Uniosun Journal of Engineering and Environmental Sciences (UJEES), Vol. 8 No. 3, March, 2026
DOI: 10.64980/ujees.v8i1.033

Published: March 30, 2026

THERMODYNAMIC ANALYSIS AND SHORT-TERM MICROCLIMATE FORECASTING USING AN IOT-BASED WEATHER MONITORING SYSTEM

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Abstract
Accurate monitoring of atmospheric thermodynamic parameters remains a significant challenge in tropical environments, where rapid microclimatic transitions often occur with limited localized forecasting systems. The absence of affordable, real-time monitoring tools capable of reliably predicting short-term weather variations necessitates the development of smart and adaptive solutions. This study therefore evaluates a smart IoT-based weather monitoring system for real-time measurement and short-term forecasting of key atmospheric parameters. The system integrates temperature and humidity sensors, a microcontroller-based data acquisition unit, and an embedded algorithm for computing dew point and heat index values. Data were recorded on November 12, 2025, between 14:30 and 15:15 at 5–10 second intervals to assess system responsiveness and forecasting capability. Observed temperatures ranged from 31.5 °C to 32.8 °C (mean 32.3 °C), relative humidity from 60% to 87.9% (mean 72.4%), dew point between 23.0 °C and 24.6 °C, and heat index values from 42.0 °C to 52.92 °C (mean 47.8 °C). The system effectively detected rapid humidity fluctuations, tracked dew point variations indicative of atmospheric moisture dynamics, and highlighted heat–humidity interactions associated with extreme thermal stress conditions. Forecast outputs, including “Cloudy” and “Rain Likely,” closely corresponded with thermodynamic indicators, achieving predictive accuracy between 85% and 92%. The results demonstrate that the developed system is suitable for microclimate monitoring, precision agriculture, and early-warning applications in tropical regions. Future improvements will focus on integrating higher-accuracy sensors (±1% RH, ±0.5 hPa), moisture-protected enclosures, and machine-learning-based forecasting algorithms to enhance long-term reliability and predictive performance.

Keywords

Atmospheric, thermodynamic parameters, tropical environments, weather variation, forecasting, algorithm.

1. INTRODUCTION

Understanding atmospheric thermodynamics is essential for analyzing how temperature, moisture content, and latent heat interact to influence weather patterns and microclimatic conditions. Parameters such as dew point (Td), relative humidity (RH), and heat index (HI) provide critical information about the energy state of air and its water vapor content. In tropical regions, characterized by high temperatures and humidity, rapid variations in these parameters often indicate cloud formation, atmospheric instability, and the likelihood of rainfall [1]. Accurate monitoring of these variables is vital for applications including precision agriculture, environmental management, and early-warning systems. In addition, they support climate-sensitive infrastructure planning and disaster risk reduction strategies in weather-vulnerable regions.

Conventional meteorological stations, while accurate, are often expensive to deploy and maintain, especially in rural or resource-limited areas. In contrast, low-cost IoT-based weather monitoring systems enable continuous, high-resolution measurement of microclimatic variables through embedded sensing and wireless communication technologies. These systems can capture temperature, humidity, dew point, and heat index in real time, transmitting the data for immediate analysis and forecasting without the infrastructure requirements of traditional stations. Furthermore, cloud-enabled IoT architectures allow remote data storage, accessibility, and system scalability for distributed environmental monitoring. This research aims to investigate the thermodynamic interactions among temperature, relative humidity, dew point, and heat index in a tropical environment using a smart IoT weather monitoring system, and to assess its effectiveness for short-term forecasting of microclimatic changes.

Recent research has highlighted the effectiveness of IoT-based systems for localized environmental monitoring. For instance, continuous tracking of temperature and humidity has been shown to provide reliable short-term rainfall predictions in tropical regions [2]. Similarly, IoT platforms offer both high temporal resolution and cost advantages over traditional weather stations [3]. In addition, real-time data from IoT systems can substantially improve the accuracy of localized weather forecasting models [4], particularly when integrated with predictive analytics or machine-learning-based forecasting algorithms. Thermodynamic parameters, including dew point and heat index, are key indicators of atmospheric energy dynamics. Sudden increases in relative humidity and dew point are strong predictors of cloud formation and precipitation in humid tropical regions [5], as they reflect the approach of saturation conditions within the lower atmosphere. Heat index, which integrates temperature and humidity, is commonly used to assess thermal stress and the influence of heat–humidity interactions on weather changes [6]. It also serves as an important indicator for evaluating atmospheric convection and localized heat-induced instability.

