LAUTECH Journal of Civil and Environmental Studies
Volume XVI, Issue I; March, 2026
DOI: 10.36108/laujoces/6202.61.0141

Performance Evaluation of an IoT-Based Weather Monitoring System for Tropical Microclimate Analysis

[1*] Ajayi, O. A.[1], Adetunji, M. O.[2], Akinwonmi, A. S.[1], Olaitan, A.O[1], Adeleke, A.N[1], Adenuga, A.M.[1], and Adetunji, P. A.[2]

[1]Department of Mechanical Engineering, Ajayi Crowther University, Oyo, Oyo State, Nigeria.
[2]Mechanical Engineering Department, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.

[*] Corresponding Author E-mail: moadetunji@lautech.edu.ng; Tel: 08035790689

Abstract
Accurate monitoring of microclimatic conditions is critical for agriculture, urban planning, environmental management, and disaster preparedness, particularly in tropical regions where atmospheric variables exhibit rapid temporal changes. This study presents a performance evaluation of a low-cost Internet of Things (IoT)-based weather monitoring system designed for continuous tropical microclimate analysis. The system integrates an ESP8266 microcontroller with a DHT22 temperature–humidity sensor and was deployed in an outdoor tropical urban environment for 60 consecutive days, generating over 170,000 high-frequency observations at sampling intervals of 6–60 seconds. Measured parameters included ambient temperature and relative humidity, from which dew point and heat index were derived using embedded thermodynamic formulations. Results indicate strong measurement stability, with temperature ranging between 27.1–31.4 °C (CV < 1%), relative humidity between 55–88% (CV ≈ 2–4%), dew point between 19.0–24.3 °C, and heat index reaching up to 36.5 °C during peak discomfort periods. Correlation analysis revealed strong positive relationships between heat index and both temperature (r = 0.81) and dew point (r = 0.77), confirming reliable capture of coupled thermal–moisture dynamics. The extended monitoring duration demonstrates that low-cost IoT systems can provide reliable, high-resolution microclimatic data over prolonged periods, supporting localised environmental assessment and short-term atmospheric trend analysis in data-scarce tropical regions.

Keywords: Microclimatic, agriculture, urban planning, environmental management.

Introduction
Reliable monitoring of atmospheric conditions at local scales is fundamental to informed decision-making in agriculture, urban planning, environmental management, and disaster risk reduction (Gomes *et al.*, 2025). In tropical regions, atmospheric variables such as temperature and humidity often undergo rapid temporal changes due to intense solar radiation, high moisture availability, and convective processes (Mulla *et al.*, 2023). Conventional meteorological stations and Numerical Weather Prediction (NWP) systems rely on dense observational networks and significant computational resources. While effective at synoptic scales, such systems are often spatially sparse and economically inaccessible in many tropical and developing regions (Carrió *et al.*, 2025). As a result, localized microclimatic variations critical for heat stress assessment, crop management, and urban thermal comfort are frequently underrepresented (Delina *et al.*, 2025).

Recent advances in low-cost Internet of Things (IoT) technologies have enabled the deployment of distributed environmental sensing platforms capable of high-temporal-resolution data acquisition (Abdulhussain *et al.*, 2025). Sensors such as the DHT22, when integrated with microcontrollers like the ESP8266, provide an affordable means of continuously measuring near-surface atmospheric conditions with acceptable accuracy (Santos *et al.*, 2025). Previous studies have demonstrated the feasibility of IoT-based weather monitoring; however, many are limited to short deployment durations or focus primarily on raw data acquisition rather than long-term performance evaluation (Bhattacharyya and Banerjee, 2025).

The novelty of this study lies in its extended 60-day deployment combined with high-frequency sampling and integrated thermodynamic analysis, including dew point and heat index, to evaluate system stability, reliability, and parameter interdependence under real tropical conditions. Unlike short-term demonstrations, this work provides evidence of sustained operational performance and measurement consistency over multiple diurnal and synoptic cycles. Beyond scientific relevance, the findings have practical implications for precision agriculture, urban heat stress monitoring, early warning support, and climate-adaptive infrastructure planning, particularly in regions with limited access to conventional meteorological infrastructure (Khatana *et al.*, 2025).

