Enhancing USDA NASS Cropland Data Layer with Segment Anything Model

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***Abstract*—Crop-specific land cover mapping is a vital application in agro-geoinformatics with the proliferation of remote sensing data and machine learning techniques. This paper presents a novel approach to enhance the well-known Cropland Data Layer (CDL) product by U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) using Meta's Segment Anything Model (SAM). The study leverages SAM's zero-shot generalization capability to automatically delineate cropland fields from Sentinel-2 images. By voting for the major crop types within each delineated land unit, a substantial number of noisy pixels is CDL can be eliminated, leading to notable improvements in mapping accuracy. Preliminary experimental results across key agricultural regions in the U.S., such as California's Central Valley and Corn Belt, suggest that SAM can significantly enhance the quality of the original CDL data. This ability to refine crop-specific land cover data, like CDL, demonstrates SAM's practical applicability within agricultural monitoring systems. Moreover, the result showcases the promising potential of integrating SAM into existing crop type classification workflows to create high-quality early- and in-season crop type maps on a national scale with minimal effort.**

***Index Terms*—Segment Anything Model, Cropland Data Layer, Field Delineation, Crop Type Mapping, AI/Machine Learning**

I. Introduction

With the proliferation of remote sensing data, crop-specific land cover mapping has been a critical application in agro-geoinformatics [1]–[3]. As the essential technology in land use land cover (LULC) mapping, machine learning has been proven an effective approach to classify crop types and discover intricate patterns in satellite images [4]–[6]. For example, machine learning algorithms such as decision tree (DT) and random forest (RF), have been widely used with Landsat and Sentinel-2 data to generate field-level crop type maps [7]–[10]. In our prior research activities, we utilized remote sensing data to generate in-season and historical crop type maps [11], [12]. As more satellite images become available throughout the growing season, the crop type classification is expected to improve in accuracy. However, the results from these classifiers usually contain noises more or less because of bad, cloudy, or mixed pixels in the raw satellite images.

To address these issues, this study will leverage cutting-edge computer vision (CV) technology to enhance crop-specific land cover mapping. In 2023, Meta released the Segment Anything Model (SAM) as a new segmentation system with zero-shot generalization to automatically segment objects in any images without additional training [13]. It has been used for not only segmentation from satellite images [14]–[16], but also many other image segmentation tasks, such as medical image analysis [17], surgical scene segmentation [18], civil infrastructure defect assessment [19], and autonomous robotic frameworks [20]. Leveraging SAM's advanced capabilities in semantic segmentation and object recognition, we employ it to delineate cropland units from remote sensing images prior to classification. Subsequently, the delineated cropland unit features will be combined with the crop type classification results to further enhance the accuracy of crop-specific land cover mapping.

This paper aims to demonstrate promising potential in applying SAM to crop-specific land cover mapping and advancing agricultural monitoring systems. The rest of the paper is organized as follows. Section II describes the data, model, and the design of the enhancement workflow. Section III demonstrates the experimental results in California and Midwestern United States. The conclusions and future research recommendations are given in Section IV.

II. Methods

A. Data

In this study, we will apply the SAM to improve the Cropland Data Layer (CDL), which is a well-known crop-specific agricultural land cover data product by U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) [21]. It covers the entire CONUS at 30-meter spatial resolution from 2008 to the present and some states from 1997 to 2007. Table summarizes the information about CDL data and its derived data products. The cropland layer provides over 140 land cover classes with around 95% accuracy for major crop types. The crop frequency layer identifies the specific planting frequency of four major crop types across the

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TABLE I
SUMMARY OF CDL AND ITS DERIVED DATA PRODUCTS.

Layer	Availability	Coverage	Spatial Resolution	Data Type
Cropland Layer	1997 to present	CONUS (2008-2022), Some states (1997-2008)	30-meter	Categorical (crop type)
Crop Frequency Layer	2008 to present	CONUS	30-meter	Continuous (percentage)
Confidence Layer	2008 to present	CONUS	30-meter	Continuous (year count)
Cultivated Layer	2013 to present	CONUS	30-meter	Categorical (crop mask)

CONUS, corn, cotton, soybeans, and wheat, based on CDL from 2008 to the present. The confidence layer represents the percentage (0-100) of confidence for each cropland pixel. The cultivated layer is a crop mask map with pixels that are identified as cultivated in at least two out of the most recent five years of CDL data.

