Climate Smart Agriculture 1 (2024) 100008

Contents lists available at ScienceDirect

Climate Smart Agriculture

journal homepage: www.sciencedirect.com/journal/climate-smart-agriculture

Regular Article

Near surface camera informed agricultural land monitoring for climate smart agriculture

Le Yu[a,b,c,*], Zhenrong Du[d], Xiyu Li[a], Qiang Zhao[a], Hui Wu[a], Duoji weise[e], Xinqun Yuan[a,f], Yuanzheng Yang[g,h], Wenhua Cai[g,h], Weimin Song[i,j], Pei Wang[k,l], Zhicong Zhao[k,l], Ying Long[m], Yongguang Zhang[n,o,p], Jinbang Peng[q], Xiaoping Xin[q], Fei Xu[r], Miaogen Shen[s], Hui Wang[t,u,v], Yuanmei Jiao[w], Tingting Li[x], Zhentao Sun[y,z,aa], Yonggan Zhao[y,z,aa], Mengyang Fang[ab,ac], Dailiang Peng[ad], Chaoyang Wu[ae,af], Sheng Li[ag], Xiaoli Shen[ah], Keping Ma[ah], Guanghui Lin[a,ai], Yong Luo[a]

[a] *Department of Earth System Science, Ministry of Education Key Laboratory for Earth System Modeling, Institute for Global Change Studies, Tsinghua University, Beijing, China*
[b] *Ministry of Education Ecological Field Station for East Asian Migratory Birds, Beijing, China*
[c] *Tsinghua University (Department of Earth System Science)- Xi'an Institute of Surveying and Mapping Joint Research Center for Next-Generation Smart Mapping, Beijing, China*
[d] *School of Information and Communication Engineering, Dalian University of Technology, Dalian, China*
[e] *Geothermal Geological Brigade, Tibet Autonomous Region Geological and Mineral Exploration and Development Bureau, Lhasa, China*
[f] *International Department, Beijing No. 35 High School, Beijing, China*
[g] *Key Laboratory of Environment Change and Resources Use in Beibu Gulf, Ministry of Education, Nanning Normal University, Nanning, China*
[h] *Guangxi Key Laboratory of Earth Surface Processes and Intelligent Simulation, Nanning Normal University, Nanning, China*
[i] *Key Laboratory of Coastal Environmental Processes and Ecological Restoration, Yantai Institute of Coastal Zone Research, Chinese Academy of Sciences, Yantai, China*
[j] *Yellow River Delta Field Observation and Research Station of Coastal Wetland Ecosystem, Chinese Academy of Sciences, Dongying, China*
[k] *Department of Landscape Architecture, School of Architecture, Tsinghua University, Beijing, China*
[l] *Institute for National Parks, Tsinghua University, Beijing, China*
[m] *School of Architecture and Hang Lung Center for Real Estate, Key Laboratory of Eco Planning & Green Building, Ministry of Education, Tsinghua University, Beijing, China*
[n] *International Institute for Earth System Sciences, Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing University, Nanjing, China*
[o] *Jiangsu Provincial Key Laboratory of Geographic Information Science and Technology, Key Laboratory for Land Satellite Remote Sensing Applications of Ministry of Natural Resources, School of Geography and Ocean Science, Nanjing University, Nanjing, China*
[p] *Jiangsu International Joint Carbon Neutrality Laboratory, Nanjing University, Nanjing, China*
[q] *State Key Laboratory of Efficient Utilization of Arid and Semi-Arid Arable Land in Northern China, National Hulunber Grassland Ecosystem Observation and Research Station, Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing, China*
[r] *Key Laboratory of the Three Gorges Reservoir Region's Eco-Environment, Ministry of Education, Chongqing University, Chongqing, China*
[s] *State Key Laboratory of Earth Surface Processes and Resource Ecology, Faculty of Geographical Science, Beijing Normal University, Beijing, China*
[t] *Institute of Qinghai-Tibetan Plateau, Southwest Minzu University, Chengdu, China*
[u] *Sichuan Zoige Alpine Wetland Ecosystem National Observation and Research Station, Chengdu, China*
[v] *Key Laboratory of Resistant Forage Germplasm Resource Exploration and Ecological Restoration of Degraded Grassland, Chengdu, China*
[w] *Faculty of Geography, Yunnan Normal University, Kunming, China*
[x] *Key Laboratory of Atmospheric Environment and Extreme Meteorology, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China*
[y] *Department of Energy and Power Engineering, Tsinghua University, Beijing, China*
[z] *Beijing Engineering Research Centre for Ecological Restoration and Carbon Fixation of Saline–Alkaline and Desert Land, Beijing, China*
[aa] *Shanxi Research Institute for Clean Energy of Tsinghua University, Shanxi, China*
[ab] *Haikou Marine Geological Survey Center, China Geological Survey, Haikou 570100, China*
[ac] *Sanya Tropical Ecosystem Carbon Source and Sink Field Scientific Observation and Research Station, Sanya, China*
[ad] *Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, China*
[ae] *The Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China*
[af] *University of Chinese Academy of Sciences, Beijing, China*
[ag] *School of Life Sciences & Institute of Ecology, Peking University, Beijing, China*

* Corresponding author. Department of Earth System Science, Ministry of Education Key Laboratory for Earth System Modeling, Institute for Global Change Studies, Tsinghua University, Beijing, China.

E-mail address: leyu@tsinghua.edu.cn (L. Yu).

https://doi.org/10.1016/j.csag.2024.100008
Received 29 June 2024; Received in revised form 4 July 2024; Accepted 5 July 2024

[ah] State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing, China
[ai] Hainan International Blue Carbon Research Center, Hainan Research Academy of Environmental Sciences, Haikou, China

ARTICLE INFO

Keywords:
Near surface camera (NSCam)
Climate-smart agriculture (CSA)
Agricultural monitoring
Data fusion
Sentinel-2

ABSTRACT

Continuous and accurate monitoring of agricultural landscapes is crucial for understanding crop phenology and responding to climatic and anthropogenic changes. However, the widely used optical satellite remote sensing is limited by revisit cycles and weather conditions, leading to gaps in agricultural monitoring. To address these limitations, we designed and deployed a Near Surface Camera (NSCam) Network across China, and explored its application in agricultural land monitoring and achieving climate-smart agriculture (CSA). By analyzing the image data captured by the NSCam Network, we can accurately assess long-term or abrupt agricultural land changes. According to the preliminary monitoring results, integrating NSCam data with remote sensing imagery greatly enhances the temporal details and accuracy of agricultural monitoring, aiding agricultural managers in making informed decisions. The impacts of abnormal weather conditions and human activities on agricultural land, which are not captured by remote sensing imagery, can be complemented by incorporating our NSCam Network. The successful implementation of this method underscores its potential for broader application in CSA, promoting resilient and sustainable agricultural practices.

1. Introduction

Climate-smart agriculture (CSA) is an integrative approach designed to address the challenges and opportunities presented by climate change in the agricultural sector [1–3]. The concept of CSA is significant as it addresses the need to adapt agricultural practices to the changing climate while also striving to mitigate its effects [1]. Specifically, CSA aims to tackle three main objectives: sustainably increasing agricultural productivity and incomes; adapting and building resilience to climate change; and reducing and/or removing greenhouse gas emissions [1]. CSA is particularly important for smallholder farmers who are more vulnerable to climate change due to their limited resources and capacity to adapt [4]. To achieve climate-smart agriculture on a global scale, access to information on agricultural production for monitoring and evaluation is the first step.

Remote sensing technologies have been widely used in agricultural fields due to their advantages in observing large areas of land surface in time, providing valuable data for monitoring and managing agricultural practices. By analyzing spectral reflectance from optical images, vegetation indices such as the Normalized Difference Vegetation Index (NDVI) can be computed to assess plant vigor and estimate crop yields [5]. This capability enables timely interventions to mitigate the adverse effects of climate change on crop production. In addition, remote sensing provides spatial and temporal soil moisture information through sensors like Synthetic Aperture Radar (SAR) [6]. This information helps farmers schedule irrigation more effectively, reducing water wastage and improving crop resilience to drought conditions. On a larger scale, remote sensing facilitates the detection of changes in agricultural land, forest cover, and pasture areas over time [7]. These insights are crucial for developing strategies to mitigate deforestation, promote sustainable land management, and enhance carbon sequestration.

