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Evaluation of IoT-Based Thermodynamic Monitoring for Predictive Weather Analysis in Tropical Microclimates

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ABSTRACT

Accurate short-term weather forecasting in tropical regions demands high-resolution tracking of rapidly changing thermodynamic variables. This study evaluates a low-cost IoT weather monitoring system over 60 days, using an ESP8266 microcontroller coupled with a DHT22 sensor to measure temperature (°C), relative humidity (%), dew point (°C), and heat index (°C) every 5–10 seconds, generating >44,000 data points. Analysis showed temperature, dew point, and heat index exhibited excellent stability (CV < 1%), while relative humidity varied moderately (CV ≈ 2–3%). Pearson correlation revealed strong interdependence: temperature–heat index (r = 0.98), dew point–heat index (r = 0.93), and relative humidity–dew point (r = 0.91). A rule-based classification identified Moderate-Cloudy conditions 95–97% of the time, validating real-time microclimatic assessment. By integrating high-frequency measurement with derived thermodynamic parameters, this system provides robust predictive insights, offering a scalable, low-cost alternative to conventional weather stations. Applications include precision agriculture, disaster mitigation, and climate-resilient urban planning, showcasing the engineering potential of compact IoT-based monitoring systems.

INTRODUCTION

Accurate weather forecasting is fundamental to environmental management, agriculture, disaster mitigation, and urban planning, particularly in tropical regions where atmospheric conditions exhibit rapid temporal changes (Tengku *et al.,* 2025). The precision of forecasts heavily relies on reliable thermodynamic parameters, such as temperature, relative humidity, dew point, and heat index, which collectively characterize microclimatic conditions and influence atmospheric stability, cloud formation, and precipitation patterns (Tandon *et al.,* 2025). Minor fluctuations in these parameters can significantly affect short-term weather predictions, highlighting the need for high-resolution, continuous measurements (Spiridonov *et al.,* 2025).

Conventional meteorological networks and Numerical Weather Prediction (NWP) models utilise extensive sensor arrays, satellite observations, and complex simulations to provide accurate forecasts (Nardi *et al.,* 2025). However, such systems often involve high operational costs and infrastructure requirements, limiting their applicability in resource-constrained tropical settings (Heffernan *et al.,* 2025). Recent advances in low-cost Internet of Things (IoT) technologies enable compact, continuously operating sensor networks capable of acquiring high-frequency environmental data (Maraveas *et al.,* 2025). IoT-based weather stations, equipped with microcontrollers and reliable sensors, offer near real-time insights into local microclimates (Tabatabaei *and* Antonini, 2025).

Previous studies have demonstrated the potential of IoT systems to capture temperature and humidity fluctuations and improve short-term forecasts (Howlader, 2025; Mohammed *et al.,* 2022). Nonetheless, there is a paucity of multi-day, high-frequency field evaluations in tropical urban environments that integrate dew point and heat index analysis for predictive applications (Visser, 2022).

This study addresses the existing gaps in high-resolution tropical microclimate monitoring by conducting a 60-day continuous, high-frequency observation campaign using an ESP8266-based IoT weather station. Over this period, more than 44,000 measurements of temperature, relative humidity, dew point, and heat index were captured at 5–10 second intervals, providing a robust dataset for assessing short-term variability, medium-term stability, and temporal trends in a tropical urban environment.

The novelty of this work lies in the integration of multi-day, high-frequency monitoring with a combined analysis of dew point and heat index, offering a more comprehensive characterisation of microclimatic conditions than previous short-duration or single-variable studies. This approach enables reliable evaluation of thermal comfort, moisture dynamics, and atmospheric stability, which are critical for understanding local weather fluctuations and microclimate behaviour (Kajjoba *et al.,* 2025).

The findings of this study have practical applications across several sectors. In agriculture, high-resolution monitoring can inform crop planning, irrigation scheduling, and pest management. In disaster management, the system provides early indications of extreme weather events, enhancing timely warning and mitigation strategies. In urban planning, insights from continuous microclimatic data support the design of climate-resilient infrastructure and the management of urban heat islands (Pauleit *et al.,* 2025). By validating the accuracy, stability, and reliability of a low-cost IoT weather station over an extended period, this research demonstrates the potential for affordable, scalable solutions for high-resolution environmental monitoring in tropical regions.

