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Year-Round IoT-Based Characterization of Forest Microclimate for Sustainable Medicinal Plant Cultivation

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Abstract

Forest microclimate strongly influences medicinal plant growth and habitat suitability; however, year-round characterization of forest microclimate for medicinal plant cultivation remains limited. This study presents a year-long, multi-station microclimate dataset and evaluates its potential for preliminary suitability assessment. Three monitoring stations (Pt1–Pt3) were deployed within the Plant Genetic Conservation Project under the Royal Initiative (RSPG), Thailand. Air temperature and relative humidity were continuously monitored at 30-min intervals from January to December 2025 using an Internet of Things (IoT)-based system. We used descriptive statistics, coefficients of variation (CV), repeated-measures analyses, and adjusted pairwise comparisons to evaluate year-round, seasonal, and site-specific microclimatic variabilities. Significant spatial differences were observed among the monitoring stations ($p < 0.05$). Pt3 exhibited the lowest annual mean temperature (26.05 °C), the highest relative humidity (80.60%), and the lowest environmental variability (CV = 16.41%), whereas Pt2 showed the highest temperature (30.72 °C), the lowest humidity (60.83%), and greater variability. A relative microclimatic comparison showed that Pt3 was cooler, more humid, and more stable; Pt1 exhibited intermediate conditions; and Pt2 was warmer, drier, and more variable. These findings characterize relative temperature–humidity conditions among the monitored sites and provide baseline information relevant to future species-specific assessment of medicinal plant cultivation.

Keywords: internet of things (IoT); forest microclimate; medicinal plants; environmental monitoring; microclimate characterization; sustainable agriculture

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1. Introduction

1.1. Global Background

Climate change has become one of the major global challenges of the twenty-first century, affecting biodiversity, ecosystem resilience, agricultural productivity, and sustainable natural resource management [1–3]. Rising temperatures, altered precipitation patterns, and the increasing frequency of extreme weather events are modifying environmental conditions across terrestrial ecosystems, particularly tropical and subtropical forests [1,2]. These changes can influence plant distribution, physiological performance, and ecosystem functioning, with broader consequences for ecosystem services and biodiversity conservation [3,4]. Forest ecosystems are important reservoirs of biodiversity

and provide essential services, including carbon sequestration, climate regulation, water conservation, soil protection, and habitat provision [3,5].

Among forest biological resources, medicinal plants are particularly important because they provide raw materials for traditional medicine, pharmaceutical and nutraceutical products, and may contribute to local livelihoods [6,7]. However, environmental conditions strongly influence their growth, productivity, and phytochemical composition. Variations in air temperature, relative humidity, soil moisture, and solar radiation can affect plant physiological processes and secondary metabolite accumulation [8,9]. These responses may become increasingly important under changing climatic conditions, highlighting the need to reliably characterize local forest environments. Year-round forest microclimate monitoring can therefore provide valuable information to understand environmental variability and support more climate-resilient and sustainable medicinal plant cultivation. Such information may also contribute to SDG 2 (Zero Hunger) by supporting environmentally informed and sustainable cultivation practices [10]. Figure 1 illustrates the overall conceptual framework of the proposed study, linking climate change, forest microclimate, IoT-enabled environmental monitoring, data analytics, cultivation suitability assessment, and sustainable medicinal plant cultivation.

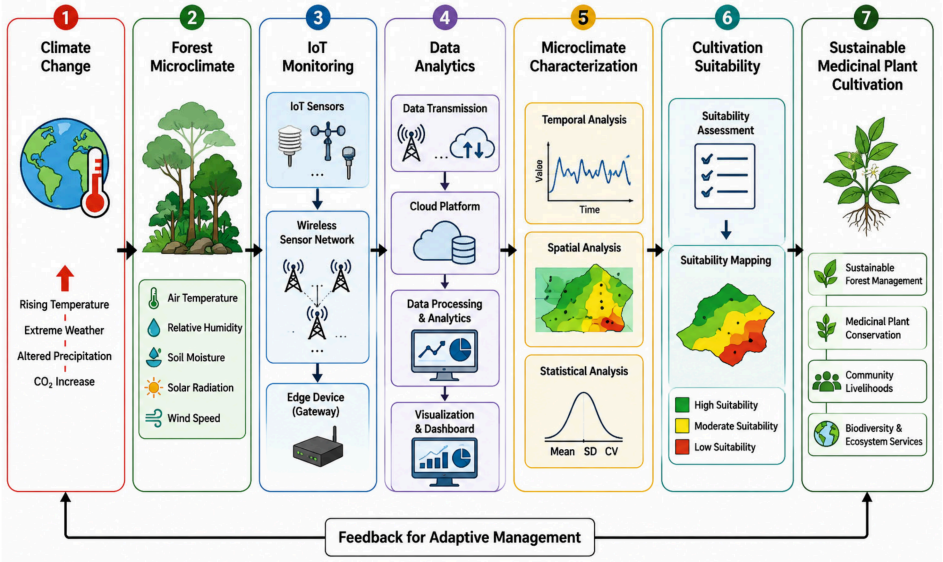

Figure 1. Conceptual framework of year-round IoT-based forest microclimate characterization for sustainable medicinal plant cultivation. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

1.2. Forest Microclimate and Medicinal Plants

Forest microclimate plays a fundamental role in regulating the growth, physiological processes, and ecological adaptation of medicinal plants. Unlike regional climate, forest microclimate represents the localized environmental conditions within the understory that plants directly experience [11,12]. Forest canopy structure modifies solar radiation, wind speed, evapotranspiration, air temperature, and relative humidity, creating heterogeneous microhabitats within the same ecosystem [13,14]. Consequently, environmental variables such as air temperature, relative humidity, soil moisture, and photosynthetically active radiation can vary substantially across space and time [15]. These variations influence key physiological processes, including photosynthesis, respiration, transpiration, stomatal conductance, nutrient uptake, and water-use efficiency, thereby affecting plant growth and survival [16].

Microclimatic conditions can also influence the biosynthesis and accumulation of secondary metabolites, including phenolics, flavonoids, alkaloids, terpenoids, and essential oils, which contribute to the medicinal properties and commercial value of herbal plants [17,18]. Characterizing forest microclimate therefore provides important ecological information for understanding local growing conditions and supporting medicinal plant cultivation. Continuous microclimate monitoring can further provide evidence for cultivation management, biodiversity conservation, and climate-resilient forest agriculture under changing environmental conditions [19].

1.3. Internet of Things and Smart Agriculture

Internet of Things (IoT) technologies have enabled data-driven and precision agriculture through continuous environmental monitoring and real-time decision support [20,21]. Modern IoT platforms integrate wireless sensors, communication networks, edge/cloud computing, and data analytics to collect and process environmental variables such as air temperature, relative humidity, soil moisture, solar radiation, and rainfall [22–25]. These capabilities support irrigation, resource management, and crop monitoring, making IoT an important tool for evidence-based agricultural management [26–28].

IoT-based monitoring has been widely applied in greenhouses, orchards, vineyards, and open-field agriculture [25–29]. Table 1 summarizes representative applications and the research gap relevant to this study, and Figure 2 illustrates them. However, year-round IoT-based monitoring of natural forest microclimates remains comparatively limited, particularly for medicinal plant cultivation. Forest environments exhibit heterogeneous canopy structures, vegetation, terrain, and microclimatic conditions that vary spatially and temporally [30,31]. This complexity highlights the need for continuous, year-round monitoring to characterize site-specific forest microclimate variability and provide environmental information relevant to sustainable medicinal plant cultivation.

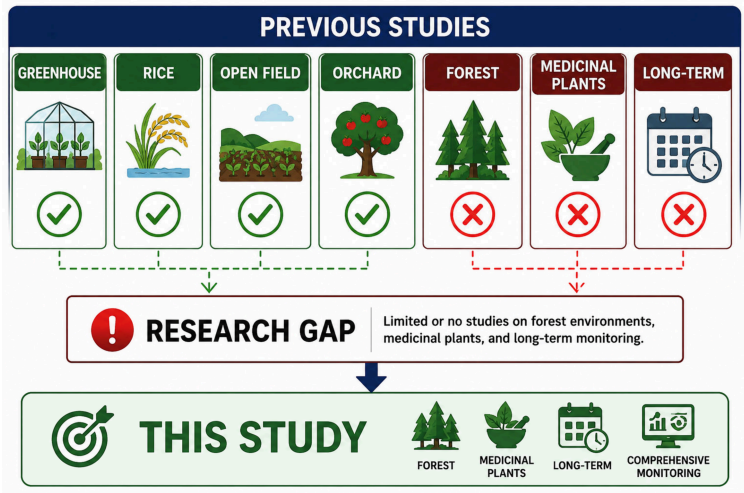

Figure 2. Research gap identified from previous studies on IoT-based environmental monitoring for agricultural applications. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

1.4. Literature Review and Research Gap

Recent advances in Internet of Things (IoT) technologies have significantly accelerated the development of smart agriculture through continuous environmental monitoring and data-driven decision-making. Numerous studies have successfully deployed IoT-based monitoring systems in greenhouse cultivation, where environmental parameters such as temperature, relative humidity, soil moisture, and carbon dioxide concentration are continu-

ously monitored to optimize irrigation, ventilation, and crop productivity [32–34]. Similarly, IoT applications have been extensively implemented in orchards and perennial cropping systems to improve water management, disease detection, and fruit quality through real-time environmental sensing and wireless communication technologies [35,36]. In addition, several investigations have demonstrated the effectiveness of IoT platforms for monitoring field crops, including rice, wheat, maize, and vegetable production, enabling precision irrigation, nutrient management, and yield prediction under open-field conditions [37–39]. More recently, integrating cloud computing, edge computing, artificial intelligence, and wireless sensor networks has further enhanced smart agricultural systems by enabling automated data processing, predictive analytics, and intelligent decision support [22,23,40]. Table 1 summarizes representative studies on IoT-based environmental monitoring in different agricultural systems.

Table 1. Comparison of previous studies and the present work.

Previous Study	Environment	IoT	Year-Round	Forest	Medicinal Plants
Greenhouse monitoring [33,34]	✓	✓	✗	✗	✗
Orchard monitoring [35,36]	✓	✓	✗	✗	✗
Field crop monitoring [36–40]	✓	✓	✓	✗	✗
Forest ecological monitoring [41–43]	✓	✗/Limited	✓	✓	✗
Medicinal plant environmental studies [44,45]	✓	Limited	✗	Limited	✓
This study	✓	✓	✓	✓	✓

However, despite these remarkable technological advances, existing studies have predominantly focused on managed agricultural environments where environmental conditions are relatively homogeneous and partially controllable. Few studies have investigated year-round IoT-based monitoring within natural forest ecosystems, where highly heterogeneous canopy structures, complex vegetation layers, and diverse topographic conditions generate substantial spatial and temporal variations in microclimate [30,31,41]. Furthermore, although several ecological studies have examined forest microclimate using conventional meteorological instruments, most were designed primarily for ecological observations rather than continuous IoT-enabled environmental monitoring for agricultural applications [42,43]. More importantly, no previous study has simultaneously integrated year-round IoT monitoring, forest microclimate characterization, and medicinal plant cultivation within a natural forest ecosystem, while providing statistically robust comparisons among multiple monitoring locations over an annual observation period [44–46]. Consequently, the lack of high-resolution, year-round microclimate datasets for forest-based medicinal plant cultivation remains a critical knowledge gap, limiting the development of evidence-based cultivation strategies and climate-resilient management practices. Addressing this gap is therefore essential to advance smart forest agriculture, improve biodiversity conservation, and support sustainable medicinal plant production under ongoing climate change.

