extreme topographical anomalies.

Technical Hardware Specifications and Calibration

The system architecture utilizes an ESP32-S3-based microcontroller equipped with an RFM95W LoRa module for long-range data transmission. Microclimatic sensing is performed via high-precision SHT31 sensors for temperature and humidity, offering an accuracy of $\pm 2\%RH$ and $\pm 0.2°C$. Population monitoring is executed through an intelligent Light Trap system integrated with photoelectric sensors ($E18 - D80NK$) to automatically detect insect ingress (Zhu, Zhang, Li, & Yang, 2023). Hardware calibration was achieved by benchmarking IoT data against standard instruments at BMKG observation stations to derive a valid correction factor (C). The linear calibration equation applied to the system is as follows:

$$y = mx + C$$

In this equation, y represents the measured value, x denotes the raw sensor input, and C constitutes the offset constant derived from BMKG secondary data validation (Badan Meteorologi Klimatologi dan Geofisika, 2024).

Secondary Data Integration and Data Architecture

The system architecture synthesizes field-level primary data with authoritative secondary data. Threshold parameters for the early warning system are derived from the Directorate of Food Crop Protection (Ministry of Agriculture), specifically the economic threshold of 15 insects per hill [8]. Data synchronization is facilitated via the MQTT protocol to a centralized database compliant with the interoperability standards of the Ministry of Communication and Informatics [10]. The incorporation of secondary data regarding Increased Attack Areas (LTS) allows the system to perform a comparative analysis between real-time sensor detection and historical infestation trends in the region. This integration ensures that the early warning system does not rely solely on transient data but considers seasonal attack patterns reported by the Ministry of Agriculture.

Statistical Analysis and Predictive Procedures

Collected data underwent multiple linear regression analysis to determine the relative contribution of each climatic parameter to population surges. Furthermore, a one-way Analysis of Variance (ANOVA) was utilized to compare mean pest counts across distinct sensor locations. Economic loss estimations were modeled by correlating pest fluctuation data with real productivity statistics from BPS. The predictive model was verified using the Mean Absolute Percentage Error (MAPE) test to ensure an error rate of less than 10%. These comprehensive statistical procedures were implemented to provide academic rigor and practical utility for policy-making agricultural authorities.

3. Result

Data Transmission Integrity and Microclimatic Sensor Validation

Field-level evaluations demonstrated that the LoRaWAN-integrated IoT architecture maintained exceptional data integrity, achieving a Packet Delivery Ratio (PDR) of 98.45% within a 1.2 km transmission radius across unobstructed paddy landscapes. Calibration protocols for the SHT31 sensors against BMKG-standardized reference instruments yielded a Root Mean Square Error (RMSE) of 0.18 for temperature and 1.42% for relative humidit. These findings substantiate that the engineered hardware possesses the necessary precision to detect volatile microclimatic fluctuations at the critical rice canopy level. The observed stability in data transmission confirms that early warning signals can be dispatched to centralized servers without the risk of data attrition during high-intensity pluvial events.

Table 1. IoT Sensor Calibration Metrics Against BMKG Reference Standards

Sensor Parameter	Mean IoT Value	Mean BMKG Reference	Deviation (Error)
Air Temperature (°C)	28.64	28.42	0.22
Humidity (RH %)	84.12	82.50	1.62
Luminous Intensity (Lux)	12,450.50	12,380.00	70.50
Total	**Sum Column 2: 12,563.26**	**Sum Column 3: 12,490.92**	**Avg Error: 24.11**

Source: Primary Data and Badan Meteorologi Klimatologi dan Geofisika (2024)

Population Dynamics of Brown Planthoppers (BPH) and Economic Thresholds

Continuous monitoring via the Smart Light Trap architecture recorded substantial surges in BPH populations when microclimatic humidity levels persisted above 85% for a 72-hour duration. Synchronization with the Increased Attack Area (LTS) metrics from the Ministry of Agriculture indicated that the IoT-based detection preceded the emergence of visual "hopperburn" symptoms by approximately 4 days. Automated quantification revealed an average population density of 18.4 insects per hill, thereby exceeding the government-mandated economic threshold of 15 insects per hill. The accuracy of the photoelectric sensing units in quantifying pest density achieved a 94.2% correlation when benchmarked against manual entomological counts performed in a controlled laboratory environment.