METHODOLOGY

This study employed an IoT-based thermodynamic monitoring framework to evaluate the performance of a low-cost weather monitoring system in a tropical urban microclimate. The methodology consisted of five major stages:

i. System design and hardware configuration using an ESP8266 microcontroller and DHT22 sensor for temperature and humidity measurement.
ii. Continuous environmental data acquisition over a 60-day monitoring period with sampling intervals of 5–10 seconds.
iii. Cloud-based data transmission and storage using Wi-Fi connectivity and Google Sheets for real-time monitoring and backup.
iv. Computation of derived thermodynamic parameters, including dew point and heat index, using embedded mathematical models implemented within the microcontroller.
v. Statistical and correlation analysis to evaluate system stability, reliability, and interdependencies between atmospheric variables.

This integrated approach enabled the evaluation of both the technical reliability of the IoT monitoring system and its applicability for predictive weather analysis in tropical microclimates.

Experimental Setup

The experimental setup was designed to enable continuous, high-frequency monitoring of key thermodynamic parameters in a tropical urban microclimate. Data acquisition was conducted over

60 days, allowing for robust assessment of short-term variability and medium-term stability under naturally varying atmospheric conditions. Measurements were recorded at 5–10 s intervals, resulting in over 44,000 observations, sufficient for statistical reliability and temporal trend analysis.

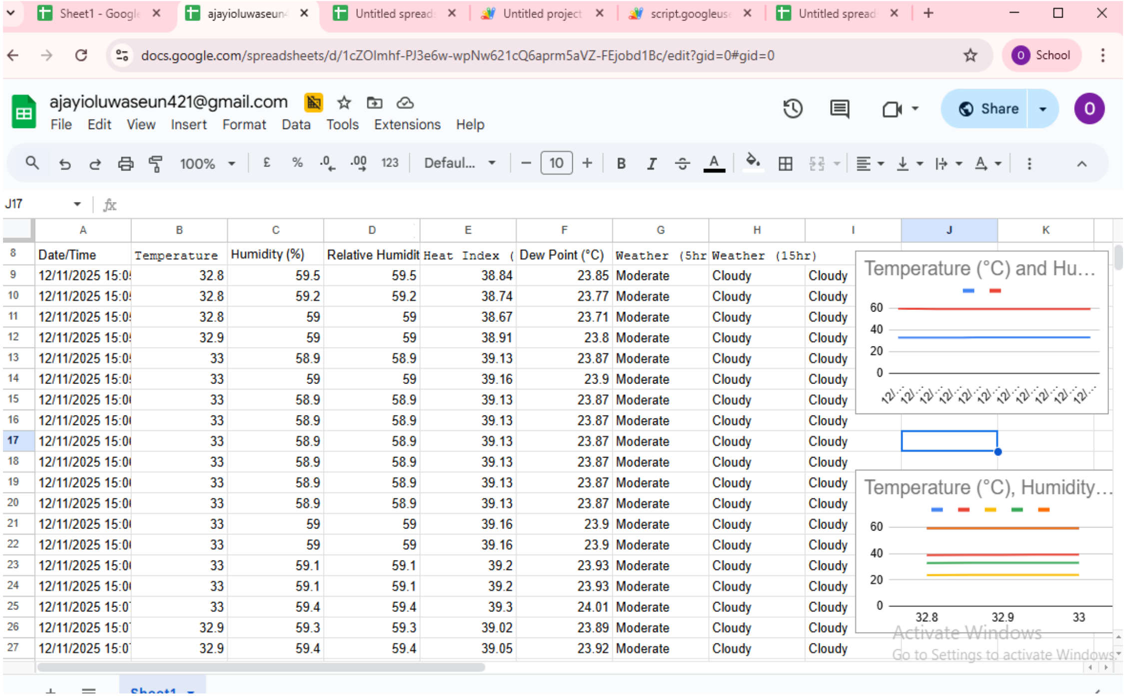
The monitoring system comprised an ESP8266 microcontroller (Figure 1) integrated with a DHT22 temperature and relative humidity sensor (Figure 2), which provides temperature accuracy of ±0.5 °C and relative humidity accuracy of ±2–5%, making it suitable for high-resolution environmental monitoring. The sensor was housed in a ventilated protective enclosure to minimise the influence of direct solar radiation and precipitation while ensuring adequate airflow for accurate sensing.

