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Ethiopia, International Aid

Satellite Monitoring of Crops: A Tool to Prevent Famines and Improve Yields

1 Introduction and Problem

In 2015 and 2016, Ethiopia experienced a massive drought, likely caused by a strong La Nina (UNICEF 2016). This led to low harvests, putting many families at risk of starvation. Sixty-eight percent of the Ethiopian people work in agriculture (World Bank 2017) meaning that a drought could lead to millions losing their livelihoods. Two years of poor rain left 18 million people in need of aid. In some areas, the drought killed up to 90 percent of crops and at least one million cattle.

Ethiopia received international attention for famines of the 1980s when musicians from around the world gathered together to raise awareness and money for aid. This crisis was caused by government instability and poor policies more so than drought conditions. Overall the public donated about 430 million dollars in today's money (Milner 2000) helping to provide an emergency response. Although about one million people still perished, it would have been much worse without international support.

Ethiopia is much improved since the 1980s. The poverty rate has decreased from 66% ($1.25/day) to 27% today ($1.90/day, World Bank 2015). Life expectancy has increased from 45 to 65 years and access to education has increased. However, this increase prosperity paired with a fertility rate of 5 births per woman has led to a population explosion. Forty percent of children under age five have stunted growth due to malnourishment from an inconstant food supply and only half of the adults are literate (Roser and Ritchie 2018). While fertility rate are dropping to more sustainable levels due to increased access to education and contraception (BBC 2015), food security will remain a top concern in Ethiopia for the foreseeable future (CIA 2018).

The population increase has also strained land resources and lead to increased environmental degradation. For example, expansion of the amount of agricultural land has resulted in a steady decline in forests and grasslands (Kibret et al. 2015). A warming climate will continue to add stress to the crop health and environment (Petersen 2016).

Because of the high poverty rates, reliance on local agriculture, and a history of hunger crises, we can conclude that Ethiopia and other Sub-Saharan African countries are prone to famine.

Aware of the risk of a hunger crisis, the Ethiopian government has increased preparation for future drought risks since the big 1984 famine by collecting and storing extra food each year (WoldeGabriel 2018, personal communication). During the 2015 and 2016 droughts, the government did use its stored food, but it was not enough. The amount of wheat distributed could only account for about a third of a each person's nutritional requirements. International relief efforts were further delayed because the government, fearing a negative international portrayal, worked to limit media attention on the drought: "The authorities refused to admit they could not cope alone" as the drought became progressively worse, "leading to a crucial delay in the international response." (Laing 2016).

With such a high percentage of the population relying on local agriculture for survival, low crop yields can be devastating. Therefore predicting the location and timing of low crop yields is a key factor in preventing famines. Given more advanced notice, international aid organizations and governments would be able to better focus labor and supplies on the people most in need. More lead time before an impending crisis would also improve the ability to coordinate important policy decisions such as communicating with local networks.

Currently, two major real-time crop prediction systems exist, but they are both costly and are specific to certain regions or crops.

The two systems include: the Famine Early Warning System Network (FEWS NET) and Global Agricultural Monitoring (GEOGLAM) Crop Monitor for Early Warning. Although Ethiopia collects kebele (district) level crop and population data, it refuses to release it even for agricultural research. I personally contacted the Ethiopian Central Statistical Agency, Mann, and Warner in an attempt to obtain this detailed, high-resolution data. Mann and Warner were only able to access it under strict conditions and after years of close collaboration with the government (Mann and Warner, 2017a).

Because sub-national crop yield reporting in Africa rarely exists, both crop prediction systems rely heavily on ground-based information to calibrate their predictions (FEWS NET 2018, GEOGLAM 2018). They spend many resources to send people into Africa to collect house-by-house survey data (Becher-Reshef 2018). Thus this method is extremely costly and cannot be implemented everywhere. Ground-based monitoring can only observe a relatively small number of people and areas and has no access to locations where there is conflict (Skakun et al. 2018, Becker-Reshef 2018).

