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Article

Internet of Things to network smart devices for ecosystem monitoring

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ABSTRACT

Smart, real-time, low-cost, and distributed ecosystem monitoring is essential for understanding and managing rapidly changing ecosystems. However, new techniques in the big data era have rarely been introduced into operational ecosystem monitoring, particularly for fragile ecosystems in remote areas. We introduce the Internet of Things (IoT) techniques to establish a prototype ecosystem monitoring system by developing innovative smart devices and using IoT technologies for ecosystem monitoring in isolated environments. The developed smart devices include four categories: large-scale and nonintrusive instruments to measure evapotranspiration and soil moisture, *in situ* observing systems for CO_2 and $\delta^{13}C$ associated with soil respiration, portable and distributed devices for monitoring vegetation variables, and Bi-CMOS cameras and pressure trigger sensors for terrestrial vertebrate monitoring. These new devices outperform conventional devices and are connected to each other via wireless communication networks. The breakthroughs in the ecosystem monitoring IoT include new data loggers and long-distance wireless sensor network technology that supports the rapid transmission of data from devices to wireless networks. The applicability of this ecosystem monitoring IoT is verified in three fragile ecosystems, including a karst rocky desertification area, the National Park for Amur Tigers, and the oasis-desert ecotone in China. By integrating these devices and technologies with an ecosystem monitoring information system, a seamless data acquisition, transmission, processing, and application IoT is created. The establishment of this ecosystem monitoring IoT will serve as a new paradigm for ecosystem monitoring and therefore provide a platform for ecosystem management and decision making in the era of big data.

1. Introduction

Ecosystem monitoring can be defined as a time series of measurements of key variables in the biosphere and is designed to detect variability in ecosystem dynamics and ultimately answer questions regarding biospheric changes. These measurements may encompass monitoring at a variety of spatial and temporal scales; multimedia approaches; and physical, chemical and biological indicators of ecological and environmental changes. Scientists and managers of natural resources readily acknowledge the importance of ecosystem monitoring for improving the understanding and management of complicated ecological systems [1]. An array of national and international programs are currently being

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conducted for the establishment of environmental monitoring networks, which include regional monitoring networks, such as the Global Environmental Monitoring System (GEMS; http://gemstat.org/) and Global Terrestrial Observing System (GTOS; http://www.fao.org/gtos/), and national monitoring networks, such as the U.S. National Ecological Observatory Network (NEON; www.nsf.gov/bio/neon/start.htm), the Terrestrial Ecosystem Research Network of Australia (TERN; http://www.tern.org.au/), and the Chinese Ecosystem Research Network (CERN; http://www.cern.ac.cn/0index/index.asp). At local and river basin scales, some monitoring networks have also been established, such as the German network of terrestrial environmental observatories (TERENO) [2], the Chinese Forest Biodiversity Network (CForBio) [3] and the Heihe Watershed Allied Telemetry Experimental Research (HiWATER) [4]. These programs have developed comprehensive design principles for monitoring networks and have collected basic monitoring data to evaluate ecosystem changes.

Driven by the advancement of smart devices and rapid development of the Internet of Things (IoT), ecosystem monitoring has entered a new paradigm: monitoring the ecosystem based on the IoT. The advancement of embedded microprocessors and wireless communication has led to the development of smart devices for field-based and *in situ* environmental monitoring. A variety of smart devices have replaced traditional monitoring approaches based on discrete or manual sampling methods, providing real-time, continuously analyzed, wirelessly transmitted data [5,6]. The low-cost, low-power, small-size, and distributed sensing technology in smart devices has simplified the proliferation of wireless sensor networks (WSNs) in ecosystem monitoring [7]. WSNs have been successfully used to observe diverse ecological variables and processes, e.g., the leaf area index (LAI) [8], soil moisture [9], microclimate variables [10], and ecohydrological process [11–13], by providing measurements at multiple spatial and temporal scales. WSNs offer a substantial foundation for ecosystem monitoring based on the IoT, in which networks and embedded monitoring devices can provide ecological information regardless of user location. Several efforts have been made to achieve ecosystem monitoring via the IoT, from the construction of a theoretical framework [14–17] to practical applications in both natural [18] and urban ecosystems [19]. However, there are still some challenges that need to be addressed for the evolution of WSNs towards the IoT.

The first challenge for achieving ecosystem monitoring via the IoT is to integrate heterogeneous WSNs into the Internet based on standard communication protocols, enabling smart devices to participate in the IoT. Several technical advancements are needed, such as energy efficient communication, the remote control of sensor nodes and devices, interoperability between different modules and different smart devices, scalability of the WSN, and fault tolerance to guarantee robust communication. The second challenge is the efficient management of massive monitoring data sets. Environmental monitoring data have been considered "big data" because of the enormous amounts of data generated by real-time monitoring. Big data, which are characterized by their large volume, rapid collection and variety, is associated with many challenges, such as difficulties in data transmission, storage, analysis, and visualization [20]. Several information systems have been employed to monitor, model, and manage environmental processes. The current trend is to develop an integrated environmental information system that includes databases, software and tools for data extraction and transformation, loading platforms for online data analysis, and application software for services. The third challenge is to design an effective ecosystem monitoring network that will provide the scientific information needed for ecosystem management and decision-making processes. The synchronous monitoring of air, water, soil, and biota variables could provide a comprehensive understanding of ecosystem change. Furthermore, it is important to establish a monitoring system that optimally integrates remote sensing observations, *in situ* measurements, and model simulations [21,22]. Multicompartmental and multiscale monitoring systems will play an important role in improving the efficiency of ecosystem monitoring and management.

To address the abovementioned challenges, we initialized an effort to develop smart devices and IoT techniques for ecosystem monitoring. The scientific objectives of this effort are as follows.

(1) Develop innovative smart devices for monitoring key air, water, soil, and biota variables that have high measurement accuracy compared to that of conventional devices. The smart devices will be able to obtain network access via wireless communication modules.
(2) Establish an ecosystem monitoring IoT that integrates automatic data acquisition and transmission, quality control, real-time data sharing, and online data visualization and analysis.
(3) Test, verify and demonstrate the applicability of the ecosystem monitoring IoT in three typical fragile ecosystems for ecosystem monitoring and management.

The initiative includes three steps (Fig. 1): developing the smart ecosystem monitoring devices, networking the devices and integrating them with the information system using the IoT, and testing the applicability of the ecosystem monitoring IoT in a variety of typical ecosystems across China. The development and demonstration of the ecosystem monitoring IoT will provide a new paradigm for ecosystem monitoring and management in the era of big data.

2. Development of ecosystem monitoring devices

2.1. Devices for energy and water flux monitoring

The multiscale and synchronous monitoring of energy and water fluxes and soil moisture is performed by combining the devices used to monitor a single plant, community, or ecosystem for monitoring at the landscape scale (Table 1 and Fig. 2).

2.1.1. Two-wavelength (near-infrared and microwave) scintillometer system

The two-wavelength (near-infrared and microwave) method is a promising way to acquire kilometer-scale water vapor and heat flux data [23]. We have developed a two-wavelength scintillometer system. The near-infrared scintillometer is used to measure the sensible heat flux at wavelengths of 850–880 nm, which are sensitive to temperature-induced fluctuations [24,25]. The microwave scintillometer is used to measure the latent heat flux (evapotranspiration) at a wavelength of 3 mm (94 GHz), which is sensitive to both humidity fluctuations and correlated temperature-humidity fluctuations and avoids the water vapor absorption band, thereby limiting interference with the measurements. The two-wavelength scintillometer can measure the water vapor and heat fluxes over a large scale (0.5–5 km) and has broad application prospects, especially in areas with heterogeneous land surfaces (Fig. S1 online).