Depending on the platform, there are usually two sources of remotely sensed datasets including satellite and Unmanned Aerial Vehicle (UAV) imagery. Satellite imagery and UAV systems have distinct advantages and limitations. Satellite imagery provides global coverage, which is particularly valuable for large-scale assessments [8–11]. However, freely available satellite data typically offer only medium spatial resolution and are constrained by temporal details, with revisit times often ranging from one to two weeks [12]. In contrast, UAVs offer greater flexibility and can achieve high spatial resolution at the meter level, enabling detailed, site-specific observations [13–15]. Nevertheless, the scalability of UAVs is limited, making them less suitable for extensive regional or global monitoring efforts [16]. Although remote sensing technology has advanced significantly, access to high-resolution data can still be costly and limited, especially for smallholder farmers in developing regions [17]. Also, the interpretation and application of remote sensing data require technical expertise that may not be readily available to all farmers. More importantly, remote sensing imagery needs to be complemented with ground-based observations for accurate validation and calibration [18–20].

Near surface camera technology holds significant potential for agricultural monitoring, offering high-resolution and real-time imagery that will be an excellent complement to existing remote sensing data sources mentioned above (Fig. 1) [21]. Due to the differences in observation angle and distance, high-resolution photos provided by the near surface camera can be more easily interpreted and can be used as ground truth to validate results from satellite observations [22]. When applied to CSA, near surface camera technology offers a range of benefits including precise monitoring of crop health, early detection of diseases and pests, and the ability to estimate yield, which are crucial for making informed decisions in agricultural management. However, despite its potential, there are challenges and areas of improvement that need to be addressed to fully harness its capabilities in CSA.

This study first introduces the concept of using near surface cameras for agricultural phenological monitoring and the advancements in their application within CSA. A detailed description of the design and deployment of our agricultural phenological monitoring network (NSCam) is then provided, covering the design concept, image processing methods, preliminary empirical results, and integration with remote sensing technology. Finally, the advantages of NSCam Network in agricultural land changes are demonstrated.

2. Near surface cameras for phenological monitoring

2.1. Importance and challenges of phenological monitoring

The phenological behavior of flora and fauna is one of the most evident outcomes of changes in environmental characteristics and processes. Phenological behaviors of the same species can vary significantly across different landscapes [23,24]. Vegetation phenology refers to the seasonal changes in plant growth and development, encompassing a series of stages such as bud burst, growth, flowering, fruiting, and leaf fall [25,26]. These phenological phenomena can influence the structure and function of entire ecosystems and serve as crucial ecological indicators for studying ecosystem and global climate changes [27–31]. However, even with the use of satellite remote sensing products, large-scale regional vegetation phenology observations at appropriate temporal scales remain challenging [23,29]. Advances in imaging technology have revolutionized the monitoring and study of plant phenology, agricultural productivity, and environmental changes, with near surface cameras playing a critical role in modern agriculture and environmental monitoring.

Phenological data are vital for identifying the environmental control factors in different ecosystems. They help identify key environmental factors affecting the seasonal behaviors of specific species or communities, revealing trends in biodiversity changes under different environmental conditions. This information is crucial for predicting the impacts of future climate change on ecosystems [32]. Analysis of phenological data also improves the accuracy of ecological models by accounting for dynamic changes over time and space. Comparing model predictions with observed phenological patterns helps identify deficiencies in models, which can then be adjusted and optimized accordingly [33]. This model evaluation method, based on phenological data, enhances the reliability and utility of ecological models.

2.2. Advances in imaging technology with near surface cameras

Advances in imaging technology have provided new approaches for acquiring phenological data, transforming the way plant phenology, agricultural productivity, and environmental changes are monitored and studied [34]. Traditional vegetation phenological monitoring involved either small-scale, high-precision manual measurements or large-scale, low-spatial-resolution satellite remote sensing. With the continuous advancement of digital photography technology, low-cost and efficient near surface cameras that provide long-term high-resolution near-surface remote sensing data are increasingly used to monitor plant phenology [35]. High-frequency digital camera images and vegetation indices allow better tracking of plants' phenological responses to environmental changes, aiding the development of improved predictive phenological models [36]. Digital camera images facilitate individual organism observation, long-term canopy monitoring, automated phenological monitoring from regional to continental scales, and tracking responses to experimental treatments [36–39].

2.3. Applications of phenological cameras

As a specific application of near surface cameras, phenological cameras are specially designed to capture the dynamics of terrestrial flora and fauna. These cameras are frequently used in ecological and environmental research to track the timing of events such as leaf emergence, flowering, and senescence [40]. They provide daily updated image sequences, crucial for understanding plant growth patterns, assessing crop growth conditions, and predicting crop yields [41]. Typically fixed at research sites, these cameras capture images to analyze patterns and trends in vegetation changes over time [23,42].

Time-lapse and interval cameras are important types of phenological cameras for monitoring phenology. Interval cameras automatically capture photos at preset time intervals. In agriculture, time-lapse cameras provide visual records of plant growth, crop development, and landscape changes due to seasonal or climatic variations [43,44]. These visual records help identify growth patterns and potential issues related to plant health and productivity [45,46]. Interval cameras, similar to time-lapse cameras, are often used where precise scientific measurements are needed, ensuring consistency in image capture timing. These cameras can be programmed to capture images at specific times of the day, which is particularly useful for studies requiring consistent lighting conditions [47,48]. Each type of camera has its unique advantages and application scenarios, collectively providing powerful tools for better understanding and managing natural environments and agricultural systems.

Vegetation phenology is a crucial factor in agricultural production, supported significantly by phenological cameras, which are integral to climate-smart agriculture. In agriculture, the application of vegetation phenology primarily includes crop planting, management, and harvesting. For instance, historical data observations can predict when specific crops will enter various growth stages in particular regions, aiding in crop yield prediction, farm management, and understanding crop responses to environmental changes [41,49,50]. Monitoring phenological changes in vegetation allows farmers to adjust irrigation, fertilization, and pest control activities timely, ensuring crops grow under optimal conditions [51]. For example, by monitoring soil moisture changes with phenological cameras and integrating with microcontrollers and smart irrigation technology, automated irrigation can be achieved. This method saves farmers time, money, and labor while ensuring the rational use of water resources in water-scarce areas [52]. Additionally, analyzing the phenological characteristics of different crops and their relationship with climatic factors can provide scientific bases for crop rotation and intercropping, improving land use efficiency and crop yield [53]. Phenological cameras provide continuous high-resolution image data, enabling scientists and agricultural practitioners to more accurately monitor plant growth cycles, crop growth conditions, and vegetation changes, enhancing our understanding of crop dynamics and supporting sustainable agricultural practices.

The PhenoCam Network is an evolving open-source tool designed to study the spatiotemporal variability of phenology at ecosystem scales