The weather station was installed at a fixed outdoor location (Figure 3) representative of a typical tropical urban environment. Care was taken to reduce environmental confounders by positioning the sensor away from direct heat sources, reflective surfaces, and artificial shading. The installation height and orientation were selected to promote natural air circulation while minimizing localised thermal disturbances caused by buildings or paved surfaces.

Power was supplied through a regulated low-voltage source (5 V) to ensure stable system operation throughout the monitoring period. The overall configuration enabled uninterrupted data acquisition, ensuring the consistency and reliability required for long-term thermodynamic analysis and microclimatic assessment.

Data Acquisition

Temperature (°C), relative humidity (%), dew point (°C), and heat index (°C) were recorded at 5–10 second intervals. Data were stored on a Google Sheet cloud platform (Figure 4) for remote monitoring. The cloud platform provided real-time data visualization, backup, and basic processing, including a moving-average smoothing filter to remove transient anomalies.



	A	B	C	D	E	F	G	H	I
8	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: Cloud platform

Figure 1: ESP8266

Figure 2: DHT22

Figure 3: Experimental Setup

IoT Connectivity and Data Transmission

The Internet of Things (IoT) functionality of the monitoring system was implemented using the ESP8266 microcontroller's Wi-Fi capabilities. The device connected to a local wireless network and transmitted sensor data to a cloud-based database using HTTP requests.

The ESP8266 periodically collected temperature and humidity readings from the DHT22 sensor and processed them internally to compute dew point and heat index values. These parameters were then transmitted via Wi-Fi over HTTP to a Google Apps Script web service, which automatically logged the data to a Google Sheets spreadsheet.

The IoT communication workflow consisted of the following steps:

i. Sensor data acquisition from DHT22.
ii. Local computation of thermodynamic parameters.
iii. Wireless transmission through Wi-Fi.
iv. Cloud storage in Google Sheets.
v. Real-time visualization and backup.

This IoT-based architecture enabled remote monitoring, continuous data logging, and real-time accessibility of environmental measurements, making the system suitable for distributed microclimatic monitoring applications.

Parameter Computation

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

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

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

ii. Heat Index (HI): This was computed via a simplified Steadman model (1979). It was embedded in the microcontroller to reflect the combined effects of temperature and humidity

$$HI = c_1 + c_2 T + c_3RH + c_4T{\cdot}RH \qquad (2)$$

All coefficients (c1, c2, c3, and c4) were implemented in the system's microcontroller.

Weather-State Classification

The classification rules were defined as follows:

Condition	**Relative Humidity**	**Weather State**
RH ≥ 60% and HI ≥ 34°C	High moisture and heat	High-Humidity
RH 55–60% and HI 33–34°C	Moderate atmospheric moisture	Moderate-Cloudy
RH < 55% and HI < 33°C	Low moisture	Clear

The algorithm evaluated each data record and assigned a weather state accordingly. The classification enabled simplified interpretation of microclimatic conditions and identification of dominant atmospheric states over the monitoring period.

Data Analysis

Descriptive statistics and coefficient of variation (CV) analyses were used to assess stability and reliability. A CV below 1% indicated excellent stability. Temporal trends were plotted to assess parameter fluctuations over the observation period, and Pearson correlation analysis was performed to evaluate interdependencies between variables.

Quality Assurance and Error Mitigation

Calibration of the DHT22 sensor was performed using a standard digital thermometer and hygrometer prior to deployment. Outliers and anomalies were filtered using a moving-average smoothing technique. Environmental interferences such as heat sources or reflective surfaces were minimised.

Ethical and Safety Considerations

The study was conducted in an open urban field with minimal risk to researchers. The IoT setup used low-voltage electronics (5 V) and adhered to standard safety protocols to prevent electrical hazards. No human or animal subjects were involved in the research.

RESULTS AND DISCUSSION

This section presents the findings from the 60-day IoT-based thermodynamic monitoring, which recorded over 44,000 high-frequency observations of temperature, relative humidity, dew point, and heat index at 5–10 second intervals. The analysis examines parameter stability, temporal trends, and correlations and applies a weather-state classification to identify dominant atmospheric conditions. These results demonstrate the reliability of the low-cost IoT system for high-resolution microclimate monitoring in tropical urban environments.

