

Threshold Based Regional Cropland Classification from Synthetic Aperture Radar using the Coefficient of Variation Method



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Introduction

- Stakeholders in the agricultural industry utilize satellite remote sensing observations as they provide a uniform measurement of mapping cropland and cropland changes globally, with limited resources and field support needed.
- Active remote sensors have long been used by stakeholders such as the U.S. Department of Agriculture (USDA) and the Foreign Agricultural Service (FAS). Active sensors have leveraged the opportunity to work in areas regardless of solar and atmospheric conditions, expanding the areas that can be continuously monitored.
- The Coefficient of Variation (CoV) method has been used to classify cropland extent, but the method involves calculating a unique threshold for each AOI using a reference dataset. Here, the relationship between dominant crop type and optimal threshold is exploited to find general thresholds for three staple crops that can be used to classify cropland extent in new regions, without the need for reference data.

Methodology

- The methodology selected for this project was modified from the workflow used in Whelen & Siqueira¹ and Rose et al.² using the CoV to determine an optimal threshold for crop/non-crop classification in multiple climates across the United States.
 - The CoV method will be used to create the Level-2 Cropland Area product in the upcoming L-band NASA ISRO SAR (NISAR) mission.
 - Three dominant crop types were studied: corn, wheat, and rice. The optimal thresholds across five years were calculated for two base AOIs per crop type and then averaged. This average was then applied to one test case AOI per crop type.
- Data:** European Space Agency (ESA) Sentinel-1 C-band VV-polarization SAR data from January – December 2018-2022 for each base AOI and January – December 2021 for each test AOI. For this study, five adjacent Sentinel-1 swaths (250 km) were processed for each base case and three for each test case.
 - The SAR data were processed using the Alaska Satellite Facility's (ASF) Vertex On-Demand Service to create 30-meter resolution radiometrically terrain corrected (RTC) products in gamma0 power.
 - This analysis was conducted using ASF's OpenScienceLab which utilizes Jupyter Notebooks and Amazon Web Services to download and process the data (See: <https://asf.alaska.edu/trainings/welcome-to-asf-opensara/>).
- Binary Crop Reference:** The reference layers used were Copernicus Global Land Service: Land Cover 100 m product³ for 2018-2019 and ESA WorldCover v100⁴ for 2020 and v200⁵ for 2021-2022.
 - A binary crop/non-crop classification was created from the reference layer for each AOI.
 - A water mask was created to exclude water pixels from the classification process. Water is often misclassified as cropland due to its high CoV.
- Calculating CoV:** CoV is a unitless metric measuring the temporal variation in backscatter response in each pixel throughout the time series. A value of 0 indicates no variation, and higher values indicate high variation over the timespan.
 - The CoV was calculated for each pixel's SAR time series to generate a CoV map where:
$$CoV = \frac{\text{Standard Deviation}}{\text{Mean}}$$
- Selecting the Optimal Threshold:** Using the reference layer, a sample of 0.01% of the non-water pixels from each base AOI CoV map was selected. The sample size was approximately 20,000 pixels per AOI.
 - To select the optimal threshold for the binary crop/non-crop classification, each threshold from 0 – 1 with a step size of 0.01 was applied to the CoV map to classify each sampled pixel as either crop or non-crop. Every sampled pixel with CoV greater than or equal to the threshold was classified as crop and anything below was classified as non-crop.
 - Youden's J Statistic (JIS) was calculated for each threshold by comparing the reference layer to the binary crop/non-crop classification where:
$$JIS = \text{sensitivity} + \text{specificity} - 1$$

$$\text{Sensitivity} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

$$\text{Specificity} = \frac{\text{true negatives}}{\text{true negatives} + \text{false positives}}$$
 - JIS ranges from 0 – 1 and a JIS of 1 indicates that there are no false positives or false negatives. The threshold with the JIS closest to 1 is the optimal threshold.
- Finding Average Crop Type Threshold:** The optimal thresholds across the pairs of base AOIs were averaged to generate a crop type threshold to apply to the test AOIs. The base and test AOIs were selected using the USDA, Foreign Agricultural Service Commodity Explorer⁶.