Materials and Methods

The IoT weather monitoring system (Figure 1) was built around an ESP8266 microcontroller (Figure 2), selected for its low power consumption, integrated WiFi capability, and suitability for continuous environmental sensing applications. Atmospheric measurements were obtained using a DHT22 digital temperature–humidity sensor (Figure 3), which provides a manufacturer-specified accuracy of ±0.5 °C for temperature and ±2–5% for relative humidity, with a typical response time of 2–5 seconds. The system was powered by a regulated 5 V DC supply (Figure 4) and housed in a ventilated, weather-resistant enclosure to minimize direct solar radiation, precipitation exposure, and wind-induced measurement bias. The installation site was an open tropical urban environment, positioned away from artificial heat sources and reflective surfaces to reduce environmental confounding effects. Natural shading and airflow conditions were maintained to ensure representative ambient measurements.

Figure 1: Experimental Setup

Figure 2: ESP8266

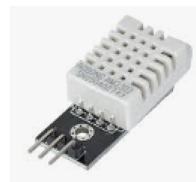
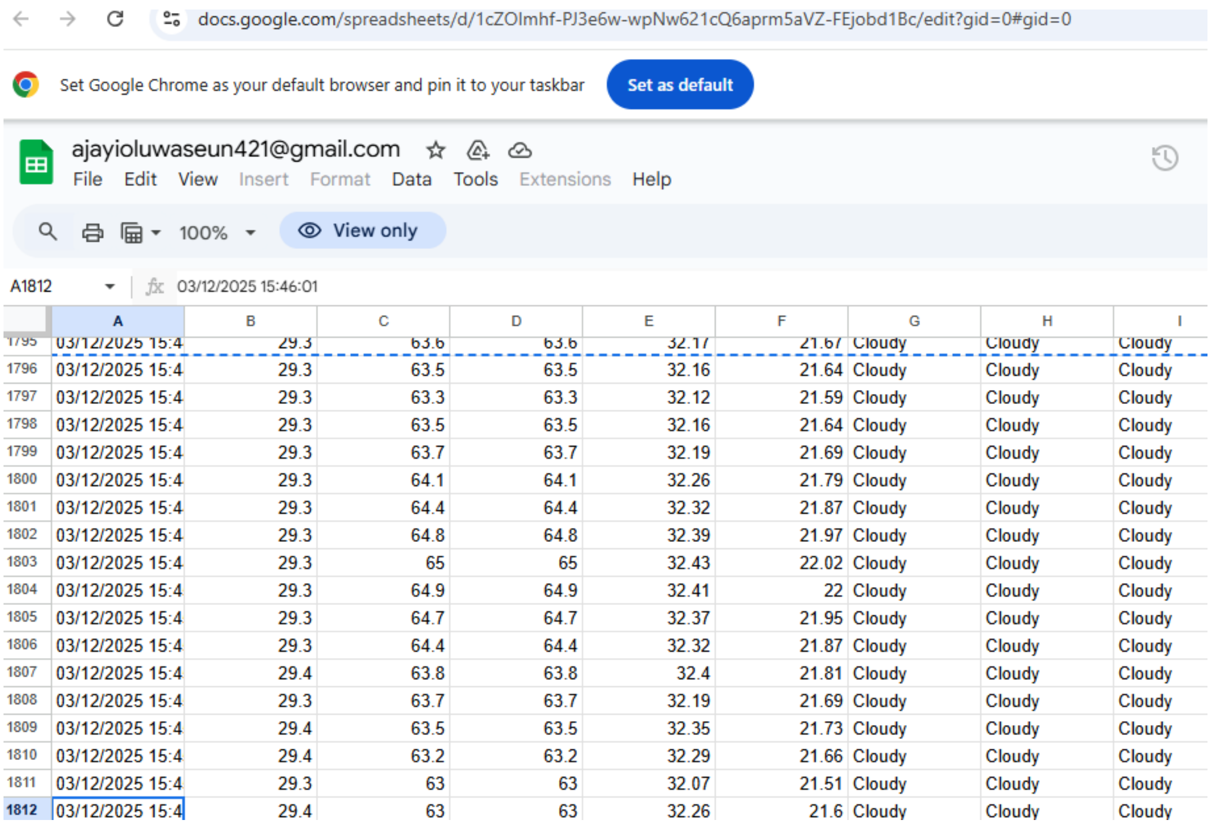