2.1.2. Sap flow gauge

Sap flow measurements are commonly used to determine the transpiration rates of individual plants under field conditions [26]. We overcome the following bottlenecks related to the design of sap flow gauges. (1) We optimize species-specific (e.g., ring- and diffuse-porous trees) coefficients in the thermal dissipation (TD)

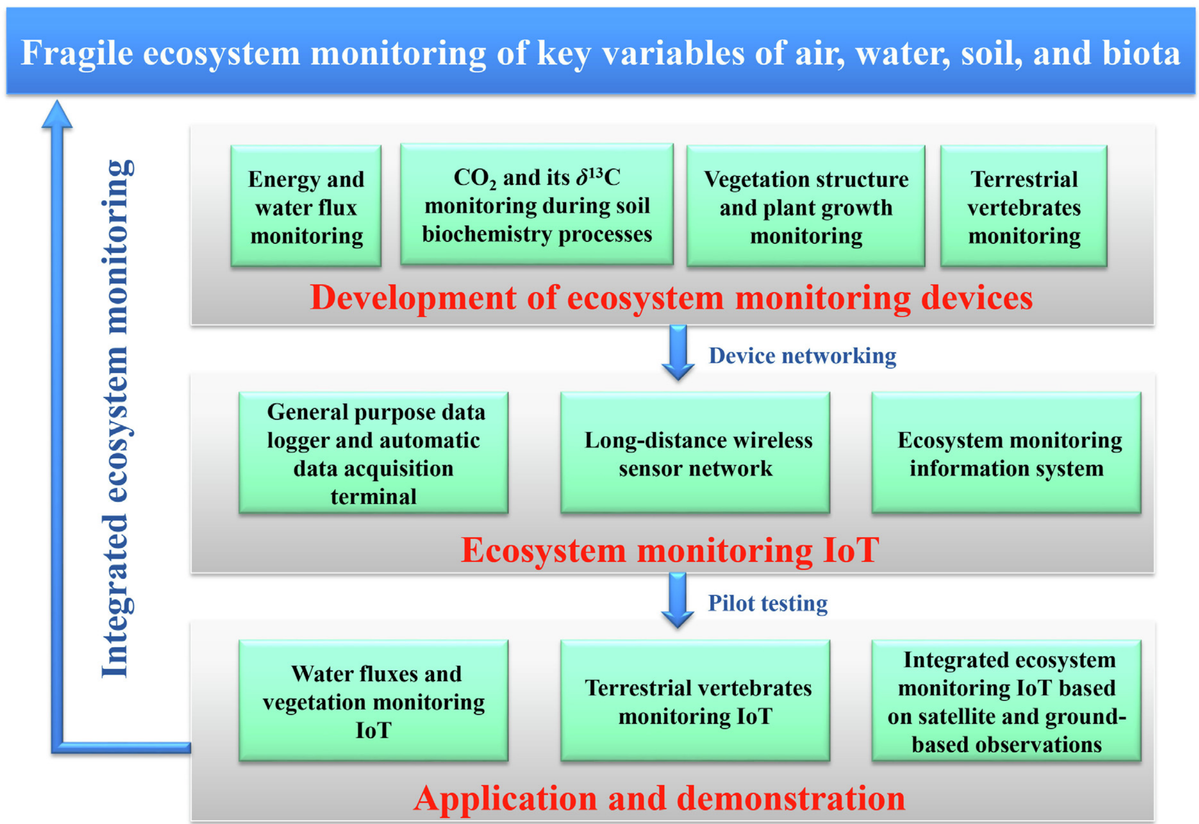

Fig. 1. (Color online) Overall architecture for the innovative development of smart devices and IoT techniques for ecosystem monitoring.

method based on Granier's empirical formula [27] by measuring the sap flow in trees with different vascular bundle structures and validate these values for 9 afforestation tree species using the live weight method (Fig. S2 online, shows the validation for the tree species *Platycladus orientalis*). (2) We develop sensor needles equipped with several thermocouples at different depths based on heat pulse methods, which allow for the assessment of radial sap flow profiles and hydraulic redistribution and reduce both thermal damage and power consumption. We develop a sensor based on heat balance methods by testing the heat balance properties of different plant types (e.g., trees, shrubs and agricultural crop species). The new sensors can be connected via a wireless network to improve the practicability of their use in field experiments.

2.1.3. Nonintrusive portable soil moisture meter

Frequency domain reflectometry (FDR), which makes use of the dielectric property of the soil, has become widely accepted for measurements of the soil moisture content at the point scale [28,29]. The current commercially available FDR sensors are difficult to install in compacted layers or soil with rocks. We develop a portable FDR sensor that sits atop the test soil layer instead of utilizing inserted probes to provide nonintrusive rapid moisture measurements. Moreover, we improve the calibration model to measure the soil moisture content of a layer at depths of 0–20 cm (target to 40 cm) and integrate data collection, control, and inspection systems into the device. The portable soil moisture meter combines high-precision microdata loggers and memory, global positioning system (GPS) cells, and adjustable wireless transmission and control modules.

2.1.4. Mesoscale soil moisture measurement system

The cosmic-ray method, which is based on the measurement of cosmic-ray neutrons above the land surface, can be used to evaluate the area-averaged soil moisture at the intermediate scale of meters to kilometers [30]. This method is now being routinely implemented in the Cosmic-ray Soil Moisture Observing System (COSMOS). We improve the precision of the cosmic-ray soil moisture sensor by measuring the cosmic-ray neutron intensity with a proportional counter filled with ^{3}He (Fig. S3 online). This method allows for the measurement of the average soil moisture over a horizontal footprint of 700 m. Furthermore, information for environmental factors such as the wind speed and direction, air temperature and humidity, air pressure, rainfall amount, solar radiation, soil temperature and moisture, and soil electrical conductivity is also collected by the data logger to measure additional eco-environment-associated elements.

2.2. Devices for carbon dioxide and δ^{13}C monitoring during soil biochemistry processes

Soil respiration is one of the largest and most important carbon fluxes in terrestrial ecosystems. Continuous *in situ* measurements of atmospheric CO_2 and the corresponding δ^{13}C are now possible due to the development of isotope ratio infrared spectroscopy (IRIS) technology [31–33], which provides a new opportunity for monitoring the generation and delivery of CO_2 during soil biochemistry processes in both field and laboratory conditions.

We developed a comprehensive observation system for measuring the isotope composition of carbon dioxide during soil biochem-

Table 1
Description of the technical parameters of the devices and the details of demonstration[a)].

Device	Device technical parameters	Cost comparison with mainstream devices	Demonstration sites	Data comparison with mainstream devices or approaches
Devices for energy and water flux monitoring				
Two-wavelength scintillometer system	Near-infrared wavelength, 880 nm. Microwave transmitter frequency 20–180 GHz. Path length, 1–5 km. C_T^2,$10^{-17}-10^{-12}$ $m^{-2/3}$. C_q^2, $10^{-14}-10^{-9}$ $m^{-2/3}$. Sensible heat fluxes, −100–800 W/m^2. Latent heat fluxes, 0–1,000 mm.	BLS450, Scintec AG, German (−30%)	HRB sites	Fig. S1 online
Sap flow gauge	Heat pulse methods. Sensor needle length, 30–50 mm; 80–100 mm. Sensor needle diameter, 1.8–2.1 mm. Resolution, 35 μV. Power consumption, 0.05–0.1 W. Operating environment, −20–40 °C	FLGS-TDP, Dynamax, USA (–60%)	HRB sites and KRD sites	Fig. S2 online
Nonintrusive portable soil moisture meter	Measurement range, 0–40 cm. Measurement accuracy, ±5%. Frequency, 100–500 MHz Settling time, < 1 min. Operating environment, −40–85 °C	Innovatively developed device	HRB sites	/
Mesoscale soil moisture measuring system	Footprint, 700 m. Power consumption, 40 mA@12 V Measurement accuracy, ±5%. Sampling interval, 1 min.	CRS-1000/B, Hydroinnova, USA (–20%)	HRB sites	Fig. S3 online
Devices for carbon dioxide and $\delta^{13}C$ monitoring during soil biochemistry processes				
Multichannel and dual-cycle observation system for soil CO_2 and $\delta^{13}C$ fluxes at the soil-atmosphere interface	Measurement accuracy of CO_2, 0.5 μmol m^{-2} s^{-1}@10 μmol m^{-2} s^{-1} (CO_2). Measurement accuracy of $\delta^{13}C$, 1‰@10 μmol m^{-2} s^{-1} (CO_2).	LI-8150, LI-COR, USA (–30%)	HRB sites	Fig. S4 online
Synergetic profile observation system of the CO_2 and $\delta^{13}C$ gradients in the soil and atmosphere	Measurement range of CO_2, 300–80,000 ppmv. Measurement accuracy of CO_2, >1%. Measurement accuracy of $\delta^{13}C$, >0.3‰.	LI-8150, LI-COR, USA (–20%––30%)	HRB sites	Fig. S5 online
Multichannel measurement system for soil microbial CO_2 and $\delta^{13}C$ fluxes	Temperature control range, −5–35 °C. Temperature ramping rate, 1 °C/1–2 min. Temperature control accuracy, ±0.5 °C. Measurement accuracy of CO_2, >1%. Measurement accuracy of $\delta^{13}C$, >0.3‰.	Innovatively developed device	Used in the laboratory	Fig. S6 online
Devices for vegetation structure and plant growth monitoring				
CanoMIS	Pixel, 1,024 × 1,024. Horizontal resolution, μm-scale. Range resolution, mm-scale. The three-dimensional frame frequency, 10 Hz.	Leica ScanStation C10, Leica Geosysytem, Germany (–30%)	HRB sites	Fig. S7 online
Distributed LAI meter	Measurement accuracy, ±0.4 m^2/m^2	LAI-2200C, LI-COR, USA (–60%)	HRB sites and KRD sites	Fig. S8 online
Recording meter for tree diameter at breast height	Measurement range, >10 mm. Measurement accuracy, <10 μm. Resolution, <5 μm. Data record interval, 1 min to 1 h, adjustable. Automatically save and transfer data.	/	HRB sites and KRD sites	Fig. S9 online
Nondestructive wood density analyzer for standing trees	Measurement range, 0.40–0.80 g/cm^3. Measurement accuracy, ±0.05 g/cm^3. Measurement rate, 20 tree/h.	Innovatively developed device	HRB sites	Fig. S10 online
Plant phenology recording system	Spectral waveband, 400–1,000 μm. Image record interval, 1 min to 1 h, adjustable. Automatically save and transfer images.	Netcam SC RGB, (–50%)	HRB sites and KRD sites	Fig. S11 online
Devices for terrestrial vertebrate monitoring				
Bi-CMOS infrared stereo camera	Frame frequency, 20 Hz. Field of view, >30°. Measurement accuracy, cm-scale.	Innovatively developed device	TLON sites	Fig. S12 online

