Forecasting NDVI values using Drought data

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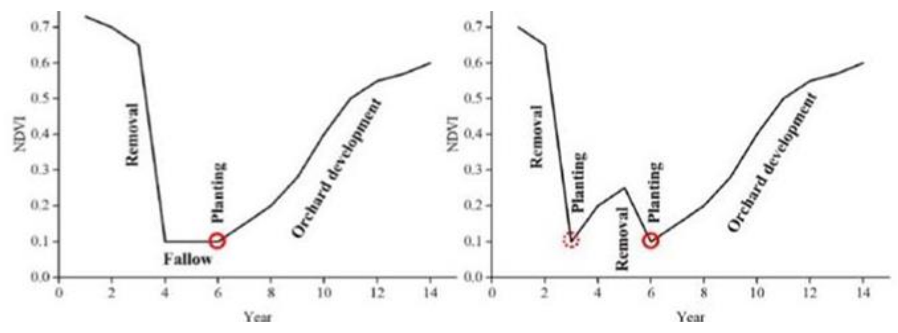
Introduction

An orchard's fallow year refers to the year that it stops producing fruit, and for water management purposes, this is important to predict ahead of time. A method to do this is to predict when the Normalized Difference Vegetation Index (NDVI) falls. Since NDVI measures plant density, a drop in NDVI signifies that the orchard is dying.



NDVI of orchards (Chen 2019)

A drought or flash drought may cause an orchard's fallow year to come early, and thus it is correlated with the NDVI values. Using drought data can help improve predicting fallow years.

Data

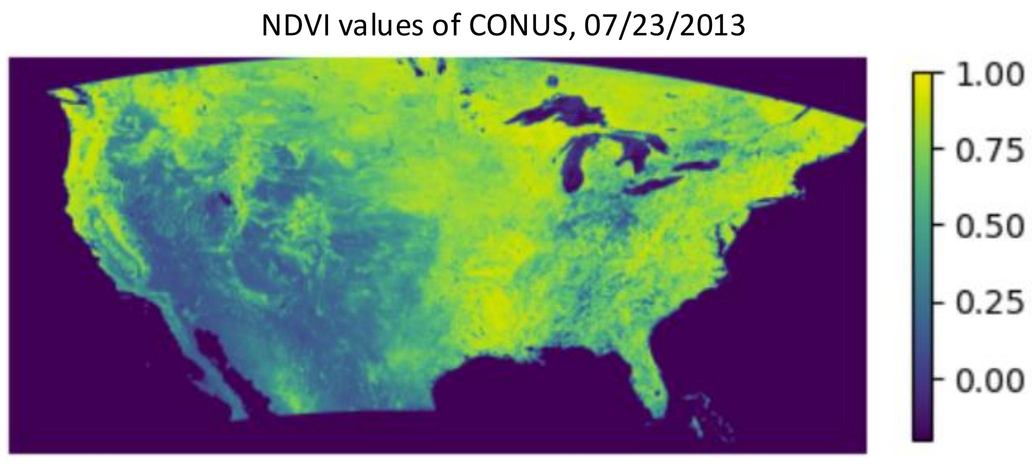
Orchard Shapefile

The shapes of the orchards were provided by Washington State University. There were 1004 orchards in total, but only 303 were included in the dataset, as the others were too small to be extracted by the other datasets

NDVI

Normalized Difference Vegetation Index (NDVI) measures the density of vegetation, and is measured on a scale of –1 to 1, where 1 signifies healthy plant growth. The NDVI data was extracted from the USGS website.