Crop Type	Base AOIs	Test AOIs	Average Threshold
Corn	Ukraine, United States	Brazil	0.54
Wheat	Morocco, France	China	0.33
Rice	Thailand, Myanmar	India/Bangladesh	0.24

Table 1. Selected thresholds for specific crop types.

Conclusions

- Areas with similar dominant crop types generate similar optimal thresholds on average (Table 1).
- Brazil (corn) generated the highest CoV on average followed by China (wheat) and India/Bangladesh (rice), which matches the average thresholds for the crop types (Figure 2).
- Applying an average crop type threshold to a new region can achieve over 80% accuracy. It is not necessary to generate an optimal threshold to adequately classify agricultural extent if the dominant crop type of the region is corn, wheat, or rice (Figure 3).
- Over 90% of false positives in Brazil were grassland (Figure 4). False positives in China were split evenly between built-up areas, grassland, and forest (Figure 5). In India/Bangladesh, 60% were forest and 20% were grassland (Figure 6).

Future Work

- Apply corn, wheat, and rice thresholds to new areas (e.g. Southern Hemisphere) and study other major crop types: soybean, cotton, sugar, cane etc.
- Further explore false positives (grassland, forest, built-up areas)
- Consider CV ranges for crop types rather than binary thresholds to classify areas with heterogeneous cropland.
- Investigate field boundary detection to classify cropland extent on a field scale rather than pixel by pixel.

Acknowledgements

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Cumulative Coefficient of Variation over China 2021

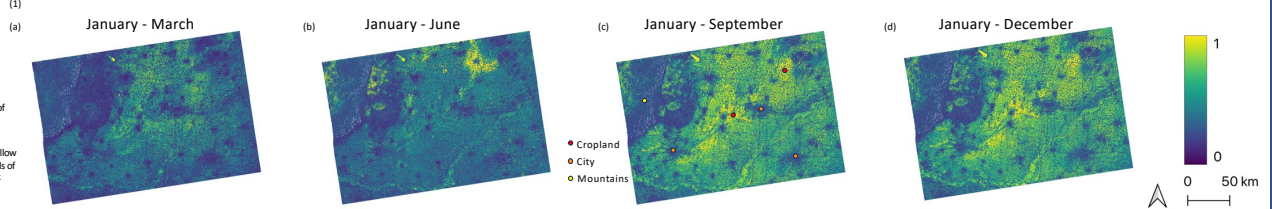


Fig. 1. Coefficient of Variation map calculated over increasing time intervals. Bright yellow indicates high levels of change, while dark blue indicates low levels of change.

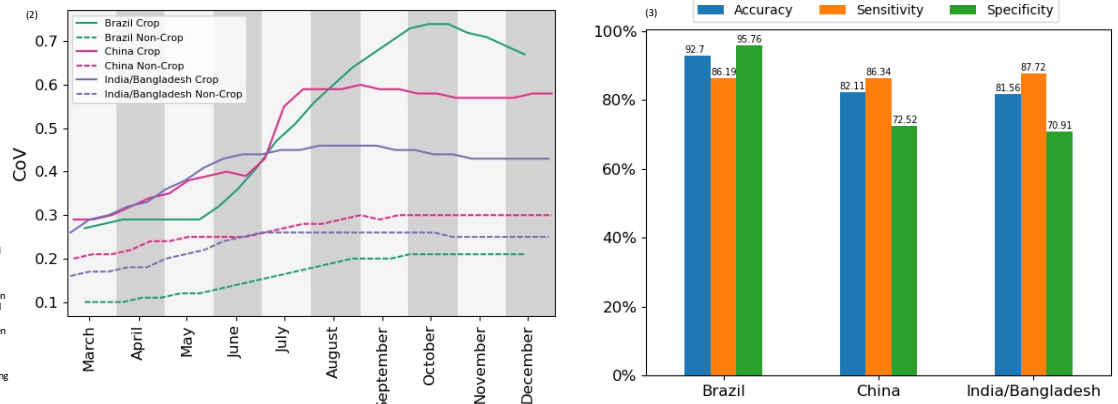


Fig. 2. Average cumulative Coefficient of Variation for cropland and non-cropland pixels from each test case. Beginning with six acquisitions (early March), each subsequent acquisition was added to the stack and the CoV was calculated. There is separation between the cropland and non-cropland curves and the cropland curves have pronounced increases during the growing season.