(*continued on next page*)

Table 1 (*continued*)

Device	Device technical parameters	Cost comparison with mainstream devices	Demonstration sites	Data comparison with mainstream devices or approaches
Pressure-plate triggering devices for monitoring small vertebrates	Detection rate of animal, >90%. Classification precision, >80%. Response time, <1 s.	Innovatively developed device	TLON sites	–

a) (−*n*%) in the column of "cost comparison with mainstream devices" represents an *n*% decrease in cost. HRB sites, Heihe river basin sites. KRD sites, karst rocky desertification sites. TLON sites, the long-term Tiger Leopard Observation Network sites.

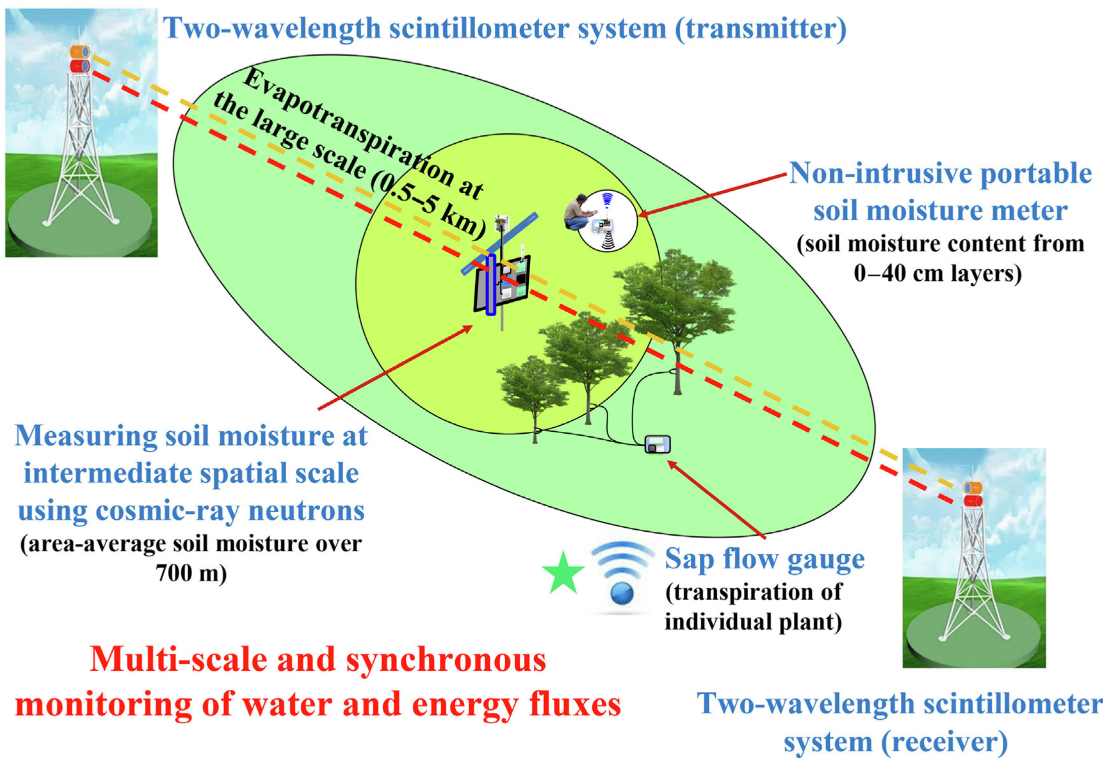

Fig. 2. Devices for the multi-scale and synchronous monitoring of water and energy fluxes, including a sap flow gauge non-intrusive portable soil moisture meter and a two-wavelength scintillometer system.

istry processes (Table 1 and Fig. 3). This observation system is composed of three devices. The first device is an *in situ* multichannel and dual-cycle observation system for soil CO_2 and $\delta^{13}C$ fluxes at the soil-atmosphere interface. The second device is an *in situ* synergetic profile observation system for monitoring the CO_2 and $\delta^{13}C$ gradients in the soil and atmosphere, and this device can directly measure the vertical generation and delivery of CO_2 and $\delta^{13}C$. The third device is a multichannel measurement system for monitoring soil microbial CO_2 and $\delta^{13}C$ fluxes that can automatically control and change the temperature, and this device can directly measure the CO_2 and $\delta^{13}C$ fluxes during the decomposition of soil organic matter at simulated temperature variations in the laboratory. Each device includes analysis, sampling, control, and calibration modules, and the third device also includes a temperature control module. The precisions of the CO_2 and its $\delta^{13}C$ measurements are better than 1% and 0.3‰, respectively. Some key scientific and technical problems are solved as follows.

2.2.1. Calibration module for the IRIS analyzer

The dependence of $\delta^{13}C$ measurements on CO_2 concentrations and instrument temporal drift are two important factors that restrict IRIS applications [34,35]. Accordingly, we focus on the development of the components of an online calibration system for the nonlinear response of instruments in both field and laboratory conditions under high and low greenhouse gas concentrations. To combat the concentration-dependent and temporal shifts in the analytical instrument, we develop an online calibration system for the nonlinear response of the instrument under different concentrations to ensure the precision and accuracy of the instrument (Figs. S4 and S5 online).

2.2.2. Sampling module for high-efficiency circulation

We focus on the development of the key components for the high-efficiency circulation of measured CO_2 and $\delta^{13}C$ based on a multichannel and dual-cycle observation design. By controlling the circuit switch, the instrument can automatically switch between and collect circular observations from multiple channels. By controlling the premixing of gas in the channel while waiting to collect an observation, the instrument can decrease the observation time required for every channel and increase the efficiency and frequency of observation collection. By premixing the gas in the channel to be monitored, the instrument can eliminate the "dead gas" disturbances in the observation results and improve the accuracy of the observations.

