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# An interactive and iterative method for crop mapping through crowdsourcing optimized field samples

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ABSTRACT

Remote sensing appears as an essential approach for crop mapping, yet the interpretation of satellite imageries requires for a large amount of labeled data as ground truth information. Traditional approaches for ground truth data collection are costly, inefficient and are mostly one-off effort, thus the up-to-date ground truth data are extremely scarce in existing crop mapping research and applications. Here, we address the challenge of ground truth data scarcity by implementing an interactive and iterative crowdsourcing framework. We developed a crowdsourcing platform, named as FarmWatch, which helped process one Sentinel-2 imagery for an unsupervised clustering and instantly for a stratified random sampling. Sample tasks and collected information are synchronized across web and mobile applications, which enables the field information to be immediately applied for crop mapping. Results of the iterative process show that: firstly, a total of 95 samples have been collected in the initial round and the overall accuracy of crop mapping was 83.33%; secondly, after four rounds of sample collection (a total of 279 samples), the classification accuracy reached to 96.30% and such accuracy did not improve even though an additional 23 samples were added in the fifth round. Such interactive and iterative mechanism indicates that ground truth data has been sufficiently collected for the current crop mapping activity. It not only promotes the opportunity of up-to-date and in-season crop mapping, but also helps to inform users where to collect field samples and how many samples are basically required for producing an accurate crop map.

## 1. Introduction

The need for spatialized information about agricultural practices is expected to rapidly increase, not only because agriculture provides food, fibers, fuel, and raw materials for human, but also because the agricultural practices managed at a farm scale would have a series of consequence at the global scale (Foley et al., 2011; Verburg et al., 2013). This has resulted in a strong requirement for monitoring crop growth and status in various locations and environmental context with various temporal resolutions, to provide up-to-date information to different actors and decision makers in support of global and national food security (Fritz et al., 2019). Remote sensing appears as an essential tool for monitoring agricultural practices by providing repetitive information on crop status at different scales and for different purposes (Bégué et al., 2018; Karthikeyan et al., 2020; Weiss et al., 2020). Multi-source satellite images above a field over time are not only useful to distinguish the agricultural areas against the non-agricultural areas, but also effective to map the spatial–temporal pattern of different crops and to monitor the crop growth throughout the growing season (Woźniak et al., 2022). Yet exploiting the great potentials of satellite remote sensing data for crop mapping and monitoring faces several critical challenges. One challenge is how to process and extract meaningful information from the massive volume of raw imageries (Ma et al., 2015).

Remote sensing data selection is the major determinant for the effectivity of information extraction in crop mapping and monitoring (Song et al., 2021; Vallentin et al., 2022; Zhao et al., 2019). The application of data processing methods is another important determinant, and more case studies have shown that the latest development of artificial intelligence algorithms, such as machine leaning and deep learning (Bergen et al., 2019; Reichstein et al., 2019), play a more pivotal role in agricultural remote sensing, crop mapping and monitoring in particular (Nguyen et al., 2020; Segarra et al., 2022; Wang et al., 2022; Xu et al.,

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2021). While these publications mainly focused on the diverse applications and the achievable accuracies based on the appropriate selection of data and choice of algorithm, few works address the problem of training data sparsity even in an era dominated by data-driven approaches (Qin and Liu, 2022). This is particularly true for crop mapping. As crop maps are usually produced at a relatively larger geographical area to depict the diversity, variability and spatial distribution of crop types, training samples are difficult to acquire in many regions through ground survey, resulting in significant challenge for large-scale crop mapping from remotely sensed images (Hao et al., 2020; Hu et al., 2021).

There are a couple of reasons causing the extremely scarce use of authentic and up-to-date ground truth data in crop mapping. Firstly, the traditional approaches to collect ground truth data heavily rely on the designated field surveys with specific purposes. This is largely originated from the hypothesis-driven scientific researches. For example, Song et al. (2018), Xia et al. (2022) and You et al. (2021) have designed and conducted custom-fitted surveys, collected 1 777, 1 751, 2 346 and 59 789 ground sample points for their crop mapping studies respectively. Even though such custom-fitted approach could be effective for most case studies, it is yet cost prohibitive and suffers a handful of limitations. For instance, researchers usually need prior knowledge about the study area to design their survey plans, it will be difficult for them to organize a field survey if the area is geographically far away or, they are not familiar with. Moreover, the entire procedure, e.g. making a survey plan, traveling to the field, collecting and prescreening sample information, and fully using the ground truth data for a crop mapping are time-consuming, which can not reflect the up-to-date status. The survey and the use of survey data are both like a "one-off" effort: on one hand, the number of samples and their spatial distribution are often empirically determined, it is not likely to revisit the study area if the collected survey information is in low quality (e.g. insufficient, unrepresentative and insignificant) to support a high mapping accuracy, while on the other hand, the usage of the ground truth data is usually for a "one-off" classification that was developed for a singular year or localized region so does not serve more than being a unique snapshot.

Secondly, some pilot studies began to derive a large amount of ground truth data from the third-party databases such as the large-scale *in-situ* surveys or farmer's self-declarations. For example, d'Andrimont et al. (2021) produced a first European crop type map based on the Land Use/Cover Area frame Survey (LUCAS) *in-situ* observation database, David et al., (2021) and Blickensdörfer et al., (2022) produced the national level crop type maps for France and Germany respectively based on the Land Parcel Information System (LPIS) database. The Crop Data Layers (CDL) for the conterminous United States have been under operation at an annual basis, with the support of the national-level June Area Survey (JAS). Such approach works for a few developed regions because the relevant third-party databases are available and accessible, although these databases are not built for the remote sensing purpose in the first place. For example, the LPIS is developed for European farmers to receive subsidies every year, based on a declaration of which parcels they have used and what crops they have grown. While the JAS is carried out by the US Department of Agriculture every year that approximately 70,000 land use tracts are identified and the farm operators are interviewed to provide complete coverage of all agriculture activity occurring on that land. Yet, such comprehensive third-party databases and data acquisition channels are largely not existing in many developing regions where the smallholder farming is prevalent (e.g. in China).

The fast development of Information and Communication Technology (ICT) enables the collection of farming practices in a standardized, high-frequency, far-ranging and low-cost manner (King, 2017; Osinga et al., 2022). Smartphone plays an essential role and benefits smallholding farmers during this transformation, not only because it creates the potential for larger gains through the transmission of more sophisticated media, but also because it provides the GPS-enabled access to geospatial servers (Zhou et al. 2022). The two-way communication with and between farmers facilitate improvements of information and other services over time (Fabregas et al., 2019; Mehrabi et al., 2020). For example, in Africa, a high-frequency mobile phone data collection through short-message service (SMS) was applied to close the social-environmental data gap for climate change and food security studies (Giroux et al., 2019; Krell et al., 2022). While a GeoFarmer App that provides near real-time and two-way dataflows, was applied to monitor agricultural production systems with interactive feedback between the users, within pre-defined geographical domains (Eitzinger et al., 2019).

In addition to using smartphone as a tool for data collection and dissemination from/to farmers, some applications amplify the scalability of the smartphone-sensed data to other end-users (Oteyo et al., 2021). For example, the eFarm App collects geotagged pictures and integrates socioeconomic information through an online survey for agricultural land mapping modeling (Yu et al., 2017). GVG (GPS-video-GIS) is a very useful APP for field trip which represents a field data collection system with integrated GPS for positioning, a video component for taking geo-tagged photographs, and a GIS system for managing geo-information (B. Wu et al., 2023; Wu and Li, 2012). The GeoreCAPTCHA gathers user-generated geographic information for land cover mapping (Hillen and Höfle, 2015). Innovative practices have been carried out in India by using the geotagged images: one was crop phenology monitoring based on the Picture-Based Insurance (PBI) project (Hufkens et al., 2019), while the other was crop mapping based on the Plantix database, a free Android application that uses image recognition to diagnose crop diseases (Wang et al., 2020). In addition, crowdsourced social media data has been used for high-resolution rice mapping in Madagascar (de Vos et al., 2023). The available evidence suggests that current ICT development provides greater potential in transforming agriculture in developing regions (Fabregas et al., 2019). With the support of advanced ICT, there are emerging opportunities in the developing regions in collecting ground truth data for crop mapping, even though the prementioned well-established data acquisition systems and the comprehensive third-party databases such as LUCAS, LPIS and JAS are currently not existing in those regions.

It is widely acknowledged that the very best crop maps rely on having a robust set of *in situ*, or "ground truth" data to build the classification models in which they are based on. However, existing studies chose to count on a higher classification accuracy achieved by algorithm improvement under the condition of less training sample (Gao et al., 2021; Wang et al., 2019), and to look for a better training sample use efficiency achieved by using archival land cover information (Johnson and Mueller, 2021; Wei et al., 2022). Facing the fact that people are seeking for secondary solutions – accuracy improvement with less authentic and up-to-date training data – rather than directly solving the problem of ground truth data sparsity itself, we propose a framework that enables a standardized and crowdsourced ground information collection in a high-frequency, far-ranging and low-cost way, and subsequently to facilitate the up-to-date crop mapping in an interactive and efficient manner. Finally, we present a case application demonstrating how this framework is effective in addressing operational-purpose-driven crop mapping tasks.