The satellite images explored in this study are the Sentinel-2 data. The Copernicus Sentinel-2 mission is operated by European Space Agency (ESA), which consists of two twin polar-orbiting satellites. The Sentinel-2A satellite was launched in June 2015, and the Sentinel-2B was launched in March 2017. They provide the higher temporal resolution of revisiting every five days under the same viewing angles and a higher spatial resolution of 10-60 m. The main instrument of the Sentinel-2 mission, the MultiSpectral Instrument (MSI), covers 13 spectral bands ranging from visible and near-infrared to shortwave infrared wavelengths.

Both CDL and Sentinel-2 data are open geospatial data products and easy to access. The CropScape (https://nassgeodata.gmu.edu/CropScape) is the most common way to explore and download CDL data [22]. The ESA Copernicus Open Access Hub (https://scihub.copernicus.eu/) provides open access to Sentinel-2 data. On the other hand, the Google Earth Engine (GEE) data catalog has archived the complete volume of CDL and Sentinel-2 data.

B. Segment Anything Model (SAM)

The Segment Anything Model [13], or SAM, is a new segmentation model that was released by Meta in April 2023. Trained on over 11 million images and 1.1 billion segmentation masks, Sam has been considered a foundation model for image segmentation, analogous to BERT and OpenAI's "GPT-n" series for natural language processing (NLP). During its creation, this model was tasked with generating a set of "valid masks" for an input image (similar to the NLP task of producing a coherent output in text completion). It also includes an option to prompt the model in the form of a bounding box or set of points on the image. SAM is primarily used for object detection, and its application extends to image enhancements, real-time masks generated for video feeds, and Augmented Reality (AR)/Virtual Reality (VR) advancements powered by accurate segmentation.

For the purposes of our experiment, SAM was allowed to automatically segment every recognized object in the satellite imagery. The Segment Anything 1 Billion (SA-1B) dataset on which SAM was trained does not appear to include remotely-sensed imagery, meaning that the main feature of SAM that we leveraged was its ability to perform zero-shot generalization. Because of this feature, there were no explicit pre-training steps taken before segmentation was performed on the satellite data.

C. Enhancing Crop Type Mapping with SAM

Crop mapping via remotely-sensed images is growing increasingly important in agriculture. Oftentimes machine learning is employed to expedite the creation of these maps. However, the results of traditional machine learning approaches, such as DT and RF, can be noisy. These methods are applied to satellite imagery pixel-by-pixel and thus can result in misclassified pixels within a cropland unit. To address this issue, we propose the incorporation of the latest CV-based image segmentation approach into the postprocessing phase, thereby enhancing the quality of crop type mapping results. As shown in Figure 1, the proposed workflow utilizes the SAM to automatically segment the original satellite image, the delineated boundaries of each cropland field can be identified and used to clean up the image.

Our experiment goes through each segmented area, finding the mode of the cropland values and reclassifying erroneous pixels to this value. To assess its effectiveness of the model, our experiment is performed on two key agricultural regions in the United States, one in California's San Joaquin Valley and the other in the U.S. Corn Belt.

III. EXPERIMENTAL RESULTS

A. Experiment Setup

Our experiment used GEE as the primary computing platform. Using the segment-geospatial module of the *geemap* library [23], we were able to set certain parameters of the model, such as "foreground" and "unique". The former was set to false to avoid SAM categorizing the satellite imagery of crops as "background", which could be because that is the case in most of its training data [24]. The latter was set to true, because in the absence of this change the model seems to tend towards grouping nearby crops in one mask. This processing was performed in Google Colab, upon which the resulting GeoTIFF mask files would be uploaded as assets in GEE and used for processing as per the workflow.