2 Solutions & Recommendations

I propose and have made substantial progress towards solutions by leveraging satellite imagery to improve crop forecasting and thus the effectiveness of international aid. Satellite monitoring will allow early detection of famine conditions, targeted development of local agriculture, and preemptive interventions according to crises risk factors.

2.1 Remote Monitoring of Crop Health to Give an Early Warning of Crop Failures

Aid organizations require a cost-effective crop monitoring system that can be applied for any crop, region, or climate without special tuning, need for high-resolution data, or labor intensive procedures of verification. The program I created provides an early warning system to predict crop yields in every country in Africa three to four months before the harvest using satellite imagery.

2.1.1 Methods

The overall goal of this research was to create a predictive measure of crop yields computed from satellite data. I wrote python code to obtain satellite images, 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 country in Africa.

MODIS (Moderate Resolution Imaging Spectroradiometer) satellite imagery was obtained from the Descartes Labs satellite platform at a resolution of 120 meters (Figure 1, Descartes Labs 2018). Clouds were identified in the images, and pixels with clouds or snow were not included in monthly averages.

Index	Description	Measures	Formula
NDVI	Normalized Difference Vegetation Index	Photosynthesis	$\text{NDVI} = \frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}}$
EVI	Enhanced Vegetation Index	Canopy Structure	$\text{EVI} = G * \frac{\text{NIR}-\text{Red}}{\text{NIR}+C_1*\text{Red}-C2*\text{Blue}+L}$
NDWI	Normalized Difference Water Index	Water Content	$\text{NDWI} = \frac{\text{Green}-\text{NIR}}{\text{Green}+\text{NIR}}$

Table 1. Definitions of indices to measure crop health. NIR is near infrared, G is the gain factor, L is the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy, and C_1, $C2$ are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band.

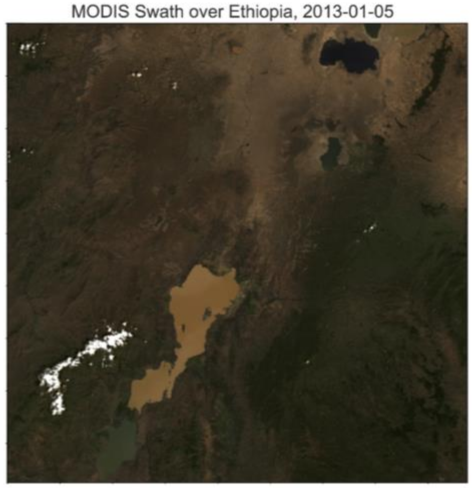

Figure 1. Snapshot of a MODIS satellite pass over a swath of Ethiopia. This daily satellite data was used to calculate crop health and predict future yields. All plots in this paper were created by the author.

To measure the health of crops throughout the growing season, three indices were computed: NDVI, EVI, and NDWI (Table 1). Then, the anomaly (difference from the average) was computed for every pixel and index. These anomalies were then correlated to national crop production data and used to predict future crop production. I came up with this method, downloaded the data, did the analysis, and made the plots. I wrote a total of 4000 lines of python code and processed 12 terabytes of raw data.

The model was first validated in Illinois, where there is a lot of high-resolution data, and was then applied to Africa.

2.1.2 Results

Figure 2 shows my calculations in Ethiopia. The wet and dry seasons are evident in the monthly NDVI values (blue). During the wet season, the crops green and the NDVI values spike. During the harvest, the values drop. Corn and sorghum were examined in Ethiopia because they are the two highest-producing crops.