## 2. Methodology

### 2.1. Conceptual framework

In the current paper, we aim to address the challenge of ground truth data scarcity in two aspects: first, to establish a low-cost and two-way data transmission channel supported by the digitalized crowdsourcing infrastructure; second, to provide a custom-fitted platform that integrates sample-designing and sample-collecting for efficient crop mapping underpinned by a feedback mechanism. The platform, named FarmWatch, is a crowdsourcing ground truth field sample collecting tool for crop mapping. The simplified data collecting procedure only requires for a few farm-level and crop-level photos taken on-site. Nevertheless, it

is embedded in an interactive sampling framework which enables the two-way data transmission channel of tasks assignment and data gathering. In the framework, data collectors are not necessarily crop map producers, which largely extends the coverage of participants. The approach, i.e. information collected from "other sources", could also greatly improve the efficiency and lower the cost of field information collection during the entire crop mapping procedure.

The framework is consisted of three parts: sample design, sample collection and image classification. Sample design begins with a preliminary processing of remotely sensed imageries. Firstly, we apply an instant unsupervised classification to the candidate image by partitioning the preliminary raw land cover clusters according to the multispectral feature space. Then we use the clusters to optimize the sample size and distribution. Sample collection is mainly supported by the FarmWatch platform that all sample tasks and collected information are synchronized between personal computers and mobile devices. Finally, based on the collected sample information, a crop type map will be produced through image classification. By assuming that the accuracy of mapping will be improved when the sample size and quality are increasing, the produced map is instantly assessed and the results will be further used to inform whether additional samples are required to update the existing map to obtain a higher accuracy. Such interactive mechanism not only promotes the opportunity of up-to-date and in-season crop mapping, but also helps to inform users the necessity to collect field samples and the number of samples required for producing an accurate crop map (Fig. 1).

### 2.2. Sample design

In the remote sensing image classification studies, how to effectively determine and distribute the sample size is largely depended on the prior information of the study area and the ready-to-be-classified images. Farmer's crop choice and the growth status of crops are highly variable (Liu et al., 2022), so that it is important to select images with good spatial and spectral resolutions that are effective to capture the unique characteristic(s) of different crops. It is also necessary to assess the quality of image, e.g. data acquisition date and cloud coverage, to ensure the performance of crop mapping. FarmWatch allows user to upload remote sensing images visualization and preliminary data processing. Some essential quality indicators, e.g. cloud coverage, can be quickly assessed. The drone images are becoming important supplement to satellite images because of its flexibility and finer spatial resolution.

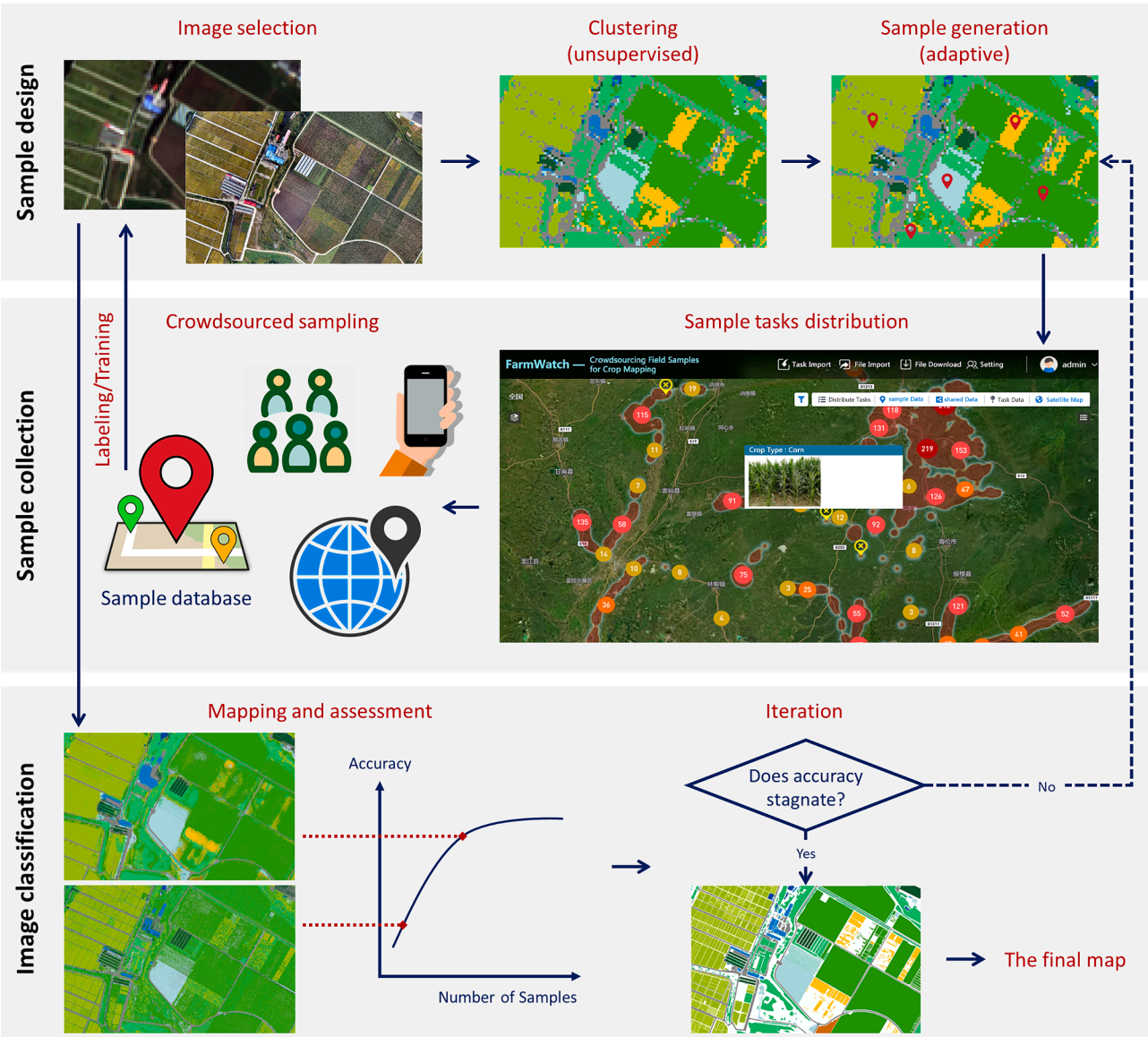


**Fig. 1.** The interactive framework for crop mapping through crowdsourcing field samples.

Users can freely switch the uploaded images to assist sample design (Fig. 2).

The selection of sampling approach is also important for sample design. Given the heterogeneity of land cover types, the stratified random sampling approach provides the desired adaptability to augment a sample to address regional or class-specific accuracy objectives (Boschetti et al., 2016; Stehman et al., 2012). However, as the stratified random sampling approach divides the population into relevant strata to increase a certain population group's representativeness, it is only achievable if relevant strata are known and distinguishable in a population group. This limits the performance of stratified random sampling in land cover mapping, because the prior knowledge is often not enough or available (Li et al., 2021). Here we provide a solution to tackle the chicken or egg dilemma. The raw land cover clusters are generated by applying an unsupervised clustering, which are further used to construct the strata. For each stratum, the simple random sampling was adopted to obtain the samples of each object category. Following previous studies, e.g., Anchang et al. (2016) and Koda et al. (2020), we created the feature space for clustering based on spectral band values and vegetation indices. Then we tested various algorithms, such as *k*-means and ISODATA (supported by the elbow criterion and q-statistic), to optimize the clustering results.

### 2.3. Sample collection

Sample points are generated and distributed on the FarmWatch platform, and are synchronized between PC and mobile devices (Fig. 3). The FarmWatch desktop app is developed on VUE, ECMAScript 6, and Mapbox, while the mobile app is developed on MUI and Mapbox. The backend of the website uses SpringBoot and the website database uses mySQL. The communication between the desktop and mobile apps uses the MQTT protocol, which enables all sample tasks and collected information are synchronized simultaneously across devices. Specifically, the desktop app is used to generate sample points and release sample tasks (Fig. 3a): sample tasks are automatically generated in the research area based on the exploitation of the candidate image, and can be adaptively adjusted and optimized according to the collecting situation and image classification results. The mobile app is used to receive sample tasks and collect sample information (Fig. 3b).

The FarmWatch mobile app is developed not only for receiving sampling tasks, but also allows users to observe agricultural fields anywhere to collect geo-tagged photos documenting crop type, phenological stage, visible damage and management practices. Given a same location may be revisited repeatedly, the app combines the records of the location and automatically track the changes over time. By collecting data, the crowd are helping to improve the quality of agricultural monitoring. The collected data will be made freely available through the FarmWatch desktop app to registered users to train and validate models and algorithms to assess crop production including aspects related to area and yields e.g., crop maps, phenology, biomass, etc. Nevertheless, in some cases that data are not ready to share, the FarmWatch platform further provides a group function: members from a given group can view the group's tasks, which will improve the data exclusiveness while keeping the sampling efficiency.