B. Experimental Result 1: California's Central Valley

The first study area is chosen from the San Joaquin Valley of California's Central Valley, located in Riverdale of Fresno County. The major crop types grown here are mainly vegetables and fruits, such as lettuce, onions, garlic, tomatoes,

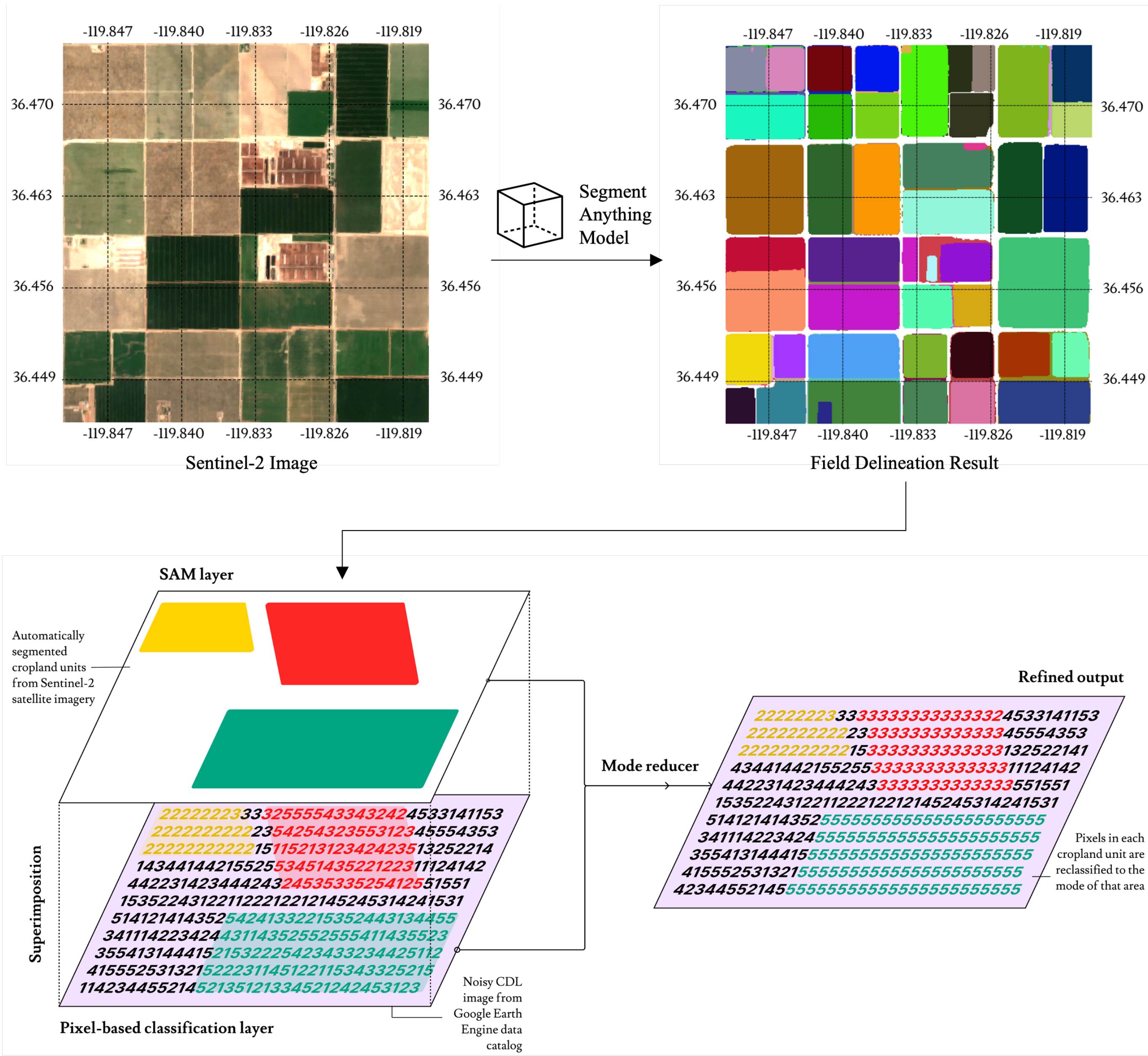
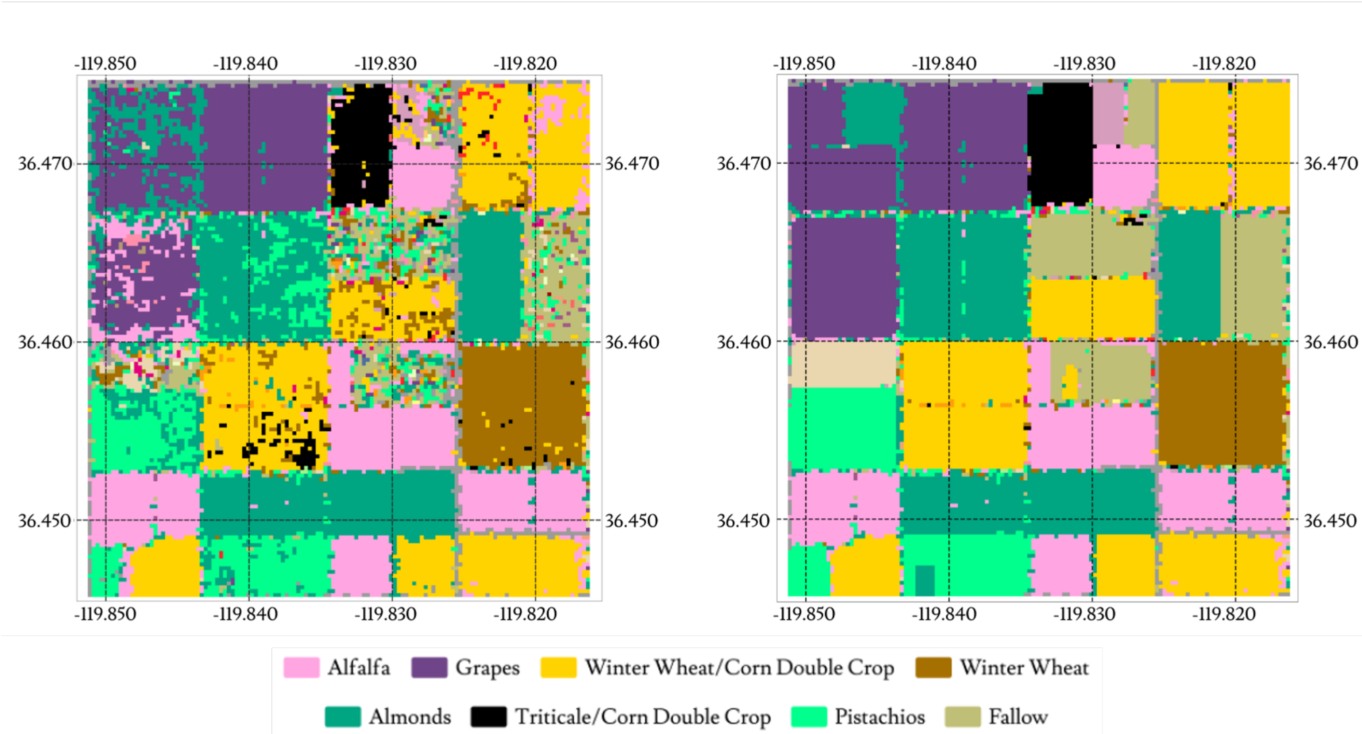