Fig. 3. Accuracy, sensitivity, and specificity for each test case. Each test case exceeded 80% accuracy. Cropland was classified correctly more often than non-cropland in China and India/Bangladesh (sensitivity > specificity), while non-cropland was classified correctly more often than cropland in Brazil (specificity > sensitivity).

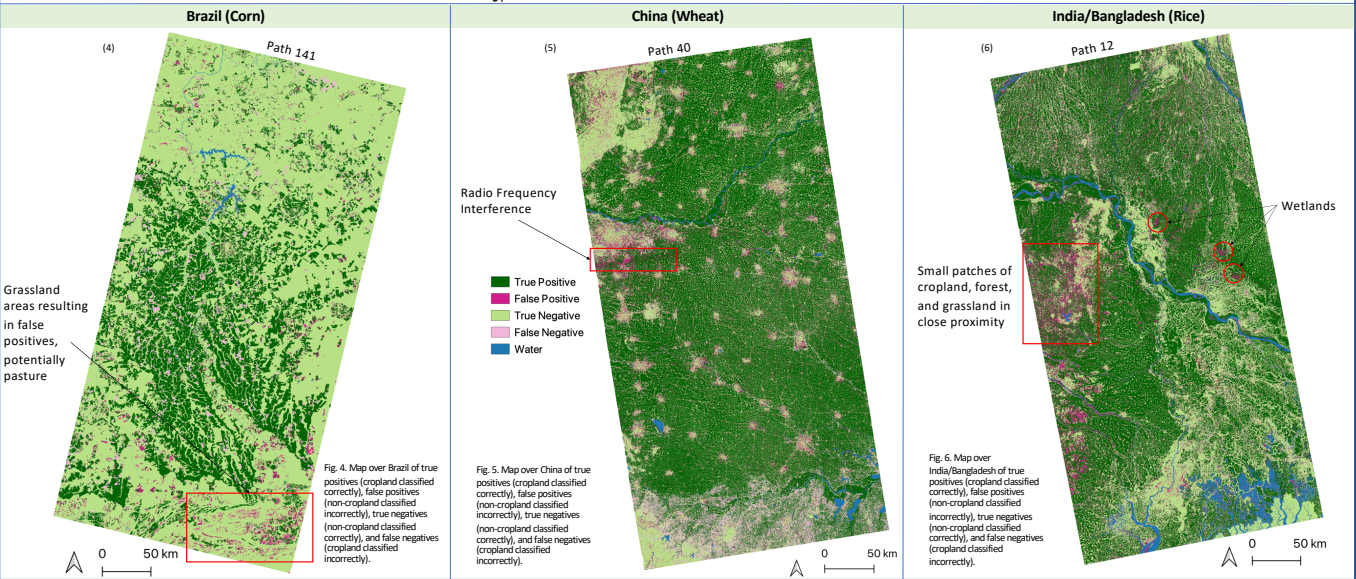


Fig. 4. Map over Brazil of true positives (cropland classified correctly), false positives (non-cropland classified incorrectly), true negatives (non-cropland classified correctly), and false negatives (cropland classified incorrectly).

Fig. 5. Map over China of true positives (cropland classified correctly), false positives (non-cropland classified incorrectly), true negatives (non-cropland classified correctly), and false negatives (cropland classified incorrectly).

Fig. 6. Map over India/Bangladesh of true positives (cropland classified correctly), false positives (non-cropland classified incorrectly), true negatives (non-cropland classified correctly), and false negatives (cropland classified incorrectly).