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Sustainable Forest Resource Management Using IoT Sensor Network

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Sustainable forest management faces challenges owing to climate change and biodiversity loss, necessitating the adoption of advanced real-time monitoring technologies. In this study, we evaluated the performance of an IoT sensor network comprising 20 nodes deployed over 180 days across four forest types in Hebei Province, China. Following long-range wide-area network communication protocols, the system transmitted 86400 environmental observations, achieving a cumulative data completeness rate of 96% across the 180-day deployment period, demonstrating high technical resilience despite gradual battery depletion. Quantitative analysis results revealed substantial microclimatic variability among forest types: pine forests exhibited the highest mean temperature (28.71 ± 4.82 °C), eucalyptus forests recorded the highest mean humidity (67.23 ± 7.67%), and indigenous forests demonstrated superior soil moisture retention (13.64 ± 7.33%). Through the simultaneous assessment of technical performance, a mean daily battery depletion rate of 0.56–0.58% was determined and 521 detection events were identified in wildlife monitoring. By integrating environmental observations with deep-learning-based species recognition, such results provide an effective sensing framework for real-time sustainable forestry management. Technical performance assessments indicated a mean daily battery depletion rate of 0.56–0.58%, with power consumption significantly affected by environmental conditions. Wildlife monitoring yielded 521 detection events encompassing 2134 individual animals across six species, with an average identification confidence score of 0.849. The system's multimodal data framework, which integrates soil dielectric permittivity, semiconductor-based thermal sensing, and machine-learning-based species recognition, proved effective in supporting ecological surveillance. Overall, the IoT network offers a scalable digital infrastructure for proactive forest conservation.

1. Introduction

Forest ecosystems enable carbon sequestration, biodiversity conservation, and hydrological regulation, providing significant socioeconomic benefits. However, it is difficult to balance

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economic viability with environmental productivity when using conventional forest management systems.(1) Such methods require periodic manual surveys and satellite imagery analysis. While they are useful to some extent, the analysis of events and corresponding rapid decision-making in appropriate spatial and temporal resolutions is difficult with conventional management systems. Such a challenge is particularly evident for incidents that require immediate intervention, including pest infestations, illegal logging, and early-stage wildfires.(2)

However, IoT offers a transformative opportunity for effective and efficient forest management since it enables a robust real-time monitoring system across diverse forest landscapes.(3) In IoT systems, sensor networks, wireless connectivity, and advanced data analytics are essential to maintain forest health. Integrating IoT in the forest management system makes it possible to overcome the physical and logistical constraints inherent in manual forestry management and enable proactive management.

Specialized sensors are deployed to monitor environmental indicators for forest management, including soil moisture, ambient temperature, humidity, dendrometric growth rates, and wildlife movement (Fig. 1). IoT networks feed high-fidelity data to sustainable models for the timely formulation of forest conservation strategies.(4) Such a digital infrastructure enables the swift adjustment of management methods based on real-time environmental feedback rather than on past data. There has been a demand for data-driven solutions to maximize forest resource utilization without deteriorating ecological soundness. As climate change, deforestation, and the rising demand for forest products intensify, such data-driven forest management systems require the processing of massive amounts of data. Therefore, we designed a system that integrates IoT

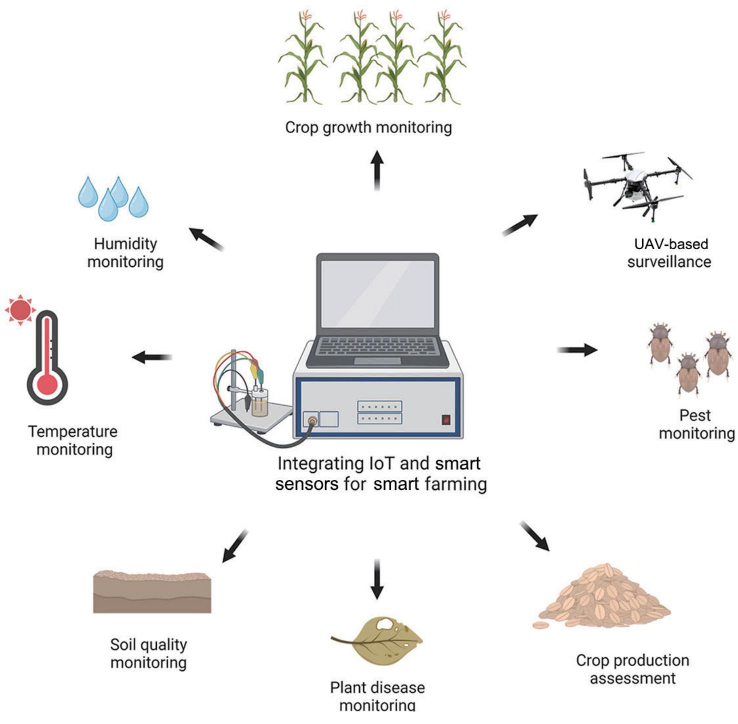

Fig. 1. (Color online) Sensors and devices used in forest management system.(4)

sensor networks into forest management systems to enhance the long-term sustainability of the forest. By analyzing architectures, data acquisition protocols, and analytical methodologies, we propose a smart forest management system to maintain ecosystem resilience.(4)

Since existing systems prioritize specific events, such as fire detection and illegal logging, the information from them is insufficient to identify the relationship between microclimatic stability and wildlife biodiversity. Therefore, it is necessary to develop a multimodal data integration framework for environmental monitoring and technical system sustainability.

The system developed in this study adopts a heterogeneous sensor array designed for long-term robustness in harsh forest environments. This aligns with recent innovations in forest monitoring techniques that emphasize data reliability over 180-day cycles. By adopting capacitive soil moisture sensors and DHT22 modules in different forest topographies from high-density pines to indigenous forests, the performance of sensing materials and IoT frameworks under various microclimatic stresses can be understood.(5) Through the integration of moisture, thermal profiles, and deep-learning-based wildlife detection, spatial information and a digital twin can also be obtained in forest environments.(6) In addition, the data on battery depletion rates across different canopy densities provide a reference for future energy-efficient sensor networks in forestry management.(7)

2. Background Knowledge

2.1 Forest management system

Forest resources have been managed using silvicultural techniques such as selective logging, prescribed burning, and rotation harvesting to sustain forest productivity. These traditional approaches' main purpose is to maintain forest inventories in the long term, during which foresters measure tree diameter at breast height, total height, and species composition within sample plots to characterize stand structure and composition.(8) Ground-based surveys are also conducted to quantify tree attributes and stand levels. However, these methods are labor-intensive and time-consuming, which restricts their spatial extent and temporal frequency.