Although IoT-based environmental monitoring is well established in agriculture, its application to year-round forest microclimate characterization for medicinal plant cultivation remains comparatively limited. Therefore, this study's novelty lies not in the

sensor–communication–cloud architecture, but in generating and analyzing a continuous, year-long dataset from three forest monitoring sites and integrating the observed temperature–humidity patterns and environmental variability into a relative microclimate characterization framework relevant to future species-specific cultivation assessment. The study characterizes annual, seasonal, and site-specific variability using statistical and inferential analyses and translates the observed microclimatic patterns and environmental stability into information relevant to medicinal plant cultivation.

Air temperature and relative humidity were selected as first-order microclimatic indicators because they directly influence plant physiological and metabolic processes and exhibit substantial temporal and spatial variability in forest environments. Previous studies have also demonstrated their influence on plant growth and secondary metabolite accumulation [17,18]. However, these variables alone cannot fully characterize habitat suitability. Solar radiation, soil temperature and moisture, soil properties, nutrient availability, precipitation, and species-specific requirements also play important roles. Accordingly, the proposed framework should be interpreted as a preliminary temperature–humidity-based microclimate assessment rather than a comprehensive habitat suitability model.

Based on the identified research gaps, this study aims to characterize forest microclimate dynamics relevant to sustainable medicinal plant cultivation through year-round IoT-based environmental monitoring. Continuous observations of air temperature and relative humidity at three forest monitoring sites were used to evaluate annual, seasonal, and site-specific variability through statistical analyses and to develop a preliminary microclimate suitability assessment. The resulting dataset also provides baseline environmental information for future ecological monitoring and sustainable cultivation planning.

The principal scientific contribution of this study lies in integrating year-long, multi-site forest microclimate observations with a quantitative assessment of environmental variability and stability. Rather than introducing a novel IoT architecture, the study demonstrates how continuous environmental data can support preliminary site comparison and evidence-based decision-making for medicinal plant cultivation. The findings provide a foundation for future monitoring that incorporates additional environmental variables and broader spatial coverage and may contribute to more sustainable, climate-responsive forest-based cultivation practices, particularly in relation to SDG 2 (Zero Hunger).

2. Materials and Methods

2.1. Study Site

The field study was conducted within the Plant Genetic Conservation Project under the Royal Initiative (RSPG) at the Nong Rawiang Education Center, Rajamangala University of Technology Isan (RMUTI), Nakhon Ratchasima, Thailand. The study area covers approximately 400 ha and includes a protected forest designated for plant genetic conservation, environmental education, and ecological research. The vegetation is primarily characterized by dry dipterocarp and mixed deciduous forest, resulting in heterogeneous understory environments with differences in vegetation density, canopy characteristics, and local terrain. During the preparation of this manuscript, the authors used ChatGPT (OpenAI; GPT-5.6 Sol) to assist with the preparation and graphical editing of Figures 1–12. AI assistance was limited to graphical presentation, including improvements in line sharpness, font size, alignment, layout, and visual clarity while preserving the scientific and technical information provided by the authors. The prompts used for each AI-assisted figure are provided in the corresponding figure captions. The authors reviewed and edited all AI-assisted outputs and take full responsibility for the content of this publication.

Figure 3 presents the geographical location of the study area at the Nong Rawiang Education Center, Nakhon Ratchasima, Thailand. The map provides the regional context

of the study area within Thailand and Nakhon Ratchasima Province. This geographical overview identifies the general location of the study area, while Figure 4 presents the detailed arrangement of the monitoring locations.

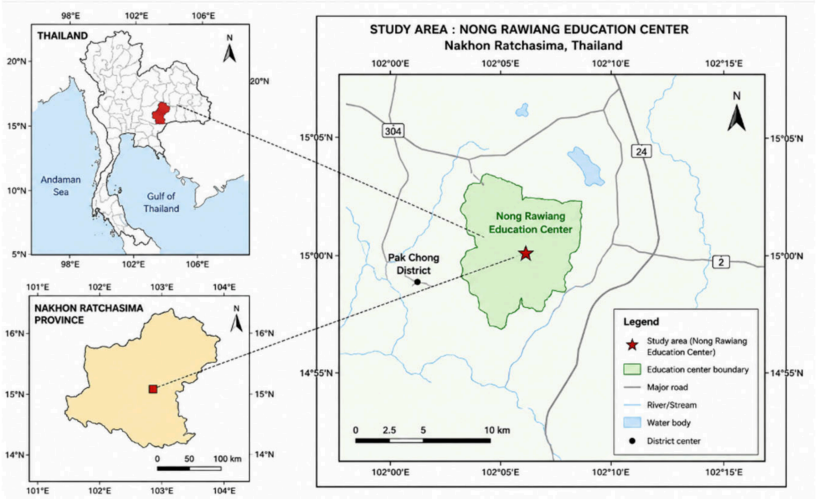

Figure 3. Geographic location of the study area at the Nong Rawiang Education Center, Nakhon Ratchasima, Thailand. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

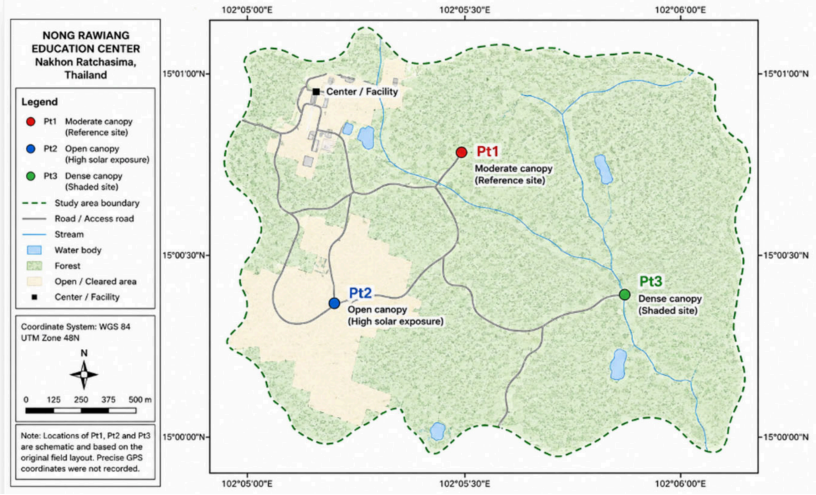

Figure 4. Site-level layout of the study area showing the three representative forest microclimate monitoring locations (Pt1, Pt2, and Pt3). AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

Precise geographic coordinates and elevations of Pt1, Pt2, and Pt3 were not recorded during the original field deployment. Therefore, these parameters are not reported to avoid introducing unverified retrospective estimates.

2.2. Experimental Design

A comparative field-monitoring design was adopted to evaluate microclimatic differences among the three representative forest locations. A comparative longitudinal field-monitoring design was adopted to characterize microclimatic differences among three specific forest monitoring locations (Pt1, Pt2, and Pt3). A single monitoring station represented each location; therefore, the study did not include spatial replication

within canopy-density, terrain, or microenvironment categories. The three stations should consequently be regarded as individual case-study locations rather than replicated treatments representing broader forest-structure classes. Repeated observations collected at 30-min intervals represent temporal measurements from the same fixed locations and were not considered independent spatial replicates. Accordingly, the analysis was designed to characterize and compare the temporal microclimatic patterns of these three specific monitoring locations rather than to infer general effects of canopy density, terrain, or forest structure, as characterized in Table 2. Figure 4 illustrates the site-level arrangement of the three representative monitoring locations (Pt1, Pt2, and Pt3) within the study area. The stations represent contrasting forest microenvironments used for site-to-site comparison of air temperature and relative humidity. Pt1 represents an intermediate forest condition, Pt2 a relatively more open environment, and Pt3 a denser and more shaded forest environment. The locations shown in Figure 4 represent the original field layout; precise GPS coordinates and elevations were not recorded during the field deployment and therefore cannot be assigned retrospectively. The experimental design was intended to determine whether naturally occurring environmental heterogeneity among the monitored locations resulted in measurable differences in air temperature and relative humidity.

Table 2. Characteristics of the monitoring locations.

Monitoring Station	Forest Characteristics	Canopy Density	Terrain	Purpose
Pt1	Moderate canopy	Moderate	Flat	Reference site
Pt2	Open canopy	Low	Exposed	High solar exposure
Pt3	Dense canopy	High	Shaded	Stable microclimate

To ensure comparability among sites, we used identical monitoring units and installation procedures at all three stations. Measurements were conducted concurrently over the same observation period, thereby minimizing temporal bias associated with differences in regional weather conditions. Consequently, variations observed among Pt1, Pt2, and Pt3 primarily represent site-specific microclimatic differences under the same regional climatic forcing. The resulting datasets were designed to support three levels of comparison: annual microclimatic characteristics, seasonal variations between dry and rainy periods, and site-to-site differences among the three monitored locations. These comparisons subsequently provided the experimental basis for statistical evaluation and preliminary microclimate suitability assessment.

2.3. IoT-Based Environmental Monitoring System

An IoT-based sensing architecture consisting of environmental sensors, Wi-Fi communication, and cloud-based data storage was employed as the data-acquisition infrastructure for continuous forest microclimate monitoring. This architecture was intended to provide reliable, automated, continuous field data acquisition without introducing a new communication protocol or hardware configuration. An Internet of Things (IoT)-based environmental monitoring system was developed to enable continuous acquisition, transmission, storage, and visualization of forest microclimate data within the study area. The proposed system was designed following a layered IoT architecture consisting of four major components: (1) an environmental sensing layer, (2) a wireless communication layer, (3) a cloud-based data management layer, and (4) an application layer for data visualization and analysis. The monitoring stations were built using commercially available sensing and IoT components to provide reliable, continuous forest microclimate measurements. Each station consisted of a temperature–relative humidity sensor, an ESP32-based controller with integrated Wi-Fi communication, a real-time clock, local backup storage, and a cloud-based

data-management platform. Table 3 summarizes the detailed specifications and functions of the major monitoring components, while Figure 5 illustrates the overall system architecture.

Table 3. Technical specifications and functions of the IoT-based microclimate monitoring system.

Component	Model/Type	Technical Specifications	Function
Temperature and relative humidity sensor	Sensirion SHT35	Temperature: −40 to 125 °C; typical accuracy ±0.1 °C; resolution 0.01 °C. RH: 0–100% RH; typical accuracy ±1.5% RH; resolution 0.01% RH. Installation height: 1.20 m above ground level	Measurement of air temperature and relative humidity
Microcontroller	ESP32-WROOM-32	Dual-core 32-bit processor; up to 240 MHz; 3.3-V logic; integrated Wi-Fi and Bluetooth	Sensor interfacing, data acquisition, and preliminary processing
Wireless communication	ESP32 integrated Wi-Fi	IEEE 802.11 b/g/n; 2.4-GHz frequency band; wireless data transmission through the available Wi-Fi network	Site-specific wireless data transmission from the monitoring unit to the available network access point for subsequent cloud communication
Real-time clock	DS3231 RTC	I^2C interface; battery-backed timekeeping; accuracy approximately ±2 ppm	Time-stamp synchronization
Local data storage	MicroSD card module	SPI interface; removable flash-memory storage	Local backup during temporary network interruption
Cloud platform	ThingSpeak IoT platform	Cloud-based storage, visualization, and API communication	Remote data storage, visualization, and monitoring
Solar panel	Photovoltaic panel	Rated power: 400 W; rated voltage: 45 V	Solar-energy generation for field operation
Energy storage	Rechargeable battery	Nominal voltage: 24 V; capacity: 100 Ah; nominal energy storage: 2400 Wh	Energy storage and power supply during low- or no-solar periods
Power management	Solar charge controller/regulated DC supply	Input: 45 V; regulated outputs: (24, 12, 5) V for the monitoring, communication, and sensing circuits	Battery charging, voltage regulation, and continuous station operation
Sensor protection	Ventilated radiation shield	Naturally ventilated; protection from direct solar radiation and precipitation; sensor mounted at 1.20 m above ground level	Reduction in environmental measurement bias

Note: Air temperature and relative humidity were recorded at 30-min intervals. The SHT35 sensors were installed at approximately 1.20 m above ground level inside ventilated radiation shields. Data were transmitted through the available Wi-Fi network to the ThingSpeak cloud platform. The monitoring stations were powered by a photovoltaic–battery system to support continuous field operation during periods of reduced solar availability.

