Technical Report for the GEO-AI challenge "Cropland mapping with satellite imagery"

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Abstract

In this report, we apply different classical classifiers and deep Learning models to find the cropland extent and intensity of four different test regions: Iran, Mozambique, Sri Lanka, and Sudan. Our work discusses a complete workflow starting from collecting training samples using Google earth engine, developing an NDVI time-series reconstruction, smoothing, and gap-filling algorithm, then proposing a novel adaptive threshold approach for intensity cycles detection through an NDVI time series, and finally running different classifiers on the training samples and generating Geo-Tiff assets. The proposed methodology achieved high accuracies in most cases ranging between (84% to 96%), and a comparison between the different classifiers is provided.

1. Data Preparing

We used Google Earth Engine provided assets to collect the training samples from each of the four regions of interest. We have followed two different approaches to collect samples for the two problems at hand. For Cropland extent, we have visually interpreted 75 cropland areas and 75 noncropland geometric points before exporting them out as CSV files that were later imported into google collaborate and appointed a binary label. On the other hand, we have used geometric polygons of water surfaces, Cropland, and noncropland for cropland intensity. Later, we sampled 157 to 174 sample points of each based on the intensity variance in the test region and exported the concatenated feature collection as a CSV file to google collaborate. As crop intensity mapping cannot be accurately assessed through visual interpretation, we developed an adaptive threshold algorithm to count the number of cycles in each time-series instance and used it to apply labels to our training samples later. Training data samples were pre-processed before being fitted into the model through the NDVI reconstruction algorithm developed, which will be discussed in the Algorithms section later in this report. It is worth mentioning that the NDVI series used for data sampling was unmasked to retain the metadata of the input image and footprint.

