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Research Article

Intelligence in Ecology: How Internet of Things Expands Insights into the Missing CO_2 Sink

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Arid region characterizes more than 30% of the Earth's total land surface area and the area is still increasing due to the trends of desertification, yet the extent to which it modulates the global C balance has been inadequately studied. As an emerging technology, IoT monitoring can combine researchers, instruments, and field sites and generate archival data for a better understanding of soil abiotic CO_2 uptake in arid region. Images' similarity analyses based on IoT monitoring can help ecologists to find sites where the abiotic uptake can temporally dominate and how the negative soil respiration fluxes were produced, while IoT monitoring with a set of intelligent video recognition algorithms enables ecologists to revisit these sites and the experiments details through the videos. Therefore, IoT monitoring of geospatial images, videos, and associated optimization and control algorithms should be a research priority towards expanding insights for soil abiotic CO_2 uptake and a better understanding of how the uptake happens in arid region. Nevertheless, there are still considerable uncertainties and difficulties in determining the overall perspective of IoT monitoring for insights into the missing CO_2 sink.

1. Introduction

Largely because of human activities after the Industrial Revolution and the produced substantial climate changes, atmospheric CO_2 levels have increased more than 30% in the past century [1]. This major environmental issue has motivated scientists to carry out a huge effort to quantify the sources and sinks of the atmospheric CO_2, and the existence of a "missing CO_2 sink" is finally concluded [1–7]. Numerous scientists ever claimed to have located the "missing sink," but each of them was finally denied [8–20]. Location of the missing CO_2 sink has become a long-sought challenge in ecology.

Recent studies of the arid and semiarid ecosystems suggest that the missing CO_2 sink can be partly attributed to unneglectable soil abiotic CO_2 uptake in arid region [21–24]. Such uptake has been long-term overlooked in estimating the net ecosystem exchange of CO_2 [NEE] around the world. The global "CO_2 flux towers" employed in current micrometeorological measurements interpret NEE as biological fluxes, exactly defined as the direct sum of photosynthetic and respiratory components [20]. Arid region characterizes more than 30% of the Earth's total land surface area and the area is still increasing due to the trends of global desertification, yet the extent to which it modulates the global C balance has been inadequately studied [25–33].

Estimates of the overall contribution of such abiotic CO_2 uptake are essentially emergent for expanding insights into the missing CO_2 sink, which further requires common huge efforts of the world scientific communities [23]. The current estimates based on very limited data collected from a few sites within several typical desert ecosystems were thought to be not convincing and even problematic [24]. Ecologists were cautioned to keep discreet minds in both data collection and the determination of the whole story of soil abiotic CO_2 uptake in arid region. Such abiotic uptake can be varying with predominant processes, site location, and climatic conditions. These are important factors affecting experimental designs because spatial-temporal heterogeneity must be taken into account. To treat these disturbances and simplify experimental designs, it is hence imperative to implement intelligent methods for ecologists to collect both convincing data and further evidences.

In previous publications for insights into the missing CO_2 sink and especially for insights into soil abiotic CO_2 uptake in arid regions, the utilized technologies are rather old. The emerging information technologies were hardly employed. These unemployed technologies include the wireless sensing networks [34–36], Internet of Things (IoT) [37–40], and cloud computing [41–46]. Particularly, IoT has been further integrated with the surveillance systems and the integrated system was termed as IoT monitoring [47–50]. Since IoT monitoring can generate images, videos, and other archival data, it is necessary to investigate whether IoT monitoring can serve for a better understanding of soil abiotic CO_2 uptake in arid region. The currently published studies are very limited and were thought to be not convincing. Geospatial images and videos from IoT monitoring help us to explain at which sites soil abiotic CO_2 uptake was observed and present more details of the whole experimental process.

Our objectives in this study were to examine the potentials of IoT monitoring as an emerging technology for insights into soil abiotic CO_2 uptake and in turn for expanding insights into the missing CO_2 sink in the unneglectable arid region. Utilizing geospatial, archival data, intelligent algorithms on videos and images were performed to theoretically expand insights into soil abiotic CO_2 uptake in unneglectable arid region, which has been overlooked for a long period. Additionally, the existing uncertainties and unresolved issues to develop such a thematic IoT monitoring system are also discussed.

2. Materials and Methods

2.1. Collection of Geospatial Data. Analyses of the potentials of IoT monitoring for insights into the missing CO_2 sink in the present study are based on the collected geospatial images and videos from the field sites at the south edge of the Gurbantunggut Desert in the north of Xinjiang Uygur Autonomous Region, China (Figure 1).