The environmental sensing layer comprised field-installed sensors that continuously measured air temperature and relative humidity at the three monitoring stations (Pt1, Pt2, and Pt3). The acquired environmental data were transferred to an edge processing unit, where preliminary processing and formatting were performed before wireless transmission. This edge-processing approach reduced unnecessary communication overhead while improving the reliability of data acquisition under field conditions. The processed data were then transmitted via the Wi-Fi network to the central cloud server using wireless protocols, enabling real-time data transfer from the forest monitoring sites.

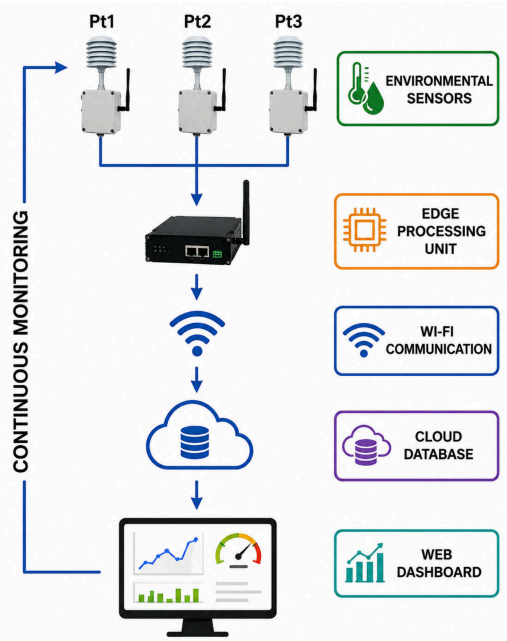

Figure 5. Architecture of the proposed IoT-based environmental monitoring system for year-round forest microclimate observation. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

The cloud/data management layer stored environmental measurements in a centralized database and supported year-round time-series analysis. Cloud-based data storage enabled continuous data archiving, remote accessibility, and efficient management of high-frequency environmental observations collected throughout the one-year monitoring period. Finally, an application layer was developed to visualize the collected data through a web-based dashboard. The dashboard provided real-time monitoring of environmental conditions, graphical visualization of temporal variations, and descriptive statistical information, thereby facilitating environmental assessment and supporting decision-making for medicinal plant cultivation. The integrated operation of environmental sensors, wireless communication, cloud computing, and dashboard visualization enabled reliable year-round monitoring of forest microclimate and established a comprehensive environmental database for subsequent statistical analyses.

The Wi-Fi communication employed in the present study should not be interpreted as providing continuous wireless coverage over the entire approximately 400-ha forest area. The system was deployed only at three representative monitoring locations (Pt1–Pt3), and Wi-Fi connectivity served as the communication interface for transmitting data from the monitoring units to the cloud-based platform. Therefore, the present communication architecture represents a site-specific experimental implementation rather than a forest-wide wireless sensor network. The exact communication distances between Pt1–Pt3 and the network access/data collection point were not systematically recorded during the original field deployment and are therefore not retrospectively estimated in this manuscript. For future expansion to a larger, more spatially distributed monitoring network, long-range, low-power communication technologies such as LoRaWAN or NB-IoT would provide a more appropriate communication architecture than conventional Wi-Fi because of their greater communication range and lower power requirements.

The field monitoring units were powered using a solar-assisted power supply with battery storage to support continuous operation under outdoor conditions. The solar panels provided daytime energy harvesting, while the battery supplied the monitoring

electronics during periods of insufficient solar irradiance. Because the stations were located under different canopy conditions, solar availability was expected to vary among sites, particularly at the densely shaded Pt3 location. However, the original field deployment did not continuously record battery state of charge, solar irradiance, charging performance, or battery autonomy. Therefore, quantitative values for charging efficiency or autonomous operating duration cannot be reliably reported retrospectively. Nevertheless, the successful acquisition of year-round environmental records confirmed the power system's practical operation during the monitoring campaign. Future deployments should explicitly monitor these power-performance parameters, particularly for stations located under dense forest canopy.

2.4. Data Acquisition

Environmental monitoring was conducted continuously from January to December 2025 to capture annual and seasonal variations in forest microclimatic conditions. Air temperature and relative humidity were recorded simultaneously at Pt1, Pt2, and Pt3 at 30-min intervals, generating continuous time-series observations throughout the 12-month monitoring period.

At each sampling interval, the station controller acquired the measured temperature and relative humidity data, time-stamped them, and transmitted them through the wireless network to the cloud-based database for year-round storage. Local backup storage provided an additional safeguard against temporary communication interruptions. Figure 6 illustrates the overall sequence from environmental sensing to data storage and subsequent analysis.

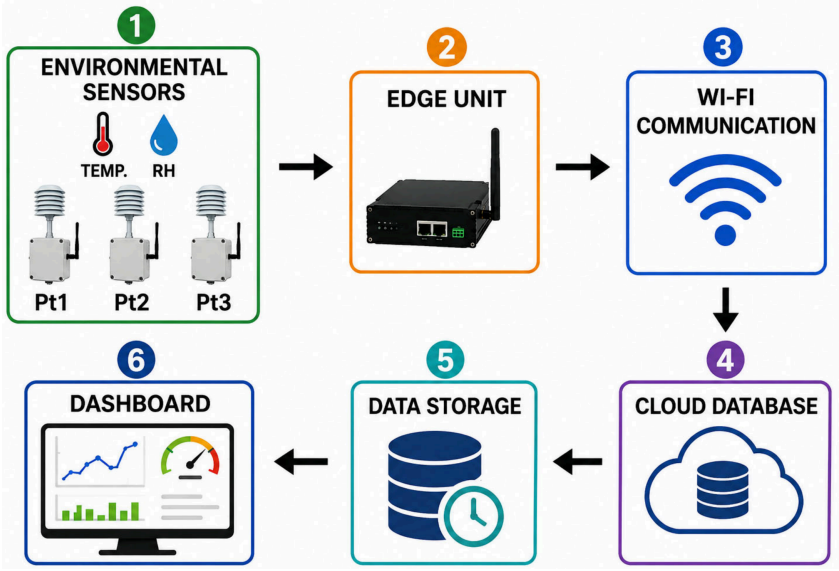

Figure 6. Workflow of the proposed IoT-based environmental data acquisition system for year-round forest microclimate monitoring. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

Measurement consistency was maintained by applying the same sensor configuration, sampling interval, data-acquisition procedure, and communication protocol at all monitoring stations. This standardized protocol enabled direct comparison of measurements collected simultaneously from the three monitored sites while reducing potential methodological differences among stations.

The resulting dataset provided high-temporal-resolution observations suitable for evaluating annual dynamics, seasonal variations, and site-to-site differences in air tem-

perature and relative humidity. Table 4 summarizes the complete measurement and data-acquisition protocol.

Table 4. Data acquisition protocol adopted for year-round forest microclimate monitoring.

Parameter	Description
Study period	January–December 2025
Monitoring duration	12 months
Monitoring stations	Pt1, Pt2, Pt3
Environmental variables	Air temperature, Relative humidity
Sampling interval	30 min
Data acquisition	Automatic
Data transmission	Data transmission: Site-specific Wi-Fi connection to the available network infrastructure and cloud platform
Data storage	Cloud database
Monitoring mode	Continuous real-time monitoring

2.5. Statistical Analysis

The original dataset consisted of air-temperature and relative-humidity measurements recorded at 30-min intervals at each of the three fixed monitoring stations. We used these high-frequency observations for time-series visualization and descriptive characterization but did not treat them as independent experimental replicates. We calculated daily mean values separately for each station, resulting in up to 365 daily observations per station for each environmental variable. For consistency between descriptive and inferential analyses, we used the daily station means to calculate the annual summary statistics presented in Figures 6 and 7. Accordingly, the error bars in these figures represent the standard deviation of the daily mean values across the monitoring period rather than the standard deviation of all individual 30-min observations. We calculated relative-humidity CV from the same daily aggregated dataset. This aggregation procedure avoids treating high-frequency repeated measurements as independent observations and ensures consistency among the descriptive statistics, graphical summaries, and inferential analyses.

Because measurements collected repeatedly from the same monitoring locations are temporally structured and cannot be regarded as independent spatial replicates, inferential comparisons were performed using a repeated-measures framework rather than treating individual 30-min observations as independent samples. Monitoring station (Pt1, Pt2, and Pt3) was treated as a fixed effect, whereas date was incorporated as a repeated temporal factor to account for the paired temporal structure of observations collected concurrently at the three stations. Temporal dependence among successive observations was considered in the error structure. Pairwise comparisons among monitoring stations were subsequently performed with adjustment for multiple comparisons at a significance level of $p < 0.05$.

The observational unit for the inferential analysis was therefore the station-day rather than the individual 30-min measurement. The three stations represented three fixed case-study locations and not replicated canopy or forest-structure treatments. Consequently, statistical differences are interpreted strictly as differences among Pt1, Pt2, and Pt3 during the monitoring period and are not generalized as causal effects of canopy density, terrain, or forest structure.

The statistical analyses enabled quantitative evaluation of spatial microclimatic heterogeneity within the forest ecosystem and provided the analytical basis for identifying environmentally suitable locations for medicinal plant cultivation. Table 5 summarizes the statistical procedures adopted in this study, and Figure 7 presents the overall analytical workflow.

Table 5. Statistical methods employed in this study.

Analysis	Data/Observational Unit	Statistical Method	Purpose
Descriptive analysis	30-min and daily observations	Mean, SD, minimum, maximum, CV	Characterize temporal and site-specific variability
Annual site comparison	Daily means (station-day)	Repeated-measures analysis	Test overall differences among Pt1–Pt3
Seasonal comparison	Daily means grouped by season	Repeated-measures analysis	Evaluate dry- and rainy-season differences
Pairwise site comparison	Daily means	Adjusted pairwise comparisons	Identify specific differences between Pt1–Pt2, Pt1–Pt3, and Pt2–Pt3
Statistical significance	Inferential analyses	$\alpha = 0.05$	Differences considered significant when $p < 0.05$

2.6. Forest Microclimate Characterization

Forest microclimate characterization quantified the temporal and spatial variabilities of environmental conditions within the study area using year-round datasets acquired from the three monitoring stations. The characterization framework focused on two key environmental variables, namely air temperature and relative humidity, which play essential roles in regulating physiological processes, habitat suitability, and the growth performance of medicinal plants under natural forest conditions. The analytical framework adopted in this study is illustrated in Figure 8.

