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Crop Area Estimation for Smallholder Farms: Integrating AI with Ground and Satellite Data[1]

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Abstract

The global agricultural landscape is dominated by smallholder farms with complex cropping systems and fragmented land parcels, posing significant challenges for traditional remote sensing methods in crop area estimation. This study proposes a comprehensive and operational methodology, namely the Crop Planting and Type Proportion (CPTP) method, which integrates artificial intelligence with stratified sampling, crowdsourced data, and satellite remote sensing. The CPTP framework deconstructs estimation into four components: high-resolution cropland mapping, Agriculture Parcel Ratio calculation using AI-driven field boundary delineation, Cultivated Arable Land Fraction (CALF) determination via time-series NDVI analysis, and Crop Type Proportion derived from rapid field surveys using a dedicated mobile application. The integrated crop area is calculated by multiplying these four factors. Validated over a decade across diverse agricultural systems, the approach achieves reliable crop area estimates of 97-98.8% and crop type proportion accuracy exceeding 98%, even in cloud-prone regions. This work provides a scalable, accurate solution for crop area estimation in challenging agricultural landscapes.

Keywords: Crop area estimation, Smallholder Farms, Artificial intelligence, Remote sensing, Crowdsource, Deep Learning.

1. Introduction

The global agricultural landscape is predominantly characterized by smallholder farms, which feature complex cropping systems and highly fragmented land parcels. This inherent complexity poses a significant challenge for traditional remote sensing methods, as the common issue of mixed pixels in medium-resolution satellite imagery leads to high uncertainty in crop area estimation. Accurate and timely seasonal crop acreage data is essential for informing agricultural policy, ensuring food security, and understanding the impacts of climate variability and market fluctuations.

Remote sensing-based crop mapping in smallholder farming regions faces several critical

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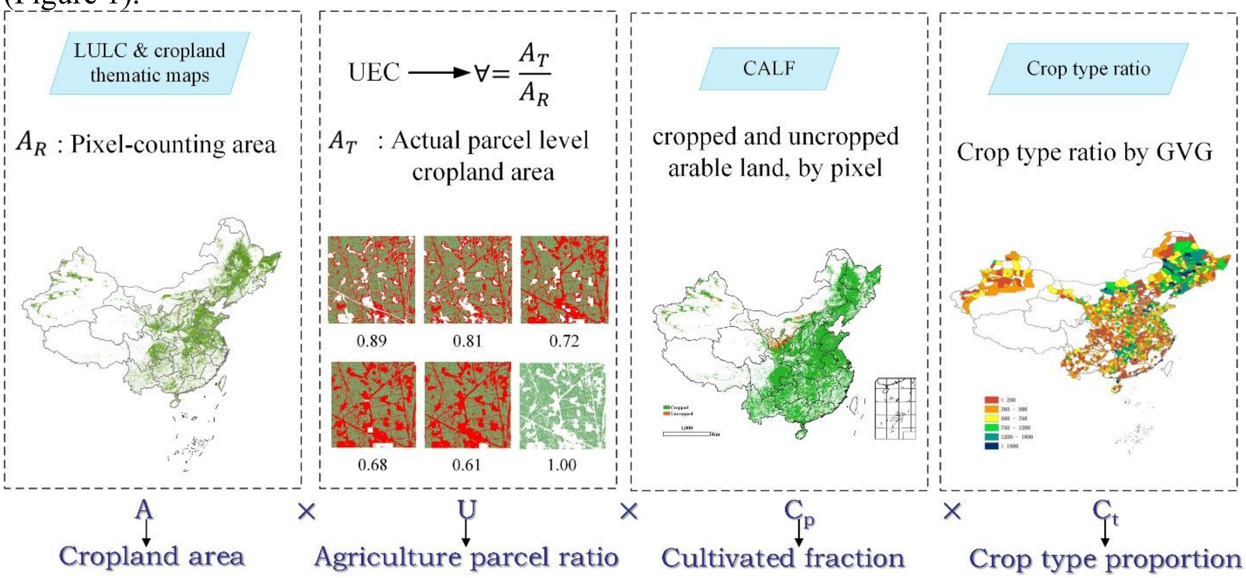
obstacles: small field sizes, diverse cropping systems, and particular management practices that vary significantly across regions(Wu et al. 2023). While various types of remote sensing data, including optical data with high spatial resolution, medium spatial resolution, and radar data are available for crop acreage estimation, pixels in remote sensing data do not always correspond to a single crop type or field(Li et al. 2023). Mixed pixels have a serious impact on crop classification accuracy in agricultural regions with small crop fields (Dimitrov et al. 2019).
To address these challenges, this study proposes a comprehensive and operational methodology, namely the Crop Planting and Type Proportion (CPTP) method(Wu and Li 2012), that overcomes these limitations by integrating advanced artificial intelligence (AI) with a synergy of stratified sampling, crowdsourced data, and satellite remote sensing.