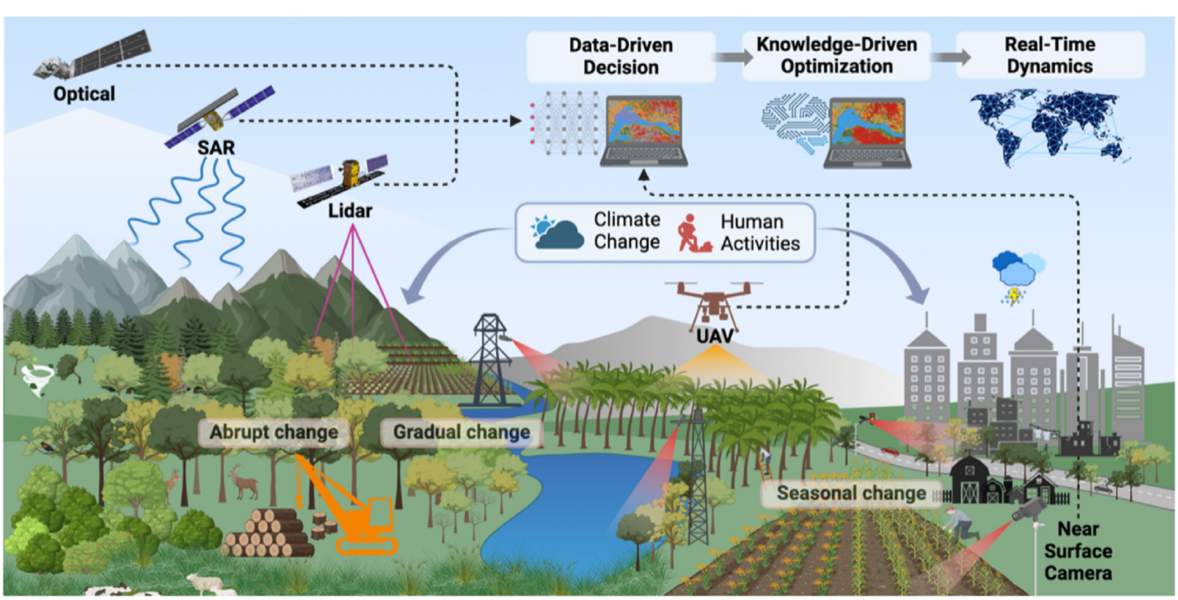

Fig. 1. A schematic diagram of land system monitoring based on near-surface cameras. The integration of satellite, UAV, and near-surface remote sensing enables the monitoring of abrupt changes, gradual changes, and seasonal variations caused by climate change and human activities.

[54,55]. It is currently an effective tool for conducting phenological monitoring from individual organisms to ecosystems, regional, and continental scales. By monitoring seasonal changes in plants, such as leaf emergence and fall and flower opening, the PhenoCam Network provides essential data on ecosystem dynamics [44,56]. These data are crucial for understanding the impacts of global climate change on ecosystems, helping scientists better predict future changes. Moreover, the open-source nature of the PhenoCam Network encourages global research collaboration in phenology, promoting knowledge sharing and innovation [57].

The application of phenological cameras extends beyond crop monitoring to forest management and biodiversity conservation. For example, data captured by PhenoCam help researchers better understand plant growth patterns in forests and how these patterns are affected by global climate change [58]. These technologies can also be combined with satellite data to enhance spatial resolution and temporal details monitoring. For instance, integrating phenological camera data with Sentinel-2 and MODIS satellite data provides detailed information on crop growth conditions, crucial for precision agriculture and crop yield prediction [59,60].

3. NSCam network: design and data processing

3.1. NSCam design

The NSCam Network encompasses hundreds of cameras distributed in China. These cameras have adopted our new design for enhancing the application of CSA. Firstly, each NSCam is capable of collecting data at hourly intervals and can be remotely activated to capture additional data at any time, facilitating real-time observations. This high-frequency data collection provides robust monitoring data for agriculture, ensuring the NSCam Network can swiftly and accurately track the impacts of climate change and human activities on agricultural production. The image data captured by each NSCam includes three bands (red, green, blue) at a resolution of 2560 × 1440, providing clear and detailed insights into the vegetation growth in the monitored regions. For managing and utilizing the collected data, each NSCam is equipped with a subscriber identity module (SIM) card utilizing the 4th generation mobile communication technology (4G). Leveraging China's extensive communication network to upload data in real-time to a cloud platform, the NSCam eliminates the need for physical network cables or WiFi connections. Additionally, the NSCam Network includes a cloud platform which aggregates and manages both historical and real-time data from all cameras, supporting the construction of phenological time series for future analyses. Addressing power supply challenges in the field and in agricultural settings, the cameras use alternating current (AC) power supplied by erected tower poles and have built-in batteries providing Uninterruptible Power Supply (UPS) backup in case of unexpected power outages. For installation sites without access to power, external solar panels can be used to power the cameras. With at least 3 h of good sunlight per day, these solar panels can support the collection of 24 images per day.

3.2. NSCam image processing

The images collected by each phenological camera in the NSCam Network are uploaded in real-time to a cloud platform. This study processes all images from different cameras on the cloud platform into dense time series for the study period, thereby obtaining agricultural land change data for the monitored areas. To detect crop phenology and growth status, this study employs the Green Chromatic Coordinate (GCC) index, which quantifies vegetation color changes based on the green characteristics of the vegetation. Considering the spatial heterogeneity of different land cover types and vegetation in each image, we divide each image into a 10 × 10 grid. For each grid cell, we calculate the average value of GCC using Eq. (1), and then construct GCC time series to represent crop phenology and growth status.

$$GCC = \frac{Green}{Red + Green + Blue} \tag{1}$$

Theoretically, we can construct hourly GCC time series for the study period. However, to avoid noise during nighttime, we retain only the hourly data collected from 8:00 to 17:00. Additionally, the daily GCC time series for all grid cells are calculated using the 90th percentile approach, which will be further used for matching with remote sensing imagery. Furthermore, considering the widespread success of PhenoCam, this study also explores integrating NSCam with PhenoCam. Specifically, for observation points equipped with both types of cameras, we match images captured by PhenoCam and NSCam during the same phenological periods with linear regression. This allows us to supplement the NSCam Network with historical data from PhenoCam, thereby extending the temporal coverage and enhancing the monitoring density of the CSA.

3.3. NSCam combined with remote sensing

Optical satellite remote sensing data has long been a crucial source for large-scale, long-term land surface and agricultural phenological monitoring. However, limitations due to satellite revisit cycles and weather conditions (e.g., clouds and rain) in monitored areas often hinder the formation of continuous daily time series observations throughout the year, significantly affecting the accuracy of phenological detection. The NSCam Network effectively addresses these issues as it is less affected by cloud cover and weather conditions, and offers dense and flexible data acquisition intervals, providing hourly observation data. The primary challenge in integrating NSCam data with remote sensing imagery lies in spatial matching despite differences in data acquisition angles, spatial resolutions, and spatio-temporal heterogeneity. To address this, we improved the data fuse algorithm upon the principles and assumptions proposed by Tran et al. [61]. Specifically, the two-band Enhanced Vegetation Index (EVI2) was selected as an example to construct the time series using data fusion. EIV2 is designed to be less sensitive to atmospheric conditions and soil background noise. It has been proved to have better correlation with biophysical parameters like Leaf Area Index (LAI), providing more accurate data for ecosystem and agricultural studies [62, 63]. With EVI2, the adopted principles and assumptions are as following: 1) EVI2 in a pixel is a linear mixture of contributions from green vegetation, colored vegetation, and exposed surface background; 2) GCC in a grid is similarly a mixture of these components; 3) EVI2 and GCC time series are temporally correlated; 4) EVI2 time series in a pixel can be geometrically scaled to the GCC temporal shape in a grid with similar surface fractions; 5) Time lags in vegetation growth due to microclimate variations must be considered; 6) EVI2 time series in a pixel can match GCC temporal shapes in nearby grids with surface digital camera data. 7) Canopy cover for the same vegetation type can vary greatly between years and locations due to weather and growing conditions.

Based on these principles and assumptions, we integrated NSCam and remote sensing images to form a fused daily observation time series using the following steps: 1) Identify the observation region of the NSCam based on the installation location and observation angle; 2) Retrieve all optical remote sensing images within the observation period for the monitoring region, using Sentinel-2 data as an example; 3) Perform remote sensing image preprocessing, such as cloud removal, to obtain all available EVI2 observations during the observation period; 4) For each available observation date, obtain all images captured by NSCam to calculate the daily GCC values, as introduced in Section 3.2, forming pairs of EVI2 images and GCC images for the dates; 5) For the target pixel in the Sentinel-2 imagery, retrieve its remote sensing EVI2 time series and the GCC time series from different grids in the NSCam images; 6) Use linear regression to calculate the mean squared deviation (MSD) and correlation coefficient (R) between the remote sensing time series $RS(t) = \{RS(t_1), RS(t_2), \ldots, RS(t_n)\}$ and the NSCam time series $NSCam(t) = \{NSCam(t_1), NSCam(t_2), \ldots, NSCam(t_n)\}$ in different grids, selecting the grid with the lowest MSD and highest R as the corresponding grid for the target pixel (Fig. 2). Obtain the linear regression results to establish the relationship between GCC and EVI2, as shown in Eq. (2); 7) Using Eq. (2) and daily GCC values from the corresponding grid cell, calculate the daily EVI2 values to supplement the observed EVI2 time series from Sentinel-2; 8) Apply Savitzky-Golay filtering to form the final fused daily EVI2 time series for the target pixel.

$$RS(t_i) = a \times NSCam(t_i) + b \quad (2)$$

where t_i is the day of year, $RS(t_i)$ and $NSCam(t_i)$ is the EVI2 and GCC values at the time of t_i captured by Sentinel-2 and NSCam, a and b are slope and intercept of the linear regression result.