To complement field inventory management, remote sensing technologies have been adopted using aerial photography and satellite imagery. Landsat and Moderate Resolution Imaging Spectroradiometer are widely used for the synoptic coverage and monitoring of deforestation and aboveground biomass from a regional to a global scale (Fig. 2).(9) However, satellite data are often constrained by coarse spatial resolution, atmospheric interference such as clouds, and limited ability to capture subcanopy conditions or fine-scale ecological processes. Light Detection and Ranging (LiDAR) enables the measurement of the vertical forest structure and canopy height, yet the adoption of LiDAR and the use of its high-resolution aerial imagery are costly, limiting their widespread application in remote or extensive forests.

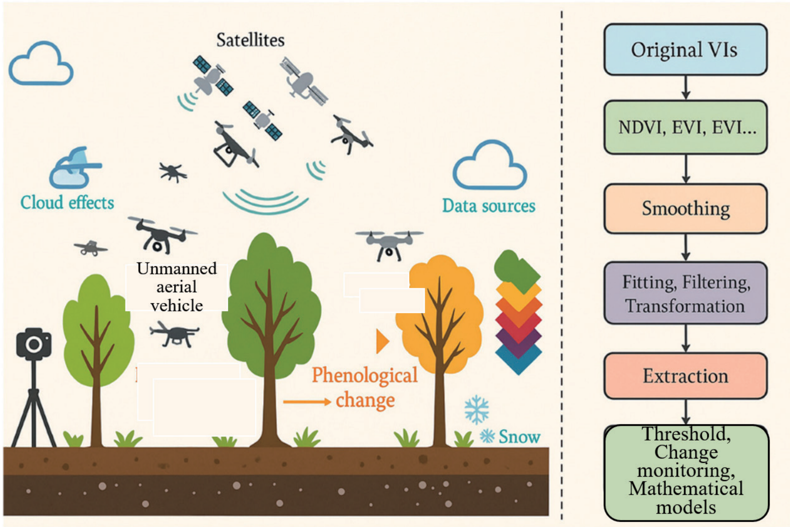

Fig. 2. (Color online) Forest monitoring system using satellite and unmmaned aerial vechicle imagery under environmental constraints.(10) (VI: vegetation index; NDVI: normalized difference vegetation index; EVI: enhanced vegetation index)

2.2 IoT in environmental monitoring

IoT represents a paradigm shift in environmental monitoring, since it utilizes distributed sensor networks to autonomously collect, transmit, and analyze data. An IoT system typically comprises sensing devices that record physical or chemical parameters, a communication infrastructure that relays data to centralized repositories, and a computing device that processes and visualizes information for end users.(11) IoT applications are widely used for precision agriculture, water quality management, air pollution monitoring, and wildlife conservation.(12) IoT networks are also deployed across diverse spatial scales, ranging from individual forest stands to entire watersheds, owing to their flexible scalability. Such flexibility is facilitated by the affordability of various sensors and lightweight open-source software platforms, and the ease of implementation to meet project-specific requirements.

IoT technologies provide forest monitoring systems with unprecedented advantages. The technologies enable continuous data acquisition for detecting rapid environmental changes, such as sudden increases in temperature and precipitation, and for monitoring fire and drought. The granularity of sensor networks enables the characterization of spatial heterogeneity at the microsite level, supporting the assessments of tree regeneration success, growth dynamics, and wildlife habitat quality.(13) Through real-time data transmission in the IoT network, the forest management system can immediately respond to sudden incidents, timely deploy fire suppression resources, adjust irrigation, and address illegal logging activities. By integrating diverse sensors, IoT networks provide a holistic view of the forest by continuously monitoring soil conditions, micro-weather, tree physiology, and ecological processes.

In using sensor data, noise reduction must be performed through statistical filtering and mathematical modeling. The most common approach is to compute the moving averages of time-series data using various filters.

$$\hat{x}_t = \frac{1}{n}\sum_{i=0}^{n-1} x_{t-1} \tag{1}$$

Here, $\hat{x}_t$ represents the filtered value at time t, x_{t-i} denotes individual sensor measurements, and n is the averaging window size. With the equation, measurement noise can be removed while preserving underlying trends in environmental parameters.

2.3 Sensor technology in forest management

Sensor technologies play a critical role in environmental monitoring and resource management. In agriculture, soil moisture sensors optimize irrigation schedules and manage water consumption to sustain crop yields. Air quality sensors are used to monitor particulate matter and gaseous pollutants to assess atmospheric conditions and guide public health interventions. In conservation, cameras and acoustic sensors integrated into IoT networks enable the monitoring of endangered species populations and the detection of poaching activities in protected areas.(14)

In forestry, diverse sensors are deployed to monitor ecosystem health and resource sustainability. Soil moisture sensors are used to quantify volumetric water content, an important indicator of drought stress, seedling establishment, and nutrient cycling, based on capacitance, resistance, or time-domain reflectometry. Temperature and humidity sensors characterize microclimatic conditions that affect tree physiology, pest dynamics, and fire risk. Temperature is measured with thermocouples or thermistors, whereas humidity is assessed using capacitive or resistive sensors. Field deployment requires an accuracy of approximately ±0.2 °C and a relative humidity of ±2%.

Soil moisture sensors are essential for forest monitoring and management, as water availability strongly affects tree growth, seedling survival, and nutrient transport. Capacitance-based sensors are used to measure soil dielectric permittivity, which varies with water content owing to the high dielectric constant of water relative to soil minerals and air.(15) These sensors employ paired electrodes to form a capacitor, with soil acting as the dielectric medium. The obtained electrical signals are proportional to volumetric water content, typically ranging from 0 to 50% in forest soils. Time-domain reflectometry sensors emit electromagnetic pulses into the soil, with travel time reflecting moisture content as water slows wave propagation.