These field sites were chosen because it has been confirmed that soil abiotic CO_2 uptake can temporally dominate and cause the apparent negative soil respiration fluxes at these sites [51–53]. Collecting the geospatial images of these sites

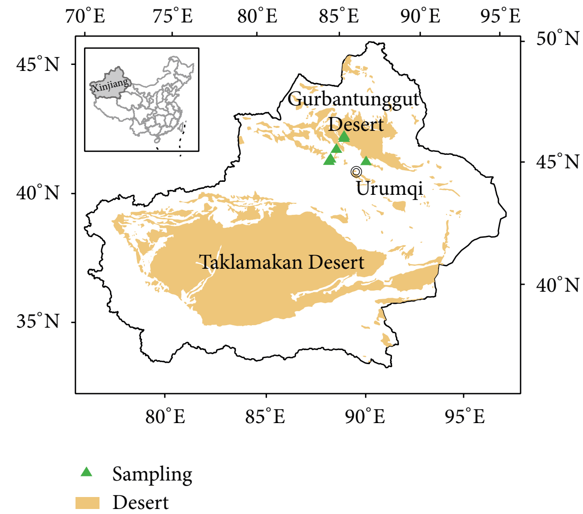

FIGURE 1: Distribution of the field sites where geospatial images and videos are collected in this study.

from IoT monitoring helps us to explain at which sites soil abiotic CO_2 uptake was observed and present more details of the experimental sites. Overall, geospatial images and videos were collected from 19 field sites, 18 of which are distributed within the Manas River Basin. These sites are close to each other. Another field site is located in the Sangong River Basin [51, 52].

A mobile communication tool (Redmi Note 4, with MATLAB software installed to operate the algorithms) was employed for the collection of geospatial images and videos. In total 70 geospatial images of these field sites were collected and 36 images were chosen to build the first database of geospatial images for the sites where soil abiotic CO_2 uptake can temporally dominate (Figure 2). As a first example of the utilization of geospatial videos in analyzing soil abiotic CO_2 uptake, a special experiment was designed to expand insights into soil texture at those sites where abiotic CO_2 uptake can temporally dominate in soil respiration fluxes.

The details of this experimental design are as follows. We aim to collect a video to record the process when one inserts the WET sensors of HH2 Moisture meter (Delta-T Devices Ltd., Cambridge, UK) into the soil and then utilize video tracking algorithms to analyze the movements of the sensors beneath the soil surface. This is really a challenge because we realized that the time of the collected video may be too short. However, the soil texture cannot be objectively displayed if we deliberately slowly insert the sensors. Therefore, the daughter of the first author (Wenfeng Wang), who is 6 years old and named Yanbo Wang, was invited to join the "scientific game." She saw this as an interesting game and naturally tried her best. A short video was collected when she was inserting the WET sensors into the soil.

2.2. Optimization and Control. A histogram-based image similarity algorithm [54–56] was further optimized and employed to analyze the match degree between the test image

Figure 2: The first images database of the sites where soil abiotic CO_2 uptake can temporally dominate.

and each image from the first database of geospatial images of the sites where soil abiotic CO_2 uptake can temporally dominate. This helps in finding the best match of the test image in the database. In a previous publication [54], to optimize the performance of the algorithm, the histograms of the Red-band H(R), the Green-band H(G), and the Blue-band H(B), respectively, were used. In the present study, the algorithm was further optimized by taking into account the weights of H(R), H(G), and H(B) to each image, where the weights/contributions were determined by calculating the information entropy [57–59]. R-G-B-weighted average correlation-efficient parameters that were employed to evaluate the histogram-based image similarity between the test image and each image from the database were calculated.

In order to objectively evaluate the potentials of IoT monitoring for insights into the missing CO_2 sink, a real challenge was carried out. The video object tracking algorithm was performed on the collected short video for the real-time video tracking of the WET sensors. Traditional algorithms, such as the mean-shift algorithm [60–62], are unsuitable for this video object tracking. Therefore, we previously specialized the video target for tracking by morphological segmentation [63], which helps to improve the performance of mean-shift algorithm.

3. Results and Discussions

3.1. Images' Similarity Analyses Based on IoT Monitoring. The further optimized histogram-based images similarity algorithm was applied to search field sites where soil abiotic CO_2 uptake can temporally dominate. The performance of the similarity detection algorithm worked out the best match of the test image among images in the first images database of the sites where the abiotic CO_2 uptake can temporally dominate. Results show that the match degree between test image and best match is approximated to 90%. Therefore, the histogram-based image similarity analyses based on IoT monitoring confirmed that the test image represents a site where soil abiotic CO_2 uptake can temporally dominate in soil respiration and cause negative soil respiration fluxes.