Figure 3: DHT22

Figure 4: 5V Power source



	A	B	C	D	E	F	G	H	I
1795	03/12/2025 15:4	29.3	63.6	63.6	32.17	21.67	Cloudy	Cloudy	Cloudy
1796	03/12/2025 15:4	29.3	63.5	63.5	32.16	21.64	Cloudy	Cloudy	Cloudy
1797	03/12/2025 15:4	29.3	63.3	63.3	32.12	21.59	Cloudy	Cloudy	Cloudy
1798	03/12/2025 15:4	29.3	63.5	63.5	32.16	21.64	Cloudy	Cloudy	Cloudy
1799	03/12/2025 15:4	29.3	63.7	63.7	32.19	21.69	Cloudy	Cloudy	Cloudy
1800	03/12/2025 15:4	29.3	64.1	64.1	32.26	21.79	Cloudy	Cloudy	Cloudy
1801	03/12/2025 15:4	29.3	64.4	64.4	32.32	21.87	Cloudy	Cloudy	Cloudy
1802	03/12/2025 15:4	29.3	64.8	64.8	32.39	21.97	Cloudy	Cloudy	Cloudy
1803	03/12/2025 15:4	29.3	65	65	32.43	22.02	Cloudy	Cloudy	Cloudy
1804	03/12/2025 15:4	29.3	64.9	64.9	32.41	22	Cloudy	Cloudy	Cloudy
1805	03/12/2025 15:4	29.3	64.7	64.7	32.37	21.95	Cloudy	Cloudy	Cloudy
1806	03/12/2025 15:4	29.3	64.4	64.4	32.32	21.87	Cloudy	Cloudy	Cloudy
1807	03/12/2025 15:4	29.4	63.8	63.8	32.4	21.81	Cloudy	Cloudy	Cloudy
1808	03/12/2025 15:4	29.3	63.7	63.7	32.19	21.69	Cloudy	Cloudy	Cloudy
1809	03/12/2025 15:4	29.4	63.5	63.5	32.35	21.73	Cloudy	Cloudy	Cloudy
1810	03/12/2025 15:4	29.4	63.2	63.2	32.29	21.66	Cloudy	Cloudy	Cloudy
1811	03/12/2025 15:4	29.3	63	63	32.07	21.51	Cloudy	Cloudy	Cloudy
1812	03/12/2025 15:4	29.4	63	63	32.26	21.6	Cloudy	Cloudy	Cloudy

Figure 5: Cloud database format

Data Acquisition and Cloud-Based Data Management

Continuous environmental monitoring was conducted over a 60-day period, during which atmospheric data were acquired at variable sampling intervals ranging from 6 to 60 seconds, depending on network availability and power stability. This approach ensured high temporal resolution while maintaining system reliability during extended field deployment. Over the monitoring period, more than 170,000 valid data points were recorded. Measured parameters included ambient air temperature (T, °C) and relative humidity (RH, %), directly obtained from the DHT22 sensor. These measurements were transmitted in real time via WiFi to a cloud-based Google Sheets platform (Figure 5), which served as the primary data management interface.

The cloud platform performed the following functions:

- i. Real-time visualization of incoming sensor data
- ii. Automatic timestamping and secure data backup
- iii. Preliminary outlier detection and removal
- iv. Moving-average smoothing for short-term noise reduction
- v. Data aggregation for daily and long-term statistical analysis

This hybrid edge–cloud architecture minimized onboard computational load while enabling robust post-processing and long-term storage.