2. Method

The CPTP framework deconstructs the estimation process into four synergistic components (Figure 1).



$$C_a = A * U * C_p * C_t$$

Figure 1: Overview of the workflow for crop area estimation for smallholder farming system

2.1 Foundational Cropland Mapping

The first component establishes a high-resolution (10-30m) dynamically updated cropland data layer. This baseline map provides the foundational extent of arable land by integrating historical and current information on general cropland types, irrigation infrastructure, and regional crop rotation patterns. It acts as the primary spatial mask, restricting subsequent analyses to plausible agricultural zones. Such cropland dataset could be mapped independently or retrieved from an existing Land Use and Land Cover (LULC) dataset.

2.2 Agriculture Parcel Ratio

Current agricultural parcels (AP) delineation methods fail to fully utilize low-level information (e.g., parcel boundary information), leading to unsatisfactory performance under certain circumstances. To address the limitation, we develop a hierarchical semantic boundary-guided network (HBGNet) (Zhao et al. 2025) to fully leverage boundary semantics, thereby improving AP delineation. It integrates two branches, a core branch of AP feature extraction and an auxiliary branch related to boundary feature mining. Specifically, the boundary extract branch employes a module based on Laplace convolution operator to enhance the model's awareness of parcel boundary. For AP feature extraction, a local–global context aggregation module is designed to enhance the semantic representation of AP, improving the adaptability across different AP scenarios. Meanwhile, a boundary-guided module is developed to enhance boundary details of high-level AP semantic information. Ultimately, a multi-grained feature fusion module is designed to enhance the capacity of HBGNet to extract APs with various sizes and shapes. We construct the large-scale very high-resolution (VHR) agricultural parcel dataset (FHAPD) across seven different areas, covering more than 10,000 km^2, using data from GaoFen-1 (2-meter) and GaoFen-2 (1-meter). The code of HBGNet and FHAPD datasets is available at https://github.com/NanNanmei/HBGNet. The resulting highly accurate field boundary maps derived from VHR satellite imagery are overlapped with the cropland thematic maps to calculate the agricultural parcel ratio using a stratified sampling approach (Figure 2).

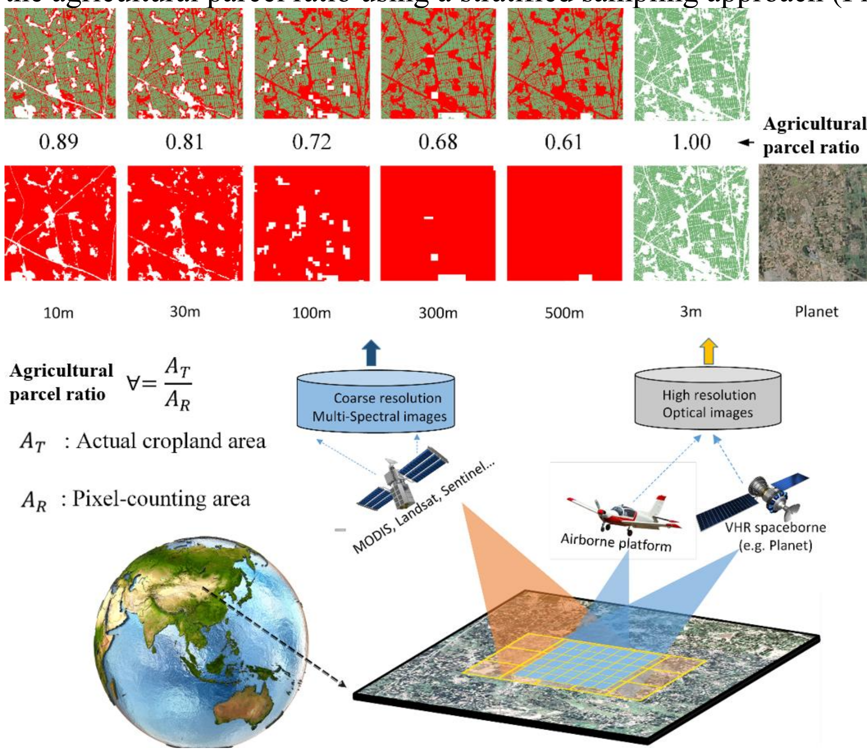


Figure 2: Illustration of how agricultural parcel ratio can be derived.

2.3 Cultivated Arable Land Fraction (CALF)

Not all arable land is planted in a given season. The third component calculates the Cultivated Arable Land Fraction (CALF) to distinguish between actively cropped land and fallow land. We utilize a dense time-series of Sentinel-2 Normalized Difference Vegetation Index (NDVI) data.
By applying a histogram-based threshold method to the phenological curves extracted from the NDVI time-series, we can identify cropping cycles, peak vegetative stages, and fallow periods with a high degree of temporal precision, even in regions with intermittent data gaps.