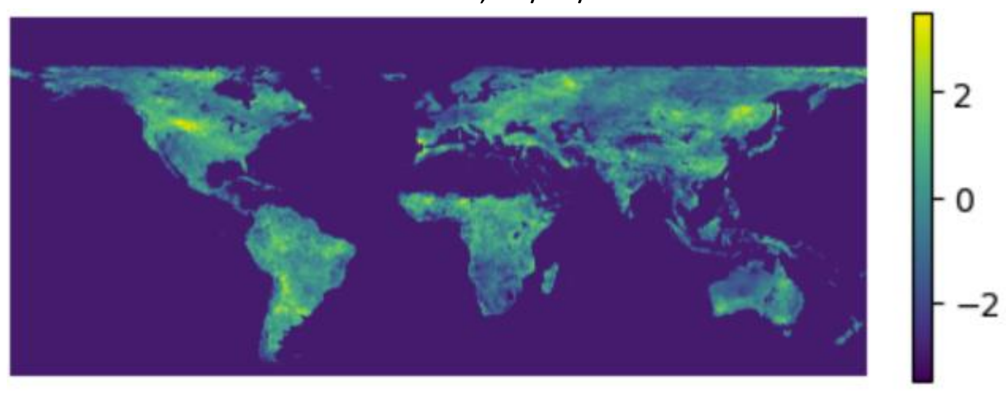
NDVI values of CONUS, 07/23/2013



ESI

Evaporative Stress Index (ESI) measures the evapotranspiration, or the amount of water use, across the land. It is calculated using z-score distribution with itself, and extremely low z-scores in ESI signifies a flash drought. The ESI data is taken from the Drought.gov website.

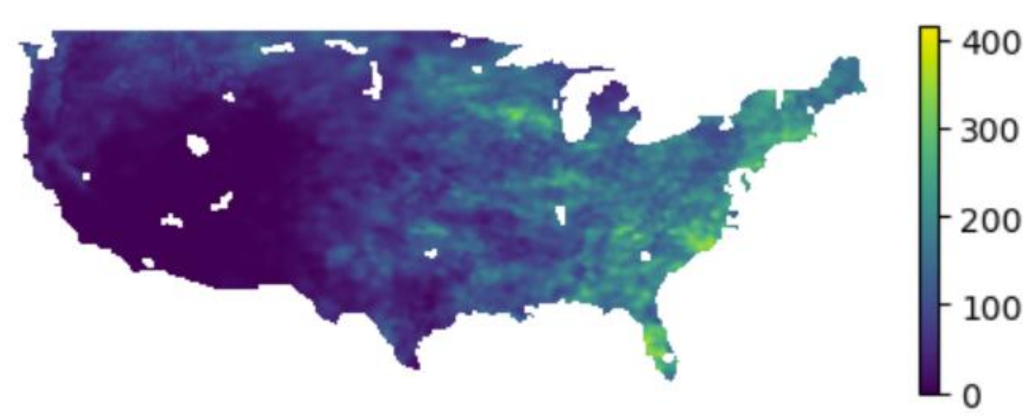
Global ESI values, 07/24/2013



PRCP

The Total Precipitation Weekly (PRCP) measures the total amount of precipitation in a week. PRCP is measured in cm and a low amount of PRCP signifies a flash drought. The PRCP is taken from the nClimGrid dataset.

PRCP values of CONUS, 07/23/2013



The NDVI, ESI, and PRCP data is taken on the months of July and August between the years 2013 – 2023, with a temporal resolution of 1 week and spatial resolution of 1 km x 1 km.

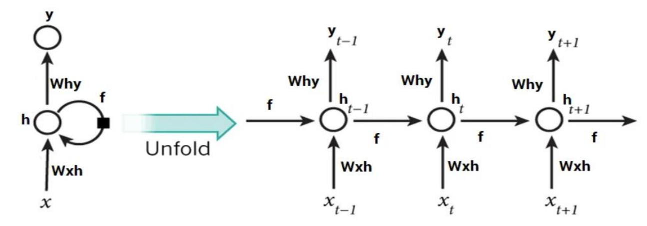
Data Cleaning

To prepare the datasets to be fed into a model, the NDVI, ESI, and PRCP values of each orchard was extracted from the respective datasets using the orchard shapefile. Then, for each orchard, the maximum NDVI, minimum ESI, and average PRCP was taken as a representative value for the entire orchard.
The weekly data for each orchard is then placed into time series vectors. Casting a time series window across these vectors with a window of 5 weeks gives us arrays of size (3, 5), or 5 weeks of data from each of the datasets.

Model

LSTM

Long Short Term Memorys, or LSTMs, are machine learning models that specifically deal with sequential data. It contains a hidden state that keeps track of previous inputs. The hidden state acts as another input and constantly updates itself at every time step. LSTMs are especially good at dealing with multiple time series vectors as input.