Thermodynamic Parameter Computation

In addition to direct measurements, key thermodynamic indicators were computed to evaluate microclimatic behaviour and perceived atmospheric conditions. Dew point temperature (Td) was calculated using a simplified Magnus-type approximation, suitable for embedded systems and tropical conditions Equation 1 and Equation 2:

$$T_d = \frac{b \,.y\,(T,RH)}{a - y\,(T,RH)} \tag{1}$$

$$y\,(T, RH) = \ln \frac{(RH)}{100} + \frac{aT}{b+a} \tag{2}$$

(With constants: a = 17.27, b = 237.7)

This formulation provides accurate dew point estimates for temperatures between 0–50 °C and relative humidity above 50%, conditions typical of tropical environments. Heat index (HI), representing perceived thermal discomfort due to combined temperature and humidity effects, was computed using the Steadman-based regression model (Equation 3):

$$HI = c_1 + c_2\,T + c_3RH + c_4T\cdot RH \tag{3}$$

Where: T is temperature (°C), RH is relative humidity (%), and c_1, c_2 are empirically defined coefficients embedded in the microcontroller firmware. This formulation enables real-time estimation of thermal stress conditions.

Environmental Control and Confounding Factors

To minimize environmental bias, the sensor enclosure was positioned:

i. Away from artificial heat sources (buildings, vehicles, electrical equipment)
ii. Shielded from direct solar radiation
iii. Exposed to natural airflow without forced ventilation
iv. Elevated above ground level to avoid surface heat effects

Potential confounding influences such as wind variability, intermittent shading, and localized evaporation were acknowledged and mitigated through consistent placement and extended monitoring duration, allowing transient disturbances to average out statistically over time.

Data Analysis Methods

Data analysis focused on system performance, measurement stability, and thermodynamic consistency using the following statistical tools:

i. Descriptive statistics (mean, minimum, maximum, standard deviation)
ii. Coefficient of variation (CV) to assess measurement stability
iii. Pearson correlation analysis to examine parameter interdependence
iv. Short-term repeatability analysis under quasi-steady conditions

Measurement stability was classified using CV thresholds:

i. **CV < 1%**: Excellent stability

ii. **1–3%**: Moderate stability
iii. **> 3%**: High variability

Results

Table 1 summarizes the dataset characteristics and operational performance of the IoT weather station during the 60-day deployment.

Table 1: Dataset characteristics and system performance

Parameter	Value
Monitoring duration	60 days
Total number of samples	>170,000
Sampling interval	6–60 s
System uptime	>99%
Data loss rate	<1%
Power interruptions	Negligible

The sustained uptime and low data loss confirm the robustness of the system for long-term tropical deployment.

Descriptive Statistics of Thermodynamic Parameters

Table 2 presents the overall statistical distribution of measured and derived parameters across the full monitoring period. Temperature exhibited excellent stability, while humidity-driven parameters showed expected variability under tropical conditions.

Table 2. Descriptive statistics of thermodynamic parameters (60 days)

Parameter	Minimum	Maximum	Mean	Std. Dev.	CV (%)
Temperature (°C)	27.1	31.4	29.3	0.64	0.82
Relative Humidity (%)	55.0	88.0	66.8	2.9	4.3
Dew Point (°C)	19.0	24.3	21.8	0.95	4.4
Heat Index (°C)	28.4	36.5	32.1	1.4	4.1