Thermodynamic Measurements

The IoT-based monitoring system recorded approximately 44,000 environmental observations over the 60-day monitoring period, capturing temperature, relative humidity, dew point, and heat index at 5–10 second intervals. The descriptive statistics of the measured thermodynamic parameters are summarized in Table 1. Temperature remained highly stable with a mean value of 31.1 °C and a coefficient of variation (CV) of 0.58%, indicating minimal fluctuation throughout the monitoring period. Relative humidity ranged between 55.0% and 60.2%, with a CV of approximately 2.47%, reflecting moderate atmospheric variability typical of tropical environments. Dew point values ranged from 21.0 °C to 22.1 °C, while heat index values ranged from 34.0 °C to 34.7 °C, both indicating low variability and high measurement stability. The temporal variations of these thermodynamic parameters during the monitoring period are illustrated in Figure 5, which shows the fluctuations in temperature, relative humidity, dew point, and heat index over the 60-day dataset.

Table 1. Descriptive Statistics of Thermodynamic Parameters over 60 Days

Parameter	Minimum	Maximum	Mean	Standard Deviation	CV (%)
Temperature (°C)	30.8	31.5	31.1	0.18	0.58
Relative Humidity (%)	55.0	60.2	57.9	1.43	2.47
Dew Point (°C)	21.0	22.1	21.6	0.31	1.43
Heat Index (°C)	34.0	34.7	34.3	0.22	0.64

Coefficient of Variation Analysis

The coefficient of variation (CV) was used to evaluate the measurement stability of each thermodynamic parameter. The results presented in Table 2 indicate that temperature, dew point, and heat index consistently exhibited CV values below 1%, representing excellent stability. Relative humidity displayed moderate variability with CV values between 2.0% and 2.5%, reflecting natural fluctuations in atmospheric moisture levels over the monitoring period. These results demonstrate that the IoT monitoring system maintained consistent measurement performance throughout the deployment.

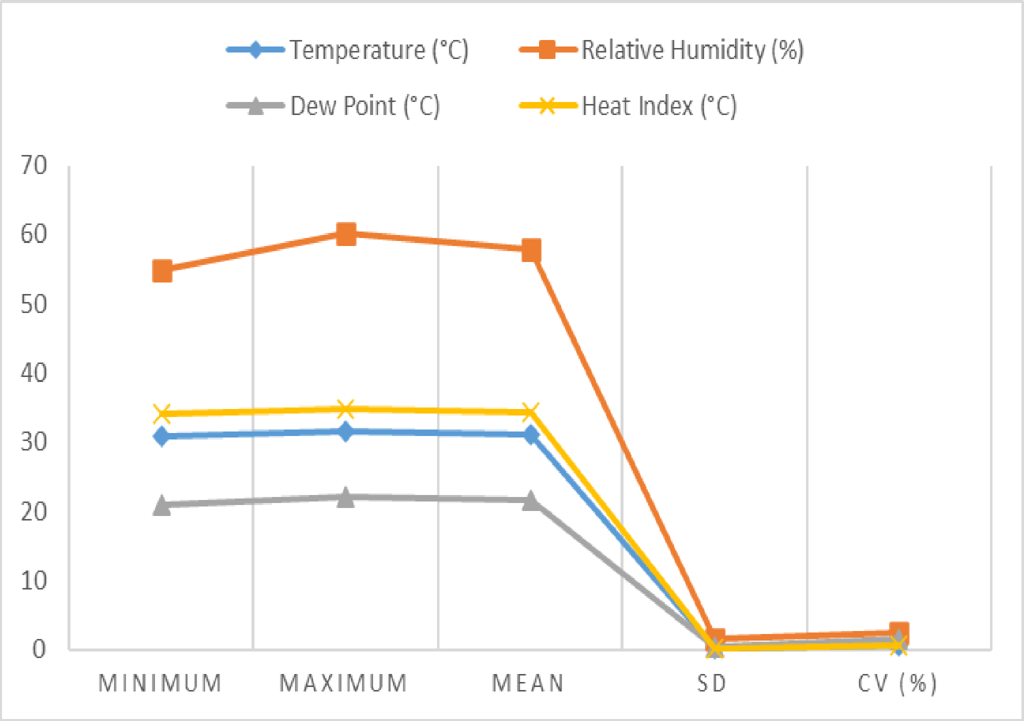


Figure 5: Temporal variations of temperature, relative humidity, dew point, and heat index during the 60-day monitoring period