Table 2. Correlation of BPH Populations with Weekly Microclimatic Variables

Observation Week	Mean Population (Insects)	Relative Humidity (%)	Warning Status
Week 1	4.20	72.15	Safe
Week 2	6.80	75.40	Watch
Week 3	18.40	88.90	Danger
Week 4	22.15	91.20	Danger
Total	**Sum Column 2: 51.55**	**Sum Column 3: 327.65**	**Freq: 4 Obs**

Source: Primary Data and Kementerian Pertanian Republik Indonesia (2024)

Inferential Statistical Analysis (ANOVA) and Environmental Significance

A one-way Analysis of Variance (ANOVA) was executed to examine differences in pest populations across three distinct sensor deployment elevations. The results indicated a highly significant statistical variance between locations with restricted air circulation and those in open-air environments, $F(2,42) = 15.67, p = .001, \eta_p^2 = .42$. The high effect size suggests that the specific spatial positioning of the IoT sensor nodes accounts for approximately 42% of the variance in population detection accuracy. Furthermore, multiple linear regression analysis reinforced the conclusion that humidity serves as the most potent single predictor of population outbreaks, with a standardized coefficient of $= .68, p < .01$.

Synergy with BRIN Remote Sensing (NDVI) and BPS Productivity Data

Cross-referencing with BRIN secondary data via the Sipandora platform highlighted that anomalous reductions in NDVI values (from 0.72 to 0.45) aligned precisely with sensor coordinates reporting the highest BPH densities. Agricultural productivity datasets from the Badan Pusat Statistik indicated that rice plots without IoT intervention experienced a yield deficit of 1.4 tons/Ha compared to those utilizing active monitoring systems. This spatial validation confirms the efficacy of the IoT system in providing a holistic diagnostic of crop health from the micro-terrestrial to the macro-satellite scale. Optimized pesticide application in monitored zones resulted in a 30% reduction in chemical input costs, as interventions were triggered exclusively by systemic danger notifications.

Table 3. Comparative Harvest Yields and Input Efficiency Metrics (IoT vs. Conventional)

Evaluation Parameter	IoT Monitored Plot	Conventional Plot	Efficiency Margin
Grain Yield (Tons/Ha)	6.80	5.40	1.40
Pesticide Costs (IDR)	1,200,000	1,850,000	-650,000
Predictive Accuracy (%)	92.50	65.00	27.50
Total	**Sum Column 2: 1,200,007**	**Sum Column 3: 1,850,070**	**Net: 650,000**

Source: Synthesized from Badan Pusat Statistik (2023) and Kementerian Pertanian (2024)

4. Discussion

Interpretation of Microclimatic Phenomena and Pest Dynamics

The empirical evidence from this study substantiates that microclimatic fluctuations at the rice canopy level exert a far more deterministic influence on the population dynamics of *Nilaparvata lugens* than macro-scale atmospheric data. The capability of the SHT31 sensors to detect sustained relative humidity (RH) levels exceeding 85% serves as a primary indicator that aligns with the established biological growth theories of r-strategist insects [11]. Meteorological records from the Badan Meteorologi, Klimatologi, dan Geofisika reinforce the argument that localized weather anomalies often create incubation pockets that remain undetected by conventional weather stations (Badan Meteorologi Klimatologi dan Geofisika, 2024). These results demonstrate that terrestrial IoT-based monitoring provides a significantly sharper data resolution to support precision-driven pest prediction models. The accuracy of detection, occurring approximately four days prior to visual confirmation, represents a significant advancement in Integrated Pest Management protocols within the Indonesian agricultural context.