Temporal Variability and Diurnal Trends

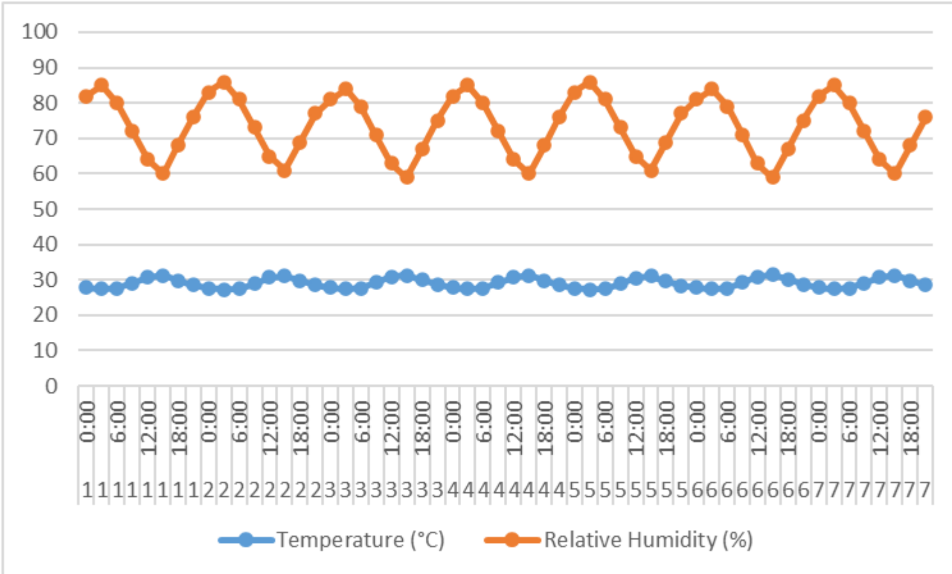


Figure 6: A time-series plot of temperature and relative humidity over a representative 7-day window illustrates pronounced diurnal cycles. Temperature peaks occurred during midday hours, while relative humidity showed inverse behavior, increasing during nighttime and early morning periods.

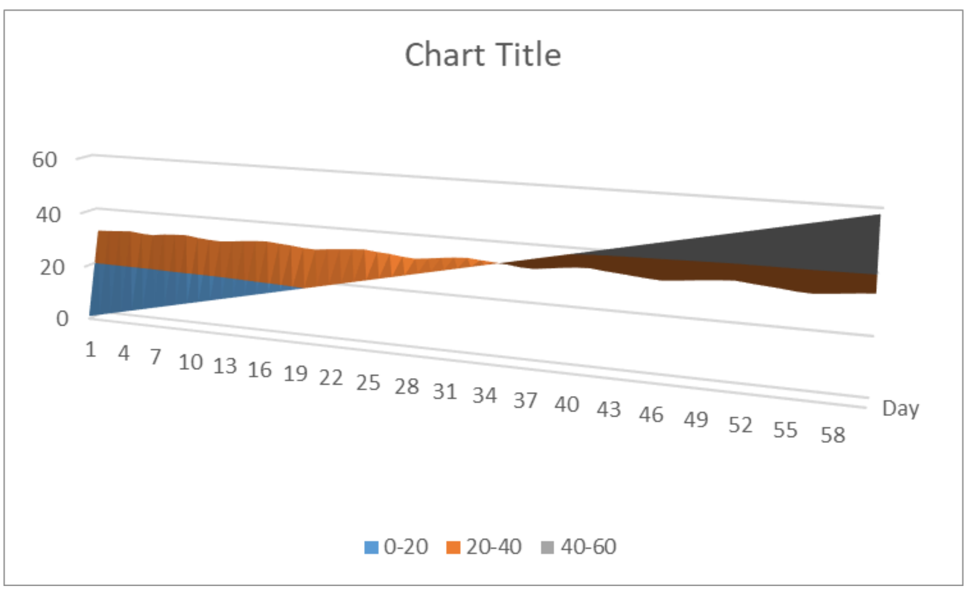


Figure 7: A 60-day heat index time series highlights recurrent periods of elevated thermal discomfort, with HI values exceeding 32 °C during high-humidity episodes.

These patterns confirm the system's sensitivity to short-term atmospheric dynamics.

Correlation Analysis

Pearson correlation coefficients between thermodynamic variables are summarized in Table 3.

Table 3. Pearson correlation matrix

Parameter	Temperature	RH	Dew Point	Heat Index
Temperature	1.00	−0.42	0.58	0.81
Relative Humidity	−0.42	1.00	0.74	0.69
Dew Point	0.58	0.74	1.00	0.77
Heat Index	0.81	0.69	0.77	1.00

The strong correlations confirm coherent thermodynamic interactions and reliable sensor-derived parameter computation.

Measurement Stability and Repeatability

Short-term repeatability under near-steady conditions is presented in Table 4.