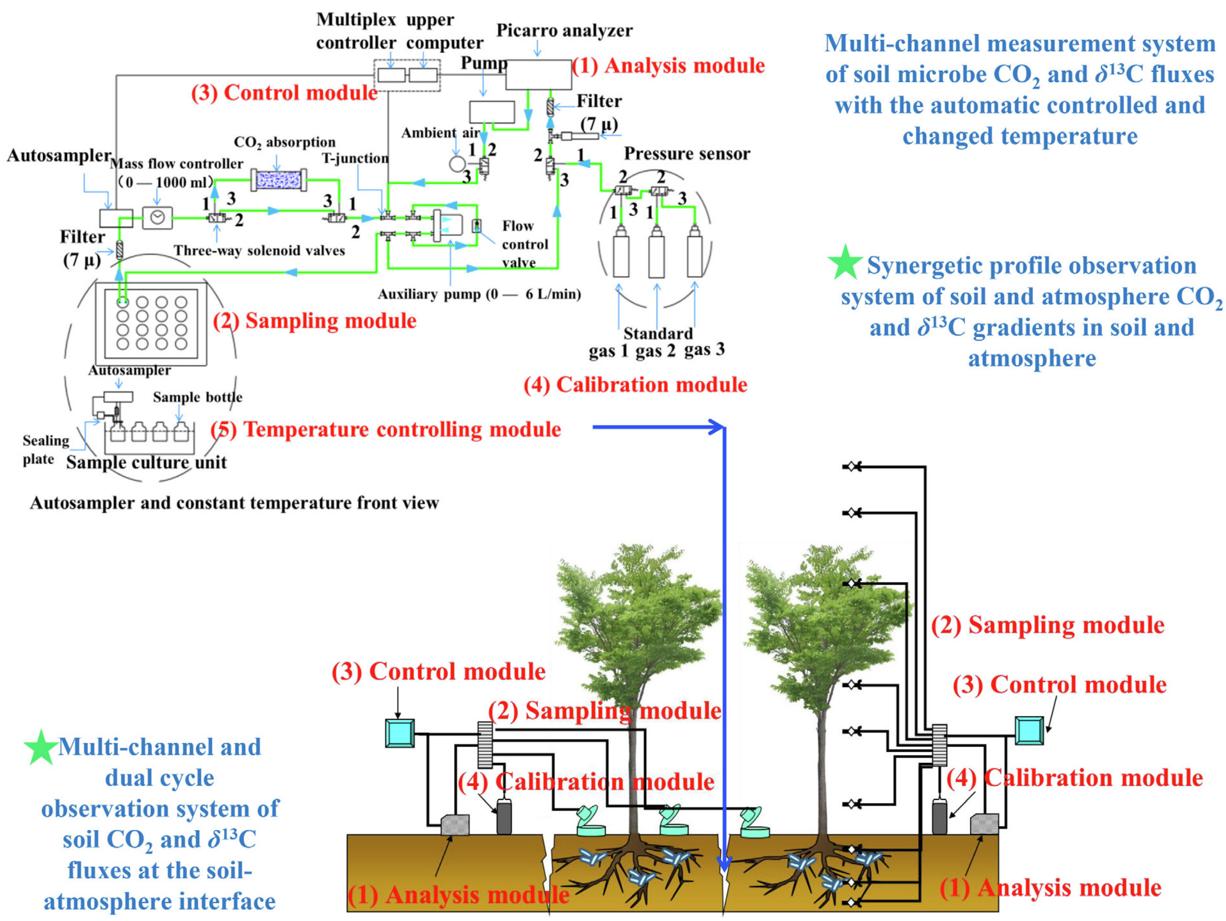

Fig. 3. Devices for monitoring the generation and delivery of CO_2 and $\delta^{13}C$ during soil biochemistry processes in both field and laboratory conditions.

2.2.3. Sampling module for the prereduction of high CO_2 concentrations

We develop key gas circuit components for the prereduction of CO_2 and $\delta^{13}C$ concentrations that are suitable for field and laboratory experiments. To overcome the large variations in greenhouse gas concentrations between the atmosphere and soil and the high greenhouse gas concentration in the soil, we use a typical CO_2 absorbent or zero gas in the bypass system to decrease the CO_2 concentration in the gas circuit. Additionally, the instrument can eliminate the effect of a "dead gas" disturbance on the observation results and improve the accuracy of the observations.

2.2.4. Temperature control module for automatic temperature adjustments

We develop a fully automatic temperature control and measurement system that can simulate the freeze–thaw process. The instrument can adjust the temperature in a culture flask under established procedures and meet the experimental requirements of simulating complex processes during the decomposition of soil organic matter (Fig. S6 online).

2.3. Devices for vegetation structure and plant growth monitoring

Vegetation structure and plant growth are key indicators that can provide information on the health of terrestrial ecosystems. We develop five devices to comprehensively observe the key parameters of the vegetation structure and ecosystem productivity (Table 1 and Fig. 4).

2.3.1. Three-dimensional canopy microstructure imaging system

Light detection and ranging (LiDAR) imaging techniques have recently been used to detect the canopy structure and subcanopy topography. However, the spatial resolution of LiDAR is still limited to mm-scale canopy microstructure measurements. Herein, we design a three-dimensional (3D) range-intensity correlation method from gate images with triangular range-intensity profiles and thus develop a 3D canopy microstructure imaging system (CanoMIS) to collect high-resolution 3D images for mm-scale microstructure measurements. We develop key technologies, including algorithms for nanosecond time synchronization control, image enhancement, and leaf feature size measurement (Fig. S7 online).

2.3.2. Distributed LAI meter

LAI measurements with traditional methods face challenges associated with the large spatial areas and high-frequency temporal scales in remote sensing and ecological applications. Thus, we develop an application called "LAISmart", which can be deployed on a smartphone and used to calculate the LAI (here, it is referred to as effective LAI because the leaf clumping effect is not taken in consideration) by classifying images captured using smartphone camera sensors. By integrating captured images and real-time computing, "LAISmart" provides an automatic measurement method that is comparable to the traditional digital hemispherical photography method. Additionally, we construct a "LAINet" on the basis of the wireless sensor network. The foundation of LAINet is that it senses canopy transmittance at several sun zenith angles

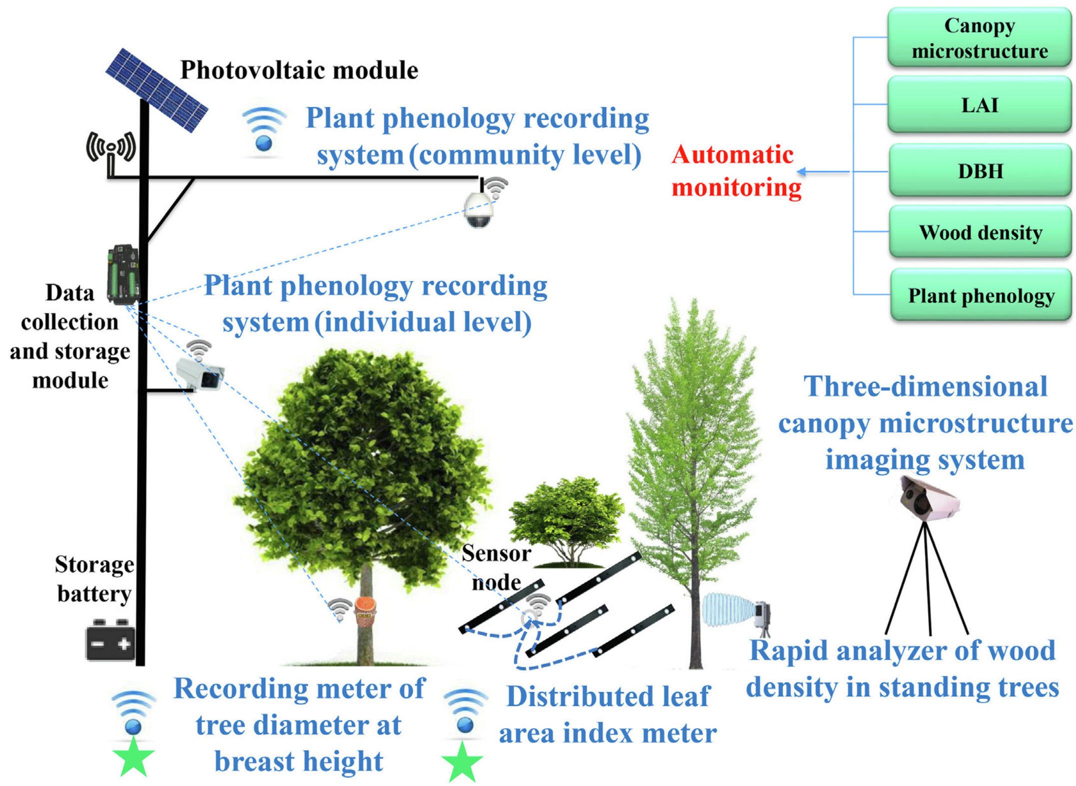

Fig. 4. Devices for monitoring the vegetation structure, LAI, tree diameter at breast height, wood density, and plant phenology.

throughout a day using a linear optical sensor array, and the transmittance data are transformed into canopy LAI data according to the Beer-Lambert law. The sensors are deployed in distributed mode, which means that they have the potential to measure LAI over a large scale via simultaneously networking distributed nodes. The LAINet facilitates the validation of satellite LAI products and decreases both labor and time requirements (Fig. S8 online).

2.3.3. Meter for recording the tree diameter at breast height

The tree diameter at breast height (DBH) can reflect tree growth dynamics and be used to estimate forest productivity. We develop a DBH recording meter that can automatically record DBH at high frequencies and high precision in the field by designing a high-precision displacement sensor and temperature compensation algorithm (Fig. S9 online). We also integrate wireless transmission modules in the meter and construct a "DBHNet" to send real-time DBH data from all trees in a forest plot to a remote server. With the developed software, tree growth dynamics can be evaluated online in real time through remote computers or smartphones.