Temperature and humidity sensors are critical for monitoring microclimate conditions that regulate forest ecosystem processes. Semiconductor-based digital temperature sensors have high accuracy (<0.1 °C) across the typical forest temperature range of −40 to +60 °C. Humidity sensors employ polymer films that absorb water vapor, altering capacitance in proportion to atmospheric humidity. Combined temperature–humidity sensors reduce deployment costs and enable co-located measurements, which are essential for calculating vapor pressure deficit, which is used as a predictor of plant water stress and evapotranspiration. These sensors are housed in weatherproof enclosures with radiation shields to prevent direct solar heating and precipitation interference, while allowing sufficient airflow for accurate measurements.

Wildlife surveillance sensors extend IoT applications by integrating ecological monitoring with technological platforms. Trail cameras combine passive infrared motion detectors with digital imaging systems to capture high-resolution photographs or video when animals enter the field of view. Modern devices feature no-glow infrared illumination for nocturnal monitoring, adjustable detection zones to reduce false triggers, and time-lapse functions to document site use over extended periods. In acoustic monitoring, directional microphones and digital signal processing are used to record animal vocalizations, with algorithms filtering background noise to isolate species-specific calls.(16) Global positioning system (GPS) collars and radio telemetry attached to large mammals transmit positional data via satellite or cellular networks, enabling the analyses of habitat use, home range size, migration routes, and behavioral responses to human disturbance.

IoT sensor networks are vital for fire management. Systems incorporating temperature, humidity, fuel moisture, and smoke particle sensors enable early fire detection, and their data are used in fire behavior modeling. The WIFIRE system in California integrates weather station data, satellite imagery, and distributed sensors to simulate fire propagation and optimize evacuation strategies.(17) Similarly, wildlife conservation programs employ sensor networks to assess habitat quality, such as soil moisture sensors to evaluate nesting sites of ground-dwelling birds and humidity sensors to characterize amphibian microhabitats in tropical forests.

Empirical studies highlight the benefits of IoT integration in forestry. In Norway, soil moisture, temperature, and tree sway sensors have been deployed to guide thinning practices and predict windthrow risk.(18) These data are used for minimizing soil compaction during harvest under wet conditions. In Brazil, IoT-based deforestation monitoring systems combine satellite imagery with acoustic sensors to detect chainsaw activity and track vehicles in logging hotspots.(19) This integrated approach reduces response times to illegal logging and enhances enforcement efficiency.

3. System Architecture

3.1 System components

The architecture of IoT systems for forest management comprises sensor nodes, gateway devices, network infrastructure, and cloud-based data management platforms. The sensor nodes were built in 20 deployment locations, adopting an ESP32-based long-range wide-area network (LoRaWAN)-enabled microcontroller. The technical specifications are summarized in Table 1.
Sensors are integrated with microcontrollers for local data acquisition, preliminary processing, and short-range wireless communication. Sensors are powered by batteries or energy-harvesting systems, necessitating low-power design to extend operational lifetimes to several years. Microcontrollers execute firmware to regulate sensor sampling rates, apply compression

Table 1
Specifications of sensors used in this study.

Parameter	Model	Manufacturer
Air temperature and humidity	DHT22 (AM2302)	Aosong Electronics, China
Soil moisture	SKU:SEN0193	DFRobot, China
Wildlife surveillance	OV2640 with PIR	AI-Thinker, OmniVision
Data transmission	SX1276	Semtech Corporation

algorithms to reduce transmission bandwidth, and manage sleep states to minimize energy consumption during idle periods.

Gateway devices serve as intermediaries between sensor nodes and the network and data management platform, aggregating and transmitting the data collected from sensors to servers through cellular, satellite, or long-range wireless communication. Gateway devices are responsible for data validation, time synchronization, and local storage to transmit information when connectivity is unavailable. In remote forest environments lacking cellular coverage, gateway devices store data for several days until periodic connectivity is restored or field personnel retrieve the information. Gateway device deployment must be carefully planned to balance communication range, terrain obstacles, and power availability.

The rate at which data is transmitted through an IoT network is estimated as

$$R_{total} = \sum_{i=1}^{N} \frac{S_i . f_i}{C} . \tag{2}$$

Here, R_{total} represents the aggregate data rate in bytes per second, N denotes the number of sensor types, S_i indicates the data size per measurement for sensor type i, f_i represents the sampling frequency in Hz, and C denotes the data compression ratio.

Effective deployment requires the consideration of spatial variability, access restrictions, and monitoring objectives. Grid-based arrangements are adopted to provide broad spatial coverage, useful for assessing average conditions and large-scale phenomena such as drought or temperature changes.(20) Stratified sampling designs are adopted to examine specific forest types or topographic features, improving reliability within management units and optimizing sensor allocation. The strategic deployment of sensors needs prioritized areas through surveys or predictive analytics: soil moisture sensors in drought-prone regions, camera traps along wildlife corridors, or monitoring stations near water sources.

3.2 Data transmission

Wireless communication in forest IoT systems must overcome challenges posed by dense vegetation, irregular terrain, and long transmission distances. The following technologies are commonly used in the system.

(1) LoRaWan

LoRaWAN is widely used in forestry owing to its extended range, up to 10 km in open areas and 2–5 km in the forest. Operating in unlicensed radio frequency bands [868 megahertz (MHz) in Europe, and 915 MHz in North America], LoRaWAN employs spread-spectrum modulation to enhance resistance to interference and multipath effects common in forested landscapes. Its low data rates [0.3–50 kilobytes per second (kbps)] are well suited for periodic sensor transmissions and contribute to extended battery life.

(2) Zigbee

Zigbee supports mesh networking over shorter ranges (10–100 m), enabling sensor nodes to relay data through multiple hops to reach a gateway. Its self-organizing topology provides redundancy and flexibility, automatically rerouting data around failed nodes or obstacles. Zigbee offers higher data rates (up to 250 kbps), enabling the transmission of larger packets such as compressed camera-trap images. However, multihop communication increases network complexity and power consumption compared with the star topology of LoRaWAN. Dense forest canopies and seasonal foliage variations significantly affect Zigbee link reliability, requiring careful network planning and periodic topology adjustments.