Fig. 1. Workflow diagram for enhancing USDA NASS CDL data using SAM.

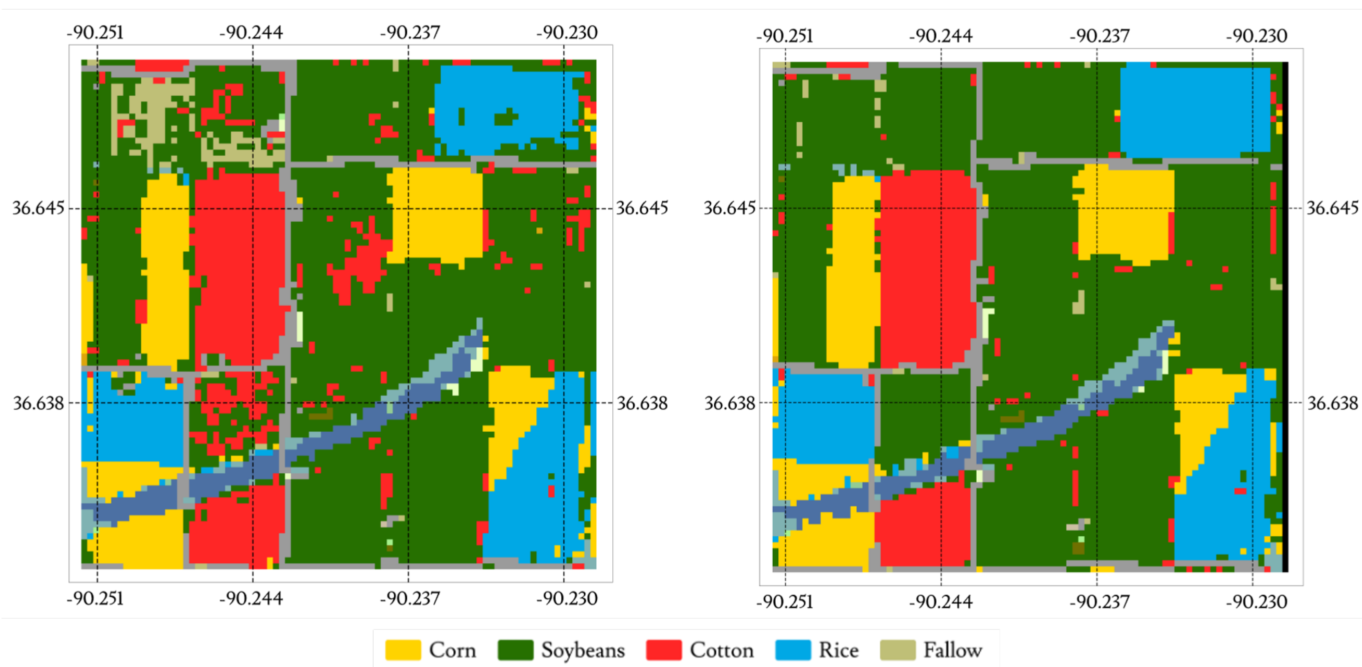
almonds, safflower, peaches, nectarines, citrus and olives. According to the USDA NASS [25], the largest share of yields from 2022 for the entire county were from tomatoes, corn, and cotton. In Figure 2a, one can see that the original CDL imagery on the left is quite noisy. While there are a few ambiguous cropland units with many different pixel colors, most units have a clear majority, such as the two adjacent almond fields with quite a few pixels misclassified as pistachios near the top left. It is these errors that SAM seems to have the greatest potential to correct, allowing the accuracy of CDL to be further enhanced. Overall, a total of 17.11% of the pixels in this image were reclassified, quantifying the improvements that SAM stands to contribute to existing agricultural data.

C. *Experimental Result 2: U.S. Corn Belt*

The second study area is chosen from U.S. Corn Belt, located in Qulin of Butler County, Missouri. The major crop types grown here are soybeans, corn, and rice according to the USDA NASS [25]. Figure 2b illustrates how the accuracy of the CDL varies depending on the study area; as compared to Fig. 2a, it is less noisy and visually closer to the Sentinel image, although there is still a significant amount of error. In particular, the cropland unit in the center contains many pixels misclassified as cotton instead of the majority, which is soybeans. Again, SAM performs relatively well in such scenarios where a clear majority is already visually apparent and the main output is removal of erroneous pixels that



(a) California's Central Valley



(b) U.S. Corn Belt

Fig. 2. Comparison of original CDL (left) and enhanced CDL with SAM (right) .

previously brought down accuracy. However, the particularly noisy cropland unit near the bottom left of the image also demonstrates a drawback of this approach: without ground-truth data, it is difficult to resolve ambiguity in cases where there is only a slight majority. For this study area, only 8.01% of pixels were reclassified, although that may be due to less initial noise than in the San Joaquin Valley study area.

IV. Conclusions and Future Works

This paper illustrated the preliminary results of enhancing crop-specific land cover map with CV-based segmentation approach. Based on the feature of zero-shot generalization to unfamiliar objects and images without the need for additional training, SAM can automatically delineate cropland units from high-resolution satellite images. By voting for the major crop types within each land unit, noisy pixels can be removed from the remote-sensing-based crop type mapping results. The preliminary experimental results suggested that SAM can significantly improve the quality of the original CDL data in key agricultural regions in U.S., including Central Valley California and Corn Belt. During this process, it was noted that in a number of scenarios SAM undersegmented the image, resulting in a mask layer that did not accurately segment every one of the cropland units visible in the image. However, this is likely to improve with pre-training in future studies.

In the next phase, we will apply SAM to further improve the crop type maps for the entire CONUS [26], the prediction of crop mapping [27], and the in-season crop mapping results for the foreign agricultural regions [28]. By integrating SAM into these classification workflows, high-quality crop type maps can be potentially generated at the national scale with minimal effort. Meanwhile, crop yield can be estimated more accurately at the early growing stage.

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