2.3.4. Nondestructive wood density analyzer for standing trees

Wood density is a critical wood property. The microwave technique, which is a nondestructive evaluation method, provides a tool for the real-time continuous characterization of wood density by measuring the dielectric properties. We develop an analyzer for the online determination of wood density in standing trees by integrating a microwave transmitter, receiver, signal processor and analysis software. The ability to predict the wood density in standing trees using a microwave signal transmitted through wood is investigated. Amplitude and phase shift measurements are related to moisture content and density values through polynomial models. The analysis software and model parameter database are built by modeling the relationship between the wood density and the corresponding microwave signal characteristics. The analyzer is fast enough for online measurements and portable enough for measurements of wood density in living trees (Fig. S10 online). The multivariate characteristics of the signal are used to precisely deduce the density of a measured object. We can continuously update the model parameter library by sharing a database of measurement densities for different tree species.

2.3.5. Plant phenology recording system

Plant phenology is a very important parameter that can reflect the cylce of plant growth considering climate variations. Visible-light digital cameras can be effectively used to investigate plant phenology [36]. We developed an observation system based on digital cameras to detect and monitor plant phenology. The system can automatically capture digital photographs at a fixed frequency (e.g., twice per day) and transmit the photographs to the remote server via integrated cameras, wireless transmission modules and control software. Wireless sensors are integrated into this system to monitor the dynamics of environmental factors, and a multi-channel data logger is developed independently to simultaneously collect numeric data. Additionally, mathematic algorithms and spectral analysis techniques are developed to detect key plant phenology events and implanted into the system as software (Fig. S11 online).

2.4. Devices for terrestrial vertebrate monitoring

Monitoring endangered vertebrates is important for animal protection [37]. Solutions for vertebrate monitoring already exist [38,39]; however, they have drawbacks, such as specialized monitoring for certain animal species, discontinuous data acquisition, and difficulty in quantifying observation data. We designed an improved animal monitoring sensor system and software for sensor node control, communication and data acquisition (Table 1 and Fig. 5).

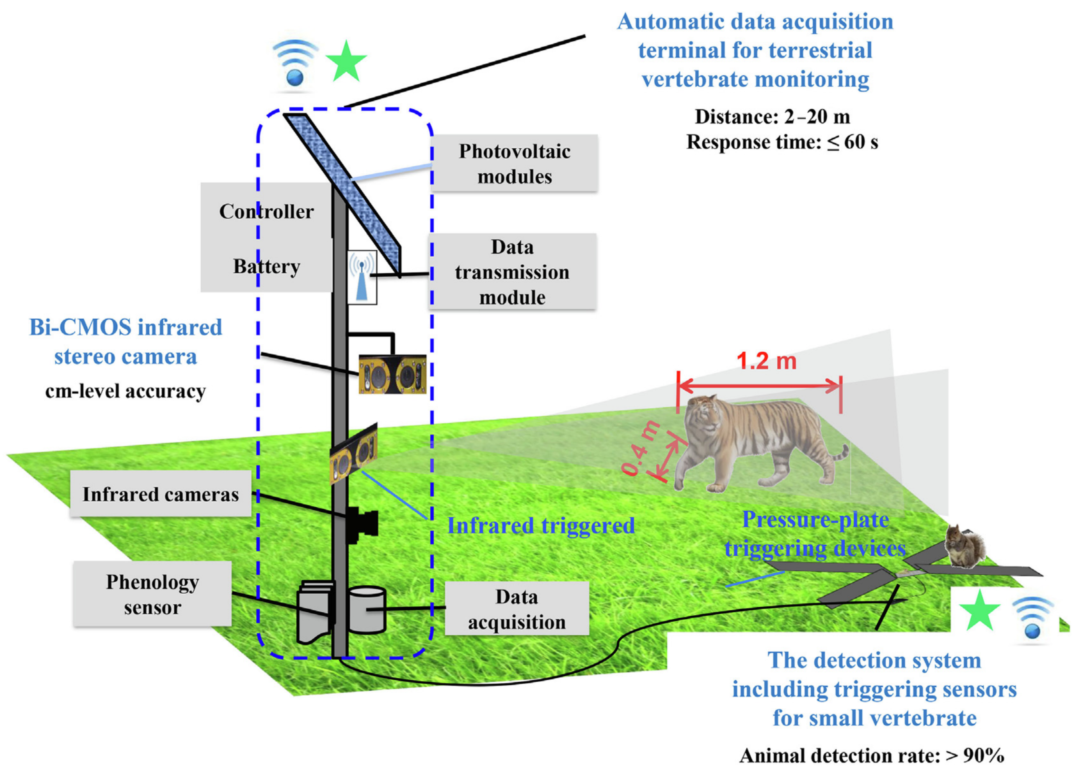

Fig. 5. Networking the devices for monitoring terrestrial vertebrates using Bi-CMOS infrared stereo cameras and pressure-plate triggering devices.

2.4.1. Bi-CMOS infrared stereo camera

A motion-sensitive infrared stereo camera provides a visual sensor to record the presence of animal species, and this camera provides location-specific information on the movement, behavior and spatiotemporal dynamics of animal activity [40]. We promote the development of a Bi-CMOS camera by improving multiple factors. (1) The inversion algorithm for the size of wildlife based on binocular stereo matching is improved to obtain target disparity maps of two pictures captured by the Bi-CMOS camera. Then, the three-dimensional spatial information and size information of the target are obtained. (2) The image matching and correction algorithm for binocular stereo vision operates under a complex background and uses the human–machine interaction feature matching method to obtain the disparities in image parts of interest. Thus, the improved method can effectively handle complex environmental disturbances. (3) Night lighting and image enhancement technology, large-field-of-view array homogenization light sources and high-power light sources that drive the circuits are developed to meet nighttime lighting requirements. A lower–upper-threshold correlation self-adaptive enhancement method is used to constrain the backgrounds and enhance the details of the targets. (4) The PC display and information processing technology are improved (Fig. S12 online), and (5) infrared trigger and timing control technology are enhanced. When the infrared detector detects animal information, the CMOS and light source are simultaneously triggered to acquire a snapshot of the target. With the Bi-CMOS camera, we can achieve all-weather wild animal detection and feature size measurements, providing quantitative data for individual identification and age, health, and other analyses of animals.

2.4.2. Pressure-plate triggering devices for monitoring small vertebrates

The infrared trigger is not applicable for the monitoring of small vertebrates, especially cold-blooded animals such as amphibians and reptiles. The infrared trigger is prone to false trigger errors or failure to photograph a target animal. Thus, we develop pressure-plate triggering devices to monitor small vertebrates by acquiring the orientation and reference distances of the sensor array and integrating multimodality information and signal processing. The system consists of modular units and central workstation unit modules; each pressure module contains a hub and several flexible pressure sensors; the workstation consists of a control module, integrated sensors, a power supply and information transfer; all modular units are placed around a central workstation; and the system unit is deployed along the paths and locations of animal activity to monitor small vertebrates.

3. Ecosystem monitoring IoT

3.1. Architecture of the ecosystem monitoring IoT

The ecological monitoring IoT establishes a high-density and intelligent remote real-time monitoring system through a variety of technical measures. In addition to providing high-density, intelligent, remote, real-time monitoring of various ecological environment elements, the intelligent diagnosis and efficient maintenance of the monitoring system status, automatic quality control of real-time massive monitoring data, data warehousing, and online analysis and processing can also be achieved.

The architecture of the ecosystem monitoring IoT contains three layers: the perception layer, the network layer, and the application layer (Fig. 6). The perception layer is responsible for the perception and acquisition of various ecological monitoring data. The network layer is responsible for the remote transmission of acquiring data from the perception layer, mainly through a variety of wireless transmission methods. The application layer includes an intelligent assistant monitoring cloud platform, which is responsible for the storage of monitoring data, quality control, and system status monitoring and control.