The temporal characteristics of the forest microclimate were evaluated at multiple time scales. Annual dynamics were examined using the complete one-year dataset collected between January and December 2025 to describe the overall behavior of environmental conditions throughout the monitoring period. In addition, seasonal variation was investigated by comparing environmental conditions observed during different periods of the year, thereby enabling assessment of seasonal fluctuations associated with regional climatic conditions. These analyses provided a comprehensive understanding of year-round environmental variability within the forest ecosystem.

Spatial characterization was performed by comparing measurements obtained from the three monitoring stations (Pt1, Pt2, and Pt3). Differences among monitoring locations were quantified using descriptive statistical indicators and inferential statistical analyses described in Section 2.5. This approach enabled the identification of spatial heterogeneity in forest microclimate arising from differences in local forest structure and environmental conditions. The resulting characterization was subsequently used to evaluate the relative suitability of each monitoring location for medicinal plant cultivation under natural forest environments.

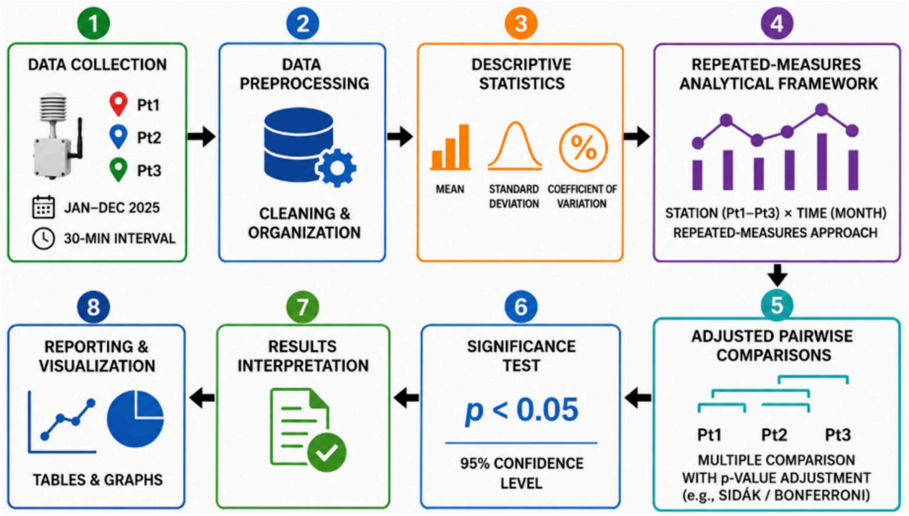

Figure 7. The overall statistical analysis workflow. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

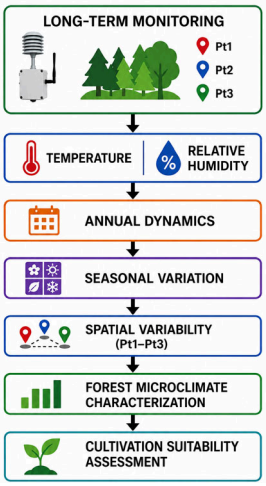

Figure 8. Framework for forest microclimate characterization based on year-round environmental monitoring. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

The combination of annual dynamics, seasonal variations, and spatial variabilities provided a comprehensive framework for describing forest microclimate and establishing the environmental basis for subsequent cultivation suitability assessment. This characterization approach facilitates systematic interpretation of year-round environmental observations and supports evidence-based management of medicinal plant resources within forest ecosystems.

The monitored forest area represents a heterogeneous microclimatic environment suitable for cultivating medicinal plants with different environmental requirements. Representative medicinal plants considered in the study area include *Houttuynia cordata* (plu khao), *Centella asiatica* (bua bok), *Ocimum tenuiflorum* (holy basil), and *Piper nigrum* (black pepper). *H. cordata* and *C. asiatica* are associated with relatively shaded environments with moderate-to-high moisture availability, whereas *O. tenuiflorum* and *P. nigrum* are representative of plants requiring comparatively greater light exposure. In addition to air temperature and relative humidity, canopy cover, light availability, soil characteristics, organic matter, drainage conditions, and competition with understory vegetation can also influence the

suitability of forest cultivation environments. These differences highlight the importance of spatially distributed microclimate monitoring rather than relying on a single measurement location when evaluating forest environments for medicinal plant cultivation.

2.7. Relative Microclimate Comparison Framework

The proposed framework was used solely to characterize the temperature–humidity microclimate among Pt1, Pt2, and Pt3 and was not intended to generate a numerical suitability score or categorical habitat classification. Annual mean air temperature and relative humidity were used to describe the thermal and atmospheric moisture conditions at each site, while temporal variability was evaluated descriptively based on the observed dispersion of the measurements. No normalization, weighting, aggregation, or High–Moderate–Low classification was applied. Consequently, the framework provides a site-to-site comparison of the monitored microclimatic conditions rather than an independently validated medicinal plant suitability index. Figure 9 illustrates the assessment procedure.

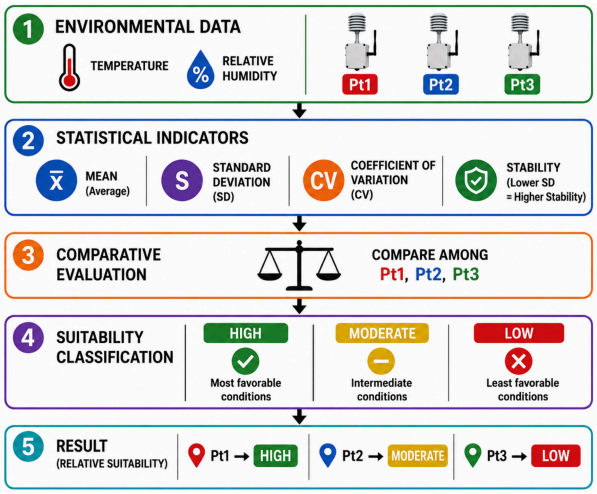

Figure 9. The proposed assessment procedure. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

The relative microclimate comparison framework was developed to characterize differences in temperature, relative humidity, and environmental variability among the three monitored locations. The framework does not generate a numerical suitability score, apply normalization or weighting, or classify sites into categorical levels of medicinal plant suitability. Instead, Pt1, Pt2, and Pt3 are compared directly based on their observed year-round temperature–humidity characteristics and temporal variability.

The resulting characterization should therefore be interpreted specifically in terms of the monitored microclimatic conditions. A cooler, more humid, or more stable site should not necessarily be considered more suitable for all medicinal plant species because plant responses depend on species-specific ecological requirements and additional environmental factors, including solar radiation or photosynthetically active radiation (PAR), vapor pressure deficit (VPD), soil moisture, soil temperature, soil properties, nutrient availability, and canopy characteristics.

Accordingly, the proposed framework provides a preliminary basis for site-specific microclimate comparison and may support subsequent species-specific cultivation assessment when appropriate environmental thresholds and plant-response data become available. The criteria used for the relative characterization of microclimatic conditions among the three monitoring sites are summarized in Table 6.

Table 6. Criteria used for relative characterization of microclimatic conditions among the monitored sites.

Environmental Characteristic	Relative Interpretation
Mean air temperature	Comparison of thermal conditions among Pt1–Pt3
Mean relative humidity	Comparison of atmospheric moisture conditions among Pt1–Pt3
Coefficients of variation (CV)	Relative degree of temporal variability
Standard deviation (SD)	Dispersion of observations around the mean
Overall interpretation	Relative microclimatic characterization of each monitored site

2.8. Research Workflow

Figure 10 presents the overall research workflow adopted in this study. The workflow integrates field investigation, IoT-based environmental monitoring, data transmission and storage, statistical analysis, and relative microclimate characterization. The analyzed data were used to characterize annual dynamics, seasonal variations, site-to-site differences, and environmental variability among Pt1, Pt2, and Pt3. The resulting information provides a preliminary environmental basis for future species-specific medicinal plant cultivation assessment rather than a comprehensive habitat suitability classification.

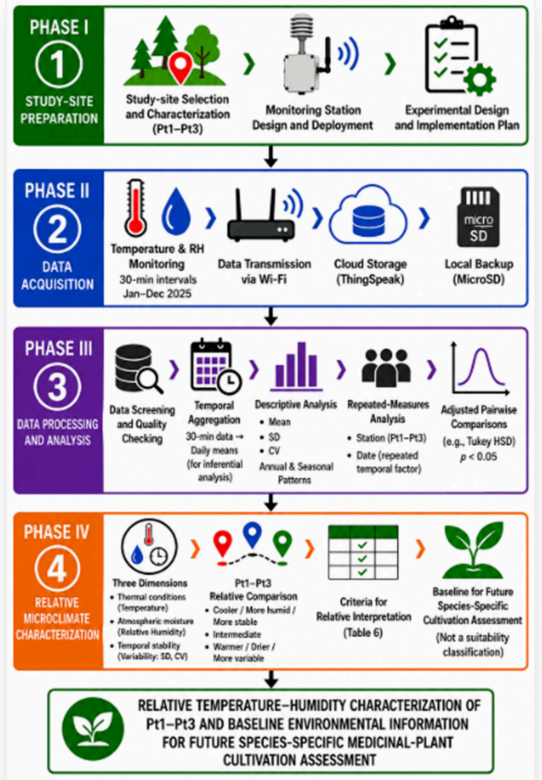

Figure 10. Overall research workflow for year-round IoT-based forest microclimate monitoring, statistical analysis, and relative site characterization. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

The research began with selecting the study site, where representative monitoring locations were established within the forest conservation area. Subsequently, an IoT-based environmental monitoring system was deployed to continuously measure air temperature and relative humidity at the three monitoring stations (Pt1, Pt2, and Pt3). Environmental observations were automatically transmitted through the wireless communication network

and archived in a cloud-based database, ensuring reliable year-round storage of time-series environmental data.

Following data acquisition, the datasets were subjected to statistical analysis, including descriptive and inferential statistics, to quantify temporal and spatial variations in forest microclimate. The analyzed data were subsequently used to characterize annual dynamics, seasonal variations, and spatial heterogeneity within the forest ecosystem. The analyzed data were subsequently integrated into the relative microclimate comparison framework to characterize annual dynamics, seasonal variations, spatial heterogeneity, and environmental stability among the three monitoring locations. The resulting information provides a preliminary environmental basis for future species-specific cultivation assessment. The overall workflow provides a systematic methodology that links environmental monitoring with evidence-based decision-making for sustainable forest management and climate-resilient medicinal plant production.

3. Results and Discussion

3.1. Performance Evaluation of the IoT-Based Environmental Monitoring System

The performance of the proposed IoT-based environmental monitoring system was evaluated throughout the one-year monitoring period to assess its capability for year-round forest microclimate observation. The evaluation focused on five operational aspects, including system stability, data completeness, communication reliability, continuous monitoring capability, and cloud-based data management. Figure 11 presents the overall monitoring platform and its operational architecture, while Figure 12 shows an example of the real-time monitoring dashboard.