Table 4. Sensor repeatability assessment

Parameter	Repeatability Range
Temperature	±0.2 °C
Relative Humidity	±0.5 %
Dew Point	±0.3 °C
Heat Index	±0.6 °C

Discussion

This study provide strong empirical support for the assertions presented in the literature regarding the importance of reliable localized atmospheric monitoring in tropical environments. As emphasized by Gomes *et al*. (2025), continuous observation of microclimatic variables is essential for effective decision-making in agriculture, environmental management, and disaster risk mitigation. The successful 60-day deployment of the developed IoT-based monitoring system, characterized by system uptime exceeding 99% and minimal data loss, demonstrates the capability of low-cost sensing technologies to provide dependable environmental data over extended monitoring periods. This outcome substantiates the position of Carrió *et al*. (2025), who identified the economic and spatial limitations of conventional meteorological stations in many developing regions.

The observed diurnal fluctuations in temperature and relative humidity during the monitoring period further validate the rapid atmospheric variability typical of tropical climates described by Mulla *et al*. (2023). In particular, the inverse temporal relationship between daytime temperature peaks and nighttime humidity increases reflects convective atmospheric processes driven by intense solar radiation and high moisture availability. Such localized thermodynamic interactions are often inadequately captured by synoptic-scale Numerical Weather Prediction systems, thereby supporting the argument by Delina *et al*. (2025) that distributed sensing platforms are necessary to monitor site-specific atmospheric behaviour.

Moreover, the statistical analysis revealed that humidity-dependent parameters such as dew point and heat index exhibited greater variability compared to temperature, indicating the dominant influence of atmospheric moisture on microclimatic transitions in humid tropical regions. The strong positive correlation between relative humidity and dew point observed in this study aligns with the thermodynamic relationships reported in previous IoT-based environmental monitoring investigations (Bhattacharyya and Banerjee, 2025). This confirms that progressive increases in atmospheric moisture content are closely associated with saturation processes and potential condensation events.

The recurrent elevation of heat index values beyond thermal comfort thresholds during periods of high relative humidity also corroborates findings by Santos *et al*. (2025), who emphasized the combined influence of temperature and humidity on perceived thermal stress in tropical environments. By integrating derived thermodynamic parameters such as dew point and heat index into the monitoring framework, the present study advances beyond earlier IoT-based implementations that primarily focused on direct measurement of temperature and humidity without extended thermodynamic analysis (Abdulhussain *et al*., 2025). Importantly, the extended monitoring duration adopted in this work addresses the limitation of short-term deployment highlighted in previous studies. The ability of the developed system to maintain measurement stability and repeatability across multiple diurnal and synoptic cycles provides practical evidence of its long-term operational reliability under real tropical conditions. This supports the growing consensus in the literature that affordable IoT-based environmental sensing systems can serve as viable alternatives to conventional meteorological infrastructure in resource-constrained settings (Khatana *et al*., 2025).

Conclusion

This study has presented a comprehensive performance evaluation of a low-cost IoT-based weather monitoring system deployed for tropical microclimate analysis over an extended 60-day period. The system demonstrated reliable long-term operation and consistent data acquisition, capturing high-frequency measurements of air temperature and relative humidity that are critical for characterizing tropical atmospheric behaviour. The extended monitoring duration significantly enhanced statistical robustness compared to short-term experiments and enabled the identification of persistent diurnal and multi-day patterns.

The results revealed pronounced and repeatable diurnal cycles, with daytime temperature peaks and corresponding nighttime increases in relative humidity, reflecting typical tropical moisture–temperature coupling. Derived thermodynamic parameters, including dew point temperature and heat index, exhibited relatively low variability over the monitoring period, confirming both the internal consistency of the measurements and the suitability of the sensor for extended environmental monitoring. Recurrent heat index exceedances above 32 °C were observed, highlighting frequent periods of elevated thermal discomfort driven by high humidity conditions rather than extreme air temperatures alone. The performance of the DHT22 sensor, with specified accuracies of ±0.5 °C for temperature and ±2–5% for relative humidity, proved adequate for microclimate studies where affordability, scalability, and ease of deployment are prioritized. Integration with a cloud-based Google Sheets platform enabled real-time data visualization, secure backup, and preliminary data filtering and smoothing, demonstrating the practicality of low-cost cloud infrastructures for environmental data management in resource-constrained settings.