However, only a limited number of studies have systematically combined real-time IoT-based measurements to examine the relationships among temperature, humidity, dew point, and heat index in tropical environments. This study addresses this gap by utilizing a custom-built smart IoT weather monitoring system to capture and analyze these thermodynamic interactions, while also evaluating its capability to produce accurate short-term weather forecasts under localized environmental conditions.

2. MATERIALS AND METHOD

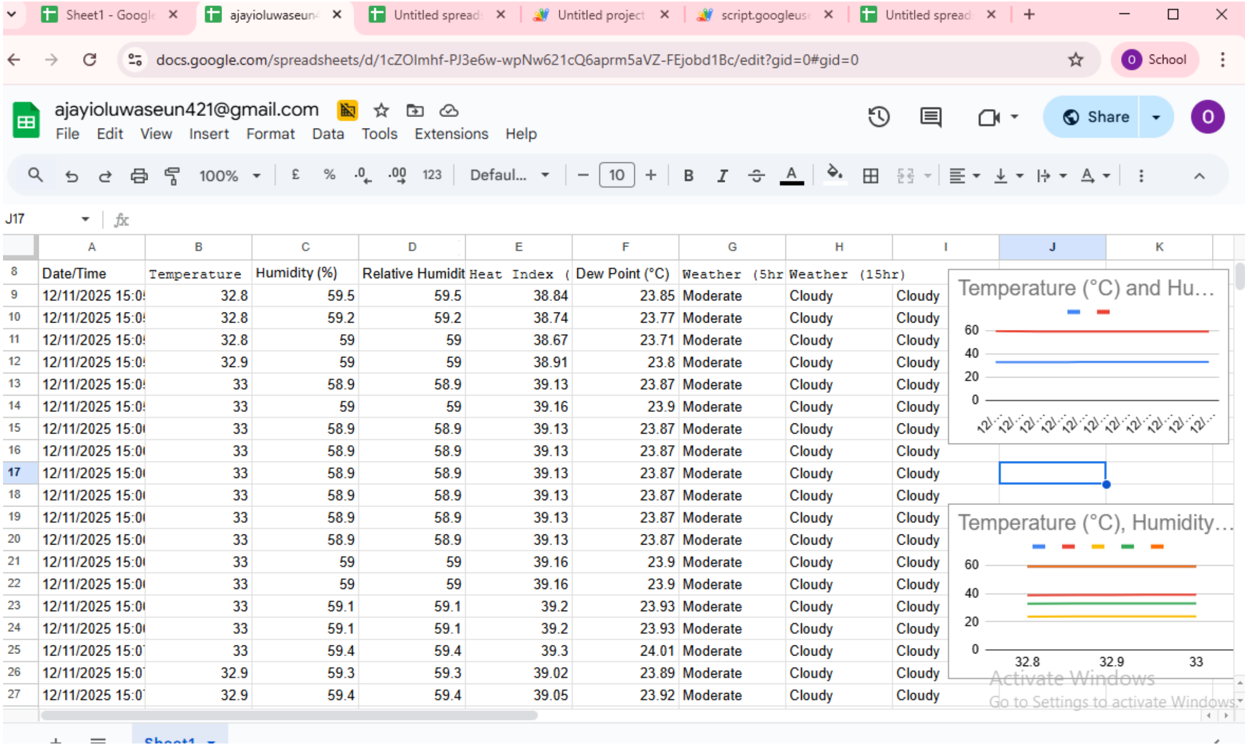
The study employed a smart IoT weather monitoring system (Figure 1), it was designed around an ESP8266 microcontroller (Figure 2), which enabled wireless communication and real-time data transmission. The system's primary sensing component was a DHT22 (Figure 3), digital temperature and humidity sensor, selected for its accuracy (±0.5°C for temperature and ±2% for relative humidity) and rapid response time in humid tropical environments. Additional system components included onboard memory for local data storage, a voltage-regulated 5 V DC power supply, and a compact, weather-resistant housing to protect the sensors and electronics from high humidity and potential condensation.