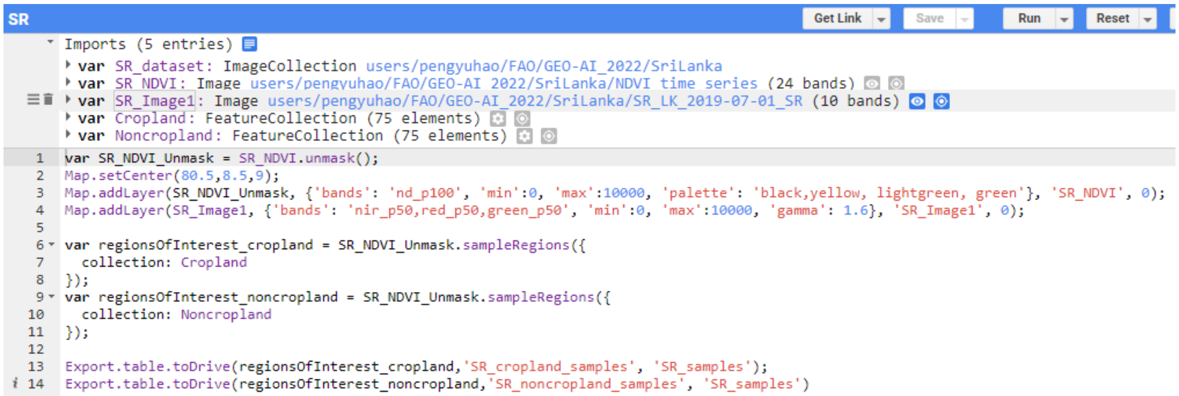

Fig. 1 Google Earth Engine code snippet for Sri Lanka

Fig. 2 Sudan samples

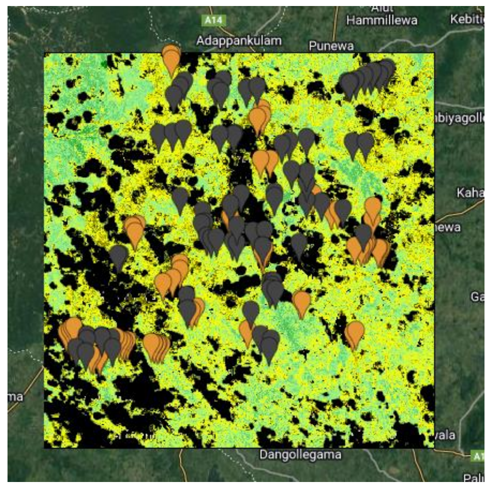

Fig. 3 Sri Lanka samples

Fig. 4 Mozambique Samples

Fig. 5 Iran Samples

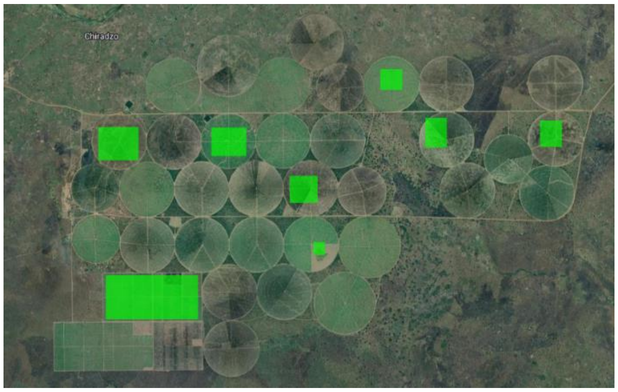

Fig. 6 Mozambique Cropland samples

Fig. 7 Mozambique Water samples

Fig. 8 Mozambique Noncropland samples

Fig. 9 Mozambique Noncropland samples zoomed in

2. Algorithms for cropland extent and crop intensity mapping

- **Timeseries reconstruction**

The time series provided contained a half-month data composition. Nonetheless, it required a gap-filling and reconstruction procedure. Hence, we decided to apply linear interpolation and Savitzky-Golay Filter to tackle this issue. Linear interpolation was applied by taking the mean of the two adjacent points if the point at that index is 0 or if the difference between it and the following point exceeds an NDVI score of 0.4 (0.5*NDVImax). Savitsky-Golay Filter was used to smoothen the time series without losing its main characteristics. Hence, a sliding window of 3 was chosen as we have 24 points only and a polynomial of the second degree, for that matter. The plots below show the NDVI time series before and after applying the NDVI reconstruction algorithm.

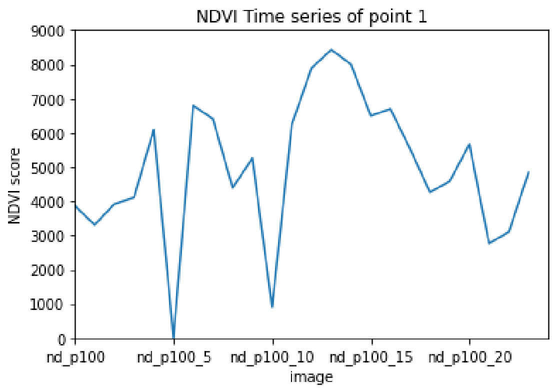

Fig. 10 NDVI Series before reconstruction

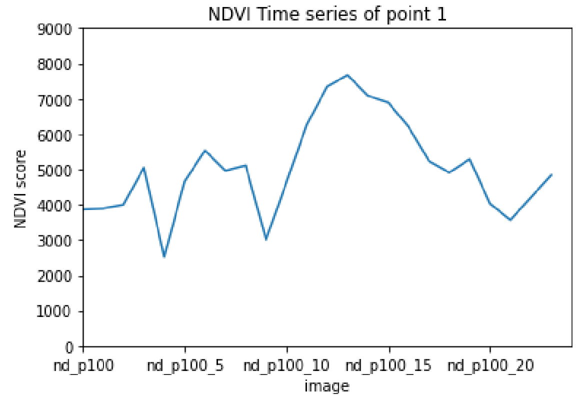

Fig. 11 NDVI Series after reconstruction

- **Adaptive threshold approach for intensity cycles detection**

To appoint labels to the crop intensity samples collected, we have developed a novel adaptive threshold algorithm for cycles labelling as visual interpretation can be misleading. The adaptive threshold algorithm is applied on the smoothened reconstructed timeseries and detects the peaks and valleys through linear interpolation. First, we traverse over the time series and detect the maxima value. Afterwards, we dynamically allocate the Threshold of that time series to be 70% of the local maxima ($0.7*NDVI_{max}$). Similarly, the minima is considered as 20% of the maximum threshold of the time-series ($0.2*NDVI_{max}$). Local maxima and minima are used as crops may vary in their respective thresholds. After detecting both critical values, we traverse through the time series and count the number of peaks and valleys based on the local threshold assumed. The flow diagram below summarizes the adaptive threshold Algorithm.