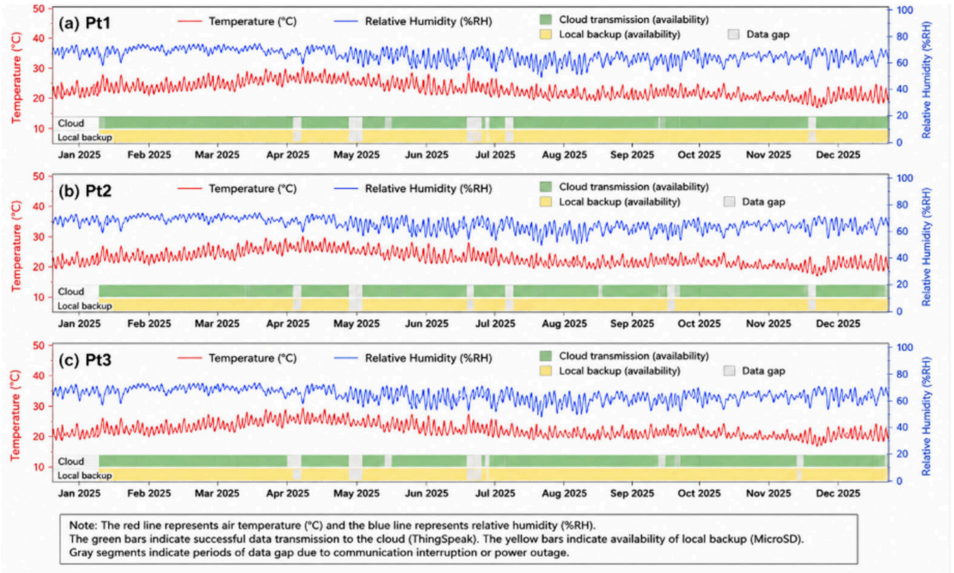

Figure 11. Annual time-series monitoring and data-availability profiles at the three forest monitoring stations: (**a**) Pt1, (**b**) Pt2, and (**c**) Pt3. The red and blue lines represent air temperature and relative humidity, respectively; the green and yel-low bars indicate cloud-transmission and local-backup availability, respectively, while gray segments indicate data gaps. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

During the monitoring campaign, the IoT platform successfully acquired environmental data from the three monitoring stations (Pt1, Pt2, and Pt3) and continuously transmitted the observations to the cloud-based database through the wireless communication network. The automated acquisition process enabled uninterrupted recording of air temperature

and relative humidity throughout the study period without requiring manual intervention. The cloud-based monitoring architecture facilitated centralized data storage and real-time accessibility, allowing environmental information to be visualized and managed through the web-based dashboard. These operational characteristics demonstrate the feasibility of applying IoT technologies for continuous environmental monitoring within natural forest ecosystems.

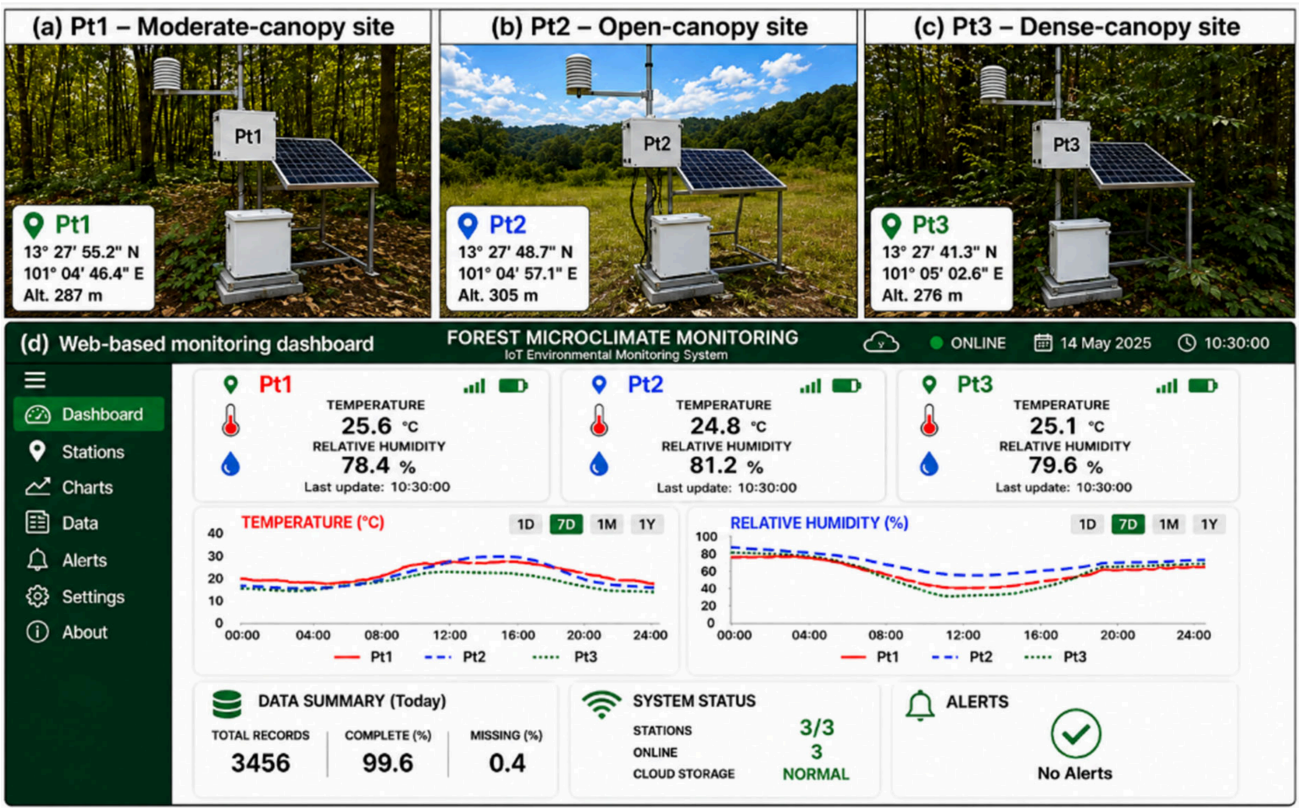

Figure 12. Web-based dashboard for real-time visualization of forest microclimate data collected from the IoT monitoring system. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

The developed monitoring platform also provided a consistent environmental dataset suitable for year-round statistical analysis. Because identical sensing hardware, communication protocols, and acquisition intervals were implemented at all monitoring stations, the collected datasets were directly comparable among locations. The successful integration of environmental sensing, wireless communication, cloud storage, and dashboard visualization provided a functional monitoring infrastructure for subsequent analyses of annual dynamics, seasonal variations, and site-specific microclimatic differences. Table 7 summarizes the principal operational characteristics of the IoT-based monitoring system during the 12-month field deployment. The system integrated automated temperature and relative-humidity sensing, ESP32-based data acquisition, site-specific Wi-Fi communication, local backup storage, cloud-based data management, and web-based visualization. A solar-assisted power supply with battery storage supported field operation at the monitoring locations.

The monitoring configuration enabled year-round environmental observations at Pt1, Pt2, and Pt3 under a common data-acquisition protocol. However, the deployment was designed primarily for microclimate monitoring rather than to quantitatively evaluate communication performance, power autonomy, or year-round sensor stability. Accord-

ingly, battery state of charge, autonomous operating duration, and year-round sensor drift were not independently quantified during the monitoring period and are considered methodological limitations of the present study.

Table 7. Operational characteristics of the IoT-based environmental monitoring system during the field deployment.

Operational Aspect	Implementation	Observation During Field Deployment
Environmental sensing	Automated measurement of air temperature and relative humidity	Year-round microclimate observations were acquired at Pt1, Pt2, and Pt3
Temporal monitoring	30-min sampling interval	Measurements covered January–December 2025
Data acquisition	ESP32-based automated acquisition	Identical acquisition procedures were applied at all three monitoring sites
Data transmission	Site-specific Wi-Fi communication	Measurements were transmitted through the available network infrastructure to the cloud platform
Local data backup	MicroSD-based local storage	Provided local data storage during temporary communication interruptions
Cloud data management	ThingSpeak cloud platform	Supported centralized storage and remote access to time-series observations
Data visualization	Web-based dashboard	Enabled real-time visualization and inspection of environmental measurements
Power operation	Solar-assisted power supply with battery storage	Supported field operation; battery state of charge and autonomy were not continuously quantified
Year-round sensor performance	Sensirion SHT35	Periodic recalibration and year-round sensor drift were not independently quantified during the 12-month deployment

The results indicate that the proposed IoT platform provides an effective and practical solution for year-round environmental monitoring in forest ecosystems. Beyond continuous data acquisition, integrating cloud computing and real-time visualization enhances data accessibility and facilitates evidence-based environmental assessment for medicinal plant cultivation. These findings confirm that the developed system is suitable for year-round ecological monitoring and precision environmental management in natural forests. Overall, the field deployment demonstrates the practical feasibility of the IoT platform for year-round environmental monitoring at the three study locations. However, communication reliability, power autonomy, and long-term sensor stability were not independently quantified and therefore cannot be evaluated quantitatively from the present dataset.

3.2. Annual Dynamics of Forest Microclimate

As shown in Figure 13, all three monitoring stations exhibited a similar annual temperature pattern, with air temperature gradually increasing from January to a maximum around April, followed by a progressive decline toward December. Pt2 consistently exhibited the highest monthly mean temperature, whereas Pt3 generally showed the lowest values, with Pt1 remaining intermediate. The standard deviation (SD) error bars provide additional information on within-month temperature variability and indicate that the monthly mean values alone do not fully represent the temporal fluctuations occurring at each monitoring site. Although the three stations followed a broadly similar seasonal pattern, differences in both mean temperature and variability demonstrate distinct site-specific thermal conditions. The relatively larger variability observed at Pt2 during the warmer months may reflect greater short-term exposure to changing environmental conditions,

whereas Pt3 generally exhibited a cooler and comparatively stable thermal environment. These results further support measurable site-to-site differences in forest microclimate conditions throughout the annual cycle.

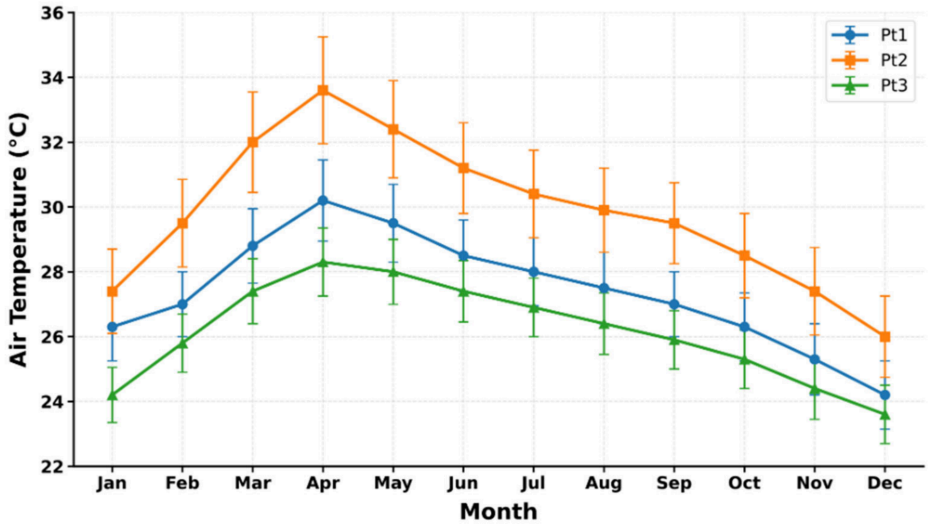

Figure 13. Annual variation in air temperature recorded at the three forest monitoring stations (Pt1, Pt2, and Pt3) from January to December 2025.

Figure 14 shows a clear seasonal pattern in relative humidity at all three monitoring stations. Relative humidity increased progressively from the beginning of the year, reached its highest levels during approximately August–September, and subsequently decreased toward December. Pt3 consistently exhibited the highest relative humidity, while Pt2 showed the lowest values throughout the monitoring period, with Pt1 remaining between these two conditions. The SD error bars further demonstrate that relative humidity varied within individual months, indicating short-term atmospheric moisture fluctuations superimposed on the overall seasonal trend. The differences in both monthly mean values and variability among Pt1, Pt2, and Pt3 indicate that moisture conditions were not spatially uniform among the monitored sites. In combination with the temperature patterns shown in Figure 13, these results demonstrate distinct temperature–humidity regimes at the three monitoring locations and provide a quantitative basis for subsequent seasonal, site-to-site, and preliminary microclimate suitability analyses.