2.4 Crop Type Proportion with GVG Mobile Application

The final component is the Crop Type Proportion, which is statistically derived from extensive and rapid field surveys. A dedicated mobile application, designated GVG, was developed to integrate Geographic Information System (GIS), video, and Global Positioning System (GPS) to efficiently collect geotagged crop samples. Furthermore, deep learning models were developed for the automated classification of these in-situ photos, ensuring scalable and high efficiency in crop type identification from the geotagged photos.
The integrated crop area is subsequently calculated as follows:
Crop Area = Arable Land Area × Agriculture Parcel Ratio × Cultivated Arable Land Fraction (CALF) × Crop Type Proportion

3. Preliminary result

We developed the integrated dataset of cropland types, irrigation, and crop rotation at a 30-meter resolution. Based on the annual mapped cropping status, we generated the dynamically updated cropland data by integration of three consecutive years of cultivation conditions using maximum composition method.

Detailed experiments are conducted on the FHAPD, a publicly European dataset (i.e., AI4boundaries), and medium-resolution Sentinel-2 images from the Netherlands and HBGNet is compared with other eight AP delineation methods. Results show that HBGNet outperforms the other eight methods in attribute and geometry accuracy. The Intersection over Union (IOU), F1-score of the boundary (Fbdy), and global total-classification (GTC) exceed other methods by 0.61 %-7.52 %, 0.8 %-36.3 %, and 1.7 %-31.8 %, respectively(Zhao et al. 2025).

This study set out to develop an automated approach to discriminate fallow areas from cropping areas in diversed cropping region. This was done by applying a mathematical algorithm of turning point detection technique to a curve fitted vegetation index time series, derived from high spatial (10 m) and temporal (5-days) resolution Sentinel-2 data. The proposed approach yielded a high and significant overall accuracy, surpassing 93% with substantial balanced accuracy (>0.9) and Kappa scores (>0.8) against more than 3000 fields for individual winter and summer seasons(Xie et al. 2024).

Although volunteered geographic information (VGI) has been proven as a possible solution for in situ data acquisition, processing and extracting valuable information from millions of pictures remains challenging. Five state-of-the-art deep convolutional neural networks including InceptionV4, DenseNet121, ResNet50, MobileNetV2, and ShuffleNetV2 were employed to compare the baseline performance. ResNet50 outperformed the others according to the overall accuracy (87.9%), and ShuffleNetV2 outperformed the others according to efficiency (13 FPS).

The decision fusion schemes major voting was used to further improve crop identification accuracy. The results clearly demonstrate the superior accuracy of the proposed decision fusion over the other non-fusion-based methods in crop type detection of imbalanced road view photos dataset. The voting method achieved higher mean accuracy (90.6–91.1%) and can be leveraged to classify crop type in crowdsourced road view photos(Wu et al. 2021).

4. Discussion

The CPTP framework tackles several core challenges inherent in operational crop monitoring within smallholder agricultural systems. By decomposing the estimation problem into distinct components, each targeting a specific source of uncertainty, the approach achieves a level of robustness that is difficult to obtain using conventional single-stage classification methods.

A key advancement lies in the integration of very-high-resolution imagery for precise field boundary delineation. Recent studies have shown that field size exerts a substantial influence on mapping accuracy, with larger fields consistently yielding higher classification accuracies than smaller ones. The HBGNet's capacity to accurately delineate parcel boundaries, even in complex landscapes featuring irregular shapes and small field sizes, effectively mitigates this well-documented challenge.

The GVG mobile application, together with its associated deep learning models for crop type classification from field photographs, introduces an innovative solution for ground truth data collection. This approach strikes an effective balance between the demand for extensive reference data and the logistical constraints of traditional field campaigns, thereby enabling efficient data acquisition over large spatial extents. Recent progress in street-view-based crop type ground truth retrieval has demonstrated overall accuracies of approximately 97% across multiple crop species, lending strong support to the validity of the method employed here.

Several limitations and promising directions for future research warrant consideration. First, although HBGNet exhibits robust performance, its computational demands may hinder operational deployment in regions with constrained computing infrastructure. Second, the dependence on very-high-resolution imagery for boundary delineation, while highly accurate, may prove cost-prohibitive for routine monitoring in many settings. Third, the performance of crop type classification from field photos is likely to vary with factors such as image quality, the crop's phenological stage at the time of capture, and the degree of visual distinguishability among different crop species.

Future efforts should prioritize: (1) enhancing the computational efficiency of the deep learning models to facilitate wider operational adoption; (2) exploring multi-source data fusion strategies, such as incorporating Sentinel-1 SAR data, to boost accuracy in persistently cloud-covered regions; (3) extending validation efforts to additional geographic areas encompassing diverse agricultural systems; and (4) developing stratified sampling strategies that explicitly account for variations in field size and water stress conditions, given mounting evidence that these factors significantly affect mapping accuracy.

5. Conclusions

Estimating crop area in highly fragmented, smallholder-dominated landscapes requires moving beyond conventional pixel-counting. The CPTP method offers a scalable, highly accurate, and operational solution by integrating a 10-30m baseline map, AI-driven VHR parcel delineation, time-series phenology (CALF), and crowdsourced deep-learning crop identification. With area estimation accuracies consistently exceeding 97%, CPTP provides agricultural stakeholders and policymakers with a robust tool to secure food systems in an increasingly volatile global landscape.

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