### 2.4. Image classification

The sample database with geo-tagged photos taken on-site is used to create labels and train the classification model. At this stage, we also selected and tested various effective classifiers in crop mapping such as Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Naïve Bayes (NB). We embed these optional image classification algorithms, together with the sample designing algorithms, to provide a user-friendly interface on the FarmWatch platform. Users can quickly select one method or compare different methods for specific purposes. As a result, it is able to accomplish a complete workflow from sample design to image classification (Fig. 1).

The interactive sampling procedure is activated at this stage: when the platform receives newly collected sample information, a crop type can be produced instantly. At the same time, an accuracy assessment for the map is performed. The metrics for accuracy assessment are also encapsulated in the platform, including overall accuracy (OA), producer's accuracy (PA), user's accuracy, kappa coefficient, etc. Following Foody (2002), we select the OA and PA to assess the classification results. While the results of accuracy assessment are further used to validate the quality of existing samples, and to inform whether additional samples are required to update the existing map to obtain a higher accuracy. This process might be repeated for several iterations until the classification accuracy meets the requirement. Once the classification accuracy is sufficiently high, the sampling task is ended and the final crop map is produced. By doing this we could know how many samples are basically required for producing an accurate crop map.

## 3. A pilot application in Northeast China

To test the interactive sampling framework for crop mapping and the performance of FarmWatch platform, we carried out a trial application in an agricultural region in Kaiyuan country, Liaoning Province, Northeast China (123°45′E and 42°23′N, Fig. 4a). We choose Kaiyuan County as a case study area because it is in the typical single cropping region with a moderate degree of complexity in cropping pattern, which

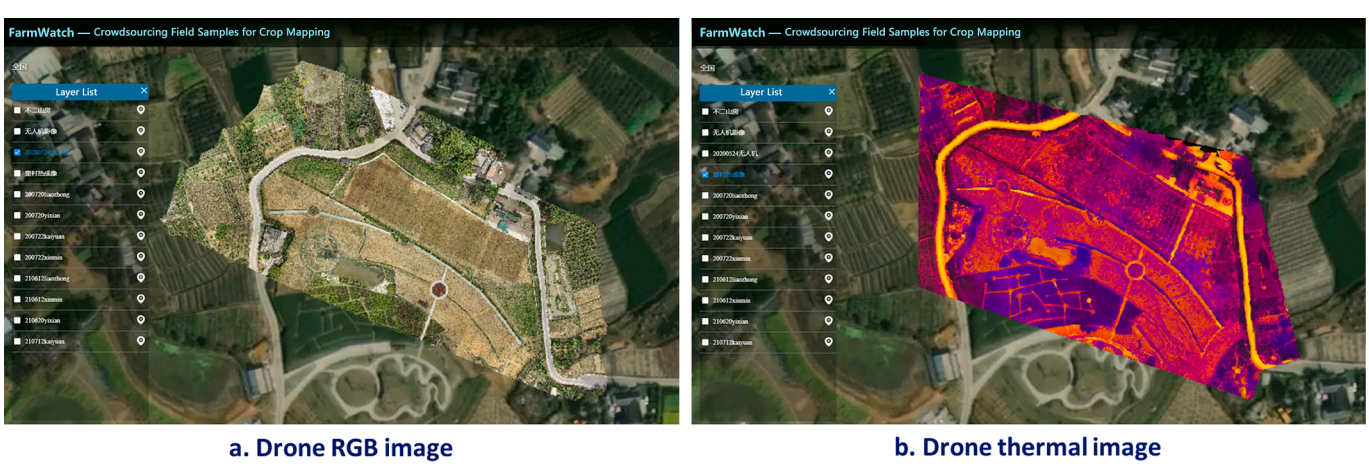


**Fig. 2.** Image visualization on the FarmWatch platform. Illustration of drone RGB image and drone thermal image visualized for an CAAS experimental site at Tongcun Village, Chengdu City, Southwest China.

a. The Web User Interface

b. The Mobile App User Interface

c. Sample design, generation and distribution

**Fig. 3.** The FarmWatch desktop (a) and mobile (b) apps, and the illustration of sample task design generation and distribution across devices (c).

could decrease the difficulties in crop mapping. The major crops include maize, soybeans, and rice (together with other crops such as peanut, leek and melon etc.) and in most cases only one crop can be harvested throughout the growing season. We organized a number of students in relevant majors (i.e. agricultural remote sensing and land management) from Shenyang Agricultural University and trained them to assist sampling tasks during the trial application. This setup is also an experiment to test whether it is possible to temporarily organize a localized and semi-skilled team that can finish the sampling tasks with low cost and high efficiency.

## 4. Results

### 4.1. Sample design and the initial round sample collection

Considering the phenological and cropping information in Northeast China, summer is the best season to capture the distinct spectral features among different crop types. We screened the available images between June and August for the case study area, and selected one Sentinel-2 scene on July 17, 2021. The selected image has very low cloud coverage and has good spatial resolution to distinguish crop types, which fully meets the requirements of trial application (Fig. 4b). We made a full use of the spectral information of Sentinel-2 bands, including visible (B2, B3, B4), red edge (B5), near-infrared (B6, B7, B8 B8A), short-wave infrared (B11, B12), and the combination of spectral bands such as NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), NDBI (Normalized Difference Built-up Index), to represent vegetation growth status and photosynthetic ability, and to extract water body and building objects information from the image.

To improve the sampling and classification efficiency, we used the cropland layer from GlobeLand30-2020 to mask out the non-cropland area. We used the Elbow Criteria approach and determined the optimal $k$ value as 7 for the $k$-means clustering, to make sure that all crops in the study area have been included and each of them can be differentiated as much as possible. We then carried out the stratified random sampling scheme by regarding these 7 clusters as the strata. We finally determined the number of samples to each stratum according to the area proportion of each cluster, and randomly distributed the sample points by their cluster layers.

Learning from the existing county-level crop mapping activities, e.g. Song et al. (2018), and Xia et al. (2022), the traditional field trips have been carried out before processing of remotely sensed images, and usually collect about 2000 random samples covering the entire study area. Considering the spatial coverage and the complexity of cropping pattern, a total of 150 samples were generated for the initial round. We summarized the main results of the unsupervised clustering and the

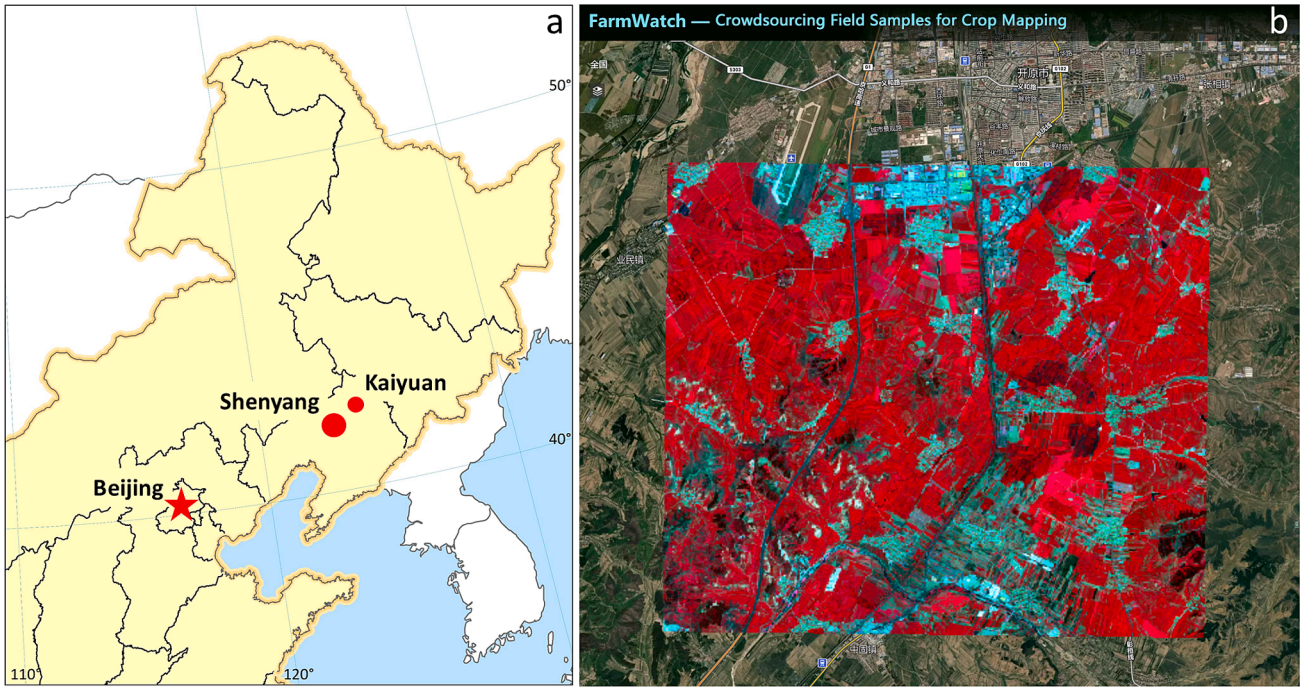


**Fig. 4.** Location of the case study area and visualization of the selected Sentinel-2 image on the FarmWatch platform (image date: July 17, 2021).

stratified random sampling in Table 1. Based on the results of unsupervised clustering and stratified random sampling, these samples were randomly distributed by their cluster layers across the entire case study area. Moreover, these samples were transformed to tasks and were opened to registered users. In this trial application, registered students were invited to visit the site and to take the geo-tagged photos. In the first round of data collection, a total of 95 sample points were visited on July 19, 2021, and the crop type for each point were identified based on the geo-tagged photos (Table 1).