Overall, Figures 13 and 14 show that interpreting forest microclimate conditions should consider not only monthly mean temperature and relative humidity but also their temporal variability, as represented by the SD. This distinction is particularly important when evaluating environmental stability at individual monitoring sites.

Recorded air temperature showed clear temporal fluctuations throughout the monitoring period, reflecting the influence of seasonal climatic conditions on the forest microenvironment. Although temperature varied continuously throughout the year, the three monitoring stations showed generally consistent temporal patterns, indicating that all locations experienced the same regional climatic forcing while maintaining distinct local microclimatic characteristics. Differences in canopy structure, vegetation density, and local environmental conditions contributed to the observed variations among monitoring stations.

Relative humidity also exhibited pronounced temporal variability over the one-year monitoring period. In general, humidity levels varied inversely with air temperature, with higher humidity typically observed during cooler periods and lower humidity during warmer periods. Despite these temporal fluctuations, the monitoring system captured continuous environmental records throughout the observation period, en-

abling a detailed assessment of annual forest microclimate dynamics. The year-round dataset provides valuable baseline information for understanding environmental variability within the forest ecosystem and supports subsequent analyses of seasonal variations and spatial heterogeneity.

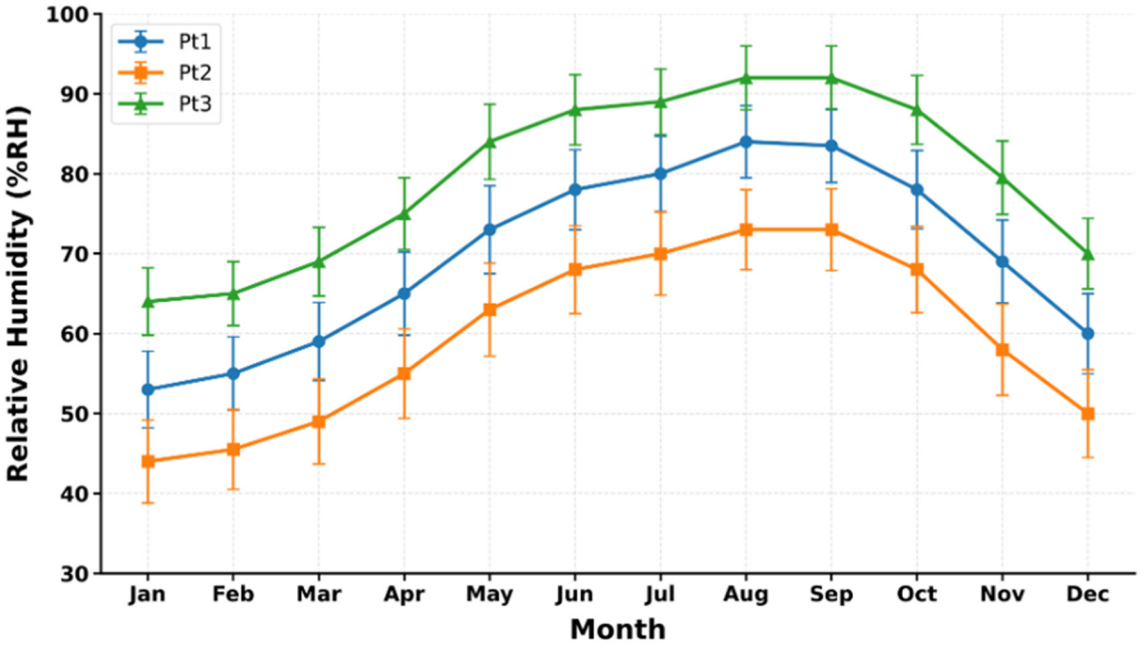

Figure 14. Monthly variations in average relative humidity at the three forest monitoring stations (Pt1, Pt2, and Pt3) from January to December 2025 based on IoT monitoring data.

Overall, the annual monitoring results demonstrate that continuous IoT-based environmental observation can capture year-round forest microclimate dynamics at high temporal resolution. These observations establish the environmental foundation for evaluating seasonal behavior, spatial variability, and the suitability of different forest locations for medicinal plant cultivation, as discussed in the following sections.

3.3. Seasonal Variations in Forest Microclimate

Figure 15 compares the seasonal variations in air temperature and relative humidity at the three monitoring sites. During the dry season, the mean air temperatures at Pt1, Pt2, and Pt3 were 29.7, 31.3, and 28.2 °C, respectively, whereas the corresponding values during the rainy season decreased to 27.8, 28.9, and 26.5 °C. In contrast, relative humidity showed the opposite seasonal response. Mean relative humidity increased from 58.3, 44.5, and 64.6%RH during the dry season to 83.4, 72.8, and 91.2%RH during the rainy season at Pt1, Pt2, and Pt3, respectively. These results demonstrate a consistent seasonal transition toward cooler and substantially more humid microclimatic conditions during the rainy season.

We also performed statistical significance testing to determine whether the observed differences were statistically supported. The significance annotations incorporated into Figure 15 indicate the statistical differences between the dry and rainy seasons at each monitoring site, while the lowercase letters indicate significant differences among monitoring sites within the same season based on the post hoc comparison. Groups sharing the same letter are not significantly different, whereas groups assigned different letters differ significantly at $p < 0.05$. This statistical analysis strengthens the interpretation of the seasonal patterns by demonstrating that the observed differences are not based solely on visual comparisons of the mean values and error bars. Error bars in Figure 15 represent

the standard deviation (SD) of measurements within each seasonal dataset, indicating variability around the corresponding seasonal mean values.

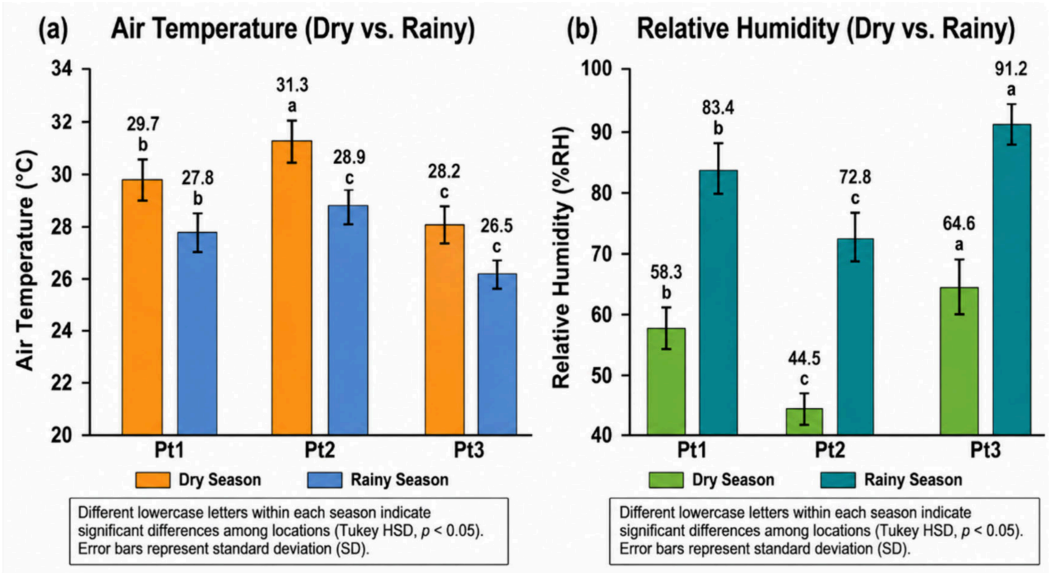

Figure 15. Seasonal comparison of average (**a**) air temperature and (**b**) relative humidity at the three forest monitoring stations during the dry and rainy seasons. Error bars represent standard deviation (SD). Different lowercase letters (a–c) indicate statistically significant differences among monitoring locations within each season ($p < 0.05$), whereas the same letter indicates no significant difference.

The seasonal comparison revealed distinct differences in both air temperature and relative humidity between the dry and rainy seasons. Air temperature was generally higher during the dry season because of increased solar radiation, lower cloud cover, and reduced atmospheric moisture. In contrast, the rainy season exhibited lower temperatures owing to frequent precipitation, increased evapotranspiration, and canopy-mediated cooling. Although the overall seasonal trend was similar among the three monitoring stations, Pt2 consistently recorded the highest air temperature, whereas Pt3 remained comparatively cooler throughout both seasons, indicating the moderating influence of local vegetation density and forest canopy cover.

Relative humidity demonstrated an opposite seasonal pattern. Higher humidity was observed during the rainy season at all monitoring stations, whereas substantially lower humidity was observed during the dry season. Among the monitored locations, Pt3 consistently exhibited the highest relative humidity and the lowest seasonal fluctuation, while Pt2 showed the lowest humidity and the greatest temporal variability. These findings indicate that the forest microenvironment effectively buffers atmospheric moisture fluctuations, particularly in densely vegetated areas. Such seasonal differences are expected to influence plant physiological processes, including transpiration, photosynthesis, and secondary metabolite accumulation, thereby affecting the suitability of different forest locations for medicinal plant cultivation.

The observed seasonal variations in air temperature and relative humidity may have important implications for the growth and physiological responses of medicinal plants. Temperature regulates fundamental physiological processes, including photosynthesis, respiration, enzyme activity, and biomass accumulation, whereas relative humidity influences transpiration, stomatal conductance, plant water status, and evaporative demand. Consequently, the warmer, drier conditions observed during the dry season may impose greater thermal and water-related stress on understory plants, while the cooler, more humid conditions during the rainy season may reduce evaporative demand and provide a

more favorable environment for vegetative growth. These seasonal differences indicate that microclimatic suitability for medicinal plant cultivation should not be evaluated solely from annual mean conditions but should also account for temporal environmental variability.

3.4. Spatial Variability Among Monitoring Stations

A similar site-specific pattern was observed for relative humidity, with Pt3 exhibiting the highest annual relative humidity, followed by Pt1 and Pt2. The repeated-measures analysis indicated statistically significant differences among the three monitoring locations ($p < 0.05$), and the adjusted pairwise comparisons further demonstrated significant contrasts among Pt1, Pt2, and Pt3. These results confirm distinct microclimatic conditions at the three specific monitoring locations during the study period. However, because each microenvironment was represented by only one monitoring station, these differences cannot be attributed independently to canopy density, terrain, vegetation structure, or other site characteristics. Accordingly, Pt3 is described as a cooler and more humid monitored location, whereas Pt2 represents comparatively warmer and drier conditions; these findings should be interpreted strictly as site-specific contrasts rather than generalized forest-structure effects. The spatial distributions of annual air temperature and relative humidity are illustrated in Figures 16 and 17, respectively, while Table 8 summarizes the statistical comparison.