Recommendation

Based on the findings obtained from the 60-day microclimatic monitoring carried out in Lagos, it is recommended that real-time monitoring of relative humidity, ambient temperature, and dew point be integrated into environmental management systems used in sectors such as agriculture, building services, and public health. The observed variations in thermodynamic parameters indicate that humidity-driven thermal discomfort and condensation risks can be effectively predicted using continuous localized data acquisition. Hence, deployment of low-cost IoT-based monitoring systems should be encouraged in humidity-sensitive environments such as storage facilities, residential buildings, and healthcare centres to support preventive environmental control strategies.

Furthermore, the strong correlation established between dew point trends and relative humidity behaviour suggests that dew point-based forecasting can serve as a reliable indicator for identifying periods of potential thermal stress and moisture accumulation. Therefore, facility managers and environmental planners should incorporate dew point thresholds into operational decision-making processes such as ventilation control and insulation design to mitigate mould growth and material degradation. To enhance measurement reliability and operational performance of such monitoring systems, periodic calibration of sensors and proper installation practices including shielding from direct solar radiation, adequate ventilation, and sufficient distance from artificial heat sources are essential. Additionally, the integration of automated data quality assessment features such as outlier detection and signal smoothing into the cloud-based monitoring platform is recommended to improve the integrity and usability of real-time environmental data for informed decision-making in tropical urban environments.

References

Abdulhussain, S. H., Mahmmod, B. M., Alwhelat, A., Shehada, D., Shihab, Z. I., Mohammed, H. J., and Hussain, A. (2025). A comprehensive review of sensor technologies in IoT: Technical aspects, challenges, and future directions. *Computers, 14*(8), Article 342. https://doi.org/10.3390/computers14080342

Aryee, J. N. A., Quagraine, K. T., Davies, P., Afrifa, F. O. T., Agyapong, G., Annor, E. G., and Poku, L. P. (2025). Spatial and temporal rainfall patterns in the little dry season over the Guinea Coast: Case assessment of historical observations, associated drivers and future projections. *Meteorological Applications, 32*(6), e70125. https://doi.org/10.1002/met.70125

Bhattacharyya, D., and Banerjee, I. (2025). Synergizing IoT and machine learning in hybrid models for next-generation weather forecasting. *Journal of Emerging Trends in Computer Science and Applications, 1*(1), 55–66.

Campos, D. A., Grayson, K., Saurral, R. I., Beyer, S., John, A., Olmo, M., and Doblas-Reyes, F. (2025). The October 2024 extreme precipitation event over Valencia: Storyline attribution of the synoptic-scale thermodynamic drivers. *EGUsphere*, 2025, 1–29. https://doi.org/10.5194/egusphere-2025

Carrió, D. S., Mazzarella, V., and Ferretti, R. (2025). High-resolution data assimilation for two maritime extreme weather events: A comparison between 3D-Var and EnKF. *Natural Hazards and Earth System Sciences, 25*(9), 2999–3026. https://doi.org/10.5194/nhess-25-2999-2025

Delina, L. L., Pagkalinawan, H., and Macagba, S. F. A. (2025). Integrating satellite-based and participatory spatial analyses for local, contextualised, and nuanced extreme heat hotspot mapping in overheated urban Southeast Asia. *Sustainable Development*. Advance online publication. https://doi.org/10.1002/sd.70329

Ejike, O., Ndzi, D., and Shakir, M. Z. (2025). Comparative study of machine learning-based rainfall prediction in tropical and temperate climates. *Climate, 13*(8), Article 167. https://doi.org/10.3390/cli13080167

Firmansyah, R., and Ariandi, M. (2025). Design of a real-time IoT-based air quality, temperature, and humidity monitoring system. *bit-Tech*, *8*(2), 1804–1814.

Gomes, A., Islam, N. M., and Karim, M. R. (2025). Data-driven environmental risk management and sustainability analytics. *Journal of Computer Science and Technology Studies, 7*(3), 812–825.