### 4.2. Iterative sample collection and image classification

Regardless of the number and quality of the sample set, we immediately applied these 95 samples collected on the first day and labeled these samples and applied the support vector machines (SVM) classifier for crop type classification. Among the collected samples, 30% of them were reserved for validating the classification results. Based on the samples collected during the initial round. the overall accuracy of crop mapping was 83.33%, and the producer's accuracy for the major crops, such as maize, soybean and rice were 92.31%, 100.00% and 25.00%, respectively (Day 1 in Fig. 5). Soybean and maize had reached a relatively high classification accuracy because of its distinguished feature:

**Table 1**
Statistical summary of the clustering and sampling results.

| Clusters (strata) | Area proportion | Generated samples | Collected samples | Major crop type(s) |
|---|---|---|---|---|
| 1 | 11.20% | 17 | 15 | Maize |
| 2 | 0.84% | 1 | 1 | Soybean |
| 3 | 5.97% | 9 | 7 | Mostly rice, and maize |
| 4 | 51.02% | 77 | 41 | Maize and rice |
| 5 | 12.68% | 19 | 17 | Soybean and maize |
| 6 | 11.37% | 17 | 10 | Woods and nursery |
| 7 | 6.92% | 10 | 4 | Woods and nursery |
| Total | 100% | 150 | 95 | |

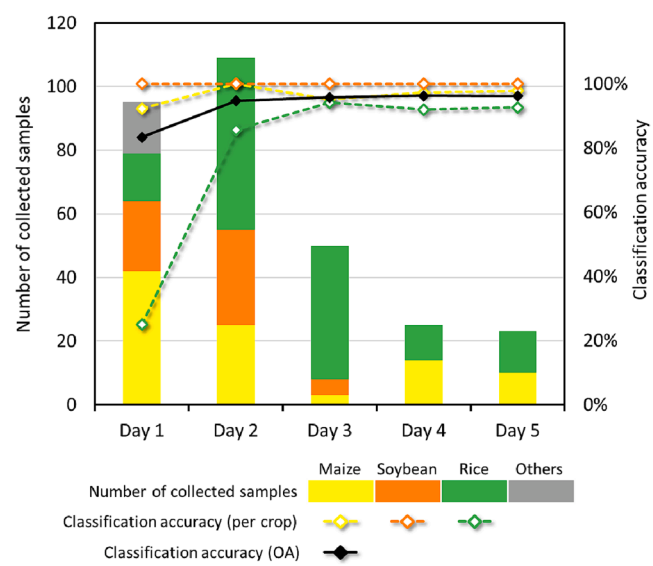


**Fig. 5.** Accuracy of crop mapping results. The bars indicate the number of collected samples (left axis). The dots indicate the accuracy of classification results (right axis). The results of these indicators are presented day by day, i.e., from the first day to the fifth day.

cluster 1 and 2 are directly classified as these two target crops even when an unsupervised classification was applied (Table 1).

We found the producer's accuracy for rice was very low at this stage. Therefore, we adjusted the sampling strategy by increasing the weight of cluster 3 and 4 for the equal-area proportionated stratified random sampling scheme, because these clusters are mostly rice (Table 1). Given the producer's accuracies for maize and soybean were high, we did not make further modification to the sampling scheme, in case that the spectral information of the collected samples was insufficient. The iterative sample collection and image classification were implemented daily. We finalized this trial experiment on the fifth day as the overall accuracy of classification did not improve significantly, i.e. less than 1%

back and forth in two consecutive days since the third day during the trial application. At the end, we have collected 302 samples in five days, among which the number of samples for maize, soybean and rice are 94, 57 and 135, respectively. Samples for these three major crops accounted for 95% of the entire sample.

We summarized the complete sampling process in Table 2, and presented the spatial details of the sampling process and the classification results in Fig. 6. As the number of rice samples are increased on the second day, the producer's accuracy for rice has been significantly increased from 25.00% to 85.71%. Moreover, the producer's accuracy for maize and soybean both researched 100% at this stage. Considering such contribution, the overall accuracy was improved to 94.74% on the second day. On the third day, more rice samples were collected and the producer's accuracy was continuedly improved. The accuracies for of maize, soybean and rice were 95%, 100% and 94%, respectively, and the overall accuracy researched to 95.83%. In the last two days, the overall accuracies were 96.30% and 96.23%, respectively. A clear marginal effect pattern emerged that the classification accuracy did not improve even though the number of samples increased. It shows that if we stopped the sampling tasks on the third day, only 254 samples are basically required for the experiment to achieve the relatively high and stable classification accuracy (Fig. 5).

## 5. Discussion

In this paper we proposed a framework for crop mapping by crowdsourcing ground truth data, which was tested and verified by a trial application in an agricultural region in Northeast China. In the current experiment, we simplified the setup by using one Sentinel image scene. Such strategy has been rarely adopted as more studies would apply time-series images for crop mapping currently (Xu et al., 2021). The selected image was taken on July, when the paddy rice is no longer at the transplanting period. It increased difficulties for identifying paddy area without the critical water flooding signal (Zhan et al., 2021). We found that the overall accuracy of other crops is high, except for rice. However, while the number of rice samples are added, the producer's accuracy of rice improves gradually. The results proved that the limitations of using a single satellite image scene can be compensated by an effective field sample collection scheme. It further indicates that our framework has greater potential in cases that high quality images are unavailable. Nevertheless, more experiments are required to test the performance of using time-series images. We have conducted an additional experiment by replacing the single Sentinel-2 image taken in July with time-series Sentinel-2 images acquired from April to July (5 observations in total). It is interesting to find that the overall classification accuracy for time-series images is 95.49%, which is only slightly higher than the OA achieved in the second day by using the single image. However, compared with the single image, the accuracy for soybeans dropped while the accuracy for rice increased markedly when using time-series images (Table 3).

As the unsupervised clustering approaches, such as *k*-means, also can be applied to time-series, adding more temporal information in our framework might further improve the efficiency of sampling and image classification. This might be particularly useful for collecting field samples in the multi-cropping agricultural region, such as Southern China (Yu et al., 2021): the rapid crop shift and rotation information can only be detected by using the time-series imageries. However, sample information at a specific time might not be enough for the multi-cropping regions, *in-situ* and continuous information collection is required when extending the applicability of FarmWatch to multi-cropping regions. Moreover, single source images might not be effective for the cloudy and rainy regions. The suitability and performance of multi-source image should be evaluated as they are the foundation for the entire crop mapping procedure (Song et al., 2021). More experiments are required to merge multi-sourced and time-series images, e.g. Sentinel-1 and Sentinel-2, to produce the sampling base map for the cloudy and rainy regions. In future studies, these challenges need to be addressed to extend the applicability of FarmWatch to different situations.

Being a specialized tool to design and collect field samples rather than being a purely data sharing platform, FarmWatch requires the ability to assist users to make more effective sampling plans. However, it is difficult to estimate how many samples are basically required, and to inform where to collect these samples for producing an accurate crop map. Geostatistical methods have been applied to select field samples by the support of existing maps showing spatial patterns in field characteristics (Arieira et al., 2011; Mulla, 1997). By adopting this idea, Wickham et al. (2021) validated the newly produced land cover map by generating a set of field samples from the existing land cover maps according to principles of statistics. However, this idea can be hardly borrowed for validating crop types maps not only because the trusted crop map products are rarely available, but also because crop types are varying greatly across the landscape in both temporal and spatial dimensions. To solve this problem, we innovatively developed a data-driven approach to assist sample design in crop type mapping: the preliminary unsupervised clusters was used to support the stratified random sampling scheme. After the initial step, the sample allocation plan is always interactively updated at a new iterative step by learning the previous classification outcome. Therefore, we have to set criteria to stop the iteration process when the classification accuracy meets the requirement. In the current case study, the number of samples are qualitatively determined as 150, 150, 70, 50 and 50 from the second day to the fifth day according to expert knowledge and the allocation of samples is comprehensively determined according to the stratified sampling layers and the classification accuracy on the previous day. In future studies, systematical sample generating approaches, e.g. active learning, are expected to fully replace the adoption of expert knowledge.