Through further reviews of the details of the test image, it is easy to find an obvious salt accumulation on the soil surface at the test site (Figure 3). The test image can be joined to the database and the extended information can be utilized. Exactly, some previous reports of negative soil respiration fluxes in arid region do not emphasize the role of salt accumulation [21].

This helps in convincing the ecologists who were not convinced by the previous reports since they may realize that the soil and groundwater are alkaline, which is advantageous to the subterranean fixation of CO_2. Taking into account the abiotic flux components, the soil CO_2 flux can be further reconciled as

$$
\begin{aligned}
F_s &= R - F_{\mathrm{DIC}} - F_{\mathrm{SIC}} = F_e - F_i, \\
F_e &= R, \qquad (1)\\
F_i &= F_{\mathrm{DIC}} + F_{\mathrm{SIC}},
\end{aligned}
$$

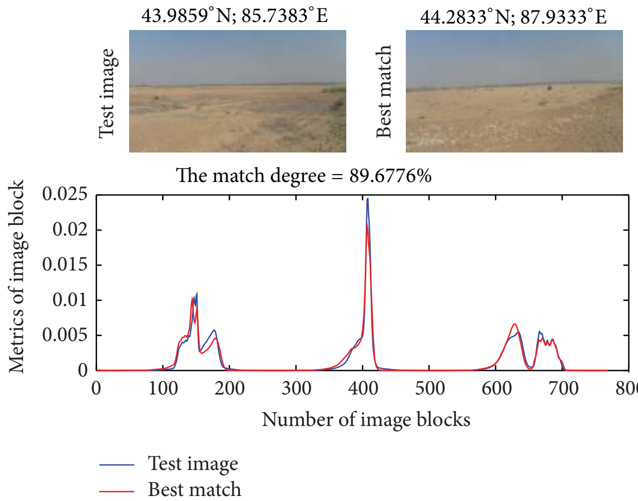

FIGURE 3: To find the best match for test image in the first images database of the sites where soil abiotic CO_2 uptake can temporally dominate, utilizing the image analysis algorithm referred to in this study.

where R is the CO_2 release from roots and soil microbial respiration and F_{DIC} and F_{SIC} are the net CO_2 fixation in the groundwater and the soil [in inorganic forms], respectively. F_e and F_i are the net soil CO_2 influx and the net soil CO_2 efflux, respectively [52].

A sketch of soil CO_2 flux formation in arid region can be hence expanded by further mathematical analyses. First, review the mechanism of how the soil CO_2 analyzer (e.g., LI-8100; see [53]) works. Assume that, after per unit time T, the CO_2 analyzer abstracts air of volume V_1 from a gas room of volume V and then supplies air of the same volume sampled from atmosphere for the CO_2 pressure balance in the gas room. Go round and begin again. To compute CO_2 flux, the following is used:

$$F_c = \frac{dC(t)}{dt}, \tag{2}$$

where $C(t)$ is the CO_2 concentration in the gas room at time t [64].

Let q be CO_2 concentration in the atmosphere. For the nth measured value, the input and output of CO_2 are $F_{\text{input}} = r_n$ and $F_{\text{output}}/r_n = p_n$, respectively, taking average within nth time interval $[nT, (n+1)T]$. The dynamic of CO_2 concentration in the gas room should be as follows.

Input-output balance equation:

$$\begin{aligned} &C(nT+T) - C(nT) \\ &\quad = \frac{(V_1 q + r_n)\cdot T - \int_{nT}^{nT+T} V_1 \cdot C(s) + r_n p_n ds}{V}, \\ &\qquad\qquad C(0) = C_0, \end{aligned} \tag{3}$$

where C_0 is the CO_2 concentration at starting time point.

Thus the nth measured value of soil CO_2 flux is

$$\begin{aligned} F_{c\text{-}n\text{th}} &= \frac{C(nT+T) - C(nT)}{T} \\ &= \frac{V_1 q + r_n(1-p_n) - C(\xi_n)\cdot V_1}{V}, \end{aligned} \tag{4}$$

where $C(\xi_n)$ is the CO_2 concentration from *mean value theorem of integrals*.