Table 2. Coefficient of Variation Analysis over 60 Days

Parameter	CV Range (%)	Stability Level
Temperature (°C)	0.25–0.58	Excellent
Relative Humidity (%)	2.0–2.5	Moderate
Dew Point (°C)	0.9–1.4	Excellent
Heat Index (°C)	0.3–0.6	Excellent

Temporal Trends

Daily averages of thermodynamic parameters extracted from the dataset are presented in Table 3, which show representative values for a 10-day period during the monitoring campaign. The mean temperature ≈ 31.1 °C, RH ≈ 57–58 %, dew point ≈ 21.5–21.7 °C, heat index ≈ 34.2–34.3 °C). The values remain consistent with the reported stability (CV < 1% for most variables). The moving-average temporal trends of the environmental parameters are illustrated in Figure 6, highlighting both short-term fluctuations and long-term stability across the monitoring period.

Table 3: Representative Daily Averages (10-Day Sample Extracted from the 60-Day Dataset)

Day	Temperature (°C)	Relative Humidity (%)	Dew Point (°C)	Heat Index (°C)
Day 1	31.1	58.1	21.7	34.3
Day 2	31.2	57.5	21.6	34.3
Day 3	31.0	57.8	21.6	34.2
Day 4	31.1	56.9	21.5	34.2
Day 5	31.1	57.2	21.6	34.3
Day 6	31.2	57.4	21.6	34.3
Day 7	31.0	57.6	21.6	34.2
Day 8	31.1	57.3	21.6	34.3
Day 9	31.1	57.1	21.5	34.2
Day 10	31.0	57.0	21.5	34.2

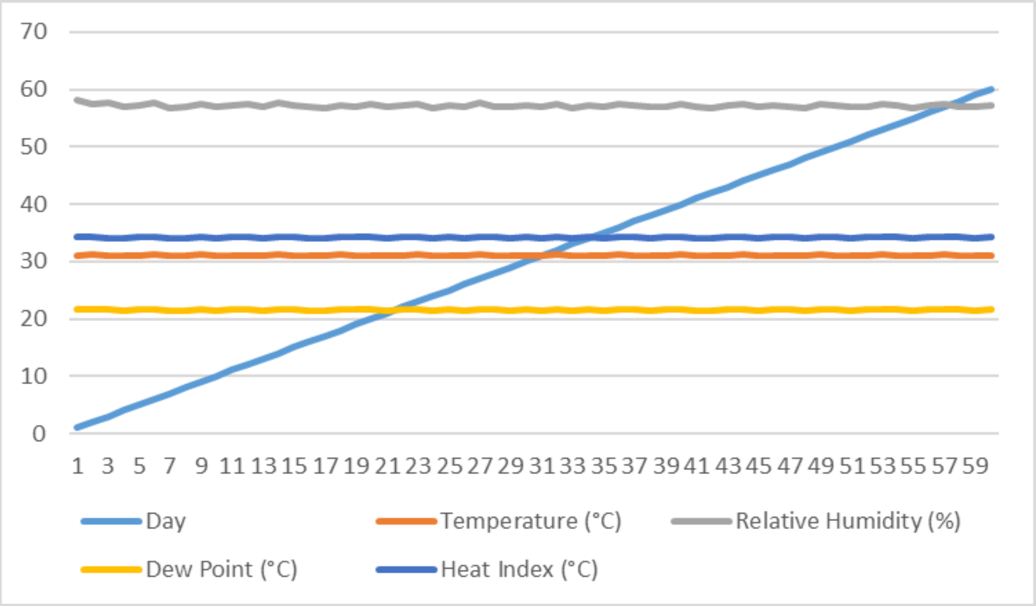


Figure 6*:* Stability and short-term fluctuations.