We have embedded such process in the FarmWatch framework and highlighted the main objective of the current study. It is not to optimize the samples as a one-off plan, instead, it tries to crowdsource the minimized sample size for effective and efficient crop mapping through an interactive and iterative process. We have chosen a relatively small area for the trial experiment, which has been lasted for five days and resulted in a visualization of temporal and spatial overlap between samples collected on different days. However, it does not mean the entire procedure is time and effort costing. Because the main purpose is to collect less but sufficient samples, rather than collecting more samples with less time. The sampling plan is dynamically updated based on the previous day's classification outcome, it means that users do not know sample locations in the next day and the neighboring samples might be collected by different users. Taking the advantages of crowdsourcing, it is assumed that there are always users around so that we do not to worry about the time and transportation cost of sample collection. As the sample tasks are released gradually until the acceptable classification accuracy is achieved, the sampling cost should be evaluated by concerning more on the number and quality of collected samples rather than the time length of sampling period. Although in the trial application, college students are asked to stay around the study area and to play a role as local users, sampling tasks are ideally crowdsourced by local

**Table 2**
Summary of sample collection during the trial experiment.

| Crop type | Number of samples | | | | | |
|---|---|---|---|---|---|---|
| | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Sum |
| Maize | 42 | 25 | 3 | 14 | 10 | 94 |
| Soybean | 22 | 30 | 5 | / | / | 57 |
| Rice | 15 | 54 | 42 | 11 | 13 | 135 |
| Woods and nursery | 12 | / | / | / | / | 12 |
| Peanut | 2 | / | / | / | / | 2 |
| Melon | 2 | / | / | / | / | 2 |
| Total | 95 | 109 | 50 | 25 | 23 | 302 |

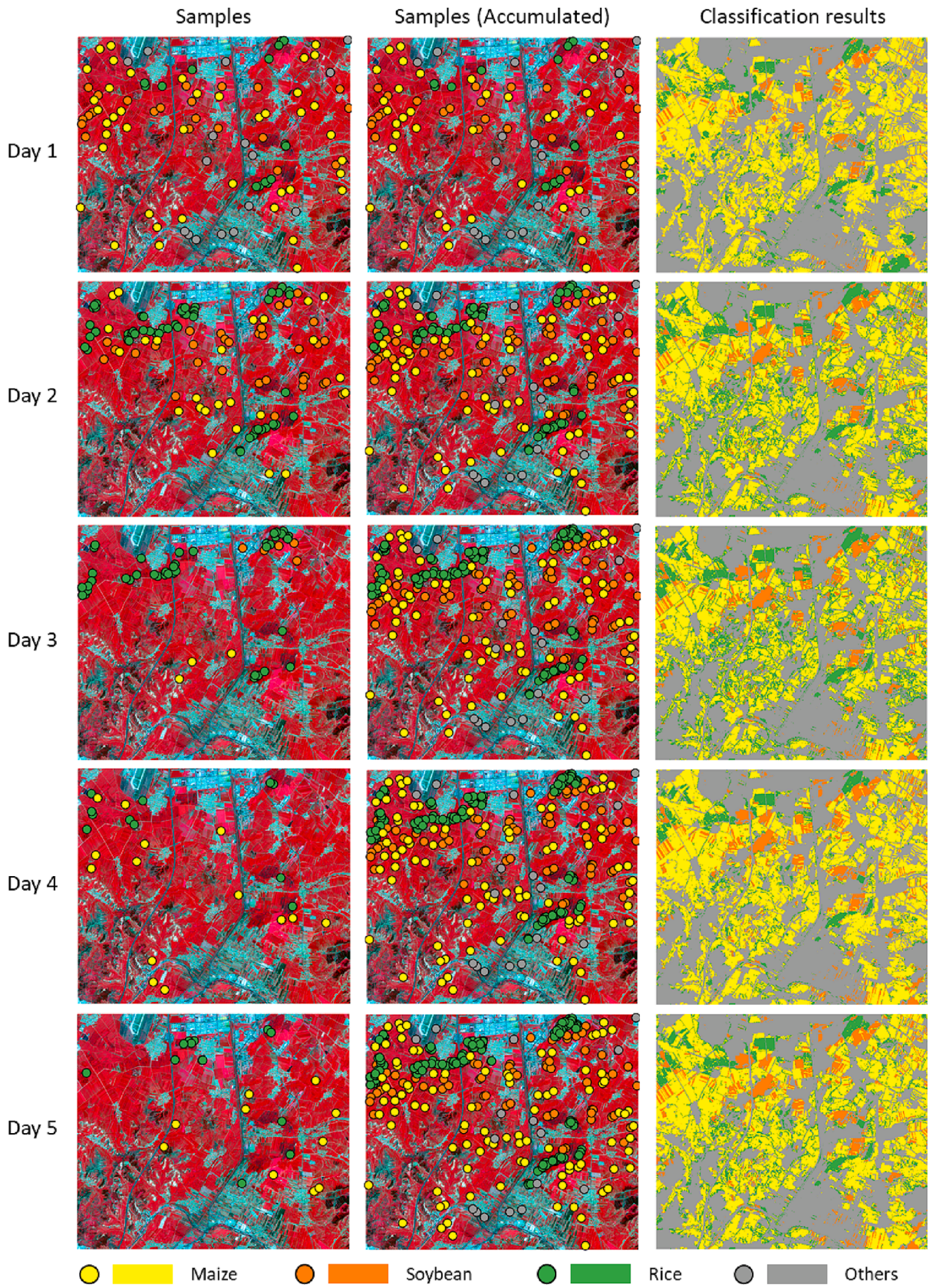


**Fig. 6.** The spatial distribution of samples the detailed crop mapping results during the trial experiment.

**Table 3**
Comparison between the classification results by using one single image and time-series images.

| Image set | Sample set | OA | Maize | Soybean | Rice |
|---|---|---|---|---|---|
| Single | Day 1 | 83.33% | 92.31% | 100.00% | 25.00% |
| | Day 2 | 94.74% | 100.00% | 100.00% | 85.71% |
| | Day 3 | 95.83% | 95.24% | 100.00% | 94.12% |
| | Day 4 | 96.30% | 97.30% | 100.00% | 92.00% |
| | Day 5 | 96.23% | 97.83% | 100.00% | 92.68% |
| Times series | Day 5 | 95.49% | 95.00% | 91.67% | 100.00% |

Note: time-series images were taken on 18th April, 18th May, 7th June, 12th June, and 17th June 2021.

people. It is important to understand the willingness of local people to play the role as sample collectors and further to develop the incentive and reward system for crowdsourcing (Hswen et al., 2022; Jia et al., 2022).

It is also important to ensure the quality of crowdsourced field samples, the existing approaches for describing and assessing the quality of crowdsourced street view imagery and social media data provide good examples on sample data quality control (Hou and Biljecki, 2022; Songchon et al., 2021). In the current case study, the planned number of samples was 470 and the collected samples were 302, which means the distributed tasks can hardly be fully finished in the crowdsourcing context. The overall quality of task accomplishment, e.g. evenness and diversity, should be assessed when using the collected information for classification. Moreover, the quality of samples collected by different users may vary and the quality of crowdsourced samples may have a certain degree of uncertainty. In the current case study, sample information is provided by college students. Yet in future applications, it is likely to involve diversified participants, e.g. local residents, farmers, visitors, and experts. There are three possible approaches to address the inevitable inconsistency or errors provided by different data collectors. Firstly, we can assign a number of fixed sample tasks and ask multiple participants to finish the tasks. By comparing the consistency of collected information, we are able to quantify the data quality among different user groups. Secondly, we can organize an expert committee to randomly check the collected information, e.g. crop type and field photo, based on high-resolution satellite images. The errors can be effectively addressed and the participants with high error rates can be also identified. Thirdly, we can embed machine vision models to automatically identify crop types from field photos. Comparisons between model outputs and manually filled information can be used to evaluate participants' performance as well.

Using unsupervised clustering and stratified random sampling to obtain the initial sample locations can avoid class imbalance (Javier Gallego et al., 2013). Active learning may help to select more informative samples in each cluster thus might improve classification accuracy (Yan et al., 2022). In the current case study, the unsupervised classification has been adopted for generating the first stratified sampling map, it is hard to know the relation between clusters and crop types at this stage. Therefore, even if the most informative samples in each cluster have been selected, it does not necessarily mean they are the most informative samples for each crop type. We carried out two informative sampling experiments by active learning, i.e. *k*-means clustering and density peaks clustering, to optimize the samples within each cluster. However, they both have resulted in a relatively lower classification results comparing to the random sampling on the first day (Table 4). The principle of informative sampling is sampling after clustering. Therefore in this case, the adoption of informative sampling needs to develop clusters within each cluster. Table 4 shows that accuracies for informative sampling are relatively low, the reason mainly lies in two aspects. Firstly, the spatial variability decreases when forming second-level clusters, which resulted an over-clustering. Secondly, the second-level clustering focuses on a very small number of outlier points, which resulted in an unbalanced sample sets that were not representative for the first-level clusters. In our previous paper, we have compared the classification results of stratified sampling and simple random sampling, i.e. without the information of first-level clusters. Results clearly show that stratified sampling performed better. Therefore, we recommend the best solution is stratified sampling, which needs to use the unsupervised classification clusters as stratum.