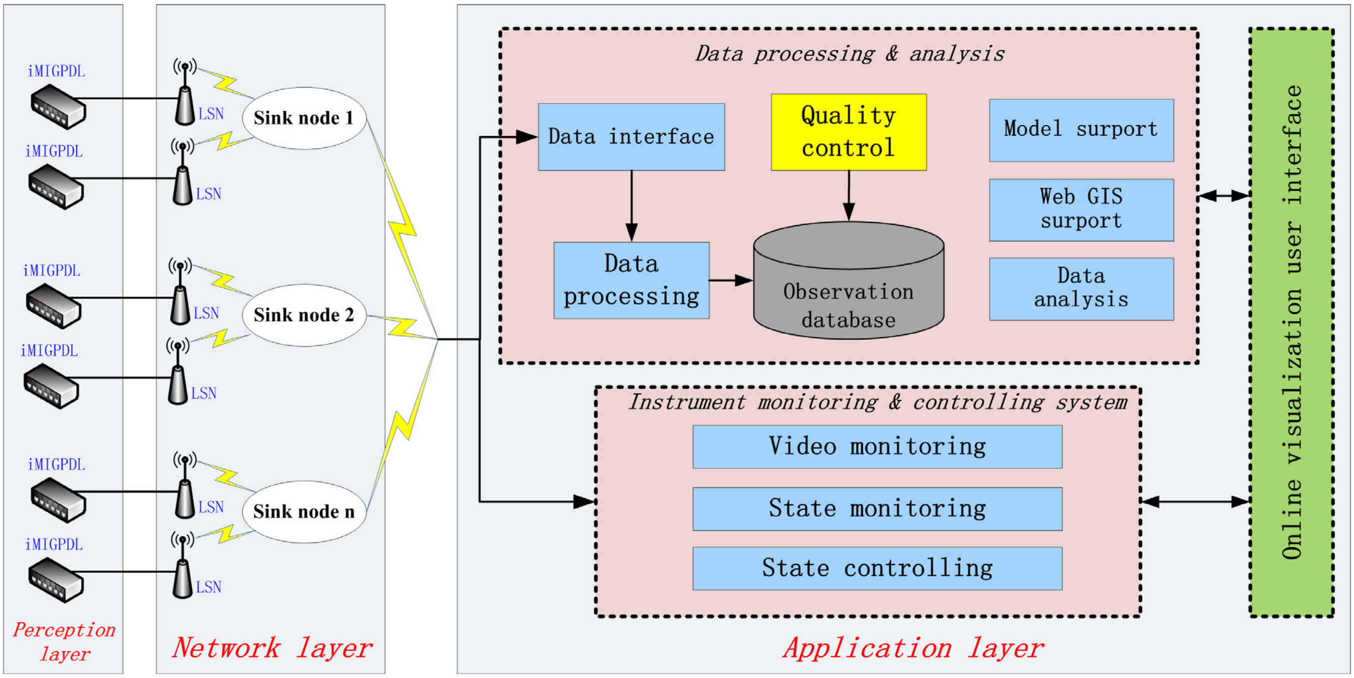

Fig. 6. Overall architecture of ecosystem monitoring IoT.

3.2. Technological breakthroughs for monitoring IoT applications

The implementation of ecosystem monitoring IoT is still restricted by data and information transmission in both the perception and network layers. In the perception layer, high-performance data loggers compatible with various sensors are rarely available to support effective IoT applications. Currently, data logger manufacturers do not provide open hardware access protocols, which has led to great difficulties in observation data integration as well as device state monitoring. Therefore, we developed a multi-interface general-purpose data logger (iMIGPDL) that supports flexible access to different hardware. In the network layer, it is difficult to establish data communication in remote areas without communication service. Thus, we developed wireless networking and relaying devices to fulfill the need for data transmission in such environments.

3.2.1. iMIGPDL – A smart data acquisition terminal

The perception layer connects the sensors and observation instruments via a data logger. Therefore, in this layer, we mainly focus on the technological development of a type of general-purpose data logger (Fig. S13 online).

The data logger is not only responsible for data collection but also for connecting the relevant sensors and observation instruments with various network technologies. Through the built-in computing capability of the data recorder and support to meet the requirements of the observation equipment, observation nodes become intelligent observation nodes to support the application requirements of the IoT.

The iMIGPDL has a maximum of 32 analog input channels and 8 pulse input channels. The maximum sampling rate of an analog channel is 100 Hz, and the A/D resolution is 24 bits. A channel can be used to measure the current, voltage, resistance and temperature. A pulse channel can be used for automatic trigger control or frequency measurements. The maximum operating frequency is 100 kHz. The maximum internal storage capacity is 512 MB, and the maximum external storage capacity is 16 GB.

The iMIGPDL also supports rich communication interfaces. The device can communicate and transmit data with external devices through Wi-Fi, Zigbee, BlueTooth, GPRS, RS232, RS485, USB, IPv4, IPv6, FTP and other protocol interfaces. At the same time, the iMIGPDL also supports the function of online calculations involving flux data.

Based on the characteristics of the monitoring IoT, we can not only obtain the real-time working status of the monitoring nodes remotely but also realize the remote control and adjustment of the working status of the monitoring nodes in the field through the relevant function in the iMIGPDL.

In terms of the hardware cost, the iMIGPDL is composed of relatively low-cost, high-performance components, and the cost is 50% lower than that of similar existing data loggers.

3.2.2. Long-distance wireless sensor network (LSN)

To meet the demand for data transmission in areas lacking commercial communication networks, we have developed a wireless networking and transmission scheme based on LSN technology, including low-power and long-distance terminal equipment, relay equipment, and related built-in software.

The end device is capable of providing interfaces with different sensors, gathering sensory information, communicating with other connected nodes in the network and transmitting information to the relay at a distance. The end device is based on a LoRa Chip SX1301 that allows the user to send data and reach extremely long ranges (12 km) at low data rates (<500 kbps). The connection mode between sensor nodes and wireless terminal devices is star topology. Wireless relays can be connected by multiple hops to extend the transmission distance.

The LSN relay receives information about sensory terminals and makes a connection between the sensor network and the Internet through the edge routers of the Ethernet/3G/4G/customized IP link.

3.3. Ecosystem monitoring information system

The application layer is the top level of the information system, including automatic data collection and normalization, data storage and management, data sharing, data analysis, and other application functions (Fig. 6). We have developed an ecosystem monitoring information system to fulfill the task. We are especially concerned with database management technology (e.g., the building of distributed monitoring databases, integration of heterogeneous data, automatic data warehousing, and automatic data quality control), online data visualization, data sharing, and statistical analysis of the monitoring data.

We used Greenplum (https://en.wikipedia.org/wiki/Greenplum), a type of MPP (massively parallel processing) database architecture, and the PostgreSQL (https://www.postgresql.org/) database management system to construct a high-performance distributed database, which can provide excellent response for large-scale queries at the level of hundreds of millions of data records. The integration of heterogeneous data was realized through a Python language-based data processing workflow, including automatic data collection, parsing and warehousing. This system shows flexible scalability and can cooperate with various ecological monitoring sensors and data collection devices. Moreover, a data quality control module was developed to ensure data quality and compliance. Multisource heterogeneous data can be automatically stored in the database after being normalized.

The application framework based on the B/S architecture (Fig. 6) and the design of a user interface based on the Web (Fig. S14 online) can provide users with effective and flexible ways to operate and access monitoring data. Users can also query and browse the observation data and download needed data through the user interface. This framework also allows real-time monitoring and remote control of field devices. For example, users can acquire and adjust their working status (system clock, sampling frequency, and other status) and network connectivity status.

4. Application and demonstration of the ecosystem monitoring IoT

The application and demonstration phase is implemented to test the performance of these new devices in real-time data collection, transmission, and management based on the IoT. We select three typical fragile ecosystems as field testing and demonstration sites, including a karst rocky desertification area in Southwest China, a rare and endangered wild vertebrate reserve—the National Park for Amur Tigers—in Northeast China, and a transition area of desert and oasis in Northwest China (Fig. 7).

The first demonstration platform is composed of three typical karst rocky desertification (KRD) sites in Southwest China, including a karst peak cluster depression in the Chenqi watershed [41], a karst plateau at Mulun, and a karst trough valley in the Qingmuguan watershed. The second demonstration area is located in the National Park for Amur Tigers and Amur Leopards [42]. The long-term Tiger Leopard Observation Network (TLON) established by Beijing Normal University [43], located in the northern portion of the Changbai Mountains in Jilin Province (Fig. 8a), China, provides a solid foundation for the demonstration of vertebrate monitoring devices. The third demonstration platform is established on the foundation of ecohydrological experiments in the Heihe River Basin (HRB), China [4]. The river basin, the second largest inland river basin in China, is represented by the mountain cryosphere in the mountainous area and the oasis-desert ecotone in the mid- and downstream areas [44].

