Crop Classification using Multispectral and Multi- temporal Satellite Imagery

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What? The availability of high spatial and temporal resolution satellite images coupled with machine learning techniques can help in generating accurate and reliable crop maps. Identification of crop type is an important precursor to mapping agricultural yield and crop price prediction. Precision agriculture requires scalable and reliable crop classification which can further be used in developing detection and early warning systems for disease/pest identification as well as optimizing nutrition and irrigation management practices.

Why? One of the major sustainable development goals is zero hunger by achieving food security and promoting sustainable agricultural practices. Earth observation provides an 'eye in the sky' to achieve this. Automated data processing pipelines can be a vital tool to provide large scale solutions to various agricultural issues based on monitoring behaviour of crops and the environment in which they grow.

Where? A substantial proportion of the agricultural produce of the US is grown in California. The area of this study is Fresno county in California, which is a prominent agriculture commodity producer of the state that grows diverse crops (Suchi et al., 2021).

How? Open datasets available as part of GEE catalog have been used. This include Landsat 8 surface reflectance, MODIS L4 Leaf Area Index and USDA NASS Cropland Data Layer.
Python packages used : ee, geemap, sklearn, pandas, numpy

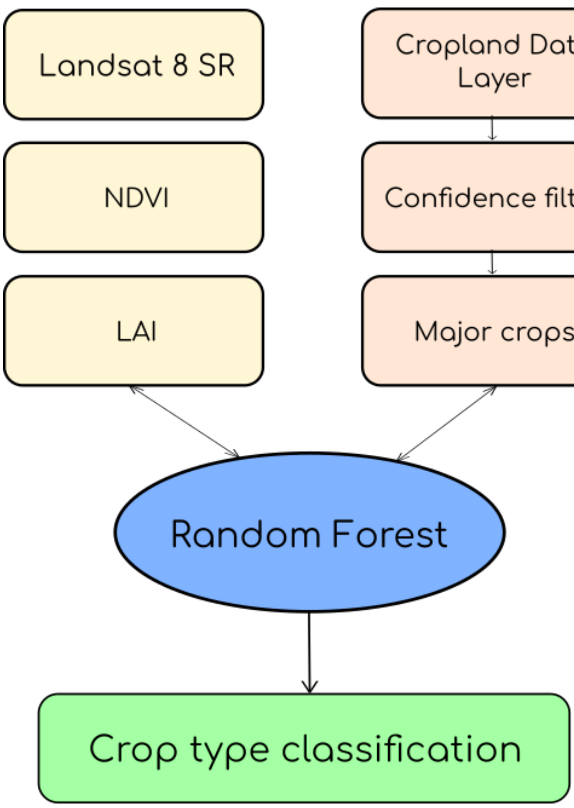
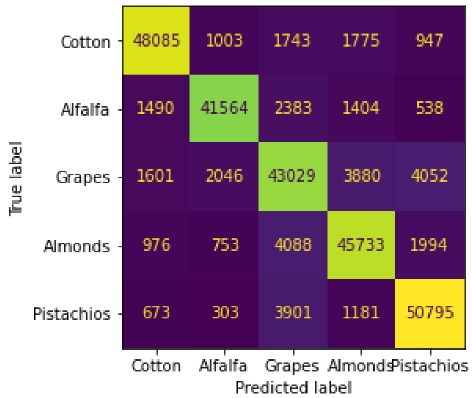


Figure 1: Methodology of this study

1 Methodology

- Landsat 8 surface reflectance data was obtained for the period from May 2019 to October 2019. June had high cloud cover and was therefore not considered for further analysis.
- NDVI was computed for each month and LAI was retrieved from MCD15A3H Version 6.1 MODIS Level 4 and resampled to 30 m.
- The label data for this study is obtained from National Agricultural Statistics Service (NASS) by United States Department of Agriculture. Cropland Data Layer (CDL) is generated annually using moderate resolution satellite imagery and extensive agricultural ground truth. Since the accuracy of CDL data depends on the crop type and geographical location, only areas containing high accuracy crops are analyzed. A threshold of 95% is applied on the CDL dataset and major crops in the region of interest are identified.
- Random Forest classifier was used with a 70-30 split for training and cross validation. Due to the inherent limitation of GEE, a larger sample size (~900k samples) was exported in the form of CSV file and trained using *sklearn* library.
- Overall accuracy of 86% was obtained.



(a) Confusion matrix

	precision	recall	f1-score
Cotton	0.91	0.90	0.90
Alfalfa	0.91	0.88	0.89
Grapes	0.78	0.79	0.78
Almonds	0.85	0.85	0.85
Pistachios	0.87	0.89	0.88

(b) Classwise precision and recall

Figure 2

- It can be seen that grapes has low F1 score and also several samples corresponding to almonds and pistachios have been classified as grapes and vice versa. Viskovic et al. (2019) noted that CDL overclassifies grapes and therefore models based on this input resulted in low precision and recall.

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