4. NSCam for CSA

4.1. NSCam network in monitoring long time series with PhenoCam

Long-term continuous monitoring is crucial for understanding historical crop phenology and provides essential basis for current crop growth management. The NSCam provides hourly monitoring data, offering several advantages over remote sensing data in this domain. Firstly, NSCam enables denser and more accurate reconstruction of historical crop phenology. Secondly, it allows for more real-time acquisition of current crop growth conditions, making it more sensitive to changes in growth status. Consequently, this allows for better assessment of current crop growth conditions compared to historical averages, enabling timely anomaly warnings and helping agricultural managers take appropriate measures promptly. Combining data from the PhenoCam Network, which has been operational since 2008, we can achieve long-term continuous and dense monitoring of the observed fields.

Based on this procedure, we conducted a long-term time series monitoring analysis of a monitored plot in Jiangsu, using the NSCam and PhenoCam Network (Fig. 3). According to photos taken by PhenoCam (Fig. 3b) and NSCam (Fig. 3c), the monitored plot is planted with rice, a major grain crop in Jiangsu and southern China. Rice in this region is typically sown in early April, transplanted in May, and harvested from September to October. The hourly observation data (Fig. 3d) and the fused daily time series curves reflect the time series of phenological changes. We can observe a rapid increase in EVI2 starting from April to May each year, corresponding to the emergence and growth of rice. However, during the transplanting period from late May to early June, the EVI2 drops rapidly due to field flooding, then rises again in June and July, reflecting the rapid growth during the tillering stage. Subsequently, as rice matures, the EVI2 begins to decline until harvest. This annual cycle of rice phenology forms a long-term phenological observation dataset. As of the most recent available surface observation data on 22nd June in 2024, the plot shows that the rice in the field has finished the post-transplanting stage. Additionally, the calculated vegetation index results are consistent with historical trends, indicating no abnormal crop growth detected at this time. These monitoring results help agricultural managers grasp more precise historical crop phenology information and provide real-time reflections of current crop growth conditions. Comparing current data with historical data facilitates timely interventions in case of growth anomalies due to meteorological disasters or pest infestations, supporting CSA.

4.2. NSCam network in capturing agricultural land changes

The dense monitoring time series obtained from NSCam and satellite remote sensing data can enhance the detection of abrupt and gradual agricultural land changes, effectively complementing the sparse observational results from satellite data alone. This is particularly crucial for agricultural monitoring, as abrupt weather changes (such as a sudden drop in temperature) can have a marked impact on crop growth. If satellite imagery during such periods is unavailable, critical information might be missed, hindering timely remedial or intervention measures. Human activities also play a significant role in causing agricultural land changes. For instance, the harvesting of mature crops leads to immediate changes in surface vegetation cover. Such changes are difficult to capture promptly using satellite data alone. The integration of NSCam data allows for detailed monitoring of these ground changes on a daily, or even hourly scale. This study addresses the two primary factors influencing agricultural land changes: climate change and human activities. Using fields in Tibet and Henan and grassland in Inner Mongolia, as case studies, we demonstrate the capability of NSCam to augment satellite remote sensing data for detecting surface changes, thereby underscoring its importance for CSA.

As illustrated in Fig. 4, we employed the method detailed in Section 3.3 to integrate hourly monitoring data from NSCam at Tibet site with data from Sentinel-2 and Landsat satellites. The monitored crop at this site is highland barley, a major grain crop on the Tibetan Plateau known for its cold resistance and short growth period. The dense observation data provided by NSCam since 5th May 2024 allowed us to capture subtle crop growth changes that might be overlooked by satellite data alone. A notable observation is the significant decline and fluctuation in the EVI2 from 30th April to 15th May, following a period of steady increase before the end of May. Correlating this with local weather data, we identified a clear drop in temperature during this period (as depicted by the temperature curve in Fig. 4). The snowfall on May 10, in particular, impacted the growth of highland barley. The NSCam Network effectively captured this weather event and its impact on crop growth, as reflected in the vegetation index time series. Additionally, the short warming period on May 8–9, which caused a slight increase in the vegetation index and would have been missed by satellite data alone, was clearly detected. The fused EVI2 time series closely matched the local temperature variations during this period. Following mid-May, a rapid rise in local temperature facilitated swift growth of highland barley in the monitored fields. However, a slight drop in temperature in early June interrupted this growth trend, a change that was also captured by our monitoring network. Therefore, the NSCam Network, when combined with satellite data, can accurately reflect the abrupt and subtle changes in crop growth conditions induced by weather or climate variations. This integration provides timely warnings about the impacts of abnormal weather conditions (such as prolonged low temperatures) on crop growth, enabling the implementation of necessary measures promptly.

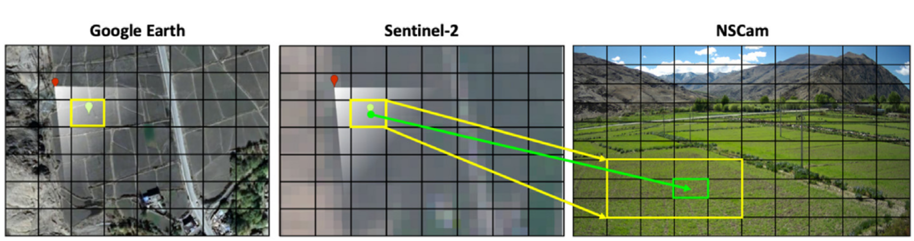

Fig. 2. Spatial match of NSCam image and remote sensing imagery. The red dot is the location of the NSCam, and the green dot is the target pixel used for data fusion (take the NSCam in Tibet as an example). The yellow and green frames illustrate the approximate spatial correspondence between remote sensing imagery and NSCam image.

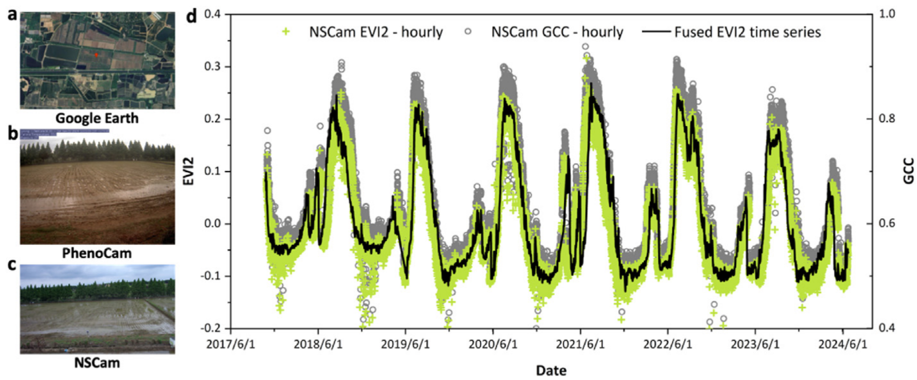

Fig. 3. Long-term monitoring during October 2017 to June 2024 by NSCam and PhenoCam in Jiangsu. a) Google Earth imagery of the site, the red dot is the location of both cameras; b) image taken by PhenoCam; c) image taken by NSCcam; d) calibrated observations and fused EVI2 daily time series.