Geiß et al. (2019) explored how does an active learning procedure improve the classification of multispectral remote sensing imagery, whether the SVM-based crop mapping results can be applied to the stratified random sampling scheme is worthy of further investigation. Moreover, the current sampling approach only considered the number and area proportion of strata represented by land cover clusters, while ignoring the spatial characteristics within each stratum. The landscape characteristics are relatively plain in the case study area which largely ensures an overall acceptable road accessibility (Table 5). Nevertheless, adding more conspicuous ground features such as road, river and terrain to the stratum layer might increase the sampling efficiency. We could embed the calculation of road accessibility in FarmWatch for future applications as an *ex-ante* criterion. Moreover, the current study area is relatively small and the landscape is not heterogeneous. When adopting the approach for larger scale application, it is necessary to analyze the indistinct and easily confused features during the sample design process.

The current sensor technologies being developed are increasing the diversity and capabilities of remote sensing data, yet the analysis and interpretation of satellite and/or aerial images require for a large amount of labeled data (Lin et al., 2022; Saralioglu and Gungor, 2020). The rapid development of information technology and location techniques have built a new paradigm of remote sensing applications: it not only leads to an increasing growth of massive geospatial big data but also raises the attention of using these data to complement with remote sensing images (Deng et al., 2019). The integration of geospatial big data and citizen science fuels the studies related to sample collection and

**Table 5**
Statistics of road accessibility for each classification group. (unit: m).

| | Average | Max | Min | Stand deviation |
|---|---|---|---|---|
| Maize | 130.61 | 280.14 | 4.36 | 59.38 |
| Soybean | 122.60 | 478.79 | 25.44 | 93.84 |
| Rice | 137.72 | 494.11 | 3.26 | 91.76 |
| Others | 62.61 | 161.25 | 2.75 | 45.30 |
| All | 128.67 | 494.11 | 3.26 | 82.80 |

**Table 4**
Comparison between the classification results by using stratified random sampling and informative sampling schemes.

| | Stratified random sampling | | Informative sampling | | | |
|---|---|---|---|---|---|---|
| | | | *k*-means clustering | | Density peaks clustering | |
| | Samples | Producer's accuracy | Samples | Producer's accuracy | Samples | Producer's accuracy |
| Maize | 42 | 92.31% | 50 | 85.00% | 47 | 77.78% |
| Soybean | 22 | 100.00% | 9 | 0.00% | 7 | 83.33% |
| Rice | 15 | 25.00% | 6 | 0.00% | 6 | 0.00% |
| Other | 16 | 83.33% | 30 | 77.78% | 35 | 80.00% |
| Total (overall) | 95 | 83.33% | 95 | 82.76% | 95 | 79.31% |

labelling remote sensing images. One successful case is to crowdsource *in-situ* data on land cover and land use using gamification: the Geo-Wiki crowdsourcing platform provides a total of 151,942 samples on human impact, land cover disagreement, wilderness and land cover and land use (Fritz et al., 2017). Such effort was very similar to LUCAS, which collects *in-situ* data during large scale campaigns. Although transferring the tasks to the crowdsourcing platform might reduce cost and improve efficient, the entire sample-collecting process was not fully integrated into the image interpretation process. The innovation of FarmWatch not only due to its cutting-edge protocol that synchronizes the sample tasks and collected information across platforms, but also lies in the new interactive mapping framework that enables a precise sample estimation and allocation. The FarmWatch mobile app is developed not only for receiving sampling tasks, but also allows users to observe agricultural fields. This fits with the concept of farmsourcing that provides a source of recommendations and inspirations for future collaborative actions in agricultural crowdsourcing (Minet et al., 2017). Moreover, as inspired by Google Earth Engine, the core features of FarmWatch such as image prescreening, sample size and location optimization, image labeling and classification, makes it possible to become a specialized cloud-based geospatial big data processing platform for instant and dynamical crop mapping without needing access to supercomputers or specialized coding expertise (Tamiminia et al., 2020).

## 6. Conclusion

In this paper, we present an innovating framework to support efficient crop mapping through crowdsourcing field samples. The framework is consisted of three parts: sample design, sample collection and image classification. The entire procedure can be initiated with limited data input: the candidate satellite image can be used for sample design before it goes for classification. The idea of crowdsourcing provides a two-way data transmission scheme to release sample tasks and to collect field information interactively, which are further unified and underpinned by a feedback mechanism. Such interactive mechanism not only promotes the opportunity of up-to-date and in-season crop mapping, but also helps to inform users where to collect field samples and how many samples are basically required for producing an accurate crop map. We embed the framework into a crowdsourcing platform named as FarmWatch and carry out an experimental application in an agricultural region in Northeast China. The experiment shows that such framework can greatly improve the performance of sample collection and thus significantly promote the efficiency of crop mapping. The main purpose of the framework, i.e. to collect less but sufficient samples rather than collecting more samples with less time, is therefore successfully realized. It is worthy to investigate the potential of increasing authentic and up-to-date training labels, along with the improvements in terms of algorithm and data quality for agricultural remote sensing. It is also important to involve local, semi-skilled and self-motived people in crowdsourcing. Integrating the sampling tasks to the fieldwork internships for college students is a possible way. Farmer users are also potential beneficiary. Firstly, crop mapping is an effective way to understand regional scale cropping structures and further to predict market price. Secondly, field photos can be further used to monitor crop growth and to identify pests and diseases. Therefore, FarmWatch could help farmers making more reasonably and competitively cropping choices, which could attract more farmer users and promote the practical applications in real-life situations. Furthermore, we will keep finding efficient ways to motivate farmer users to use FarmWatch directly. On the one hand, paying users a certain amount of money based on the number of sample tasks completed might be the simplest and most effective way. It can also be considered to assign basic permissions to users and completing more tasks would cause an elevation to use more functions of FarmWatch. On the other hand, we plan to introduce a pilot area of FarmWatch to illustrate how the software assists farmers in managing their croplands.

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## 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.

## Data availability

No data was used for the research described in the article.

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## References

Anchang, J.Y., Ananga, E.O., Pu, R., 2016. An efficient unsupervised index based approach for mapping urban vegetation from IKONOS imagery. Int. J. Appl. Earth Obs. Geoinf. 50, 211–220. https://doi.org/10.1016/J.JAG.2016.04.001.

Arieira, J., Karssenberg, D., de Jong, S.M., Addink, E.A., Couto, E.G., Nunes Da Cunha, C., Skøien, J.O., 2011. Integrating field sampling, geostatistics and remote sensing to map wetland vegetation in the Pantanal, Brazil. Biogeosciences 8, 667–686. https://doi.org/10.5194/BG-8-667-2011.

Bégué, A., Arvor, D., Bellon, B., Betbeder, J., de Abelleyra, D., Ferraz, R.P.D., Lebourgeois, V., Lelong, C., Simões, M., Verón, S.R., 2018. Remote Sensing and Cropping Practices: A Review. Remote Sens. 10 (2), 99. https://doi.org/10.3390/rs10010099.

Bergen, K.J., Johnson, P.A., de Hoop, M.v., Beroza, G.C., 2019. Machine learning for data-driven discovery in solid Earth geoscience. Science 1979, 363. https://doi.org/10.1126/SCIENCE.AAU0323/ASSET/E01F2E56-540A-4836-991B-3D3E7652D547/ASSETS/GRAPHIC/363_AAU0323_F5.JPEG.

Blickensdörfer, L., Schwieder, M., Pflugmacher, D., Nendel, C., Erasmi, S., Hostert, P., 2022. Mapping of crop types and crop sequences with combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data for Germany. Remote Sens. Environ. 269, 112831 https://doi.org/10.1016/J.RSE.2021.112831.

Boschetti, L., Stehman, S.v., Roy, D.P., 2016. A stratified random sampling design in space and time for regional to global scale burned area product validation. Remote Sens. Environ. 186, 465–478. https://doi.org/10.1016/J.RSE.2016.09.016.

d'Andrimont, R., Verhegghen, A., Lemoine, G., Kempeneers, P., Meroni, M., van der Velde, M., 2021. From parcel to continental scale – A first European crop type map based on Sentinel-1 and LUCAS Copernicus in-situ observations. Remote Sens. Environ. 266, 112708 https://doi.org/10.1016/J.RSE.2021.112708.

David, N., Giordano, S., Mallet, C., 2021. Investigating operational country-level crop monitoring with Sentinel~1 and~2 imagery. Remote Sens. Lett. 12, 970–982. https://doi.org/10.1080/2150704X.2021.1950940.

de Vos, K., Campforts, B., Tits, L., van Tricht, K., Bonte, K., Govers, G., Jacobs, L., 2023. Potential and limitations of crowdsourced data for high-resolution rice mapping in Madagascar: The importance of representation. Int. J. Appl. Earth Obs. Geoinf. 117, 103204 https://doi.org/10.1016/J.JAG.2023.103204.

Deng, X., Liu, P., Liu, X., Wang, R., Zhang, Y., He, J., Yao, Y., 2019. Geospatial Big Data: New Paradigm of Remote Sensing Applications. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 12, 3841–3851. https://doi.org/10.1109/JSTARS.2019.2944952.