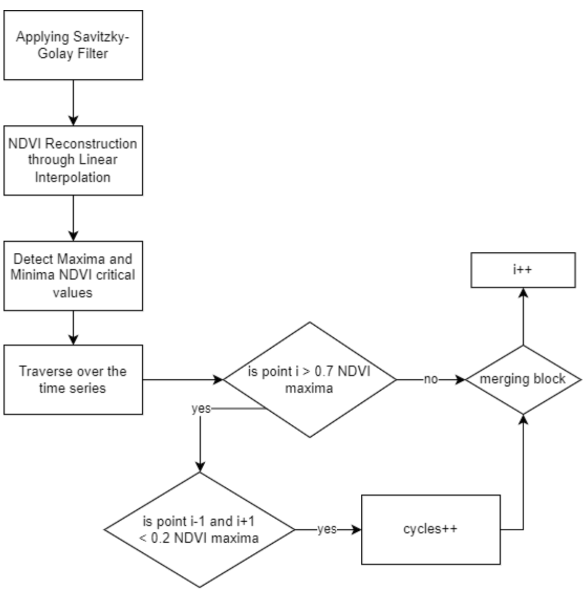

Fig. 12 Workflow diagram

- **Models used for training and comparison**

1. **Random Forest Classifier**

Random forest is a classification algorithm. It is builds up of multiple decision tress. It is supervised and can also be used in regression problems.

2. **XGBoost Classifier**

XGBoost is short for Extreme Gradient Boosting. It is a distributed gradient-boosted decision tree. The trees are boosted by parallel trees and used for regression classification ad well as ranking problems

3. **Long Short-Term Memory (LSTM)**

LSTM is short for Long short-term memory. It can process the entire sequence of data. LSTM has feedback. It is one input flow, can be either backwards or forwards.

4. **Bidirectional LSTM**

Bidirectional LSTM works similar to LSTM but the main difference is that bidirectional can make input flow in both directions, backwards and forward.

5. **KNN with DTW**

KNN is the K-nearest neighbors algorithm. It is well known for classification and works by finding the distances between a value and other examples in the data and then chooses the most frequent label for classification. Stands for Dynamic Time Warping and is used in time series analysis. It measures the similarity between two temporal sequences.

3. Accuracy assessment

Cropland extent				
	Mozambique	**Sudan**	**Iran**	**Sri Lanka**
Models	**Accuracy**			
Random Forest	0.74	0.84	0.92	0.86
XGBoost	0.82	0.92	0.92	0.88
LSTM	0.82	0.84	0.96	0.90
Bidirectional LSTM	0.80	0.90	0.98	0.80
Crop Intensity				
	Mozambique	**Sudan**	**Iran**	**Sri Lanka**
Models	**Accuracy**			
Random Forest	0.87	0.84	0.91	0.80
XGBoost	0.92	0.84	0.90	0.85
KNN DTW	0.75	0.91	0.86	0.81