Devices used to measure water and heat fluxes, vegetation variables, and soil respiration were installed at the demonstration sites for field testing and data comparison (Table 1). At the HRB sites, several LSNs have been established. In particular, a sap flow gauge, LAI meters, and DBH meters integrated with a developed LSN end device and relay are used to construct SapflowNet, LAINet, and DBHNet, respectively. The devices producing large amounts of data, such as the two-wavelength scintillometer system, COSMOS, carbon dioxide and δ^{13}C monitoring system and plant phenology recording system, transmit real-time monitoring data to data servers over the 3G/4G network. At the TLON sites (Fig. 8a), the Bi-CMOS camera and pressure-plate triggering devices, which are accompanied by automatic data acquisition terminals, are installed to form camera traps to monitor large cats (Fig. 8b) and small vertebrates. The data acquisition terminal has a multisensor synchronization trigger and control technology and can ensure continuous power supply for real-time monitoring data transmission. TLON has established a comparatively complete wired and wireless hybrid data transmission network based on the radio and television fiber network in China and network relays installed on local forest fire towers (Fig. 8c). A terrestrial vertebrate monitoring IoT

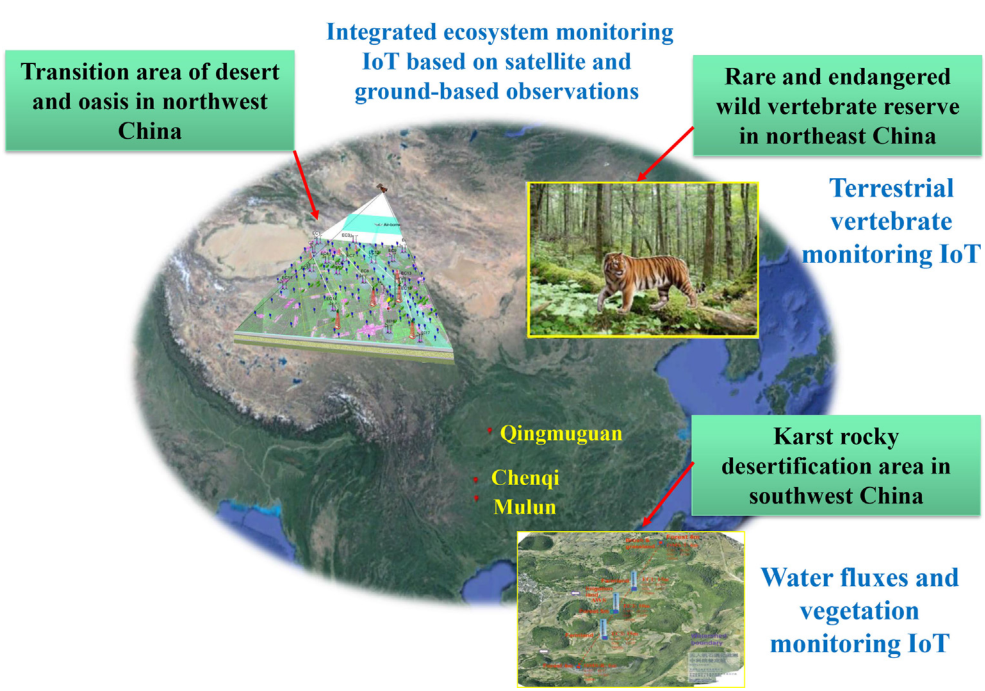

Fig. 7. Application and demonstration of the ecosystem monitoring IoT in three typical fragile ecosystems in China.

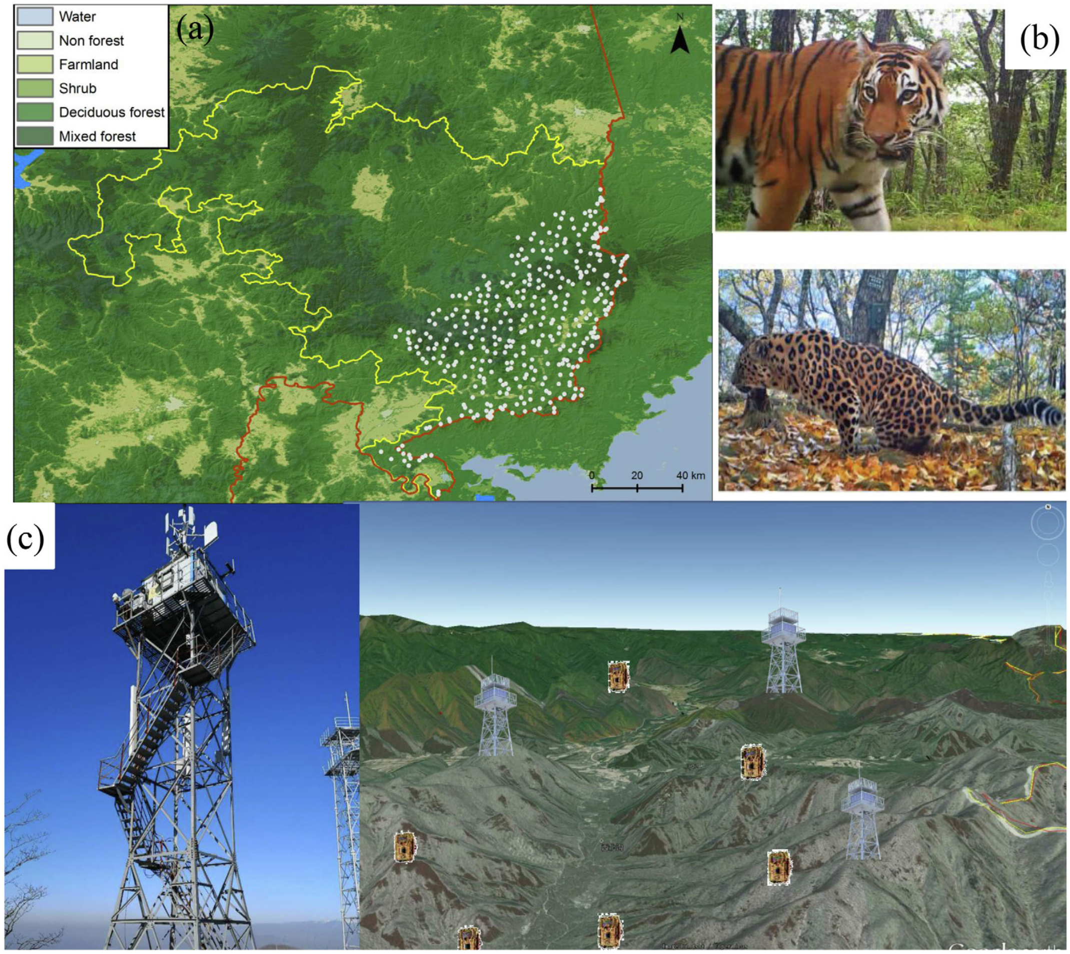

Fig. 8. Terrestrial vertebrate monitoring IoT in northeast China. (a) The cover range of the Chinese National Park for Amur Tigers and Amur Leopards. Colored dots represent the monitoring plots of TLON. (b) Captured images of Amur Tigers and Amur Leopards. (c) Wired and wireless hybrid networks based on the radio and television fiber networks in China and network relay on local forest fire towers.

is established with improved network coverage. This method can provide all-weather field monitoring for wild vertebrates and thus provide valuable and efficient support for the protection of rare and endangered animals.

5. Discussion and conclusions

We introduce a study on the innovative development of smart devices and IoT techniques for ecosystem monitoring. The smart devices we developed have high accuracy, low cost, and improved automation, intelligence, and network access abilities compared to traditional devices. These devices include a two-wavelength scintillometer system to measure evapotranspiration at a large scale, a sap flow gauge to measure the transpiration of individual plants, a nonintrusive soil moisture meter, a mesoscale soil moisture measurement system that utilizes cosmic-ray neutrons, a comprehensive observation system for carbon dioxide and $\delta^{13}C$ monitoring during soil biochemistry processes, a CanoMIS, a distributed LAI meter, a tree diameter recording meter, a nondestructive wood density analyzer, a plant phenology recording system, a Bi-CMOS infrared stereo camera to capture terrestrial vertebrates, and pressure-plate triggering devices to monitor small vertebrates. All these devices are networked via an ecosystem monitoring IoT, in which we overcome two bottlenecks: a general-purpose data logger enables high-speed data collection and versatile network connection, and LSN technology is used to network monitoring devices in remote areas without a commercial communication network. Finally, by integrating these new devices and technologies with an ecosystem monitoring information system, a seamless data acquisition, transmission, processing, visualization, and application IoT is created.

The laboratory and pilot testing of smart devices has been completed, and the networking, application, and demonstration of the devices are being performed in fragile ecosystems, including karst rocky desertification areas, the National Park for Amur Tigers, and oasis-desert ecotones in China. Through these verification experiments, a mature ecosystem IoT will be achieved. Compared with the IoT technology being applied in urban areas [45–47] and regional [18] environmental management methods, we expect to build an integrated space-ground monitoring system that optimally combines remote sensing and ground-based observations by further taking advantage of the IoT. This system can capture the multiscale spatial and temporal dynamics of key ecosystem variables and fluxes, thereby offering effective, reliable, and representative information services to scientists and stakeholders.

This effort could provide a new paradigm for real-time ecosystem monitoring and management in the era of big data. We anticipate that the ecosystem monitoring IoT could be used in operational ecosystem monitoring and aid in ensuring national ecological security.

Conflict of interest

The authors declare that they have no conflicts of interest.