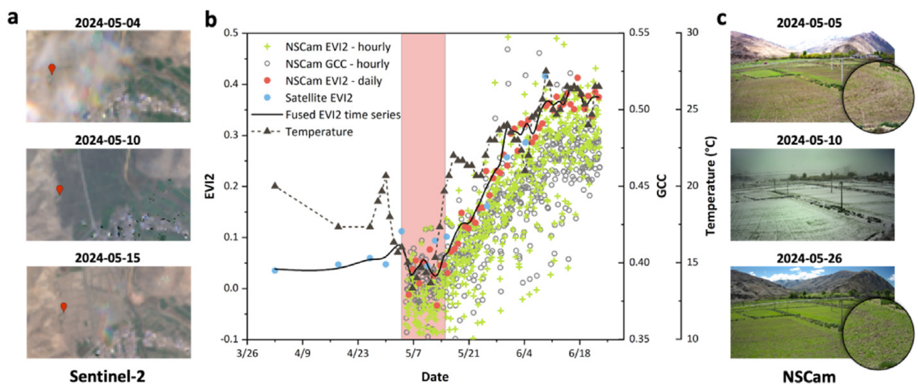

Fig. 4. Highland Barley monitoring during April to June of 2024 by NSCam Network site in Tibet. a) Sentinel-2 images of the site, the red dot is the location of the NSCam; b) original observations of NSCam and satellite, and fused EVI2 daily time series against three-day average temperature; c) NSCam images which captured the brief snowfall on 10th May 2024.

For monitoring agricultural land changes caused by human activities, the NSCam installed in Henan was selected as a representative study region to illustrate the effectiveness of the NSCam Network in capturing agricultural land changes due to harvesting. Monitoring such agricultural land changes aids in the precise observation of crop phenology and growth cycles. The monitored field is planted with winter wheat, a major grain crop in Henan and northern China, typically maturing and being harvested in early June. Generally, to maximize agricultural land use, local farmers usually plant summer corn after harvesting winter wheat. The NSCam at this site recorded this entire process, from winter wheat maturity to harvesting and subsequent summer corn planting (Fig. 5).

By integrating NSCam and satellite remote sensing data, we observed a stabilizing EVI2 at a lower value after mid-May. On 7th June, the fused EVI2 time series curve in Fig. 5b shows a sudden change due to the harvesting activity. Notably, this abrupt change was not precisely reflected in the satellite remote sensing data, as there was no sudden fluctuation in the EVI2 observed by satellites around 6th June. Furthermore, after harvesting winter wheat, summer corn was planted in the monitored field. As the corn emerged, a clear upward trend in the fused EVI2 time series can be observed after 12th June. This change was also

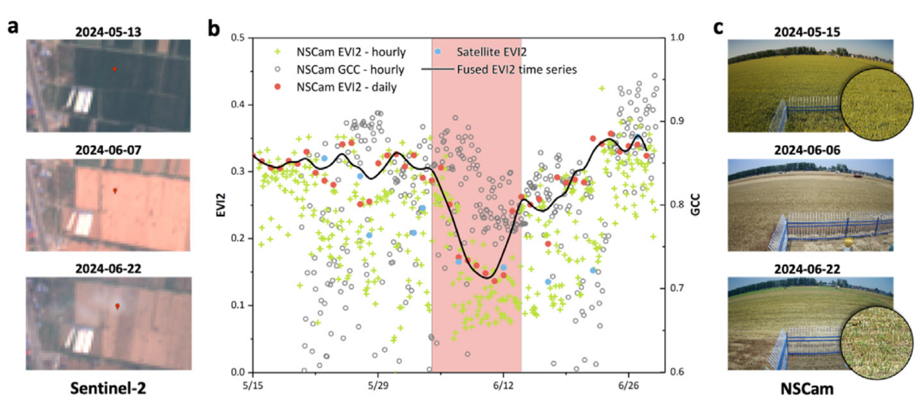

Fig. 5. Agricultural land monitoring during May to June of 2024 by NSCam Network site in Henan. a) Sentinel-2 images of the site, the red dot is the location of the NSCam; b) original observations of NSCam and satellite, and fused EVI2 daily time series; c) NSCam images which captured the harvesting of winter wheat on 6th June 2024, and emergence of summer corn on 22nd June 2024.

not reflected in the EVI2 calculated from satellite remote sensing data in time, shown by the continued low values and sudden increased value on 27th June for the blue observation points in Fig. 5b. This discrepancy could be due to thin cloud cover in the satellite images during this period (Fig. 5a). These experimental results demonstrate that the NSCam Network is highly effective in capturing abrupt agricultural land changes caused by both climatic events (e.g., temperature drops as shown in Fig. 4) and human activities (e.g., crop harvesting as shown in Fig. 5). Additionally, the NSCam Network is sensitive to subtle phenological changes in crops, such as corn emergence (Fig. 5). Therefore, the NSCam Network provides a crucial data foundation for supplementing satellite remote sensing data with dense observation time series, which is significant for implementing CSA.

In addition to cropland, pasture is another important type of agricultural land. This study also conducted phenological monitoring of pasture in Hulunbuir, Inner Mongolia, using a combination of NSCam and satellite remote sensing data. The Hulunbuir grassland, located in northeastern China, is a world-renowned natural pasture. However, since the 21st century, climate change and human activities have led to land desertification and grassland degradation in this ecologically fragile region. Monitoring the phenology of pasture in this area can provide real-time information on grass growth, aiding in grassland conservation efforts. The monitoring results shown in Fig. 6 indicate that since May, the vegetation cover in the Hulunbuir grassland has been gradually increasing. It is important to note that although grassland growth is also influenced by temperature, it exhibits a lag compared to the barley in Fig. 4. For example, the persistent low temperatures in late May resulted in stagnated grass growth in early June, while the temperature rise in early June facilitated further growth of the grassland by mid-June.

5. Discussion

In this paper, we explore the application of near surface camera technology in the monitoring of agricultural land and its role in achieving climate-smart agriculture. Our results prove the advantages of monitoring ground vegetation using NSCam Network and also the great potential value of applying this technology into CSA.

With the high spatial and temporal details (hourly to daily observations) to capture rapid phenological changes, NSCams make a direct link between observations and individual plants/canopies [36]. Also, NSCam records can be used to validate and scale up to landscape/satellite observations. Therefore, it creates many new possibilities for monitoring agricultural fields. Firstly, recording from NSCams can be integrated with satellite imagery to map agricultural land changes with high resolution and high frequency [23,64]. Secondly, it provides a new visual angle for monitoring vegetation and crop status automatically [65]. Besides, NSCams also provide sufficient ground truth for vegetation phenology, human activities, and extreme weather events [23].

It is worth mentioning that satellite remote sensing products can be integrated with near-earth cameras to achieve complementary results [66]. NSCams at the ground or plot scale provide an important ground reference for large-scale monitoring of satellites (usually at a global or regional scale) [55]. With the advantage of high spatial resolution in NSCams, the combined use of these two data sources can improve monitoring accuracy [61,67]. As for time scale, continuous monitoring of cameras improves the observing frequency of satellites, which could generate continuous records of vegetation changes that are ignored in satellites' observations [68]. In addition, NSCams are less affected by weather and atmospheric conditions due to the differences in observation angle and distance, its observation data provide key supplementary data when satellite data is missing.

We admit that some aspects limited the development of NSCam's application in CSA. Firstly, NSCams are typically deployed on fixed structures or platforms, which limits their coverage area compared to satellite or high-altitude UAV systems [40,64]. Consequently, monitoring large agricultural fields or extensive regions requires multiple deployments, increasing operational complexity and cost [43]. Considering the differences in data collection density and angles between NSCams and satellite remote sensing, a potential solution is to develop the relationships between the GCC for different land types and the satellite-based EVI2. These relationships can then be used to reconstruct the gap-free EVI2 time series for remote sensing imagery near the monitoring site. Furthermore, the deployment, maintenance, and data retrieval from NSCam Network can be labor-intensive. Regular adjustments and calibrations are necessary to ensure data accuracy, which demands significant human and financial resources [36]. There is also a lot of space left to deal with inconsistency when integrating results from satellite remote-sensing products and that from NSCam photos [69,70].

In the future, the technological improvements of the digital camera used in our network will be developed, such as enhancements for 4G signal reception in complex field environments, more flexible and controllable shooting angles, and a more efficient data management platform. Additionally, with the development of data fusion technology which improves data processing efficiency and accuracy, thus enhancing ground-to-satellite scale conversion capabilities, NSCam Network will have wider applications in achieving CSA. First of all, photos from this network can provide essential calibration and validation for satellite remote sensing data, ensuring data accuracy and reliability [49,58]. In addition, continuous time-lapse images from this network allow precise observation of plant growth, flowering, and fruiting, offering critical information for ecological and climate change research [41,71]. On a larger scale, this network also monitors changes in ecosystem structure and function, including vegetation cover, biodiversity, and land use changes [23,35,36,72]. In some circumstances, continuous monitoring of NSCam Network could capture subtle or abrupt environmental changes, such as seasonal variations and extreme climate events [23]. For example, our site in Tibet captured dramatic weather changes and resulting environmental changes in a day that snow quickly covered the grass in the evening, and the snow cover melted at noon without affecting the cattle and sheep grazing in the afternoon.