Eitzinger, A., Cock, J., Atzmanstorfer, K., Binder, C.R., Läderach, P., Bonilla-Findji, O., Bartling, M., Mwongera, C., Zurita, L., Jarvis, A., 2019. GeoFarmer: A monitoring and feedback system for agricultural development projects. Comput. Electron. Agric. 158, 109–121. https://doi.org/10.1016/j.compag.2019.01.049.

Fabregas, R., Kremer, M., Schilbach, F., 2019. Realizing the potential of digital development: The case of agricultural advice. Science 1979, 366. https://doi.org/10.1126/SCIENCE.AAY3038/SUPPL_FILE/AAY3038_FABREGAS_SM.PDF.

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., Tilman, D., Zaks, D.P.M., 2011. Solutions for a cultivated planet. Nature 478, 337–342. https://doi.org/10.1038/nature10452.

Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ. 80, 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4.

Fritz, S., See, L., Perger, C., McCallum, I., Schill, C., Schepaschenko, D., Duerauer, M., Karner, M., Dresel, C., Laso-Bayas, J.C., Lesiv, M., Moorthy, I., Salk, C.F., Danylo, O., Sturn, T., Albrecht, F., You, L., Kraxner, F., Obersteiner, M., 2017. A global dataset of crowdsourced land cover and land use reference data. Sci. Data 4, 1–8. https://doi.org/10.1038/SDATA.2017.75.

Fritz, S., See, L., Bayas, J.C.L., Waldner, F., Jacques, D., Becker-Reshef, I., Whitcraft, A., Baruth, B., Bonifacio, R., Crutchfield, J., Rembold, F., Rojas, O., Schucknecht, A., van der Velde, M., Verdin, J., Wu, B., Yan, N., You, L., Gilliams, S., Mücher, S., Tetrault, R., Moorthy, I., McCallum, I., 2019. A comparison of global agricultural monitoring systems and current gaps. Agric. Syst. 168, 258–272. https://doi.org/10.1016/J.AGSY.2018.05.010.

Gao, H., Wang, C., Wang, G., Fu, H., Zhu, J., 2021. A novel crop classification method based on ppfSVM classifier with time-series alignment kernel from dual-polarization SAR datasets. Remote Sens. Environ. 264, 112628 https://doi.org/10.1016/J.RSE.2021.112628.

Geiß, C., Aravena Pelizari, P., Blickensdörfer, L., Taubenböck, H., 2019. Virtual Support Vector Machines with self-learning strategy for classification of multispectral remote sensing imagery. ISPRS J. Photogramm. Remote. Sens. 151, 42–58. https://doi.org/10.1016/J.ISPRSJPRS.2019.03.001.

Giroux, S.A., Kouper, I., Estes, L.D., Schumacher, J., Waldman, K., Greenshields, J.T., Dickinson, S.L., Caylor, K.K., Evans, T.P., 2019. A high-frequency mobile phone data collection approach for research in social-environmental systems: Applications in climate variability and food security in sub-Saharan Africa. Environ. Model. Softw. 119, 57–69. https://doi.org/10.1016/J.ENVSOFT.2019.05.011.

Hao, P., Di, L., Zhang, C., Guo, L., 2020. Transfer Learning for Crop classification with Cropland Data Layer data (CDL) as training samples. Sci. Total Environ. 733, 138869 https://doi.org/10.1016/J.SCITOTENV.2020.138869.

Hillen, F., Höfle, B., 2015. Geo-reCAPTCHA: Crowdsourcing large amounts of geographic information from earth observation data. Int. J. Appl. Earth Obs. Geoinf. 40, 29–38. https://doi.org/10.1016/j.jag.2015.03.012.

Hou, Y., Biljecki, F., 2022. A comprehensive framework for evaluating the quality of street view imagery. Int. J. Appl. Earth Obs. Geoinf. 115, 103094 https://doi.org/10.1016/j.jag.2022.103094.

Hswen, Y., Nguemdjo, U., Yom-Tov, E., Marcus, G.M., Ventelou, B., 2022. Individuals' willingness to provide geospatial global positioning system (GPS) data from their smartphone during the COVID-19 pandemic. Humanit. Soc. Sci. Commun. 9, 336. https://doi.org/10.1057/s41599-022-01338-7.

Hu, Q., Yin, H.e., Friedl, M.A., You, L., Li, Z., Tang, H., Wu, W., 2021. Integrating coarse-resolution images and agricultural statistics to generate sub-pixel crop type maps and reconciled area estimates. Remote Sens. Environ. 258, 112365. https://doi.org/10.1016/J.RSE.2021.112365.

Hufkens, K., Melaas, E.K., Mann, M.L., Foster, T., Ceballos, F., Robles, M., Kramer, B., 2019. Monitoring crop phenology using a smartphone based near-surface remote sensing approach. Agric. For Meteorol. 265, 327–337. https://doi.org/10.1016/J.AGRFORMET.2018.11.002.

Javier Gallego, F., Jürgen Stibig, H., 2013. Area estimation from a sample of satellite images: The impact of stratification on the clustering efficiency. Int. J. Appl. Earth Obs. Geoinf. 22, 139–146. https://doi.org/10.1016/j.jag.2012.03.003.

Jia, B., Gong, H., Zong, Z., Zhou, T., Baker, T., Al-Shamma'a, A., Jia, Y., 2022. An incentive mechanism in expert-decision-based crowdsensing networks. Appl. Soft. Comput. 122, 108834 https://doi.org/10.1016/j.asoc.2022.108834.

Johnson, D.M., Mueller, R., 2021. Pre- and within-season crop type classification trained with archival land cover information. Remote Sens. Environ. 264, 112576 https://doi.org/10.1016/J.RSE.2021.112576.

Karthikeyan, L., Chawla, I., Mishra, A.K., 2020. A review of remote sensing applications in agriculture for food security: Crop growth and yield, irrigation, and crop losses. J. Hydrol. (Amst.) 586, 124905. https://doi.org/10.1016/J.JHYDROL.2020.124905.

King, A., 2017. Technology: the future of agriculture. Nature 544, S21–S23. https://doi.org/10.1038/544s21a.

Koda, S., Melgani, F., Nishii, R., 2020. Unsupervised Spectral-Spatial Feature Extraction with Generalized Autoencoder for Hyperspectral Imagery. IEEE Geosci. Remote. Sens. Lett. 17, 469–473. https://doi.org/10.1109/LGRS.2019.2921225.

Krell, N., Davenport, F., Harrison, L., Turner, W., Peterson, S., Shukla, S., Marter-Kenyon, J., Husak, G., Evans, T., Caylor, K., 2022. Using real-time mobile phone data to characterize the relationships between small-scale farmers' planting dates and socio-environmental factors. Clim. Risk Manag. 35, 100396 https://doi.org/10.1016/J.CRM.2022.100396.

Li, C., Ma, Z., Wang, L., Yu, W., Tan, D., Gao, B., Feng, Q., Guo, H., Zhao, Y., 2021. Improving the accuracy of land cover mapping by distributing training samples. Remote Sens. 13, 4594. https://doi.org/10.3390/RS13224594.

Lin, J., Yu, T., Wang, Z.J., 2022. Rethinking Crowdsourcing Annotation: Partial Annotation with Salient Labels for Multi-Label Aerial Image Classification. IEEE Trans. Geosci. Remote Sens. 60, 1–12. https://doi.org/10.1109/TGRS.2022.3191735.

Liu, Y., Yu, Q., Zhou, Q., Wang, C., Bellingrath-Kimura, S.D., Wu, W., 2022. Mapping the Complex Crop Rotation Systems in Southern China Considering Cropping Intensity, Crop Diversity and Their Seasonal Dynamics. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 15, 9584–9598. https://doi.org/10.1109/JSTARS.2022.3218881.

Ma, Y., Wu, H., Wang, L., Huang, B., Ranjan, R., Zomaya, A., Jie, W., 2015. Remote sensing big data computing: Challenges and opportunities. Future Gener. Comput. Syst. 51, 47–60. https://doi.org/10.1016/J.FUTURE.2014.10.029.

Mehrabi, Z., McDowell, M.J., Ricciardi, V., Levers, C., Martinez, J.D., Mehrabi, N., Wittman, H., Ramankutty, N., Jarvis, A., 2020. The global divide in data-driven farming. Nat. Sustain. 4, 154–160. https://doi.org/10.1038/s41893-020-00631-0.

Minet, J., Curnel, Y., Gobin, A., Goffart, J.P., Mélard, F., Tychon, B., Wellens, J., Defourny, P., 2017. Crowdsourcing for agricultural applications: A review of uses and opportunities for a farmsourcing approach. Comput. Electron. Agric. 142, 126–138. https://doi.org/10.1016/J.COMPAG.2017.08.026.

Mulla, D.J., 1997. Geostatistics, Remote Sensing and Precision Farming. CIBA Foundation Symposia 100–119. https://doi.org/10.1002/9780470515419.CH7.