Negative soil respiration CO_2 fluxes are observed if

$$p_n > \frac{V_1[q - C(\xi_n)]}{r_n} + 1. \tag{5}$$

Finally, it must be cautioned that infimum of the negative values of soil CO_2 flux may exist. Let $T \to 0$; we obtain

$$\frac{dC(t)}{dt} = \frac{V_1 q + r_n - r_n p_n}{V} - \frac{V_1}{V}\cdot C(t), \quad C(0) = C_0. \tag{6}$$

Hence,

$$C(t) = \frac{V_1 q + rp}{V_1} + \left(C_0 - \frac{V_1 q + rp}{V_1}\right)\cdot e^{-V_1 t/V}. \tag{7}$$

Stable negative fluxes may happen within a small measurement interval T when

$$\frac{V_1 q + rp}{V_1} > C_0. \tag{8}$$

Let $t \to \infty$; we get

$$\lim_{t\to\infty} C(t) = \frac{V_1 p + r}{V_1}. \tag{9}$$

This is the infimum of the CO_2 concentration.

3.2. IoT Monitoring with Intelligent Video Recognition Algorithm. The trajectory analysis of soil sensors is realized in performance of IoT monitoring with intelligent video recognition algorithm. Such video object tracking algorithm not only enables ecologists to revisit these sites and the experiments details by geospatial videos, but also helps ecologists to further understand the compact soil texture so that the whole process costs 21 seconds. The footprint of the WET sensors revealed that the process is difficult for this little girl (Figure 4).

Consequently, a part of soil respiration (R) temporally gathers in soil (R_g) or is ventilated in subterranean cavity (R_v) and contributes to the abiotic release later. This also is advantageous for a chemical fixation of CO_2 in the soil-groundwater system (Figure 5).

This expands a perspective frame of IoT for insights into the missing CO_2 sink (Figure 6).

Therefore, the potentials of IoT monitoring for insights into soil abiotic CO_2 uptake and hence for the insights into the missing CO_2 sink are highlighted. A part of soil inorganic CO_2 (SIC) remained in soil layers [SR] and a part of DIC is carried away and might go out at the terminal of the

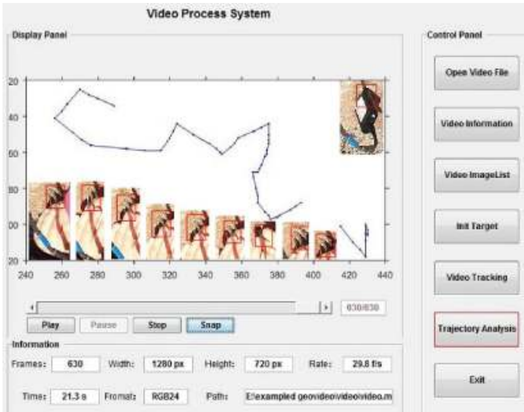

FIGURE 4: Trajectory analysis of soil sensors by the video object tracking algorithm referred to in this study.

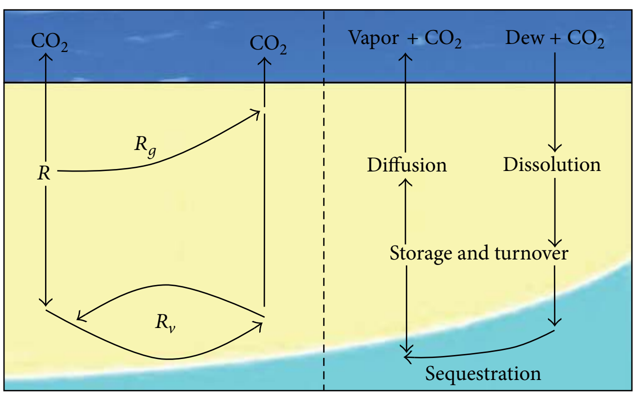

FIGURE 5: Integrated story of soil abiotic CO_2 uptake/release, where parts of soil respiration (R) temporally gather in soil (R_g) or are ventilated in subterranean cavity (R_v) and then contribute to abiotic release later.

groundwater-soil system [TO], while the other parts of SIC and DIC form the final absorption in groundwater [GA]. SR falls into three phases, solid SR [SSR forms hydrogen carbonate and changes molar number of carbon atoms], liquid SR [LSR dissolved part of SR], and gaseous SR [GSR increases the CO_2 concentration in soil pores]; GA is a single phase: liquid phase [consisting of liquor diverse carbon species]; TO falls into two phases: liquid TO [LTO recharged DIC] and gaseous TO [GTO released CO_2]. Assignment of missing carbon should be formulated as follows:

$$\begin{aligned} C_{\text{missing}} &= \text{SR} + \text{GA} + \text{TO} \\ &= \text{SSR} + \text{LSR} + \text{GA} + \text{GSR} + \text{LTO} + \text{GTO}. \end{aligned} \tag{10}$$

The carbon assignment equation can be further hypothetically expanded. We can classify soil pores as three types: dry pore [DP], small water pore [SWSP], and big water pore [BWSP] according to their size and water content. DP is distributed in shallow soil layers and can absorb CO_2 if coupled with the condensing of vapor or the infiltration of precipitation; SWSP is distributed in moist layers around the roots system, dissolving CO_2 in it; BWSP is distributed in deep layers, dissolving CO_2 and then migrating it into groundwater. Note that these three types of soil pores may convert to each other with the changes or movements of soil water.