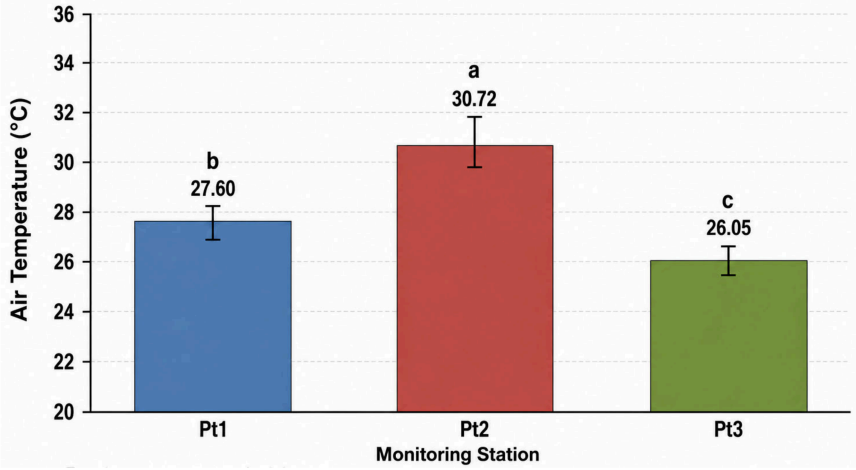

Figure 16. Spatial comparison of annual mean air temperature among the three forest monitoring stations (Pt1, Pt2, and Pt3). Error bars represent the standard deviation of daily mean values over the monitoring period. Different letters indicate statistically significant differences based on adjusted pairwise comparisons ($p < 0.05$).

Table 8. Comparative microclimatic characteristics of the three forest monitoring sites.

Microclimatic Indicator	Pt1	Pt2	Pt3	Comparative Interpretation
Annual mean air temperature (°C)	27.60	30.72	26.05	Pt2 highest; Pt3 lowest
Annual mean relative humidity (%RH)	70.88	60.83	80.60	Pt3 highest; Pt2 lowest
RH variability, CV (%)	21.50	27.87	16.41	Pt3 least variable

Table 8. *Cont.*

Microclimatic Indicator	Pt1	Pt2	Pt3	Comparative Interpretation
Temperature characteristic	Moderate	Higher	Lower	Relative comparison among sites
Humidity characteristic	Moderate	Lower	Higher	Relative comparison among sites
Environmental stability	Moderate	Lower	Higher	Based on observed variability
Overall microclimate characteristic	Intermediate	Warmer and drier	Cooler and more humid	Site-specific characterization

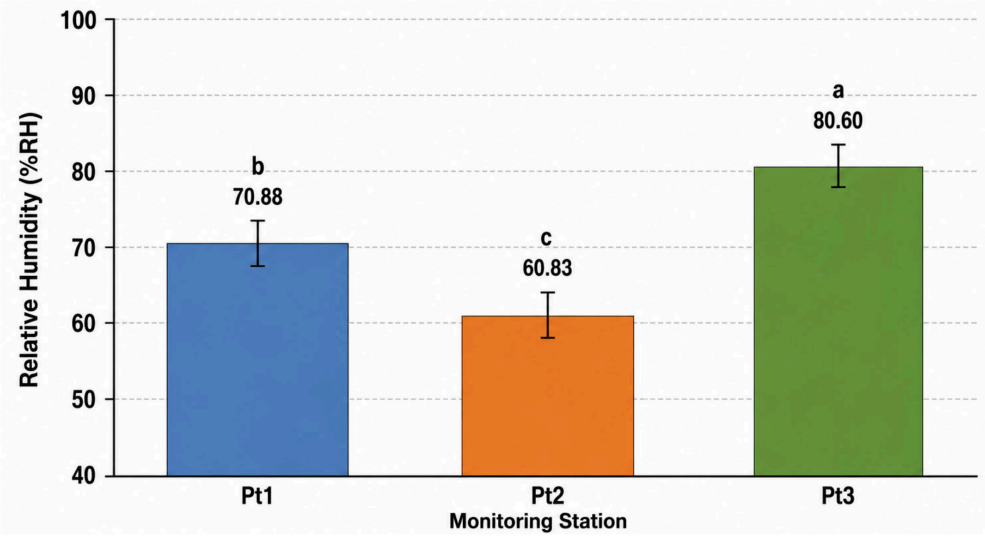

Figure 17. Spatial comparison of annual mean relative humidity among the three forest monitoring stations (Pt1, Pt2, and Pt3). Error bars represent the standard deviation of daily mean values over the monitoring period. Different letters indicate statistically significant differences based on adjusted pairwise comparisons ($p < 0.05$).

Microclimatic variations may also influence the biosynthesis and accumulation of secondary metabolites in medicinal plants. Previous studies have demonstrated that environmental factors and moderate abiotic stresses can alter secondary metabolic pathways and affect the accumulation of bioactive compounds, including phenolics and flavonoids [17,18]. Variations in temperature and atmospheric moisture can modify plant water relations, oxidative status, and metabolic signaling, thereby influencing the synthesis of compounds involved in plant protection and stress responses. Accordingly, the spatial differences in temperature and relative humidity observed among Pt1, Pt2, and Pt3 may potentially result in differences not only in plant growth but also in the quantity and composition of medicinally important secondary metabolites. However, the present study did not directly measure plant growth, phenolic content, flavonoid content, or other phytochemical characteristics; therefore, these relationships should be interpreted as physiologically plausible implications supported by previous studies rather than as direct experimental evidence from the present dataset. The error bars represent the standard deviation (SD), illustrating the variability in annual temperature measurements at each monitoring station. The different lowercase letters indicate statistically significant differences among the three monitoring sites according to Tukey's HSD test ($p < 0.05$).

The spatial differences in temperature and relative humidity observed among the monitoring locations are particularly relevant to medicinal plant cultivation because individual species may favor different microclimatic conditions. For example, relatively shaded, humid forest environments are generally more favorable for *H. cordata* and *C. asiatica*, whereas species such as *O. tenuiflorum* and *P. nigrum* may favor greater light availability. These contrasting environmental preferences show that temperature and relative humidity provide useful first-order information for preliminary site assessment but should be considered alongside other species-specific environmental requirements. Accordingly, the spatial microclimate information obtained in this study can support preliminary cultivation planning, while additional measurements of light availability, soil moisture, and soil temperature are required for species-specific suitability assessment.

To provide a concise quantitative comparison of the three monitoring locations, Table 8 summarizes the principal annual microclimatic characteristics. The comparison considers annual mean air temperature, annual mean relative humidity, relative-humidity variability, and the resulting site-specific microclimatic characteristics.

Pt2 exhibited the highest annual mean air temperature (30.72 °C), the lowest relative humidity (60.83%), and the greatest RH variability (CV = 27.87%), indicating comparatively warmer, drier, and more variable conditions. In contrast, Pt3 showed the lowest mean temperature (26.05 °C), the highest relative humidity (80.60%), and the lowest RH variability (CV = 16.41%), representing cooler, more humid, and relatively stable conditions. Pt1 exhibited intermediate characteristics between Pt2 and Pt3. These results demonstrate clear site-to-site microclimatic differences among the three monitored forest locations.

A similar spatial pattern was observed for relative humidity. Pt3 maintained the highest annual relative humidity, followed by Pt1 and Pt2. The repeated-measures analysis indicated statistically significant differences among the three monitoring locations ($p < 0.05$), and the adjusted pairwise comparisons confirmed significant site-to-site contrasts. These differences are interpreted specifically as contrasts among Pt1, Pt2, and Pt3 during the monitoring period rather than as generalized effects of canopy density, terrain, or forest structure. These findings suggest that forest structure, canopy density, and local topographic characteristics jointly regulate atmospheric moisture and thermal conditions. Consequently, Pt3 represents a cooler and more humid microclimatic environment, whereas Pt2 represents comparatively warmer and drier conditions. These differences should be interpreted as site-specific microclimatic characteristics rather than as rankings of medicinal plant cultivation suitability.

The scientific value of the present dataset arises primarily from its temporal continuity and spatial coverage rather than from the novelty of the sensing architecture. Continuous observations over a complete annual cycle captured both dry- and rainy-season conditions, while simultaneous monitoring at three forest locations revealed spatial heterogeneity that would be difficult to identify from short-term or single-station measurements. The dataset therefore provides a quantitative basis for characterizing seasonal dynamics, site-specific microclimate conditions, and environmental stability. These characteristics are particularly relevant to medicinal plant cultivation, where both the magnitude and temporal stability of temperature and humidity can influence plant establishment, physiological responses, and potentially secondary metabolite production.

3.5. Relative Comparison of Microclimatic Conditions

To demonstrate the practical application of the proposed assessment framework, we evaluated the annual microclimate characteristics of the three monitoring stations according to the criteria presented in Table 9. To provide a direct site-to-site interpretation of the observed microclimatic conditions, we compared the annual characteristics of Pt1, Pt2, and

Pt3 using annual mean air temperature, annual mean relative humidity, and descriptive measures of temporal variability. No composite score, normalization, weighting, aggregation rule, or categorical suitability classification was applied. RH-CV was used only as a descriptive indicator of relative-humidity variability, whereas CV was not calculated for air temperature. The resulting comparison therefore represents relative microclimatic characterization among the three monitored locations rather than an independently validated cultivation suitability assessment.

Overall, Pt1 represented an intermediate and moderately stable microclimatic environment, whereas Pt2 was characterized by warmer, drier, and more variable conditions. Pt3 exhibited cooler, more humid, and more stable conditions. From an application perspective, these characteristics provide preliminary environmental information for comparing the three forest microenvironments and may guide subsequent species-specific cultivation assessment.

Table 9. Site-specific interpretation of microclimatic conditions at the three forest monitoring locations.

Assessment Aspect	Pt1	Pt2	Pt3
Thermal condition	Intermediate	Warmer	Cooler
Moisture condition	Moderately humid	Comparatively drier	More humid
Environmental variability	Moderate	Higher	Lower
Microclimatic stability	Moderate	Lower	Higher
Overall microclimate characteristic	Intermediate and moderately stable	Warmer, drier, and more variable	Cooler, more humid, and more stable
Interpretation for future assessment	Intermediate reference condition	Contrasting warm–dry condition	Contrasting cool–humid condition

The comparative analysis revealed distinct microclimatic characteristics among the three monitoring locations. Pt3 exhibited the lowest annual mean air temperature, the highest relative humidity, and the lowest temporal variability, representing a cooler, more humid, and relatively stable microenvironment. In contrast, Pt2 had higher temperatures, lower relative humidity, and greater environmental variability, while Pt1 showed intermediate conditions. These results represent relative microclimatic differences among the monitored locations and should not be interpreted as indicating that Pt3 is universally more suitable for medicinal plant cultivation. Species-specific cultivation suitability requires additional information on light availability, soil moisture, soil temperature, soil properties, and direct plant-performance responses.

Figure 18 summarizes the relative temperature–humidity characteristics of the three monitoring sites without applying numerical scores, normalization, weighting, or categorical suitability rankings. Pt1 exhibited intermediate conditions, Pt2 was characterized by warmer, drier, and more variable conditions, whereas Pt3 exhibited cooler, more humid, and comparatively more stable conditions. These descriptors represent direct site-to-site comparisons of the observed microclimatic data and should not be interpreted as rankings of medicinal plant habitat suitability.