Besides, observational data from NSCam Network can be used to develop and validate ecological process models, supporting ecosystem management and decision-making [73,74]. Those cameras could serve as educational tools as well, raising public awareness about ecosystem dynamics and environmental changes, and fostering public engagement in ecological protection and scientific research [75–77]. We also believe this NSCam Network could facilitate data exchange and collaborative research with international networks like PhenoCam Network (https://phenocam.sr.unh.edu/webcam/) [40,64], European Phenology Camera Network (http://european-webcam-network.net) [78], Phenological Eyes Network (http://pen.envr.tsukuba.ac.jp) [79], Australian PhenoCam Network (http://phenocam.org.au/) [80], promoting global scientific cooperation and knowledge sharing.

6. Conclusion

The paper explores the application of near surface camera technology in the phenological monitoring of agricultural fields and its role in achieving CSA. This study begins with a review of the advancements in the application of near surface camera technology in the agricultural field, particularly within the realm of CSA. It then introduces our novel NSCam Network and its proof-of-concept applications. The preliminary monitoring results illustrate that integrating NSCam data with remote sensing imagery greatly enhances the temporal details and accuracy of agricultural land changes caused by abnormal weather and human activities. Along with its potential applications and existing limitations in the context of CSA, we discuss the necessity of establishing a national network of near surface cameras in China. By analyzing the image data captured by NSCam, we can more accurately assess key agricultural parameters such as crop health, pest and disease incidence, and soil moisture levels. This information is crucial for developing agricultural management strategies that are resilient to climate change.

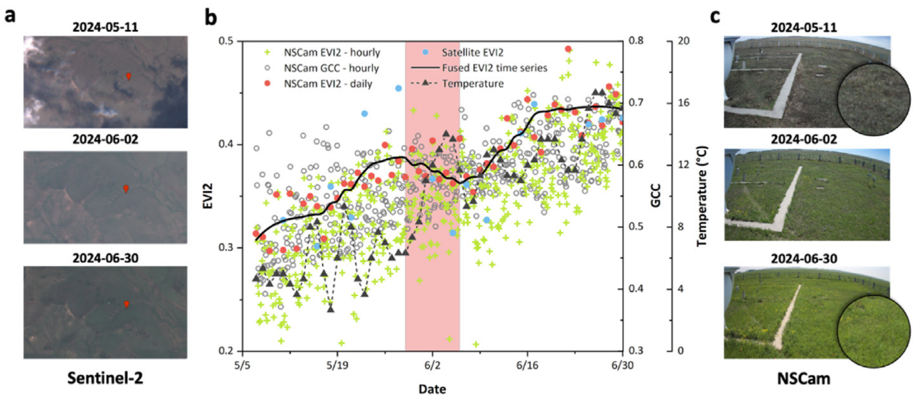

Fig. 6. Pasture monitoring during May to June of 2024 by NSCam Network site in Inner Mongolia. a) Sentinel-2 images of the site, the red dot is the location of the NSCam; b) original observations of NSCam and satellite, and fused EVI2 daily time series against three-day average temperature; c) NSCam images which captured the growth of grass.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Le Yu: Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Data curation, Conceptualization. **Zhenrong Du:** Writing – review & editing, Data curation. **Xiyu Li:** Writing – review & editing, Data curation. **Qiang Zhao:** Writing – review & editing. **Hui Wu:** Writing – review & editing. **Duoji weise:** Writing – review & editing. **Xinqun Yuan:** Writing – review & editing. **Yuanzheng Yang:** Writing – review & editing. **Wenhua Cai:** Writing – review & editing. **Weimin Song:** Writing – review & editing. **Pei Wang:** Writing – review & editing. **Zhicong Zhao:** Writing – review & editing. **Ying Long:** Writing – review & editing. **Yongguang Zhang:** Writing – review & editing. **Jinbang Peng:** Writing – review & editing. **Xiaoping Xin:** Writing – review & editing. **Fei Xu:** Writing – review & editing. **Miaogen Shen:** Writing – review & editing. **Hui Wang:** Writing – review & editing. **Yuanmei Jiao:** Writing – review & editing. **Tingting Li:** Writing – review & editing. **Zhentao Sun:** Writing – review & editing. **Yonggan Zhao:** Writing – review & editing. **Mengyang Fang:** Writing – review & editing. **Dailiang Peng:** Writing – review & editing. **Chaoyang Wu:** Writing – review & editing. **Sheng Li:** Writing – review & editing. **Xiaoli Shen:** Writing – review & editing. **Keping Ma:** Writing – review & editing. **Guanghui Lin:** Writing – review & editing. **Yong Luo:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Key R&D Program of China (2022YFE0209400), the National Natural Science Foundation of China (42201367).

References

[1] FAO, Climate Smart Agriculture Sourcebook, 2024. https://www.fao.org/climate-smart-agriculture-sourcebook/en/. (Accessed 3 July 2024).

[2] World Bank, Climate-smart agriculture - world bank group. https://www.worldbank.org/content/dam/Worldbank/document/CSA_Brochure_web_WB.pdf, 2024. (Accessed 3 July 2023).

[3] L. Lipper, N. McCarthy, D. Zilberman, S. Asfaw, G. Branca (Eds.), Climate Smart Agriculture: Building Resilience to Climate Change, Springer International Publishing, Cham, 2018, https://doi.org/10.1007/978-3-319-61194-5.

[4] J. Atta-Aidoo, et al., Adoption of climate-smart agricultural practices by smallholder farmers in rural Ghana: an application of the theory of planned behavior, PLOS Climate 1 (2022) e0000082, https://doi.org/10.1371/journal.pclm.0000082.

[5] D.J. Mulla, Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps, Biosyst. Eng. 114 (2013) 358–371, https://doi.org/10.1016/j.biosystemseng.2012.08.009.

[6] D. Entekhabi, et al., The soil moisture active passive (SMAP) mission, P IEEE 98 (2010) 704–716, https://doi.org/10.1109/JPROC.2010.2043918.

[7] L. Yu, et al., FROM-GLC Plus: toward near real-time and multi-resolution land cover mapping, Gisci Remote Sens 59 (2022) 1026–1047, https://doi.org/10.1080/15481603.2022.2096184.

[8] M.A. Wulder, et al., Fifty years of Landsat science and impacts, Remote Sens. Environ. 280 (2022) 113195, https://doi.org/10.1016/j.rse.2022.113195.

[9] M.C. Hansen, et al., High-resolution global maps of 21st-century forest cover change, Science 342 (2013) 850–853, https://doi.org/10.1126/science.1244693.

[10] J.-F. Pekel, A. Cottam, N. Gorelick, A.S. Belward, High-resolution mapping of global surface water and its long-term changes, Nature 540 (2016) 418–422.

[11] P. Gong, et al., Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data, Int J Remote Sens 34 (2013) 2607–2654, https://doi.org/10.1080/01431161.2012.748992.

[12] M. Burke, A. Driscoll, D.B. Lobell, S. Ermon, Using satellite imagery to understand and promote sustainable development, Science 371 (2021), https://doi.org/10.1126/science.abe8628 eabe8628.

[13] H. Zhang, et al., A non-destructive method for rapid acquisition of grassland aboveground biomass for satellite ground verification using UAV RGB images, Glob Ecol Conserv. 33 (2022) e01999, https://doi.org/10.1016/j.gecco.2022.e01999.

[14] S. Adar, et al., Estimation of aboveground biomass production using an unmanned aerial vehicle (UAV) and VENμS satellite imagery in Mediterranean and semiarid rangelands, Remote Sens. Appl.: Society and Environment 26 (2022) 100753, https://doi.org/10.1016/j.rsase.2022.100753.

[15] A.L. Fytsilis, A. Prokos, K.D. Koutroumbas, D. Michail, C.C. Kontoes, A methodology for near real-time change detection between Unmanned Aerial Vehicle and wide area satellite images, ISPRS J Photogramm 119 (2016) 165–186, https://doi.org/10.1016/j.isprsjprs.2016.06.001.

