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Interim Report: Predicting Food Shortages from Satellite Imagery

In the United States, there are over 2,500 weather stations recording daily temperature and precipitation data, many of which record back before 1950. The USDA also provides crop yield data at the county level since 1910. With this substantial amount of publicly available data, crop health can be closely monitored, and crop yields may be predicted based on historical records. However, not all parts of the world have open, reliable data. The availability of weather and crop data depends on the government's ability to collect it, financial resources, and willingness of authorities to share it. Lack of data is an especially important problem in developing countries where crop yields are less stable and droughts can lead to famines, death, government instability, and war. Therefore, there is a major need to monitor crop health in the developing world. Satellites provide coverage over the entire earth and certain bands may be used to assess plant health and drought conditions. This would enable scientists to monitor risks of food shortages and alert governments and international aid organizations in real time.

Crop yields in developing countries do not benefit from the same level of agricultural technology as the US, and therefore have much lower yields. Since 1970, corn yields have doubled in the US from 80 bu/acre to 160 bu/acre due to improvements in agricultural technology such as irrigation, pesticides, herbicides, fertilizers, and plant breeding (Fig. _). In developing countries, crop yields are both much lower and much more variable than in the US, both geographically and in time (Mann and Warner 2017). For example, Ethiopia's corn yield has increased from 15 to 55 bu/acre since 1960, which is still one-third the corn yield of the US. Poor farmers in developing countries do not have the financial resources or education to use the advanced technology that is in the US and Europe. Therefore, crop yields in developing countries are much more susceptible to the dangers of heat waves and droughts.

I am currently writing python code in order to obtain satellite images through the Descartes Satellite Platform, mask out clouds, calculate vegetation and water indices, compute monthly anomalies since 2000, and correlate the anomalies of the satellite indices with crop yield anomalies for every county in Illinois.

MODIS (Moderate Resolution Imaging Spectroradiometer) imagery was obtained from the Descartes Labs satellite platform at a resolution of 120 meters. MODIS, hosted on the satellites Aqua and Terra, has a return time of one to two days, giving almost continuous imagery of every location on earth since 2000. The instruments capture 36 spectral bands ranging from wavelengths of 0.4 μm to 14.4 μm.

Clouds in images can disrupt data and distort values. In order to account for cloud contamination, cloud masks were computed based on the bands blue, red, NIR, and SWIR. Pixels with clouds were not averaged in and images with over 80% clouds were not used.

To measure the health of crops throughout the growing season, three indices are being computed: NDVI (normalized difference vegetation index), EVI (enhanced vegetation index), and NDWI (normalized difference water index).

All three indices range between -1 and 1. Areas containing dense vegetation will show high NDVI and EVI values, between 0.3 and 0.8, desert sands will register as about 0, and snow and clouds are negative. NDVI is sensitive to chlorophyll, which absorbs visible light, from 0.4 to 0.7 µm, for use in photosynthesis. In contrast, EVI detects canopy structural variations, including leaf area, canopy type, and canopy architecture. NDWI detects water content, where positive values indicate higher water content and negative values imply less. Combined, all three indices complement each other on the detection of vegetation changes.

For every pixel in Illinois and every month, the NDVI, EVI, and NDWI monthly averages and climatologies are computed. The climatology is defined as the average over years 2000 through 2016, but for each month and pixel. Next, the monthly climatology will be subtracted from the monthly average for every pixel, resulting in the monthly anomaly. The pixels in each county will then be averaged together to find the monthly anomaly for NDVI, EVI, and NDWI.

Annual crop yield data was downloaded for every county in Illinois for years 2000 through 2016 from the USDA (USDA 2016). Because each county has different growing conditions (soil quality, hills, etc.), the mean was subtracted out of each county's corn yield. Correlations will next be found between each county's corn anomaly and the three satellite indices.

As a next step, I hope to use a multivariate regression in order to find even better correlations between satellite imagery and crop yields. Then, I hope to extend this research to Africa, where there is very little if any crop data, but predicting a drought is much more important.

I predict that my correlations between crop anomalies and NDVI, EVI, and NDWI anomalies will be very high in Illinois because of consistent government and technology. However, the correlations in Africa will likely be much lower because yields change with frequent changes in government and less technology influence. The correlations will also likely be lower because many countries, such as Ethiopia, only give one number for the entire country

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