Fig. 13 Accuracy assessment

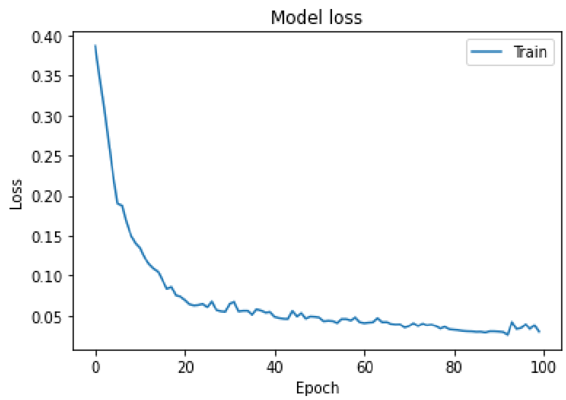

Fig. 14 LSTM Loss vs Epoch curve for Iran

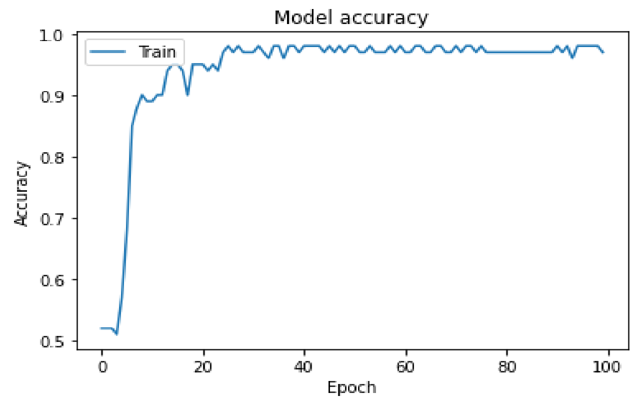

Fig. 15 LSTM Accuracy vs Epoch curve for Iran

Cropland

Noncropland

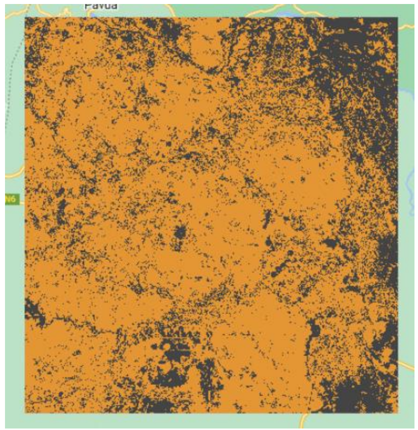

Fig. 16 Mozambique Cropland Extent

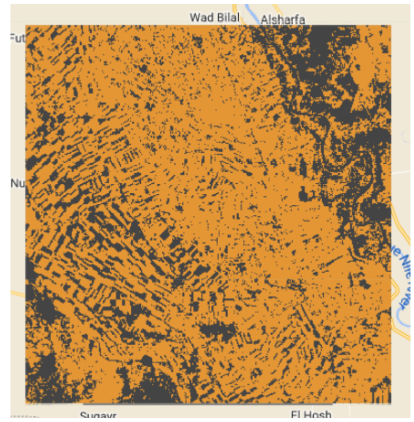

Fig. 17 Sudan Cropland Extent

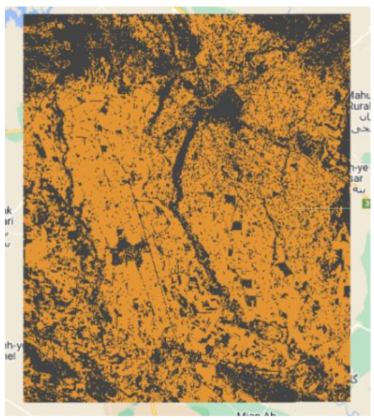

Fig. 18 Iran Cropland Extent

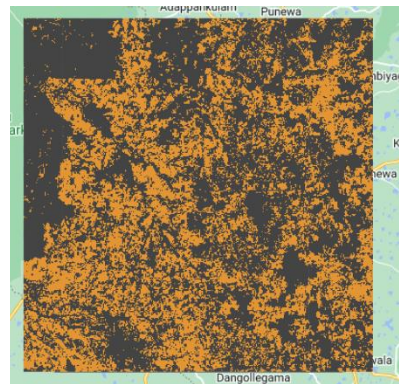

Fig. 19 Sri Lanka Cropland Extent

Non-Crop

Single

Double

Triple

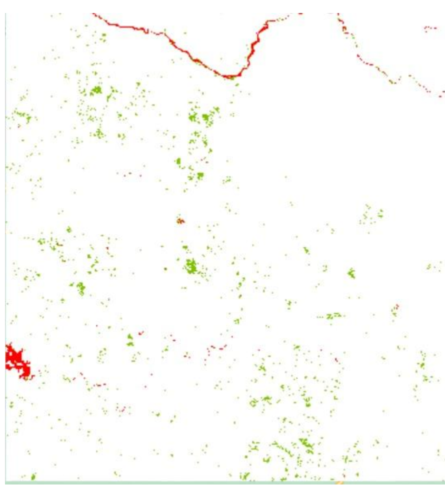

Fig. 20 Mozambique Cropland Intensity

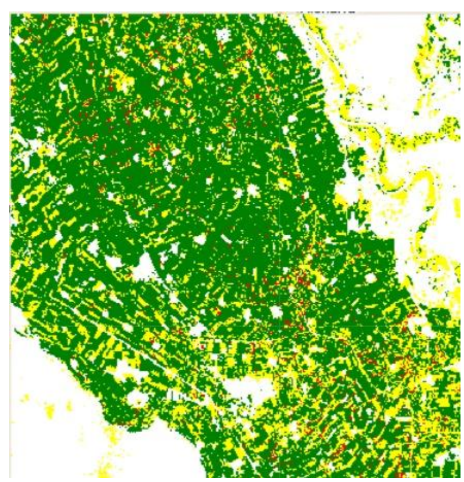

Fig. 21 Sudan Cropland Intensity

Fig. 22 Iran Cropland Intensity

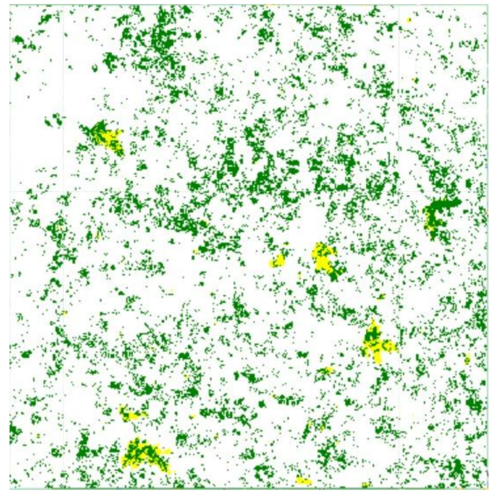

Fig. 23 Sri Lanka Cropland Intensity

Results

We used random forest for the final Geotiff image despite LSTM having better accuracy in some countries. The reason we chose random forest was because the speed–accuracy tradeoff as the LSTM model takes a long time to run than random forest.

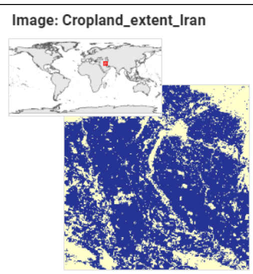

Fig. 24 Iran Cropland Extent

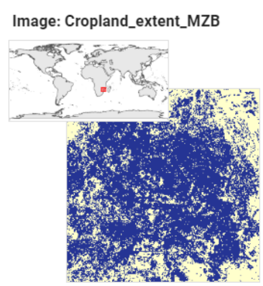

Fig. 25 MZB Cropland Extent

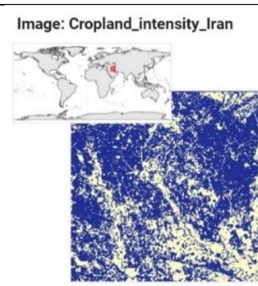

Fig. 26 Iran Cropland Intensity

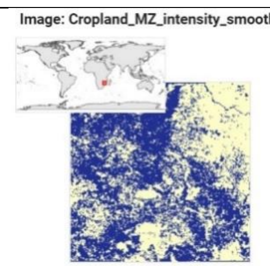

Fig. 27 Mozambique Cropland Intensity

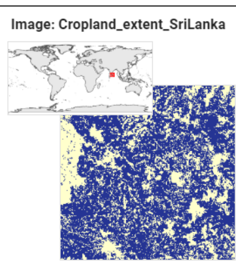

Fig. 28 Sri Lanka Cropland Extent

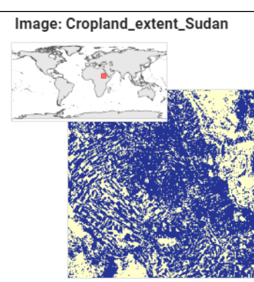