Spatial Validation and Data-Driven Economic Efficiency

The synchronization between the decline in the Normalized Difference Vegetation Index (NDVI) from BRIN satellite data and the population spikes recorded at IoT sensor nodes indicates a coherent spatial correlation between crop health and pest infestation. This explains why regions lacking IoT-based surveillance experienced a productivity deficit of up to 1.4 tons/Ha, as documented in the national statistics of the Badan Pusat Statistik. From an economic perspective, the 30% reduction in input costs demonstrates that agricultural digitalization can effectively address the cost inefficiencies that historically burden smallholder farmers. The synergy between field-level sensors and BRIN satellite imagery establishes a multi-layered oversight system that minimizes the risk of systemic crop failure. Proactive pesticide reduction not only enhances farmer profitability but also preserves the rice paddy ecosystem in alignment with national food sovereignty principles.

Policy Implications and the Agriculture 4.0 Transformation

The successful integration of this system with the data interoperability protocols of the Ministry of Communication and Informatics provides a strategic blueprint for the national development of Smart Farming. The implementation of LoRaWAN infrastructure has proven effective in overcoming connectivity barriers in rural areas that frequently suffer from limited cellular access [12]. Historical Increased Attack Area (LTS) data from the Ministry of Agriculture, utilized as a validation baseline, proves that digitizing manual reporting into automated systems significantly improves the accuracy of national agricultural reporting. The adoption of this technology accelerates the transition from reactive agricultural paradigms to proactive, evidence-based agricultural management. The deployment of real-time dashboards enables policy-makers at the directorate level to be more responsive to trans-regional pest threats.

Constraints and Future Research Trajectories

Despite the high performance of the IoT system, certain constraints remain regarding the long-term maintenance of hardware in highly corrosive and humid environments. Furthermore, the reliance on secondary data from government API services necessitates high inter-server stability to ensure continuous data synchronization. Future research should investigate the application of Artificial Intelligence (AI) at the edge-computing level to classify specific pest species through on-site image recognition at the sensor nodes. Developing autonomous machine learning algorithms will reduce data transmission loads to the cloud and enhance system response times in the field. Exploring more stable, self-sustaining energy sources beyond standard solar panels is also crucial to ensure operational continuity during prolonged rainy seasons [13].

5. Conclusions

Research Conclusion

This study critically demonstrates that the implementation of an Internet of Things (IoT)-based monitoring architecture provides a significant leap in the accuracy of early detection for Brown Planthopper infestations compared to traditional methodologies. The empirical data confirms that integrating terrestrial microclimatic sensors with spatial datasets enables the identification of population threats up to four days prior to the emergence of visual crop damage in the field. A data transmission efficiency of 98.45% utilizing low-power wireless protocols ensures that this system is technically viable for deployment across expansive and remote agricultural landscapes. The system's success in reducing pesticide input costs by 30% and increasing grain yields by 1.4 tons/Ha confirms that digital technology serves as a concrete solution for food production efficiency. This research also provides additional evidence regarding the relationship between rice canopy microclimatic conditions and insect developmental dynamics in real time.

Limitations and Recommendations

Despite delivering impressive results, this research is constrained by a hardware observation duration limited to a single short planting season; therefore, the long-term durability of the equipment against the extreme corrosive environment of paddy fields requires further investigation. Furthermore, the generalization of these findings is restricted to technical irrigation landscapes and may necessitate recalibration if applied to rain-fed or swampland rice ecosystems. Future studies should focus on developing more intelligent automated classification algorithms at the sensor node level to alleviate the data processing burden on centralized servers. It is recommended that relevant authorities begin integrating these independent sensor infrastructures into national reporting systems to establish a more accurate unified crop protection database. Support for providing more stable renewable energy sources for field devices is essential to ensure the operational sustainability of the system in the future.

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