[16] S. Zhang, et al., Integrated satellite, unmanned aerial vehicle (UAV) and ground inversion of the SPAD of winter wheat in the reviving stage, Sensors 19 (2019) 1485, https://doi.org/10.3390/s19071485.

[17] M. Weiss, F. Jacob, G. Duveiller, Remote sensing for agricultural applications: a meta-review, Remote Sens. Environ. 236 (2020) 111402, https://doi.org/10.1016/j.rse.2019.111402.

[18] R. D'Andrimont, et al., Crowdsourced street-level imagery as a potential source of in-situ data for crop monitoring, Land 7 (2018) 127, https://doi.org/10.3390/land7040127.

[19] S. Fritz, et al., A comparison of global agricultural monitoring systems and current gaps, Agric. Syst. 168 (2019) 258–272, https://doi.org/10.1016/j.agsy.2018.05.010.

[20] L.D. Estes, et al., A platform for crowdsourcing the creation of representative, accurate landcover maps, Environ. Model. Software 80 (2016) 41–53, https://doi.org/10.1016/j.envsoft.2016.01.011.

[21] P. Gong, Wireless sensor network as a new ground remote sensing technology for environmental monitoring, Journal of Remote Sensing 11 (2007) 545–551, https://doi.org/10.11834/jrs.20070475.

[22] P. Gong, Some essential questions in remote sensing science and technology, Journal of Remote Sensing (2009) 13–23, https://doi.org/10.11834/jrs.20090101.

[23] T.B. Brown, et al., Using phenocams to monitor our changing Earth: toward a global phenocam network, Front. Ecol. Environ. 14 (2016) 84–93, https://doi.org/10.1002/fee.1222.