Fig. 29 Sudan Cropland Extent

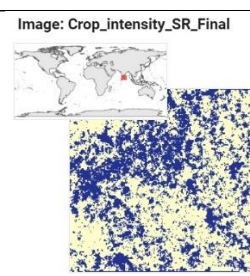

Fig. 30 Sri Lanka Cropland Intensity

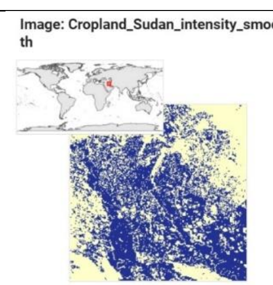

Fig. 31 Sudan Cropland Intensity

4. Novelty and conclusion

We have generated four maps for cropland extent and intensity in four different test regions; Sudan, Sri-Lanka, Iran, and Mozambique using different times of classifiers including Random Forests, XGboost, LSTMs, CNNs, and Dynamic Time Wrapping (DWT). We have developed a time series reconstruction Algorithm as a combination of linear interpolation and Savitzky-Golay Filter. We have also developed a novel adaptive threshold intensity labelling algorithm to eliminate differences of crops thresholds and to rely on a mathematical procedure instead of visual interpretation. We have managed to achieve high accuracies ranging between 84% to 96% in some cases. The test region of Mozambique achieved a relatively lower accuracy (74%) as it was difficult to distinguish between croplands and noncroplands even with visual interpolation. We decided to use Random Forest to generate the GeoTiff images as other models consumes so much time to do the same task on our local machines [~5 minutes for Random Forest Models, ~ 45 minutes for other models] with a small trade off accuracy (-4-8%). Further improvements can be made by adding more training samples, making use of existing landcover datasets through transfer learning, and utilities faster GPUs to lessen the time aspect.