The balance equations can be represented as

$$\begin{aligned} \Delta\text{GSR} &= \Delta\text{DP}, \\ \Delta\text{SSR} &= \Delta\text{SWSP}, \end{aligned} \tag{11}$$

where the groundwater recharge/discharge is the major regulator of the balance.

4. Conclusions and Outstanding Remarks

As an emerging technology, IoT monitoring combines researchers, instruments, and field sites and generates archival data for a better understanding of soil abiotic CO_2 uptake in arid region and in turn has great potentials for insights into the missing CO_2 sink. By histogram-based image similarity analyses of image data collected from IoT monitoring, ecologists can easily find field sites where soil abiotic uptake of CO_2 can temporally dominate and further improve their understanding of the negative soil respiration flux values. Video object tracking algorithms based on IoT monitoring not only enable ecologists to revisit these sites and the experiments details by geospatial videos, but also help the ecologists to further understand other details, such as the footprint of soil sensors, which in turn can help ecologists to understand the integrated story of soil abiotic CO_2 uptake. In subsequent studies, the employed algorithms can be more and more complex and the uncertainties of the presented algorithms must be explicitly discussed.

Nevertheless, it must be pointed out that there are still considerable uncertainties and difficulties in developing such a thematic IoT monitoring system. One major challenge is how to conceptualize ecosystem as a volume with explicitly defined top, bottom, and sides. The other major challenge is how to estimate the SIC/DIC assignment proportion of the carbon fluxes in soil layers and groundwater, which should be also analyzed in complicated cases due to great difference in soil types and the groundwater levels. The possible scheme is relating the field sites, instruments, and researchers together by a stable IoT monitoring system and conceptualizing each block of terrestrial ecosystem. In this case, net ecosystem carbon balance equals the total C input minus the total C output from the ecosystem over a specified time interval.

To reduce the increased complexity, one can analyze the situation in the different layers of the local groundwater-soil system. A research priority is the explicit characterization of the situation in different layers of the local groundwater-soil system, which deserves subsequent studies on the field collection of geospatial data for soil abiotic CO_2 uptake [65–73], the visualization of CO_2 footprints [74], and 2D-3D video treatments technology to enhance the visualization effect [75].

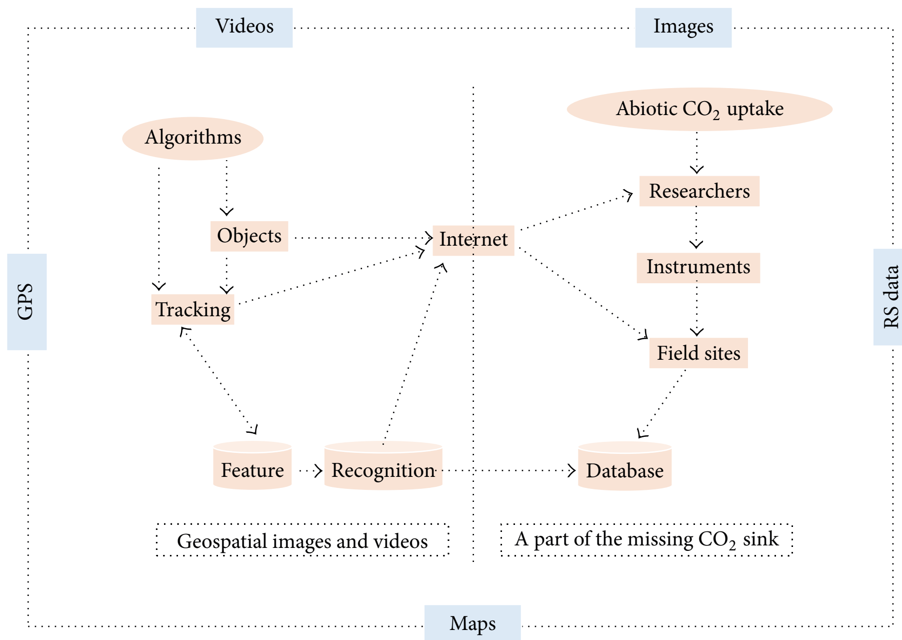

FIGURE 6: The first perspective frame of IoT monitoring for insights into the missing CO_2 sink.

Competing Interests

The authors declare that they have no competing interests.

Acknowledgments

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