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Author contributions

Xin Li led the writing of the manuscript. All authors conceived the ideas and designed the experiments. All authors contributed to the drafts and gave final approval for publication.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scib.2019.07.004.

References

[1] Yao T. Tackling on environmental changes in Tibetan Plateau with focus on water, ecosystem and adaptation. Sci Bull 2019;64:417.
[2] Bogena HR. TERENO: German network of terrestrial environmental observatories. J Large-Scale Res Facil 2016;2:52.
[3] Feng G, Mi X, Yan H, et al. CForBio: a network monitoring Chinese forest biodiversity. Sci Bull 2016;61:1163–70.
[4] Li X, Cheng G, Liu S, et al. Heihe watershed allied telemetry experimental research (HiWATER): scientific objectives and experimental design. Bull Amer Meteorol Soc 2013;94:1145–60.
[5] Spencer BF, Ruiz-Sandoval ME, Kurata N. Smart sensing technology: opportunities and challenges. Struct Control Health Monit 2010;11:349–68.
[6] Mukhopadhyay SC, Jiang JA. Wireless sensor networks and ecological monitoring. Berlin Heidelberg: Springer-Verlag; 2013.
[7] Liu S, Li X, Xu Z, et al. The Heihe integrated observatory network: a basin-scale land surface processes observatory in China. Vadose Zone J 2018;17:180072.
[8] Qu Y, Zhu Y, Han W, et al. Crop leaf area index observations with a wireless sensor network and its potential for validating remote sensing products. IEEE J Sel Top Appl Earth Observ Remote Sens 2014;7:431–44.
[9] Kang J, Jin R, Li X, et al. High spatio-temporal resolution mapping of soil moisture by integrating wireless sensor network observations and MODIS apparent thermal inertia in the Babao River Basin. China. Remote Sens Environ 2017;191:232–45.
[10] Collins SL, Bettencourt LM, Hagberg A, et al. New opportunities in ecological sensing using wireless sensor networks. Front Ecol Environ 2006;4:402–7.
[11] Anderson SP, Bales RC, Duffy CJ. Critical zone observatories: building a network to advance interdisciplinary study of Earth surface processes. Mineral Mag 2008;72:7–10.
[12] Jin R, Li X, Yan B, et al. A nested ecohydrological wireless sensor network for capturing the surface heterogeneity in the midstream areas of the Heihe River Basin. China. IEEE Geosci Remote Sens Lett 2014;11:2015–9.
[13] Li X, Cheng G, Ge Y, et al. Hydrological cycle in the Heihe River Basin and its implication for water resource management in endorheic basins. J Geophys Res-Atmos 2018;123:890–914.
[14] Wang H, Zhang T, Quan Y, et al. Research on the framework of the Environmental Internet of Things. Int J Sustain Dev World Ecol 2013;20:199–204.
[15] Ma HD. Internet of things: objectives and scientific challenges. J Comput Sci Technol 2011;26:919–24.
[16] Gubbi J, Buyya R, Marusic S, et al. Internet of things (IoT): a vision, architectural elements, and future directions. Futur Gener Comp Syst 2013;29:1645–60.
[17] Atzori L, Iera A, Morabito G. The internet of things: a survey. Comput Netw 2010;54:2787–805.
[18] Fang S, Xu LD, Zhu Y, et al. An integrated system for regional environmental monitoring and management based on internet of things. IEEE Trans Ind Inform 2014;10:1596–605.
[19] Zhao J, Zheng X, Dong R, et al. The planning, construction, and management toward sustainable cities in China needs the Environmental Internet of Things. Int J Sustain Dev World Ecol 2013;20:195–8.
[20] Chen CLP, Zhang CY. Data-intensive applications, challenges, techniques and technologies: a survey on Big Data. Inf Sci 2014;275:314–47.
[21] Pasetto D, Arenas-Castro S, Bustamante J, et al. Integration of satellite remote sensing data in ecosystem modelling at local scales: practices and trends. Methods Ecol Evol 2018;9:1810–21.
[22] Bühne HST, Pettorelli N. Better together: integrating and fusing multispectral and radar satellite imagery to inform biodiversity monitoring, ecological research and conservation science. Methods Ecol Evol 2018;9:849–65.
[23] Liu S, Xu Z. Micrometeorological methods to determine evapotranspiration. In: Ecohydrology – observation and measurement of ecohydrological processes. Berlin Heidelberg: Springer-Verlag; 2019. p. 201–39.
[24] Liu SM, Xu ZW, Wang WZ, et al. A comparison of eddy-covariance and large aperture scintillometer measurements with respect to the energy balance closure problem. Hydrol Earth Syst Sci 2011;15:1291–306.
[25] Shi S, Huang B, Liu S, et al. Development of a measuring system for surface energy and water vapor fluxes at large scale. Adv Earth Sci 2010;25:1128–38.
[26] Zhao P, Lu P, Ma L, et al. Combining sap flow measurement-based canopy stomatal conductance and ^{13}C discrimination to estimate forest carbon assimilation. Chin Sci Bull 2005;50:2021.
[27] Granier A. Une nouvelle méthode pour la mesure du flux de sève brute dans le tronc des arbres. Annal Sci Forest 1985;42:193–200.
[28] Veldkamp E, O'Brien JJ. Calibration of a frequency domain reflectometry sensor for humid tropical soils of volcanic origin. Soil Sci Soc Am J 2000;64:1549–53.
[29] Link RE, Rohini K, Singh DN. Methodology for determination of electrical properties of soils. J Test Eval 2004;32:62–8.
[30] Zreda M, Desilets D, Ferré TPA, et al. Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons. Geophys Res Lett 2008;35:L21402.
[31] Griffis TJ. Tracing the flow of carbon dioxide and water vapor between the biosphere and atmosphere: a review of optical isotope techniques and their application. Agric For Meteorol 2013;174–175:85–109.
[32] Pang J, Wen X, Sun X. Mixing ratio and carbon isotopic composition investigation of atmospheric CO_2 in Beijing. China. Sci Total Environ 2016;539:322–30.
[33] Chen C, Pang J, Wei J, et al. Inter-comparison of three models for $\delta^{13}C$ of respiration with four regression approaches. Agric For Meteorol 2017;247:229–39.
[34] Wen XF, Meng Y, Zhang XY, et al. Evaluating calibration strategies for isotope ratio infrared spectroscopy for atmospheric $^{13}CO_2/^{12}CO_2$ measurement. Atmos Meas Tech 2013;6:1491–501.
[35] Pang J, Wen X, Sun X, et al. Intercomparison of two cavity ring-down spectroscopy analyzers for atmospheric $^{13}CO_2/^{12}CO_2$ measurement. Atmos Meas Tech 2016;9:3879–91.
[36] Graham EA, Riordan EC, Yuen EM, et al. Public Internet-connected cameras used as a cross-continental ground-based plant phenology monitoring system. Glob Change Biol 2010;16:3014–23.
[37] Wang T, Feng L, Yang H, et al. A science-based approach to guide Amur leopard recovery in China. Biol Conserv Part B 2016;210:47–55.
[38] Wang T, Feng L, Mou P, et al. Amur tigers and leopards returning to China: direct evidence and a landscape conservation plan. Landsc Ecol 2016;31:491–503.
[39] Zviedris R, Elsts A, Strazdins G, et al. LynxNet: wild animal monitoring using sensor networks. In: International Workshop on Real-world Wireless Sensor Networks. Berlin, Heidelberg: Springer-Verlag; 2010. 170–3.
[40] Kays R, Kranstauber B, Jansen P, et al. Camera traps as sensor networks for monitoring animal communities. Int J Res Rev Wireless Sensor Network 2011;1:811–8.
[41] Ni J, Wang S, Liu L, et al. Establishment and monitoring of biological plots at Puding karst ecosystem research station. Earth Environ 2017;45:106–13.
[42] Mclaughlin K. Tiger land. Science 2016;353:744–5.
[43] Wang T, Royle JA, Smith JLD, et al. Living on the edge: opportunities for Amur tiger recovery in China. Biol Conserv 2018;217:269–79.
[44] Cheng GD, Li X, Zhao WZ, et al. Integrated study of the water-ecosystem-economy in the Heihe River Basin. Natl Sci Rev 2014;1:413–28.
[45] Zanella A, Bui N, Castellani A, et al. Internet of things for smart cities. IEEE Internet Things J 2014;1:22–32.
[46] Ahlgren B, Hidell M, Ngai EC. Internet of things for smart cities: interoperability and open data. IEEE Internet Comput 2016;20:52–6.
[47] Zhao J, Liu H, Dong R. Sustainable urban development: policy framework for sustainable consumption and production. Int J Sustain Dev World Ecol 2008;15:318–25.

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