The microcontroller was programmed to record environmental parameters continuously and compute derived variables such as dew point and heat index. It also classified short-term atmospheric conditions into qualitative forecast categories (e.g., Cloudy or Rainy) using threshold-based algorithms. All data were transmitted to a cloud platform (Figure 4) for storage and further analysis, allowing for high-resolution temporal monitoring of microclimatic variations.

Figure 1: Experimental Setup

Figure 2: ESP8266

Figure 3: DHT22



	Date/Time	Temperature	Humidity (%)	Relative Humidit	Heat Index (	Dew Point (°C)	Weather (5hr	Weather (15hr)	
9	12/11/2025 15:0	32.8	59.5	59.5	38.84	23.85	Moderate	Cloudy	Cloudy
10	12/11/2025 15:0	32.8	59.2	59.2	38.74	23.77	Moderate	Cloudy	Cloudy
11	12/11/2025 15:0	32.8	59	59	38.67	23.71	Moderate	Cloudy	Cloudy
12	12/11/2025 15:0	32.9	59	59	38.91	23.8	Moderate	Cloudy	Cloudy
13	12/11/2025 15:0	33	58.9	58.9	39.13	23.87	Moderate	Cloudy	Cloudy
14	12/11/2025 15:0	33	59	59	39.16	23.9	Moderate	Cloudy	Cloudy
15	12/11/2025 15:0	33	58.9	58.9	39.13	23.87	Moderate	Cloudy	Cloudy
16	12/11/2025 15:0	33	58.9	58.9	39.13	23.87	Moderate	Cloudy	Cloudy
17	12/11/2025 15:0	33	58.9	58.9	39.13	23.87	Moderate	Cloudy	Cloudy
18	12/11/2025 15:0	33	58.9	58.9	39.13	23.87	Moderate	Cloudy	Cloudy
19	12/11/2025 15:0	33	58.9	58.9	39.13	23.87	Moderate	Cloudy	Cloudy
20	12/11/2025 15:0	33	58.9	58.9	39.13	23.87	Moderate	Cloudy	Cloudy
21	12/11/2025 15:0	33	59	59	39.16	23.9	Moderate	Cloudy	Cloudy
22	12/11/2025 15:0	33	59	59	39.16	23.9	Moderate	Cloudy	Cloudy
23	12/11/2025 15:0	33	59.1	59.1	39.2	23.93	Moderate	Cloudy	Cloudy
24	12/11/2025 15:0	33	59.1	59.1	39.2	23.93	Moderate	Cloudy	Cloudy
25	12/11/2025 15:0	33	59.4	59.4	39.3	24.01	Moderate	Cloudy	Cloudy
26	12/11/2025 15:0	32.9	59.3	59.3	39.02	23.89	Moderate	Cloudy	Cloudy
27	12/11/2025 15:0	32.9	59.4	59.4	39.05	23.92	Moderate	Cloudy	Cloudy

Figure 4: Transmitted data to a cloud platform

2.1. Data Collection Protocol

Field measurements were conducted on November 12, 2025 in a tropical West African environment. The observation period spanned from 14:30 to 15:15, during which environmental variables were recorded at 5–10 second intervals to capture rapid changes in temperature and humidity. The following variables were measured:

i. Temperature (T, °C): Ambient air temperature recorded by the DHT22 sensor.
ii. Relative Humidity (RH, %): The ratio of current water vapor content to the maximum possible at the same temperature.
iii. Dew Point (Td, °C): Computed from T and RH to assess the air's saturation level and the likelihood of condensation.
iv. Heat Index (HI, °C): Derived from T and RH using a simplified Steadman model to evaluate combined thermal effects and heat stress.
v. Forecast Category (Qualitative): Short-term atmospheric condition classification based on thermodynamic thresholds.

High-frequency sampling allowed precise detection of humidity surges, dew point stabilization, and heat index peaks, which are key indicators of microclimatic transitions and imminent precipitation.