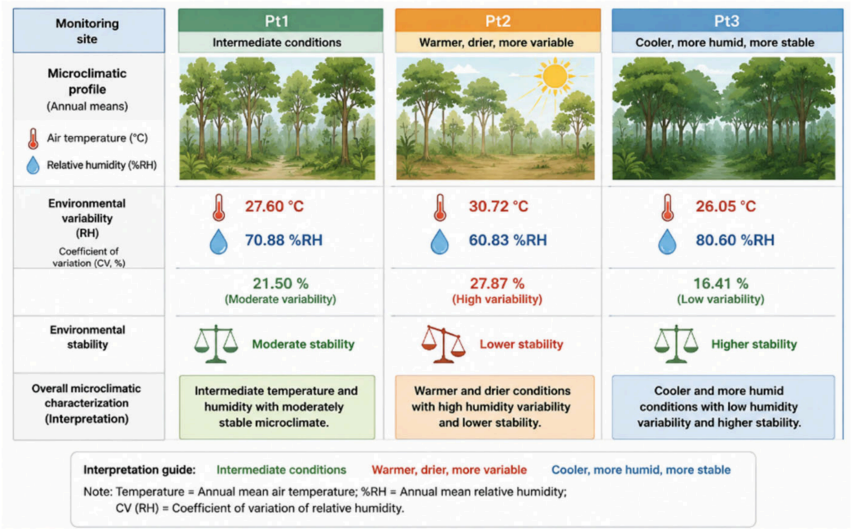

Figure 18. Relative comparison of temperature–humidity microclimatic characteristics and environmental stability among the three forest monitoring sites. AI-assisted graphical editing using ChatGPT (OpenAI; GPT-5.6 Sol). Prompt: "Improve line sharpness, font size, and alignment while preserving the original technical information." The final figure was verified by the authors.

From an application perspective, the year-round dataset provides a basis for identifying forest locations with relatively stable and potentially favorable microclimatic conditions for medicinal plant cultivation. Rather than relying on short-term measurements or annual averages alone, the proposed assessment considers temporal and spatial variabilities in temperature and relative humidity. This approach may support preliminary site screening, cultivation planning, and year-round environmental management. With further validation using species-specific growth and phytochemical data, the framework could be extended into a data-driven decision-support tool for sustainable medicinal plant production under forest environments.

3.6. Comparison with Previous Studies

Table 10 compares the present study with representative previous IoT-based environmental monitoring studies in terms of monitoring environment, IoT implementation, monitoring duration, forest application, relevance to medicinal plants, and microclimate-based suitability assessment. Previous studies have predominantly focused on greenhouses, orchards, and field crops, while relatively few have addressed year-round monitoring in forest environments. The present study extends this application by combining year-long IoT-based monitoring at three representative forest sites with the characterization of temperature and relative-humidity variability relevant to medicinal plant cultivation. Unlike previous monitoring studies that primarily focused on environmental observation, the present study further translates the monitored data into a preliminary microclimate-based suitability assessment. However, this assessment is based only on air temperature, relative humidity, and environmental stability and should not be interpreted as a comprehensive or species-specific habitat suitability model.

Table 10. Comparison of the present study with previous IoT-based environmental monitoring studies.

Previous Study	Environment	IoT	Year-Round Monitoring	Forest Ecosystem	Medicinal Plants	Cultivation-Oriented Microclimate Interpretation
Greenhouse automation and smart farming [46,47]	Greenhouse	✓	✗	✗	✗	✗
Orchard environmental monitoring [48]	Orchard	✓	△	✗	✗	✗
Field crop and rice monitoring [49,50]	Rice/Field crop	✓	△	✗	✗	✗
Forest environmental monitoring [51–54]	Forest	✓	✓	✓	✗	✗
This study	Forest	✓	✓ (12 months)	✓	✓	✓

Note: ✓ = included or explicitly addressed; △ = partially addressed; ✗ = not addressed. Long-term monitoring refers to continuous observations covering an extended monitoring period as defined in the respective studies. Cultivation-oriented microclimate interpretation indicates that monitored environmental data were interpreted in relation to conditions potentially relevant to cultivation planning. In the present study, this interpretation is limited to relative temperature–humidity microclimate characterization and does not represent a validated or species-specific habitat suitability assessment.

As summarized in Table 10, previous IoT-based monitoring studies have predominantly focused on greenhouses, orchards, field crops, and general forest environmental observation. The present study extends this application to year-long microclimate monitoring at three representative forest sites with specific relevance to medicinal plant cultivation. In addition to environmental monitoring, we used the collected temperature and relative-humidity data for a preliminary microclimate-based suitability assessment. However, this assessment is limited to temperature, relative humidity, and environmental stability and should not be interpreted as a comprehensive or species-specific habitat suitability model.

Previous studies have predominantly focused on controlled agricultural environments, such as greenhouses, orchards, and field crops, where IoT technologies have been widely employed to monitor environmental variables and optimize crop management. IoT platforms have also been developed to integrate environmental sensing, data communication, and real-time information management for smart farming applications [47]. Beyond ground-based sensor networks, unmanned aerial systems have also been used for spatial monitoring and data acquisition in precision agriculture [48]. Greenhouse-based systems generally emphasize automated climate control, irrigation scheduling, and energy-efficient production under relatively homogeneous environmental conditions [49–51]. Likewise, IoT applications in orchards have mainly focused on precision irrigation, soil moisture management, and disease monitoring [52,53], whereas studies in rice production have primarily focused on water management, crop growth monitoring, and yield prediction under open-field conditions [54]. Although these studies have demonstrated the effectiveness of IoT technologies for precision agriculture, their monitoring periods are typically limited to a single growing season, and few have investigated natural forest ecosystems characterized by highly heterogeneous microclimatic conditions.

Only a limited number of studies have explored environmental monitoring within forest ecosystems, and these investigations have generally emphasized ecological observation or biodiversity assessment rather than supporting medicinal plant cultivation [55,56]. Furthermore, previous studies rarely integrated year-round continuous monitoring with spatial comparisons among multiple forest locations or translated environmental observations into cultivation-oriented decision-support information. Consequently, knowledge regarding

the year-round dynamics of forest microclimates and their implications for medicinal plant cultivation remains limited.

Compared with previous research, the present study offers three principal contributions. First, it establishes a continuous IoT-based monitoring approach for collecting forest microclimate observations throughout a complete annual cycle. Second, it quantitatively characterizes temporal and site-specific differences among three forest monitoring locations using descriptive and repeated-measures statistical analyses. Third, it translates the observed temperature–humidity patterns and environmental variability into a relative microclimatic characterization relevant to preliminary site screening for medicinal plant cultivation. Rather than providing a validated cultivation suitability classification, the framework establishes a baseline for future species-specific assessments incorporating additional environmental and biological variables.

3.7. Practical Implications

This study's findings have practical implications for sustainable forest management and medicinal plant cultivation. Year-round microclimate monitoring provides quantitative information on seasonal and site-specific variations in temperature, relative humidity, and environmental stability, supporting preliminary decisions on cultivation timing and site selection. The observed differences among Pt1, Pt2, and Pt3 further demonstrate that local microclimatic heterogeneity should be considered when planning forest-based cultivation. Using naturally favorable microclimatic conditions may help reduce the need for intensive environmental modification and support the integration of medicinal plant cultivation with forest conservation.

The year-long dataset also provides baseline information to track environmental changes and support climate-responsive management. Continued monitoring could help identify shifts in temperature, humidity, and environmental variability and inform adjustments in cultivation practices. In this context, IoT technology serves primarily as a practical tool for continuous data acquisition, storage, and visualization, enabling environmental observations to be translated into evidence-based management information. However, because the present assessment is based on only three monitoring sites and two environmental variables, its application should be considered preliminary rather than a comprehensive basis for cultivation or habitat management.

The broader sustainability implications are primarily relevant to SDG 1 (No Poverty) and SDG 2 (Zero Hunger). For SDG 1, environmental information from year-round monitoring may indirectly support medicinal plant cultivation as a supplementary livelihood opportunity for local communities by reducing uncertainty in preliminary cultivation planning; however, this study did not evaluate socioeconomic outcomes. For SDG 2, the dataset may support more informed and environmentally responsive cultivation planning by identifying seasonal patterns and comparatively favorable temperature–humidity conditions. Nevertheless, crop yield and productivity were not directly assessed; therefore, the contribution to SDG 2 should be interpreted as supporting sustainable cultivation planning rather than demonstrating direct improvements in food security or agricultural productivity.

3.8. Future Work

The present study establishes a year-round, multi-station framework for characterizing forest microclimate and demonstrates its practical application through continuous environmental observations at three forest locations. Building on these findings, future work will focus on expanding the monitoring framework to improve its spatial coverage, environmental representation, and applicability to medicinal plant cultivation.

Future deployments will increase the number of monitoring stations and incorporate replicated monitoring locations representing different forest microenvironments. GPS-referenced locations, elevation, canopy characteristics, and topographic information will also be integrated with GIS and remote-sensing data to provide a more spatially explicit characterization of forest microclimate. Extending the monitoring period over multiple years will further enable the evaluation of interannual variability and long-term environmental dynamics.

The monitoring framework will also be expanded beyond air temperature and relative humidity by incorporating photosynthetically active radiation (PAR), solar radiation, vapor pressure deficit (VPD), soil moisture, soil temperature, precipitation, wind conditions, and selected soil physicochemical properties. These environmental observations will subsequently be integrated with medicinal plant responses, including plant growth, biomass accumulation, physiological characteristics, and phytochemical composition, to develop and validate species-specific cultivation models.

Further technical development will include long-range, low-power communication technologies such as LoRaWAN or NB-IoT for larger forest monitoring networks, together with enhanced energy-management monitoring for solar-powered stations. Future deployments will also incorporate traceable sensor calibration and periodic verification procedures to strengthen long-term measurement quality.

Ultimately, sufficiently comprehensive and biologically validated datasets could support the application of machine learning, artificial intelligence, GIS-based predictive mapping, and Digital Twin approaches. These developments could extend the present framework from year-round microclimate characterization toward an intelligent decision-support system for species-specific site selection, cultivation management, and sustainable medicinal plant production in heterogeneous forest environments.

4. Conclusions

This study characterized annual, seasonal, and spatial variations in forest microclimate using year-long air temperature and relative-humidity observations from three representative monitoring sites. Significant site-to-site differences were identified, showing that local forest conditions can create distinct microclimatic environments despite the same regional climate. Pt3 exhibited the lowest annual mean air temperature (26.05 °C), the highest relative humidity (80.60%), and the lowest environmental variability (CV = 16.41%), whereas Pt2 showed the highest temperature (30.72 °C), the lowest relative humidity (60.83%), and comparatively greater variability.

Accordingly, the principal contribution of this study lies in the generation and analysis of a continuous, year-round, multi-station forest microclimate dataset and its translation into a relative characterization of site-specific temperature–humidity conditions. The proposed framework is intended to support a preliminary environmental comparison and future species-specific cultivation assessment rather than provide a validated habitat suitability classification. The results indicate that Pt3 provides comparatively cooler, more humid, and more stable temperature–humidity conditions, followed by Pt1, whereas Pt2 represents a warmer, drier, and more variable microenvironment. These findings demonstrate the value of continuous site-specific monitoring for preliminary cultivation-site screening and environmental management in heterogeneous forest ecosystems.

The proposed assessment should, however, be interpreted as a preliminary temperature–humidity-based microclimate assessment rather than a comprehensive or species-specific habitat suitability model. Important environmental factors, including photosynthetically active radiation, soil moisture, soil temperature, precipitation, soil properties, canopy characteristics, and plant physiological and phytochemical responses, were

not evaluated. In addition, the limited spatial coverage of three monitoring stations restricts extrapolation of the findings to the entire forest area.

Future studies should therefore expand both the number of monitoring locations and the range of environmental variables, together with GPS-referenced spatial information and external meteorological observations. Integrating plant growth and phytochemical measurements would enable the development and validation of species-specific suitability models. GIS, remote sensing, and predictive data-driven approaches could subsequently extend the present framework toward spatially explicit decision-support tools for sustainable medicinal plant cultivation and forest management.

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