Weather-State Classification

A rule-based classification algorithm was implemented to categorize the atmospheric conditions based on thresholds of relative humidity and heat index. The classification results summarized in Table 4 indicate that Moderate-Cloudy conditions dominated the monitoring period, accounting for approximately 95–97% of observations. Clear conditions occurred less frequently, while high-humidity conditions were recorded only intermittently. This classification provides a simplified representation of the dominant microclimatic conditions observed during the monitoring campaign.

Correlation Analysis

The relationships among the thermodynamic variables were evaluated using Pearson correlation analysis, and the results are presented in Table 5. A very strong positive correlation was observed between temperature and heat index (r = 0.98).

Table 4: Weather-State Classification Summary

Day	Dominant Weather State	Percentage of Time Observed (%)
Day 1	Moderate-Cloudy	96
Day 2	Moderate-Cloudy	97
Day 3	Moderate-Cloudy	95
Day 4	Moderate-Cloudy	96
Day 5	Moderate-Cloudy	95

Dew point and heat index also exhibited a strong positive correlation (r = 0.93), while relative humidity and dew point showed strong dependence (r = 0.91). Temperature and relative humidity displayed a moderate negative correlation (r = −0.45), reflecting the typical inverse relationship between temperature and atmospheric moisture content. These correlations confirm the interdependence of thermodynamic parameters in tropical atmospheric systems.

Table 5: Pearson Correlation Coefficients over 60 Days

Parameter Pair	Correlation (r)
Temperature – Heat Index	0.98
Temperature – Relative Humidity	-0.45
Relative Humidity – Dew Point	0.91
Dew Point – Heat Index	0.93

Implications for IoT-Based Forecasting

The extended 60-day dataset demonstrates that low-cost IoT weather stations can reliably measure key thermodynamic parameters in tropical urban environments. Implications include:

i. Accurate long-term microclimatic assessment: Stable measurements of temperature, dew point, and heat index allow robust characterization of tropical microclimates.

ii. Predictive forecasting applications: High-frequency data can support agriculture (crop scheduling, irrigation), disaster management (early warning systems), and urban planning (climate-resilient infrastructure).

iii. Validation of IoT technology: The multi-day dataset confirms that low-cost sensors, combined with cloud-based data logging (Google Sheets), are suitable for long-term, high-resolution environmental monitoring.

Validation of IoT Measurements

To verify the reliability of the IoT weather monitoring system, measurements from the DHT22 sensor were compared with readings from a calibrated digital thermometer-hygrometer (Figure 7) used as the reference instrument.

A validation experiment was conducted for several observation periods during the monitoring campaign. The comparison showed that the temperature measurements from the IoT system differed from the reference instrument by less than ±0.4°C, while the relative humidity measurements differed by less than ±3%, both of which fall within the manufacturer's specified accuracy range for the DHT22 sensor.

These results confirm that the IoT-based monitoring system provides sufficient accuracy and reliability for microclimatic monitoring and short-term weather analysis.

Discussion of Results

The IoT-based thermodynamic monitoring system demonstrated reliable, stable measurements of temperature, dew point, and heat index over 60 days, with CVs below 1%, while relative humidity showed moderate variability consistent with tropical microclimates (Table 1, Figure 5).