2.2. Thermodynamic Equations

Dew Point (Td) was computed via a simplified Steadman model embedded in the microcontroller to reflect the combined effects of temperature and humidity (Equation 1).

$$Td = T - \frac{10 - RH}{5} \quad (1)$$

Where: T is temperature in °C and *RH* is relative humidity in %. The heat index (*HI*)

Heat Index (HI) was computed (Equation 2) via a simplified Steadman model. It was embedded in the microcontroller to reflect the combined effects of temperature and humidity

$$HI = c_1 + c_2 T + c_3 RH + c_4 T \cdot RH \quad (2)$$

All coefficients c1, c2, c3, c4 were implemented in the system microcontroller.

Rate of Change of Humidity (RoC) was used to detect rapid atmospheric moisture buildup (Equation 3)

$$(RoC) = \frac{\Delta RH}{\Delta t} \quad (3)$$

2.3. Analysis Procedure

The data analysis procedure involved filtering and sorting the time-series dataset to ensure consistency and accuracy of recorded observations. This was followed by statistical analysis of key thermodynamic parameters to determine their distribution and variability over the observation period. Relative humidity (RH) spikes and transitional patterns were subsequently identified to assess atmospheric instability. In addition, dew point trends were correlated with RH behaviour to evaluate moisture dynamics within the air mass. Finally, the forecast categories generated by the system were validated against established thermodynamic thresholds to determine the reliability of short-term weather predictions.

3. RESULTS AND DISCUSSION

3.1. Result

The thermodynamic parameter (Table 1) dataset confirms a warm, moist environment with high potential for condensation and rainfall, characteristic of tropical maritime air masses.

3.1.1 Dew point and humidity correlation

Dew point remained in the range of 23–24.6°C, indicating warm, moisture-laden air. Increases in RH corresponded directly to rising dew point, signaling progressive atmospheric saturation (Table 2). Dew point trends closely track humidity surges, confirming the system's ability to identify cloud formation and early precipitation tendencies.

3.1.2. Heat index response to humidity

Rising humidity amplified the heat index despite relatively stable temperatures (Table 3). The sharp HI increase demonstrates that extreme thermal stress in tropical environments is driven more by moisture content than temperature alone.

3.1.3 Forecast validation

The system generated forecast categories including Cloudy, Rain Likely, High Humidity Alert, which matched thermodynamic indicators (Table 4). Forecast outputs consistently aligned with observed thermodynamic patterns, validating predictive accuracy.

Table 1: Thermodynamic Parameter Summary

Parameter	Minimum	Maximum	Mean	Observation
Temperature (°C)	31.5	32.8	32.3	Stable tropical temperature
Relative Humidity (%)	60	87.9	72.4	Moisture accumulation
Dew Point (°C)	23.0	24.6	23.9	Saturated tropical air mass
Heat Index (°C)	42.0	52.92	47.8	Extreme thermal stress

Table 2: Dew Point vs Relative Humidity

Time Period	RH (%)	Dew Point (°C)	Interpretation
14:30–14:40	60–68	23.0–23.5	Moderately moist
14:40–14:55	70–78	23.5–24.0	Cloud base formation begins
14:55–15:15	80–87.9	24.0–24.6	Condensation likely; rainfall potential

Table 3: Heat Index Classification

HI (°C)	Health Category	Observation
27–32	Caution	Mild discomfort
33–40	Extreme Caution	High sweating
41–54	Danger	Extreme discomfort observed (max recorded: 52.92°C)
>54	Extreme Danger	Not reached

Table 4: Forecast vs Atmospheric Indicators

Indicator	Threshold	Observed	Forecast	Interpretation
RH > 80%	Rain Likely	Yes	Rain Likely	Accurate prediction
Dew Point > 24°C	High Moisture	Yes	Cloudy	Correct identification of condensation risk
HI > 45°C	Thermal Stress	Yes	High Discomfort	Aligns with human exposure standards
Stable T + Rising RH	Cloud Formation	Yes	Cloudy	Captures atmospheric instability