(3) Cellular IoT

Narrowband IoT and Long Term Evolution for machines leverage existing cellular infrastructure, eliminating the need for dedicated gateways. These technologies provide secure, encrypted communication and reliable backhaul to cloud platforms. However, limitations exist, including poor coverage in remote forests, higher power consumption, and recurring subscription costs. Consequently, cellular IoT is well suited for high-value monitoring applications or as supplementary connectivity for critical sensor hubs.

Given the diversity of sensors, sampling frequencies, and data formats, IoT systems require robust integration and management frameworks. Web-based applications enable scalable architectures for data storage and computational analysis while enforcing database structures that link measurements to location, time, and sensor type. Application programming interfaces (APIs) facilitate interoperability between IoT platforms and external systems, including forest management databases, meteorological services, and remote sensing repositories.(21) Datastream processing software is applied for quality-control filters to detect anomalies and generate alerts when measurements exceed predefined thresholds, enabling timely interventions in forest management.

4. Methods

In this study, we evaluated the performance and effectiveness of IoT sensor networks in enhancing forest management. The feasibility of the system was examined by integrating multiple sensors and identifying essential environmental parameters for assessing forest ecosystem health and productivity. Experimental plots were drawn across different forest types, terrain conditions, and management regimes. Control plots were drawn as baselines, enabling comparative analyses and supporting management and forecasting to identify areas requiring remediation through silvicultural treatments or assessing environmental health risks. Temporal replication was incorporated into the design, with multiyear monitoring periods capturing seasonal, inter-annual climatic, and long-term variations under forest conditions. Replication across multiple sites enhances the generalizability of findings beyond individual locations.

The performance of the IoT forest management system was evaluated in terms of sensor accuracy and precision, data completeness and continuity, communication reliability under adverse environmental conditions. In addition to this, the system's operational costs were compared with those of conventional management systems. Management effectiveness was assessed in terms of decision-making quality, the efficiency of resource allocation, and the sustainability of forest productivity, biodiversity conservation, and ecosystem service. Statistical analyses were conducted using regression models, time-series methods, and machine learning techniques to identify correlations between sensor data and forest responses to construct a predictive model of future forest status.

4.1 Study area

The IoT sensor network was deployed in Hebei Province, a region with strategic importance to China's forest management and ecological security. As the ecological barrier for the Beijing-Tianjin-Hebei urban cluster, Hebei hosts the world-renowned Saihanba reforestation project and serves as a cornerstone of the "Three-North Shelter Forest Program" (Great Green Wall). In this program, Hebei is regarded as a critical windbreak and sand-fixation zone, protecting northern cities from desertification and underscoring the province's role in national environmental policy. Hebei also shows its diverse topography, ranging from the Bashang Plateau to the Yanshan Mountains, and its forests' exposure to extreme seasonal fluctuations, high fire risks, and climate-induced moisture stress. These geographic characteristics of Hebei are appropriate for testing the robustness of IoT-based monitoring systems across various altitudes and microclimates. In the study area, four distinct zones, including pine plantations and indigenous forests, were chosen to capture canopy heterogeneity and biological diversity. This design enabled comparative analysis of LoRaWAN signal propagation and sensor data accuracy under different forest structures, ranging from dense plantations to sparse native covers.

4.2 Data collection

Sensors were deployed in selected sites, considering species composition, tree size distribution, canopy cover, understory vegetation, and soil properties. Topographic surveys were carried out using GPS and digital elevation models to determine elevation gradients, slope aspects, and terrain features that affect microclimates and hydrological processes. Sensor deployment strategies can be made on the basis of the obtained baseline data to capture spatial variability and ensure optimal installation and maintenance.

Soil moisture sensors were installed at multiple depths (15, 30, and 60 cm) to monitor vertical moisture distribution and root-zone availability. Installation protocols minimized soil disturbance, ensured close sensor–soil contact, and avoided proximity to tree stems to capture representative stand-level conditions. Temperature and humidity sensors were mounted at a height of 1.5 m above ground on posts or existing trees, housed in radiation shields that prevent solar heating while allowing adequate ventilation. Multiple sensors were used to capture microclimatic variability across canopy gaps, closed-canopy areas, and edge environments.

Wildlife surveillance cameras were installed along animal tracks, near water bodies, and in areas of high wildlife activity. Placement strategies were formulated to minimize false triggers from vegetation movement and reduce risks of tampering. Cameras were implemented, considering trigger sensitivity, resolution, burst mode, and delay intervals, which were standardized to balance data quality, storage capacity, and battery life. GPS collars were attached to selected wildlife species following institutional animal care protocols to balance fix frequency, trajectory resolution, and battery longevity.

The environmental data collected included a continuous time series of volumetric water content in soil, ambient temperature, relative humidity, active radiation for photosynthesis, and precipitation. Ecological data comprised wildlife presence and abundance from camera-trap imagery, movement paths from GPS telemetry, and phenological observations of leaf flush, flowering, and senescence based on photography. Additional periodic measurements were conducted for tree growth (diameter and height), seedling regeneration density and survival, and understory vegetation and litter composition. The integration of sensor data with conventional forest inventory measurements facilitated validation and enabled the analysis of correlations between environmental drivers and forest structural and compositional attributes.

4.3 Datastream

Research data were analyzed using a modular Python code within Jupyter notebooks (IPYNB format), designed for execution on cloud-based Jupyter environments to ensure scalability without requiring dedicated infrastructure. The code architecture was constructed following an object-oriented programming model, with each sensor represented by a class encompassing data acquisition, calibration, and filtering routines to meet quality standards. Base classes were established to provide common interfaces for data access, timekeeping, and exception handling, while derived classes implemented sensor-specific behaviors for different devices and protocols.

Data acquisition modules were interfaced with the IoT platform and APIs, retrieving information from cloud repositories using authentication and query parameters to specify time intervals, sensor identifiers, and geographic bounding boxes. Robustness was ensured through the retry logic and timeout handling to mitigate intermittent connectivity and API interruptions. Retrieved data underwent preprocessing to calibrate raw sensor data using manufacturer-provided coefficients or reference-probe calibration equations.