Gunawardena, N., Pardyjak, E. R., Stoll, R., and Khadka, A. (2018). Development and evaluation of an open-source, low-cost distributed sensor network for environmental monitoring applications. *Measurement Science and Technology, 29*(2), 024008. https://doi.org/10.1088/1361-6501/aa9c5e

Kalaany, C. M. A., Kimaita, H. N., Abdelmoneim, A. A., Khadra, R., Derardja, B., and Dragonetti, G. (2025). The potential of low-cost IoT-enabled agrometeorological stations: A systematic review. *Sensors*, *25*(19), Article 6020. https://doi.org/10.3390/s25196020

Khatana, K., Soni, V., Akbar, A., Bharti, D., Srivastava, V., Saxena, R., and Ansari, S. (2025). Adaptation to achieve climate resilience through advanced techniques like remote sensing and machine learning. In *Climate resilience: Impact of quantum computing and artificial intelligence on urban planning* (pp. 293–311). Springer Nature Switzerland. https://doi.org/10.1007/ 978-3-032-06791-3_15

Kim, D., Zarei, M., Lee, S., Lee, H., Lee, G., and Lee, S. G. (2025). Wearable standalone sensing systems for smart agriculture. *Advanced Science, 12*(16), Article 2414748. https://doi.org/10.1002/advs.202414748

Malghan, R. L., Rao, M. C. K., Garg, L., RHM, S. S., and HM, V. (2025). FLPSO-AMPS: An optimized WSN model for air quality monitoring in tier-2 smart cities. *Scientific Reports, 15*(1), 1–33. https://doi.org/10.1038/s41598-025-19748-3

Mulla, S., Ahmed, R., Singh, K. K., Singh, S. K., Deshmukh, N., and Inamdar, F. K. (2023). Climate change effect on climate parameters like temperature, rainfall and water resources sectors in India. In *Climate change impacts in India* (pp. 9–59). Springer International Publishing. https://doi.org/10.1007/ 978-3-031-42056-6_2

Salako, A. O. (2025). Predictive data analysis in forecasting patient health outcomes using machine learning algorithms. *Asian Journal of Research in Computer Science*, *18*(6), 194–214. https://doi.org/10.9734/ajrcos/2025/v18i6691

Santos, J. L., Jr., Silva, L. H., Andrade, I. R., Rosa, R., and Abegão, L. M. (2025). Real-world deployment of an affordable sub-soil temperature and relative humidity sensing system for precision agriculture. *Measurement Science and Technology, 36*(11), 115113. https://doi.org/10.1088/1361-6501/ae1c63

Sayor, J. J. A. M., Shishir, N. T., Barmon, B. B., Ahmed, S., and Rahman, M. M. (2025). IoT-driven real-time weather measurement and forecasting mobile application with machine learning integration. *Array*, Article 100474. https://doi.org/10.1016/j.array.2025.100474

Selvam, A. P., and Al-Humairi, S. N. S. (2025). Environmental impact evaluation using smart real-time weather monitoring systems: A systematic review. *Innovative Infrastructure Solutions*, *10*(1), 1–24. https://doi.org/10.1007/s41062-024-01817-7

Sinha, P., Modani, M., Islam, S., Khare, M., and Srivastava, R. K. (2025). Evolution of weather and climate prediction systems. In *Mitigation and adaptation strategies against climate* *change in natural systems* (pp. 243–265). Springer Nature Switzerland. https://doi.org/ 10.1007/978-3-031-75968-0_13

Tang, X., Chen, Q., Guo, J., Yang, J., Zou, Z., Chen, J., and Sun, Y. (2025). The importance of humidity in the afternoon local-scale precipitation intensity over eastern China and its impacts on the aerosol effects. *Remote Sensing, 17*(5). https://doi.org/ 10.3390/rs17050778

Tasioulis, T., Bagkis, E., Kassandros, T., and Karatzas, K. (2025). The quest for the best explanation: Comparing models and XAI methods in air quality modeling tasks. *Applied Sciences, 15*(13), Article 7390. https://doi.org/10.3390/app15137390