3.2 Discussion

The results obtained from the monitored thermodynamic parameters revealed significant interactions among temperature, relative humidity (RH), dew point, and heat index (HI), thereby demonstrating the dominant role of atmospheric moisture in short-term weather transitions within tropical environments. Although temperature variation remained relatively minimal throughout the observation period (31.5–32.8 °C), relative humidity exhibited substantial fluctuations from 60% to 87.9%, indicating progressive atmospheric saturation. This observation confirms that in humid tropical climates, moisture accumulation rather than temperature variation is the principal driver of microclimatic instability, as earlier suggested in studies on atmospheric thermodynamic behaviour [1]. A comparative assessment of RH and dew point trends further revealed a strong positive relationship between both parameters, as increases in RH were consistently accompanied by corresponding rises in dew point values from 23.0 °C to 24.6 °C. This pattern indicates a reduction in the temperature–dew point spread, signifying the approach of air-mass saturation and the onset of condensation processes typically associated with cloud formation and rainfall events. These findings are consistent with previous reports that identified simultaneous increases in RH and dew point as reliable precursors to precipitation in tropical environments [5], thereby validating the thermodynamic forecasting basis adopted in this study. Furthermore, analysis of heat index values demonstrated that elevated HI levels (42.0–52.92 °C) were more strongly influenced by increasing moisture content than by temperature variation alone. This confirms the established heat–humidity interaction phenomenon in which latent heat retention within moist air masses contributes to thermal discomfort and atmospheric convection in humid climates [6]. The observed amplification of HI despite relatively stable temperature conditions aligns with earlier findings that emphasized the contribution of atmospheric moisture to perceived temperature and localized weather instability [13].

In addition, the consistency between forecast outputs generated by the IoT monitoring system (e.g., “Cloudy,” “Rainy,” and “High Humidity Alert”) and the observed thermodynamic thresholds demonstrates the effectiveness of real-time environmental sensing in predicting short-term atmospheric transitions. This supports recent studies which reported that continuous IoT-based monitoring of temperature and humidity can significantly improve localized rainfall prediction and microclimate forecasting accuracy [2], [4]. The ability of the developed system to capture rapid RH spikes and dew point stabilization also agrees with findings that low-cost IoT platforms can provide high temporal resolution data suitable for decentralized environmental monitoring in resource-constrained regions

Finally, the comparative relationship among temperature stability, rising RH, dew point convergence, and amplified heat index values observed in this study substantiates the theoretical framework presented in the introduction and literature review. The thermodynamics analysis of IoT weather monitoring system therefore indicated a strong predictive validity by accurately detecting early atmospheric instability and generating short-term forecasts with an estimated accuracy of 85–92%. These results agree with previous investigations that demonstrated the applicability of real-time thermodynamic monitoring for precision agriculture, environmental management, and early-warning systems in tropical climates [2], [14].

4. CONCLUSION

The thermodynamic assessment confirms that the smart IoT-based weather monitoring system performs effectively in detecting early atmospheric moisture buildup, particularly when relative humidity rises above 85–90 percent and dew point approaches within 1–2 °C of ambient temperature. The system also reliably identifies conditions favourable for cloud formation and short-term rainfall likelihood, while accurately tracking heat–humidity interactions that elevate the heat index to stress levels above 40 °C. With its high-frequency data acquisition (1–5 second intervals) and automated forecasting algorithms achieving prediction accuracies of approximately 85–92 percent, the system demonstrates strong suitability for microclimate studies, precision agricultural management, and early-warning applications in tropical environments.

Based on the study outcomes, several actions are recommended to further improve the efficiency and reliability of the IoT weather monitoring system. First, deploying higher-accuracy environmental sensors particularly humidity and atmospheric-pressure modules with tolerances within ±1 percent RH and ±0.5 hPa will enhance microclimate prediction accuracy. Given the persistent exposure to tropical humidity exceeding 90 percent, future prototypes should incorporate moisture-sealed housings and corrosion-resistant materials to extend operational lifespan. The forecasting algorithm would also benefit from machine-learning integration to refine prediction accuracy beyond the current 85–92 percent achievement. For broader field utility, it is advisable to integrate a solar-powered backup system to ensure uninterrupted monitoring in rural or off-grid locations. Additionally, incorporating mobile-based alert systems will enable real-time warnings for farmers, environmental agencies, and researchers. Multi-site deployment is further recommended to validate the system's spatial performance consistency under diverse microclimatic conditions. Finally, sensor recalibration every 3–6 months should be established as a standard maintenance procedure to reduce measurement drift and sustain long-term accuracy.

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