For quality control, algorithms were used to automatically detect sensor faults, communication errors, and implausible values. Ranges of the data were verified for the data and the physical limits of measurement. Temporal consistency was tested by comparing neighboring sensors to detect anomalies and identify abrupt changes or oscillations indicative of malfunction and spatial consistency. Flagged data were assigned new values to determine inclusion based on analytical requirements.

Preprocessed data were standardized to ensure interoperability across analytical workflows. Time-series data were stored and manipulated using pandas DataFrames, enabling efficient subsetting and aggregation by timestamp, location, and sensor type. The datasets were hosted on a secure cloud-based platform integrated with the Hebei provincial forest management infrastructure. Forest managers and government officials are utilizing the dataset on a web-based dashboard utilizing Geographic JavaScript Object Notation (GeoJSON) mapping. Authorized investigators are allowed to query Postgre Structured Query Language (PostgreSQL) (Postgres)/PostGIS (PostgreSQL Geographic Information System) and Humongous Database (MongoDB) databases through authenticated API calls.

Table 2 shows examples of the data export formats of comma-separated values, network common data form, and GeoJSON in tabular, gridded, and geospatial data structures. This integrated database supports secure, multiuser access through a tiered authentication system, enabling administrative users and forest rangers to monitor ecological conditions in real time, while researchers conduct complex queries and batch downloads through a representational state transfer API. Data exports included comma-separated values for tabular records, network common data form for gridded spatiotemporal datasets, and GeoJSON for web-based mapping. For long-term storage, database integration tools processed data in PostgreSQL (optionally with PostGIS for geospatial support) or MongoDB, enabling secure, multiuser access within operational forest management systems.

5. Results and Discussion

5.1 Environmental monitoring and sensor performance

The IoT sensor network was deployed in the Hebei forest region, China, to generate a dataset comprising 86400 time-stamped observations from 20 IoT nodes. Temporal replication was integrated into the system's architectural design to support multiyear monitoring. The data presented in this study were collected for a 180-day validation period between January and June 2024 (Fig. 3), to capture multiseasonal transitions and the resulting variations in microclimatic and biological conditions. This approach allows for the assessment of sensor stability and power management during the transition from extreme cold to peak vegetation periods.

Table 2
Examples of system data exports.

Data structure	Example
Comma-separated value	Timestamp, Node_ID, Temp_C, Humidity_pct, Soil_VWC_pct 2024-03-15 12:00:01, Node_04, 18.2, 54.3, 12.1

GeoJSON	{
	"type": "Feature",
	"geometry": {"type": "Point", "coordinates": [115.4, 40.2]},
	"properties": {"node_id": "Node_04", "status": "active", "temp": 18.2}
	}

Network common data form	Dimensions: time 86400, lat: 4, lon: 5 Variables: temperature (time, lat, lon), soil_moisture (time, lat, lon)

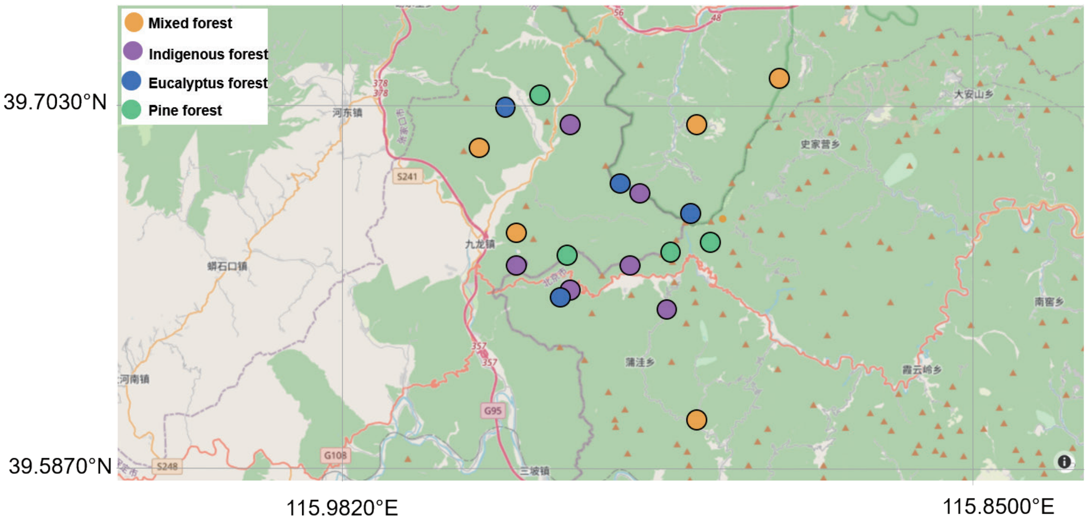

Fig. 3. (Color online) Distribution of IoT sensors in different forest types.

Such a data collection method led to high temporal resolution and broad spatial coverage across four forest types: mixed (pine, eucalyptus, and indigenous), pine, eucalyptus, and indigenous forests. The study area covers 800 ha. In the area, the indigenous forest accounts for the largest share, occupying 250 ha or 31.25% of the study site. Pine forest follows with 220 ha (27.5%). Mixed forest occupies 180 ha (22.5%), whereas eucalyptus forest occupies 150 ha (18.75%). Such a distribution highlights the ecological heterogeneity of the study region for evaluating IoT sensor performance across different forest types. The study area was selected to capture the ecological diversity of Hebei Province and for broader forest management policies in Northern China.

Data completeness was 96%, and the data were transmitted and stored in the cloud database. The 96% data completeness was the average for the 180-day observation data. To evaluate the impact of power levels on transmission reliability, we analyzed the loss rate in 30-day increments. Despite the battery charge decreasing from 100% to approximately 65–68% by Day 180, the data completeness remained stable, varying by only ±1.5% between Months 1 and 6. This indicated that the 0.56–0.58% daily battery depletion rate did not reach a critical threshold that would impair the LoRaWAN transceiver's performance. The majority of the 4% data gaps were attributed to temporary signal attenuation during peak precipitation events in the indigenous forest zone, rather than power-related node failures.