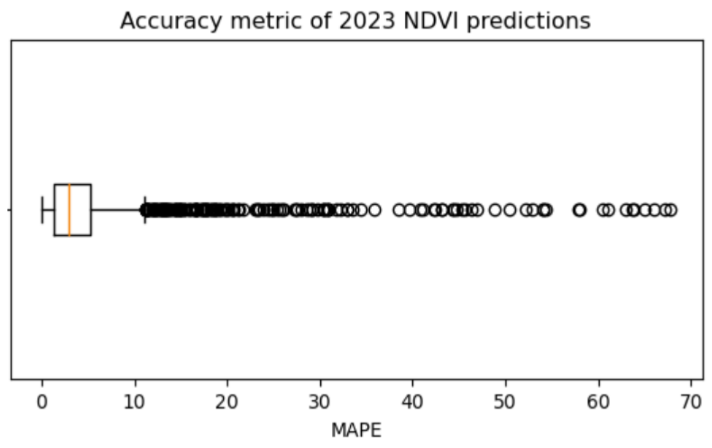
LSTM model (Srivistava 2024)

The LSTM model used had 50 LSTM nodes and 1 dense layer. The LSTM nodes had an input shape of (3, 5) and the dense layer compiles the outputs of the nodes into one predicted NDVI value for the next week.

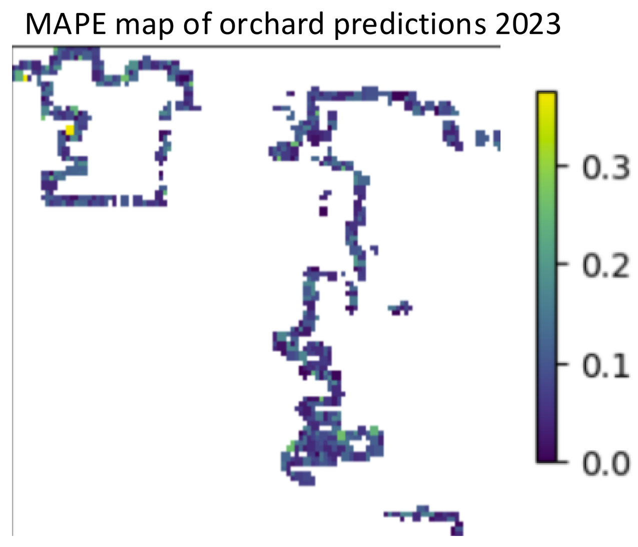
Results

The LSTM had a mean absolute percent error (MAPE) of 5.351%, with a mean absolute error of 0.032. In context of the scale of –1 to 1 of NDVI, this model is quite strong at predicting fallow years of orchards, as typically the NDVI of an orchard will fall over 0.5 during a fallow year. A spatial graph of the MAPE shows no obvious areas of error.

Accuracy metric of 2023 NDVI predictions

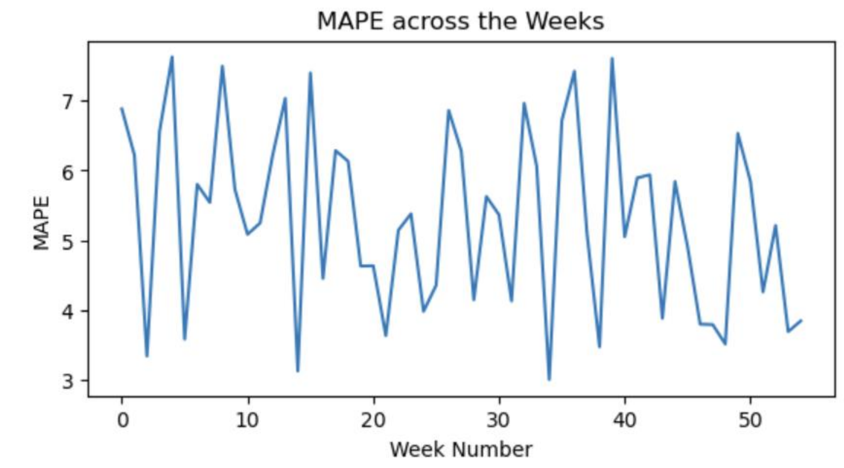


MAPE map of orchard predictions 2023



In addition, the accuracy of the NDVI is consistent over the years, as there are no obvious outliers in the MAPE across the weeks of every year.

MAPE across the Weeks



Future Work

More drought datasets can be added to the model to ensure even higher accuracies. In addition, datasets with more specific spatial resolutions should be used to have a more accurate reading of the state of an orchard.

References

Bin Chen, Yufang Jin, and Patrick Brown. Automatic mapping of planting year for tree crops with landsat satellite time series stacks. ISPRS Journal of Photogrammetry and Remote Sensing, 151, 2019.

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