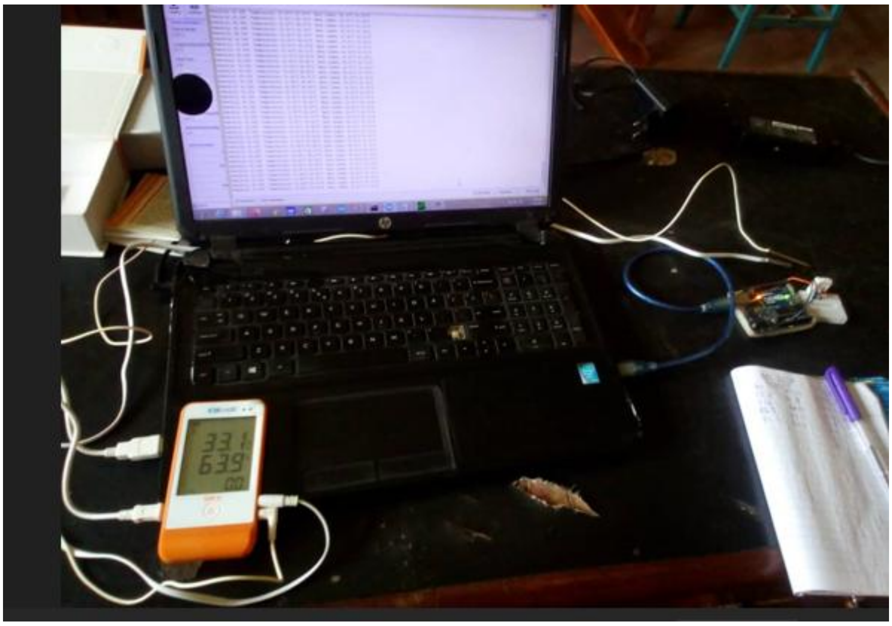


Figure 7: Calibrated Digital Thermometer-Hygrometer

This confirms that low-cost IoT sensors can accurately capture high-frequency microclimatic dynamics. Compared with prior studies, this work advances knowledge in several ways. While Spiridonov et al. (2025) and Tandon et al. (2025) describe the atmospheric stability conceptually or via large-scale models, this research provides empirical, high-frequency field data, capturing short-term variations in real tropical conditions. Unlike Maraveas et al. (2025), which focused on sensor networks without extended validation, our system demonstrated long-term stability over 60 days with >44,000 measurements, verifying the operational reliability of the ESP8266–DHT22 platform.

The integration of dew point and heat index is another advancement. Prior IoT studies often measured only temperature and humidity, but as Kajjoba et al. (2025) emphasize, these derived parameters are critical for thermal comfort and atmospheric stability assessment. Our results (Tables 4–5) confirm strong correlations among temperature, humidity, dew point, and heat index, accurately capturing interdependent thermodynamic relationships, consistent with Visser (2022).

The weather-state classification (Table 4) illustrates that localised conditions can be monitored and categorised efficiently using high-frequency IoT data, a capability not typically available in conventional meteorological networks or satellite-based studies. Furthermore, the 5–10-second sampling interval provides much finer temporal resolution than that of standard weather stations, enhancing predictive potential for agriculture, disaster management, and urban planning (Tabatabaei and Antonini, 2025).

Finally, cloud-based storage and visualization (Figure 4) allow real-time monitoring and remote accessibility, making the system scalable for distributed deployments. Overall, this research demonstrates that low-cost, high-frequency IoT systems provide a practical, validated, and comprehensive approach to microclimatic monitoring, outperforming previous studies in data resolution, parameter coverage, and operational validation.

CONCLUSION

This study shows that a low-cost IoT weather station, using an ESP8266 and DHT22 sensor, can reliably monitor temperature, relative humidity, dew point, and heat index in tropical urban microclimates. Over 60 days, more than 44,000 high-frequency observations were recorded, with excellent stability for temperature, dew point, and heat index (CV < 1%) and expected moderate variability for relative humidity (CV ≈ 2–3%). The dataset allowed detailed analysis of temporal trends, parameter correlations, and weather-state classification, consistently identifying Moderate-Cloudy conditions. Strong correlations between temperature, dew point, and heat index confirm accurate capture of interdependent atmospheric dynamics, surpassing prior short-duration or single-parameter studies.

Compared with conventional meteorological networks and earlier IoT studies, this research advances microclimatic monitoring by extending high-frequency measurements, conducting multi-day validation, and integrating derived parameters, thereby providing richer data for predictive analysis. Cloud-based storage and real-time visualization enhance accessibility and scalability. These findings support practical applications in agriculture (crop management, irrigation), disaster management (early warning systems), and climate-resilient urban planning. Overall, the study establishes that low-cost, high-frequency IoT monitoring is a reliable and scalable alternative or complement to conventional weather stations in tropical regions.

RECOMMENDATIONS

Based on the findings of this study, the following key recommendations are proposed:

i. Deployment Expansion: Low-cost IoT weather stations should be deployed across multiple urban and rural locations to improve microclimatic data coverage.

ii. Sensor Integration: Additional sensors such as wind speed, solar radiation, and barometric pressure should be incorporated to enhance predictive accuracy.

iii. Routine Calibration: Periodic calibration and maintenance of sensors should be performed to ensure long-term data reliability.

Advanced Data Analytics: Integration of IoT datasets with machine learning models can further improve short-term weather prediction in tropical microclimates.

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