Temperature measurements revealed seasonal patterns consistent with the temperate continental climate of northern China. Daily temperatures ranged from approximately 10 °C in January to 28 °C during the summer. The mean temperature of all sensors was 26.82 °C, with a standard deviation (SD) of 5.19 °C, indicating moderate variability. Microclimatic differences among different forest types were statistically significant. Pine forests exhibited the highest mean temperature (28.71 ± 4.82 °C), owing to relatively open canopies and increased solar radiation. In contrast, eucalyptus forests recorded the lowest mean temperature (25.64 ± 5.19 °C), attributed to denser canopy structures and elevated evapotranspiration rates. Mixed and indigenous forests showed intermediate temperatures (26.64 ± 5.39 and 26.54 ± 5.00 °C, respectively) (Table 3).

Seasonal humidity patterns followed atmospheric dynamics, showing an inverse relationship with temperature. The average relative humidity across the forests was 60.87%, with significant diurnal and seasonal fluctuations. The minimum values of humidity reached 30% during hot, dry afternoons, whereas the maximum values approached 87.6% during cooler mornings and precipitation periods. Forest type affected humidity levels: eucalyptus forests maintained the highest mean humidity (67.23 ± 7.67%), followed by indigenous (60.78 ± 11.33%), pine (59.36 ± 10.23%), and mixed forests (57.71 ± 10.70%) (Table 1). These differences reflect variations in canopy density, understory development, and transpiration dynamics. A significant negative correlation ($r = -0.453$) was observed between temperature and relative humidity (Fig. 4), consistent with atmospheric principles. As air temperature increases, its capacity to hold moisture rises, resulting in lower relative humidity under constant moisture conditions.

Soil moisture levels varied notably among forest types, reflecting differences in canopy structure, root system development, and organic matter accumulation. Indigenous forests

Table 3
Environmental parameters collected from sensors.

Forest type	Parameter	Mean ± standard deviation (SD)	Minimum value	Maximum value	Median	Covariance (%)	*N*
Mixed (pine + eucalyptus + indigeneous)	Temperature (°C)	26.64 ± 5.39	10.9	38.73	26.86	20.22	25920
Mixed	Humidity (%)	57.71 ± 10.70	30	82.21	59.8	18.54	25920
Mixed	Soil moisture (%)	12.43 ± 5.56	10	45	10	44.71	25920
Pine	Temperature (°C)	28.71 ± 4.82	14.76	39.36	28.69	16.77	17280
Pine	Humidity (%)	59.36 ± 10.23	38.13	84.61	58.01	17.24	17280
Pine	Soil moisture (%)	13.09 ± 6.33	10	45	10	48.38	17280
Eucalyptus	Temperature (°C)	25.64 ± 5.19	9.62	37.12	25.77	20.24	17280
Eucalyptus	Humidity (%)	67.23 ± 7.67	44.56	86.54	69.05	11.41	17280
Eucalyptus	Soil moisture (%)	13.87 ± 7.33	10	45	10	52.89	17280
Indigenous	Temperature (°C)	26.54 ± 5.00	11.01	38.53	26.57	18.83	25920
Indigenous	Humidity (%)	60.78 ± 11.33	36.84	87.56	57.9	18.64	25920
Indigenous	Soil moisture (%)	13.64 ± 7.33	10	45	10	53.72	25920

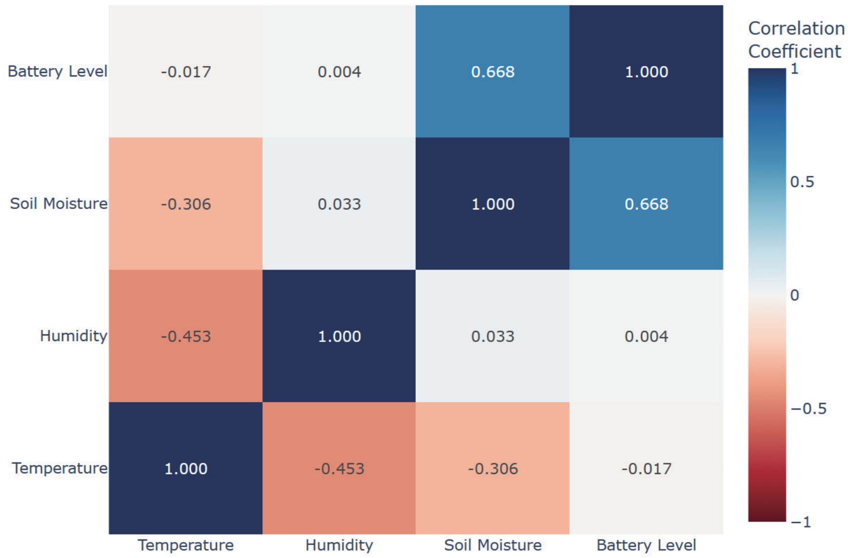

Fig. 4. (Color online) Correlation matrix of parameters.

exhibited the highest average soil moisture (13.64 ± 7.33%), suggesting superior water retention capacity, likely supported by mature root systems and higher soil organic content. Eucalyptus and pine forests followed with mean values of 13.87 ± 7.33 and 13.09 ± 6.33%, respectively. Mixed forests recorded the lowest average soil moisture (12.43 ± 5.56%), which may be attributed to their younger successional status, reduced root biomass, and limited organic matter input (Table 3).

The correlation matrix (Fig. 4) revealed meaningful relationships among environmental and operational variables. Temperature exhibited a moderate negative correlation with humidity (r = –0.453) and soil moisture (r = –0.306), consistent with the following principle: as air temperature increases, its moisture-holding capacity rises, resulting in lower relative humidity and reduced soil moisture retention. Humidity and soil moisture showed a weak positive correlation (r = 0.033), suggesting limited interaction under the observed conditions. The battery level was strongly correlated with soil moisture (r = 0.668), indicating that sensor performance is affected by moisture, owing to soil conductivity effects or power draw variations in wet environments.