Nguyen, T.T., Hoang, T.D., Pham, M.T., Vu, T.T., Nguyen, T.H., Huynh, Q.T., Jo, J., 2020. Monitoring agriculture areas with satellite images and deep learning. Appl. Soft. Comput. 95, 106565 https://doi.org/10.1016/J.ASOC.2020.106565.

Osinga, S.A., Paudel, D., Mouzakitis, S.A., Athanasiadis, I.N., 2022. Big data in agriculture: Between opportunity and solution. Agric. Syst. 195, 103298 https://doi.org/10.1016/J.AGSY.2021.103298.

Oteyo, I.N., Marra, M., Kimani, S., de Meuter, W., Boix, E.G., 2021. A Survey on Mobile Applications for Smart Agriculture. SN Comput. Sci. 2, 293. https://doi.org/10.1007/S42979-021-00700-X.

Qin, R., Liu, T., 2022. A Review of Landcover Classification with Very-High Resolution Remotely Sensed Optical Images—Analysis Unit. Model Scal. Transferability. Remote Sens. 14, 646. https://doi.org/10.3390/RS14030646.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., Prabhat, 2019. Deep learning and process understanding for data-driven Earth system science. Nature 566, 195–204. https://doi.org/10.1038/s41586-019-0912-1.

Saralioglu, E., Gungor, O., 2020. Crowdsourcing in Remote Sensing: A Review of Applications and Future Directions. IEEE Geosci. Remote Sens. Mag. 8, 89–110. https://doi.org/10.1109/MGRS.2020.2975132.

Segarra, J., Araus, J.L., Kefauver, S.C., 2022. Farming and Earth Observation: Sentinel-2 data to estimate within-field wheat grain yield. Int. J. Appl. Earth Obs. Geoinf. 107, 102697 https://doi.org/10.1016/J.JAG.2022.102697.

Song, X.-P., Huang, W., Hansen, M.C., Potapov, P., 2021. An evaluation of Landsat, Sentinel-2, Sentinel-1 and MODIS data for crop type mapping. Sci. Remote Sens. 3, 100018 https://doi.org/10.1016/J.SRS.2021.100018.

Song, Q., Xiang, M., Hovis, C., Zhou, Q., Lu, M., Tang, H., Wu, W., 2018. Object-based feature selection for crop classification using multi-temporal high-resolution imagery. Int. J. Remote Sens. 40, 2053–2068. https://doi.org/10.1080/01431161.2018.1475779.

Songchon, C., Wright, G., Beevers, L., 2021. Quality assessment of crowdsourced social media data for urban flood management. Comput. Environ. Urban Syst. 90, 101690 https://doi.org/10.1016/j.compenvurbsys.2021.101690.

Stehman, S.V., Olofsson, P., Woodcock, C.E., Herold, M., Friedl, M.A., 2012. A global land-cover validation data set, II: augmenting a stratified sampling design to estimate accuracy by region and land-cover class. Int. J. Remote Sens. 33 (22), 6975–6993. https://doi.org/10.1080/01431161.2012.695092.

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., Brisco, B., 2020. Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. ISPRS J. Photogramm. Remote. Sens. 164, 152–170. https://doi.org/10.1016/J.ISPRSJPRS.2020.04.001.

Vallentin, C., Harfenmeister, K., Itzerott, S., Kleinschmit, B., Conrad, C., Spengler, D., 2022. Suitability of satellite remote sensing data for yield estimation in northeast Germany. Precis. Agric. 23, 52–82. https://doi.org/10.1007/s11119-021-09827-6.

Verburg, P.H., Mertz, O., Erb, K.H., Haberl, H., Wu, W., 2013. Land system change and food security: Towards multi-scale land system solutions. Curr. Opin. Environ. Sustain. 5, 494–502. https://doi.org/10.1016/j.cosust.2013.07.003.

Wang, S., Azzari, G., Lobell, D.B., 2019. Crop type mapping without field-level labels: Random forest transfer and unsupervised clustering techniques. Remote Sens. Environ. 222, 303–317. https://doi.org/10.1016/J.RSE.2018.12.026.

Wang, D., Cao, W., Zhang, F., Li, Z., Xu, S., Wu, X., 2022. A Review of Deep Learning in Multiscale Agricultural Sensing. Remote Sens. 14, 559. https://doi.org/10.3390/RS14030559.

Wang, S., di Tommaso, S., Faulkner, J., Friedel, T., Kennepohl, A., Strey, R., Lobell, D.B., 2020. Mapping Crop Types in Southeast India with Smartphone Crowdsourcing and Deep Learning. Remote Sens. 12, 2957. https://doi.org/10.3390/rs12182957.

Wei, P., Huang, R., Lin, T., Huang, J., 2022. Rice Mapping in Training Sample Shortage Regions Using a Deep Semantic Segmentation Model Trained on Pseudo-Labels. Remote Sens. 14, 328. https://doi.org/10.3390/rs14020328.

Weiss, M., Jacob, F., Duveiller, G., 2020. Remote sensing for agricultural applications: A meta-review. Remote Sens. Environ. 236, 111402 https://doi.org/10.1016/J.RSE.2019.111402.

Wickham, J., Stehman, S.V., Sorenson, D.G., Gass, L., Dewitz, J.A., 2021. Thematic accuracy assessment of the NLCD 2016 land cover for the conterminous United States. Remote Sens. Environ. 257, 112357. https://doi.org/10.1016/J.RSE.2021.112357.

Woźniak, E., Rybicki, M., Kofman, W., Aleksandrowicz, S., Wojtkowski, C., Lewiński, S., Bojanowski, J., Musiał, J., Milewski, T., Slesiński, P., Łączyński, A., 2022. Multi-temporal phenological indices derived from time series Sentinel-1 images to country-wide crop classification. Int. J. Appl. Earth Obs. Geoinf. 107, 102683 https://doi.org/10.1016/J.JAG.2022.102683.

Wu, B., Li, Q., 2012. Crop planting and type proportion method for crop acreage estimation of complex agricultural landscapes. Int. J. Appl. Earth Obs. Geoinf. 16, 101–112. https://doi.org/10.1016/J.JAG.2011.12.006.

Wu, B., Tian, F., Nabil, M., Bofana, J., Lu, Y., Elnashar, A., Beyene, A.N., Zhang, M., Zeng, H., Zhu, W., 2023. Mapping global maximum irrigation extent at 30m resolution using the irrigation performances under drought stress. Glob Environ. Change 79, 102652. https://doi.org/10.1016/J.GLOENVCHA.2023.102652.

Xia, T., He, Z., Cai, Z., Wang, C., Wang, W., Wang, J., Hu, Q., Song, Q., 2022. Exploring the potential of Chinese GF-6 images for crop mapping in regions with complex agricultural landscapes. Int. J. Appl. Earth Obs. Geoinf. 107, 102702 https://doi.org/10.1016/J.JAG.2022.102702.

Xu, J., Yang, J., Xiong, X., Li, H., Huang, J., Ting, K.C., Ying, Y., Lin, T., 2021. Towards interpreting multi-temporal deep learning models in crop mapping. Remote Sens. Environ. 264, 112599 https://doi.org/10.1016/J.RSE.2021.112599.

Yan, X., Nazmi, S., Gebru, B., Anwar, M., Homaifar, A., Sarkar, M., Gupta, K.D., 2022. A clustering-based active learning method to query informative and representative samples. Appl. Intell. 52, 13250–13267. https://doi.org/10.1007/s10489-021-03139-y.

You, N., Dong, J., Huang, J., Du, G., Zhang, G., He, Y., Yang, T., Di, Y., Xiao, X., 2021. The 10-m crop type maps in Northeast China during 2017–2019. Sci. Data 8, 41. https://doi.org/10.1038/s41597-021-00827-9.

Yu, Q., Shi, Y., Tang, H., Yang, P., Xie, A., Liu, B., Wu, W., 2017. eFarm: A tool for better observing agricultural land systems. Sensors (Switzerland) 17, 453. https://doi.org/10.3390/s17030453.

Yu, Q., Xiang, M., Sun, Z., Wu, W., 2021. The complexity of measuring cropland use intensity: An empirical study. Agric. Syst. 192, 103180 https://doi.org/10.1016/j.agsy.2021.103180.

Zhan, P., Zhu, W., Li, N., 2021. An automated rice mapping method based on flooding signals in synthetic aperture radar time series. Remote Sens. Environ. 252, 112112 https://doi.org/10.1016/J.RSE.2020.112112.

Zhao, L., Shi, Y., Liu, B., Hovis, C., Duan, Y., Shi, Z., 2019. Finer Classification of Crops by Fusing UAV Images and Sentinel-2A Data. Remote Sens. 11, 3012. https://doi.org/10.3390/RS11243012.

Zhou, H., Wang, J., Wilson, K., 2022. Impacts of perceived safety and beauty of park environments on time spent in parks: Examining the potential of street view imagery and phone-based GPS data. Int. J. Appl. Earth Obs. Geoinf. 115, 103078 https://doi.org/10.1016/j.jag.2022.103078.