[24] E.A. Graham, E.C. Riordan, E.M. Yuen, D. Estrin, P.W. Rundel, Public Internet-connected cameras used as a cross-continental ground-based plant phenology monitoring system, Global Change Biol. 16 (2010) 3014–3023.
[25] S. Piao, A. Mohammat, J. Fang, Q. Cai, J. Feng, NDVI-based increase in growth of temperate grasslands and its responses to climate changes in China, Global Environ. Change 16 (2006) 340–348, https://doi.org/10.1016/j.gloenvcha.2006.02.002.
[26] M. Peaucelle, J. Peñuelas, H. Verbeeck, Accurate phenology analyses require bud traits and energy budgets, Nat. Plants 8 (2022) 915–922, https://doi.org/10.1038/s41477-022-01209-8.
[27] F.S. Chapin, G.R. Shaver, A.E. Giblin, K.J. Nadelhoffer, J.A. Laundre, Responses of arctic tundra to experimental and observed changes in climate, Ecology 76 (1995) 694–711, https://doi.org/10.2307/1939337.
[28] R. de Jong, M.E. Schaepman, R. Furrer, S. de Bruin, P.H. Verburg, Spatial relationship between climatologies and changes in global vegetation activity, Global Change Biol. 19 (2013) 1953–1964, https://doi.org/10.1111/gcb.12193.
[29] L. Deng, et al., Urban plant phenology monitoring: expanding the functions of widespread surveillance cameras to nature rhythm understanding, Remote Sens. Appl.: Society and Environment 15 (2019) 100232, https://doi.org/10.1016/j.rsase.2019.05.001.
[30] L. Lemordant, P. Gentine, A.S. Swann, B.I. Cook, J. Scheff, Critical Impact of Vegetation Physiology on the Continental Hydrologic Cycle in Response to Increasing CO2, 115, Proceedings of the National Academy of Sciences, 2018, pp. 4093–4098.
[31] O.G. del Arroyo, W.L. Silver, Disentangling the long-term effects of disturbance on soil biogeochemistry in a wet tropical forest ecosystem, Global Change Biol. 24 (2018) 1673–1684, https://doi.org/10.1111/gcb.14027.
[32] G.K. Phoenix, A.H. Khafsha, Untangling the influences of air quality and climate change on biodiversity in space and time, Global Change Biol. 29 (2023) 5115–5116, https://doi.org/10.1111/gcb.16858.
[33] O. Allouche, A. Tsoar, R. Kadmon, Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS), J. Appl. Ecol. 43 (2006) 1223–1232, https://doi.org/10.1111/j.1365-2664.2006.01214.x.
[34] P. Gong, Towards more extensive and deeper application of remote sensing, Journal of Remote Sensing 23 (2019) 567–569, https://doi.org/10.11834/jrs.20199223.
[35] B. Alberton, et al., Introducing digital cameras to monitor plant phenology in the tropics: applications for conservation, Perspect Ecol Conser. 15 (2017) 82–90, https://doi.org/10.1016/j.pecon.2017.06.004.
[36] A.D. Richardson, Tracking seasonal rhythms of plants in diverse ecosystems with digital camera imagery, New Phytol. 222 (2019) 1742–1750, https://doi.org/10.1111/nph.15591.
[37] P.J. Mayhew, M.A. Bell, T.G. Benton, A.J. McGowan, Biodiversity Tracks Temperature over Time, 109, Proceedings of the National Academy of Sciences, 2012, pp. 15141–15145, https://doi.org/10.1073/pnas.1200844109.
[38] A.S. Thorpe, et al., Introduction to the sampling designs of the national ecological observatory network terrestrial observation system, Ecos 7 (2016) e01627, https://doi.org/10.1002/ecs2.1627.
[39] P. Tiselius, An in situ video camera for plankton studies: design and preliminary observations, Mar. Ecol. Prog. Ser. 164 (1998) 293–299, https://doi.org/10.3354/meps164293.
[40] A.D. Richardson, et al., Tracking vegetation phenology across diverse North American biomes using PhenoCam imagery, Sci. Data 5 (2018) 180028, https://doi.org/10.1038/sdata.2018.28.
[41] H. Aasen, N. Kirchgessner, A. Walter, F. Liebisch, PhenoCams for field phenotyping: using very high temporal resolution digital repeated photography to investigate interactions of growth, phenology, and harvest traits, Front. Plant Sci. 11 (2020), https://doi.org/10.3389/fpls.2020.00593.
[42] K. Hufkens, et al., Linking near-surface and satellite remote sensing measurements of deciduous broadleaf forest phenology, Remote Sens. Environ. 117 (2012) 307–321, https://doi.org/10.1016/j.rse.2011.10.006.
[43] A. Burkart, V.L. Hecht, T. Kraska, U. Rascher, Phenological analysis of unmanned aerial vehicle based time series of barley imagery with high temporal resolution, Precision, Agric. For. 19 (2018) 134–146, https://doi.org/10.1007/s11119-017-9504-y.
[44] Y. Liu, et al., Using PhenoCams to track crop phenology and explain the effects of different cropping systems on yield, Agric. Syst. 195 (2022) 103306, https://doi.org/10.1016/j.agsy.2021.103306.
[45] J. Han, et al., Real-time detection of rice phenology through convolutional neural network using handheld camera images, Precis. Agric. 22 (2021) 154–178, https://doi.org/10.1007/s11119-020-09734-2.
[46] A.R. Petach, M. Toomey, D.M. Aubrecht, A.D. Richardson, Monitoring vegetation phenology using an infrared-enabled security camera, Agric. For. Meteorol. 195–196 (2014) 143–151, https://doi.org/10.1016/j.agrformet.2014.05.008.
[47] H.E. Ahrends, et al., Tree phenology and carbon dioxide fluxes: use of digital photography for process-based interpretation at the ecosystem scale, Clim. Res. 39 (2009) 261–274, https://doi.org/10.3354/cr00811.
[48] R. Ide, H. Oguma, Use of digital cameras for phenological observations, Ecol. Inf. 5 (2010) 339–347, https://doi.org/10.1016/j.ecoinf.2010.07.002.
[49] C. Diao, G. Li, Near-surface and high-resolution satellite time series for detecting crop phenology, Rem. Sens. 14 (2022) 1957, https://doi.org/10.3390/rs14091957.
[50] M. Ruml, T. Vulić, Importance of phenological observations and predictions in agriculture, Journal of Agricultural Sciences, Belgrade 50 (2005) 217–225.
[51] M. Herbei, F. Sala, Remote sensing for describing vegetation dynamics under agricultural land conditions, Life Science and Sustainable Development 3 (2022) 60–69, https://doi.org/10.58509/lssd.v3i1.168.
[52] S. Sagar, K.A. Singh, G. Sirisha, K. Vaishnavi, Enhanced agriculture using image processing and sensors. 2018 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), 2018, pp. 1–5, https://doi.org/10.1109/SCEECS.2018.8546988.
[53] I. Rodriguez-Iturbe, P. D'Odorico, A. Porporato, L. Ridolfi, On the spatial and temporal links between vegetation, climate, and soil moisture, Water Resour. Res. 35 (1999) 3709–3722, https://doi.org/10.1029/1999WR900255.
[54] T. Milliman, et al., Vegetation CollectionPhenoCam dataset v2.0: digital camera imagery from the PhenoCam network, 2000-2018. https://doi.org/10.3334/ORNLDAAC/1689, 2019.
[55] D.M. Browning, J.W. Karl, D. Morin, A.D. Richardson, C.E. Tweedie, Phenocams bridge the gap between field and satellite observations in an arid grassland ecosystem, Rem. Sens. 9 (2017) 1071, https://doi.org/10.3390/rs9101071.
[56] X. Zhang, et al., Evaluation of land surface phenology from VIIRS data using time series of PhenoCam imagery, Agric. For. Meteorol. 256–257 (2018) 137–149, https://doi.org/10.1016/j.agrformet.2018.03.003.
[57] A.D. Richardson, PhenoCam: an evolving, open-source tool to study the temporal and spatial variability of ecosystem-scale phenology, Agric. For. Meteorol. 342 (2023) 109751, https://doi.org/10.1016/j.agrformet.2023.109751.
[58] S. Thapa, V.E. Garcia Millan, L. Eklundh, Assessing forest phenology: a multi-scale comparison of near-surface (UAV, spectral reflectance sensor, PhenoCam) and satellite (MODIS, sentinel-2) remote sensing, Rem. Sens. 13 (2021) 1597, https://doi.org/10.3390/rs13081597.
[59] R. d'Andrimont, G. Lemoine, M. van der Velde, Using Sentinel-1 and -2 Satellite Time Series to Monitor Crop Phenology at the Parcel Level, EGU General Assembly Conference Abstracts, 2020 15171, https://doi.org/10.5194/egusphere-egu2020-15171.
[60] D. Ichikawa, K. Wakamori, The integrated use of Landsat, sentinel-2 and PlanetScope satellite data for crop monitoring. IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium, 2018, pp. 7707–7710, https://doi.org/10.1109/IGARSS.2018.8519024.
[61] K.H. Tran, et al., A novel algorithm for the generation of gap-free time series by fusing harmonized Landsat 8 and Sentinel-2 observations with PhenoCam time series for detecting land surface phenology, Remote Sens. Environ. 282 (2022) 113275, https://doi.org/10.1016/j.rse.2022.113275.
[62] L. Zeng, B.D. Wardlow, D. Xiang, S. Hu, D. Li, A review of vegetation phenological metrics extraction using time-series, multispectral satellite data, Remote Sens. Environ. 237 (2020) 111511, https://doi.org/10.1016/j.rse.2019.111511.
[63] Z. Zhen, S. Chen, T. Yin, J.-P. Gastellu-Etchegorry, Globally quantitative analysis of the impact of atmosphere and spectral response function on 2-band enhanced vegetation index (EVI2) over Sentinel-2 and Landsat-8, ISPRS J Photogramm 205 (2023) 206–226, https://doi.org/10.1016/j.isprsjprs.2023.09.024.
[64] B. Seyednasrollah, et al., Tracking vegetation phenology across diverse biomes using Version 2.0 of the PhenoCam Dataset, Sci. Data 6 (2019) 222, https://doi.org/10.1038/s41597-019-0229-9.
[65] Y. Zhu, Z. Cao, H. Lu, Y. Li, Y. Xiao, In-field automatic observation of wheat heading stage using computer vision, Biosyst. Eng. 143 (2016) 28–41, https://doi.org/10.1016/j.biosystemseng.2015.12.015.
[66] K.H. Tran, et al., HP-LSP: a reference of land surface phenology from fused Harmonized Landsat and Sentinel-2 with PhenoCam data, Sci. Data 10 (2023) 691, https://doi.org/10.1038/s41597-023-02605-1.
[67] M. Moon, A.D. Richardson, M.A. Friedl, Multiscale assessment of land surface phenology from harmonized Landsat 8 and Sentinel-2, PlanetScope, and PhenoCam imagery, Remote Sens. Environ. 266 (2021) 112716, https://doi.org/10.1016/j.rse.2021.112716.
[68] C.J. Watson, N. Restrepo-Coupe, A.R. Huete, Multi-scale phenology of temperate grasslands: improving monitoring and management with near-surface phenocams, Front. Environ. Sci. 7 (2019), https://doi.org/10.3389/fenvs.2019.00014.
[69] D.M. Browning, et al., Monitoring agroecosystem productivity and phenology at a national scale: a metric assessment framework, Ecol. Indicat. 131 (2021) 108147, https://doi.org/10.1016/j.ecolind.2021.108147.
[70] A.D. Richardson, K. Hufkens, T. Milliman, S. Frolking, Intercomparison of phenological transition dates derived from the PhenoCam Dataset V1.0 and MODIS satellite remote sensing, Sci. Rep. 8 (2018) 5679, https://doi.org/10.1038/s41598-018-23804-6.
[71] D. Ganeva, M. Chanev, L. Filchev, G. Jelev, D. Valcheva, Evaluation of PhenoCam phenology of barley, Remote Sensing for Agriculture, Ecosystems, and Hydrology XXIV 12262 (2022) 28–39, https://doi.org/10.1117/12.2636335.
[72] B. Alberton, et al., Relationship between tropical leaf phenology and ecosystem productivity using phenocameras, Front. Environ. Sci. 11 (2023), https://doi.org/10.3389/fenvs.2023.1223219.
[73] H. Wang, G. Jia, H.E. Epstein, H. Zhao, A. Zhang, Integrating a PhenoCam-derived vegetation index into a light use efficiency model to estimate daily gross primary production in a semi-arid grassland, Agric. For. Meteorol. 288–289 (2020) 107983, https://doi.org/10.1016/j.agrformet.2020.107983.
[74] D. Yan, R.L. Scott, D.J.P. Moore, J.A. Biederman, W.K. Smith, Understanding the relationship between vegetation greenness and productivity across dryland ecosystems through the integration of PhenoCam, satellite, and eddy covariance data, Remote Sens. Environ. 223 (2019) 50–62, https://doi.org/10.1016/j.rse.2018.12.029.
[75] K.K. Fuccillo, T.M. Crimmins, C.E. de Rivera, T.S. Elder, Assessing accuracy in citizen science-based plant phenology monitoring, Int. J. Biometeorol. 59 (2015) 917–926, https://doi.org/10.1007/s00484-014-0892-7.
[76] M. Kosmala, et al., Season spotter: using citizen science to validate and scale plant phenology from near-surface remote sensing, Rem. Sens. 8 (2016) 726, https://doi.org/10.3390/rs8090726.

[77] S.D. Taylor, J.M. Meiners, K. Riemer, M.C. Orr, E.P. White, Comparison of large-scale citizen science data and long-term study data for phenology modeling, Ecology 100 (2019) e02568, https://doi.org/10.1002/ecy.2568.

[78] L. Wingate, et al., Interpreting canopy development and physiology using a European phenology camera network at flux sites, Biogeosciences 12 (2015) 5995–6015, https://doi.org/10.5194/bg-12-5995-2015.

[79] K.N. Nasahara, S. Nagai, Review: development of an in situ observation network for terrestrial ecological remote sensing: the Phenological Eyes Network (PEN), Ecol. Res. 30 (2015) 211–223, https://doi.org/10.1007/s11284-014-1239-x.

[80] C.E. Moore, et al., Reviews and syntheses: Australian vegetation phenology: new insights from satellite remote sensing and digital repeat photography, Biogeosciences 13 (2016) 5085–5102, https://doi.org/10.5194/bg-13-5085-2016.