Wildlife surveillance results yielded 521 detection events encompassing 2134 individual animals across six taxonomic categories, offering a quantitative assessment of biodiversity and habitat utilization. Monkeys were the most frequently detected species, with 156 observations accounting for 29.9% of total detections, indicating their high activity and abundance in monitored areas. Birds represented the second most observed group with 214 detections. However, the aggregated classification includes multiple species, necessitating further refinement of an identification algorithm. Antelopes were detected 136 times and were confined to habitats at the forest edge. Larger-bodied species such as buffalo (27 detections), leopard (40 detections), and elephant (18 detections) exhibited lower detection frequencies, consistent with their naturally lower population densities and extensive home ranges, which require broader spatial monitoring coverage.

A machine learning model predicted tree growth based on environmental parameters. The model prediction showed an R^2 value of 0.172 on the test dataset, indicating that 17.2% of the variance in dendrometric growth rates was explained by temperature, humidity, and soil moisture data obtained from the IoT sensor network (Fig. 5). The explanatory power is limited owing to the multifactorial nature of tree growth, largely affected by genetic variation, nutrient availability, interspecies competition, and pest pressures. The model's root mean square error for dendrometric growth rate was 0.570 mm/year, suggesting that forecasted growth rates fall within approximately ±1.14 mm/year (two standard errors).

5.2 Energy efficiency

The implementation of IoT sensor networks in forest management demonstrated substantial potential for energy optimization and enhanced operational sustainability. In the Hebei forest management, energy efficiency was evaluated across multiple forestry operations, considering sensor power management and logistical optimization. The deployment of 20 IoT sensors across the different forest types showed certain energy consumption patterns and information for improving sustainable practices.

Battery performance monitoring is important for energy efficiency evaluation. The results indicated that sensor power consumption varied according to environmental conditions and data transmission frequency. The mean daily battery depletion rate was determined to be 0.56% in pine forests and 0.58% in mixed forests. The higher rate observed in mixed forests is attributed to increased data transmission, which is necessary for greater environmental heterogeneity. Several sensors' batteries were discharged completely during the monitoring period, which highlights the necessity of robust power management protocols (Fig. 6).

In the 180-day deployment of the system developed, the residual battery levels highlighted a divide in node longevity. Of the 20 nodes, 12 nodes (60%) depleted their power reserves, stopping transmission once the battery reached the critical shutdown threshold. Only 8 nodes

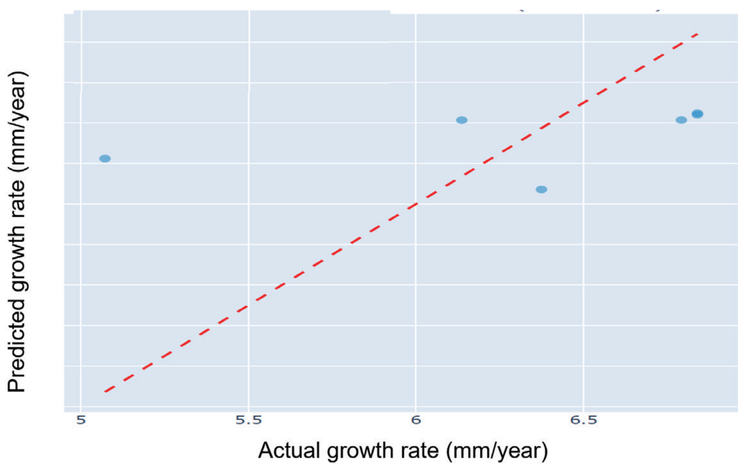

Fig. 5. (Color online) Predicted (red dotted line) and measured (blue dot) growth rates.

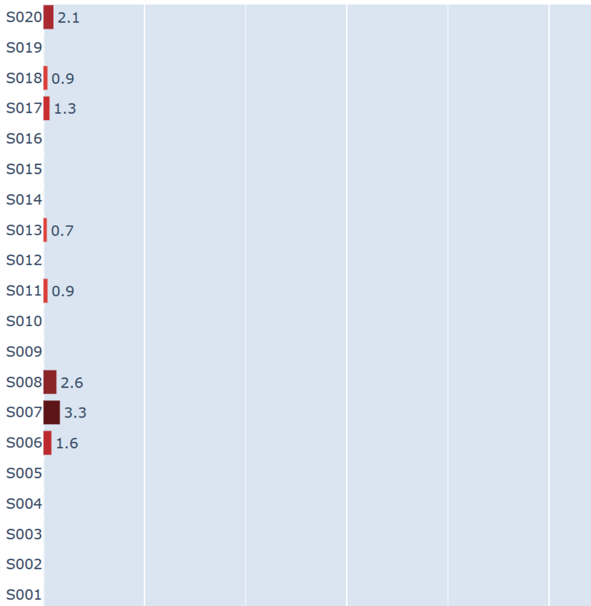

Fig. 6. (Color online) Residual battery current levels recorded across sensors (%) (numbers on the left axis are depolyed sensor numbers).

remained operational, with residual battery levels ranging from 0.7 to 3.3%. The validity of the final readings was cross-referenced with the physical limits of the battery's discharge profile to ensure data integrity during the end-of-life phase. These differences suggest site-specific effects on power consumption, potentially linked to microclimatic conditions and operational workload. The energy consumption data can be used for the optimization of forest management logistics. Real-time sensor feedback enables the adjustment of vehicle routing and equipment deployment schedules. Harvest operations can be scheduled using soil moisture data to reduce fuel consumption by heavy machinery, resulting in an estimated 1.5-fold decrease compared with conventional calendar-based scheduling. Temperature and humidity monitoring facilitate precise forest management and minimize the need for manual interventions and associated resource expenditure.

5.3 Wildlife monitoring

IoT-based camera traps and acoustic sensors were deployed in the forests to monitor wildlife activity to explore biodiversity and habitat utilization. During the study period, the traps and sensors recorded 521 wildlife detection events encompassing 2134 individual animals across six species. The result was used for developing conservation strategies and analyzing species distribution, activity cycles, and habitat preferences.

The species detected varied significantly across forest types, with implications for conservation. Monkeys exhibited the highest detection rate, with 156 detections concentrated in mixed and indigenous forests. This pattern reflects the structural connectivity of these forest types, which facilitates movement between feeding sites. Birds accounted for 214 detections, with peak activity observed during early morning (06:00–09:00) and late afternoon (16:00–18:00), consistent with foraging times. Antelopes totaled 136 detections, predominantly at the edges of pine forests, where the visibility of predators is enhanced while proximity to dense cover is maintained.

The reliability of automated species identification algorithms in the IoT system was evaluated using average confidence scores. These scores were used to quantify the model's certainty in correctly identifying a species and calculated by averaging the confidence values assigned to each detection within a category. Mathematically, the average confidence score C_{avg} for a species was computed as

$$C_{avg} = \frac{1}{n}\sum_{i=1}^{n} c_i \,. \tag{3}$$

Here, c_i is the confidence score for the ith detection and n is the total number of detections for that species.

Across all wildlife detections, the overall average confidence score was 0.849, indicating the high reliability of the classification model. Species-specific confidence scores varied, reflecting differences in morphological distinctiveness and image quality. Larger species such as buffalo and elephant achieved higher average confidence scores of 0.852 and 0.847, respectively, owing to their distinguishable features. In contrast, birds showed a lower score of 0.840, owing to their smaller size and greater morphological variability, which complicates automated recognition. Figure 7 presents confidence scores and their relative detection frequencies. Monkeys were most often detected with an average confidence score of 0.846. Antelopes scored 0.843, while leopards

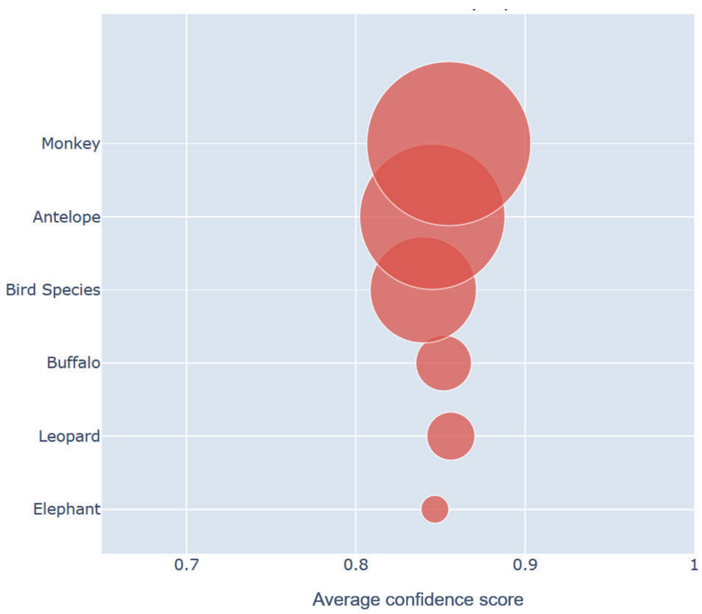

Fig. 7. (Color online) Detected species in forests.

and buffaloes scored 0.850 and 0.852, respectively. Elephants, though least frequent, maintained a high confidence score of 0.847. These results underscore the effectiveness of the machine learning model in distinguishing species with various body sizes and ecological behaviors.

5.4 Implication to sensor technology

While the data were collected for 180 days, the high data completeness (96%) and low battery depletion rates (0.56–0.58%/day) validate the system's readiness for the intended multiyear deployment. Similar pilot-phase validations are essential for calibrating sensor networks before large-scale longitudinal expansion, as shown in recent spatial information for forest management. The results of this study underscore the effectiveness of distributed IoT sensor networks in capturing high-fidelity environmental data. The observed 96% data completeness across 86400 observations confirms that low-power, long-range protocols such as LoRaWAN are viable for dense forest environments. The significant microclimatic differences found, such as the indigenous forest's superior soil moisture retention (13.64 ± 7.33%) compared with mixed forests (12.43 ± 5.56%), highlight how sensor granularity enables precise site-specific management.

The results of this study contribute to the development of sensor technology that enables the integration of multimodal data, soil dielectric permittivity, microweather patterns, and wildlife movement. For similar research, sensors with energy autonomy, edge intelligence, and environmental ruggedness need to be developed. Then, the sensors can be equipped with (1) advanced energy-harvesting ability to extend the operational lifetime of microcontrollers beyond current battery constraints, (2) sophisticated data compression and anomaly detection algorithms directly on the sensor node to reduce transmission bandwidth, and (3) enhanced housing and radiation shields to withstand the extreme conditions (–40 to +60 °C) and humidity fluctuations found in continental climates. These technological advancements enable more effective forest management by providing more data to respond instantly to early-stage wildfires or illegal logging.

6. Conclusion

An IoT sensor network system for sustainable forest management was developed in this study, presenting high data reliability across diverse ecological zones. The integration of the IoT sensor network advances forest management, overcoming the limitations of manual surveys. The integrated approach enables microclimatic monitoring with wildlife detection and technical performance analysis, offering an efficient tool for forest health compared with single-metric systems.

We validated the deployment of 20 IoT nodes for 180 days, demonstrating that LoRaWAN-based digital infrastructures achieved high reliability in dense forest environments, with a data completeness rate of 96%. The system provides ecological baselines, showing that indigenous forests maintained a higher soil moisture level (13.64%) than mixed forests (12.43%). Operational efficiency was confirmed through real-time battery monitoring, which recorded residual levels as high as 3.3% in certain nodes, and through high-accuracy wildlife classification, with an average confidence score of 0.849. Quantitative results regarding soil moisture retention and species-specific detection events validate the system's effectiveness as a decision-support tool.

Sensor technology in an object-oriented data framework needs to be employed in forest management to integrate heterogeneous data streams, such as volumetric water content and infrared imaging. A strong correlation between battery and soil moisture levels (r = 0.668) indicates the importance of future developments in adaptive power management and edge intelligence. IoT-based monitoring also reduces energy consumption in forestry. The results of this study provide technical and financial justification for scaling digital sensor networks to forest ecosystems. Such advancements are essential for the development of smart forest management, enabling rapid responses to wildfires, illegal logging, and long-term impacts of climate change. Future sensor developments can be made on the basis of the results to create more resilient materials for long-term environmental sensing, particularly for smart cities and ubiquitous networking in remote natural resource management.

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