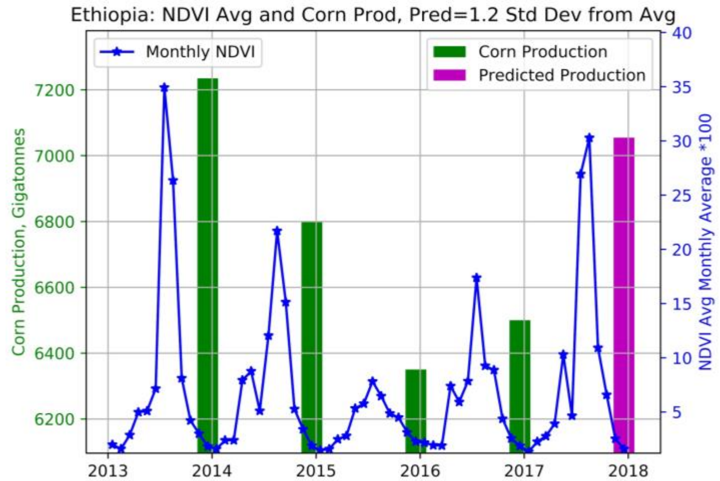

Figure 2. The monthly NDVI anomaly in Ethiopia (blue), the historical yearly corn production (green, USDA 2018), and my prediction for the 2017 growing season (pink). The correlation is extremely high at 0.98, meaning that my model can predict future crop productions almost perfectly.

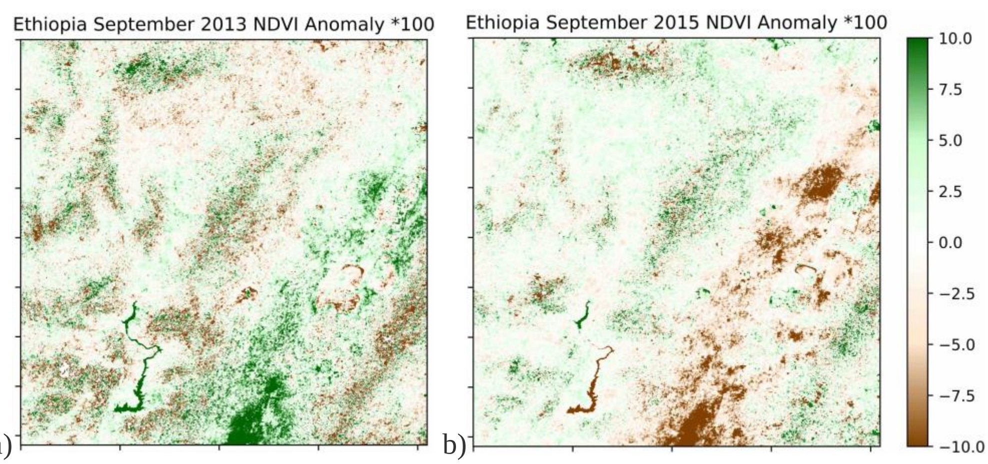

Figure 3. Part of Ethiopia during a wet year (a) and a dry year (b). The NDVI anomalies are especially evident in the rift valley, where farming is the most dense.

There was a major drought in Ethiopia in 2015, and 2013 was a very wet year by comparison. These vegetation differences can also be seen on the pixel level (Figure 3).

Ethiopia's maximum NDVI values, which usually occur in August, are extremely well correlated with grain production, at 0.98 and 0.99 for corn and sorghum respectively. That is an almost perfect correlation between the crop production harvested in December and satellite imagery four months earlier. Next, I processed satellite data up to the current date and predicted future crop production. Luckily, the predicted production for Ethiopia's 2017 harvest is much higher than the previous two years, indicating healthy crop conditions and hopefully an end to the current crisis.

Next, I applied this method to every country in Africa and created a publicly-viewable interactive map of the predicted production for harvests in the next few months (Figure 4, Petersen 2018). The hope is that this method can be used as an early warning system to give advance notice of impending food shortages.

2.1.3 Implications

The power of the method developed here is that it can predict future crop yields three to four months before the harvest for any crop, for any location or climate. It is unique because of its versatility and easy to apply due to its simplicity. Because of this new capability, I was invited to give institution-wide seminars at several international aid and research organizations last May in Washington DC including the International Food Policy Research Institute (IFPRI), GEOGLAM, and the USDA. Additionally I am scheduled to give talks later this year at UCSD, FEWS NET, and at the next American Geophysical Union (AGU) conference. GEOGLAM's co-head, Dr. Inbal Becker-Reshef, stated that GEOGLAM would be interested in continuing to run my model in real time as part of their analysis (Becker-Reshef 2018).

International aid organizations could now have the ability to better prepare supplies, transportation, and manpower for a rapid response.

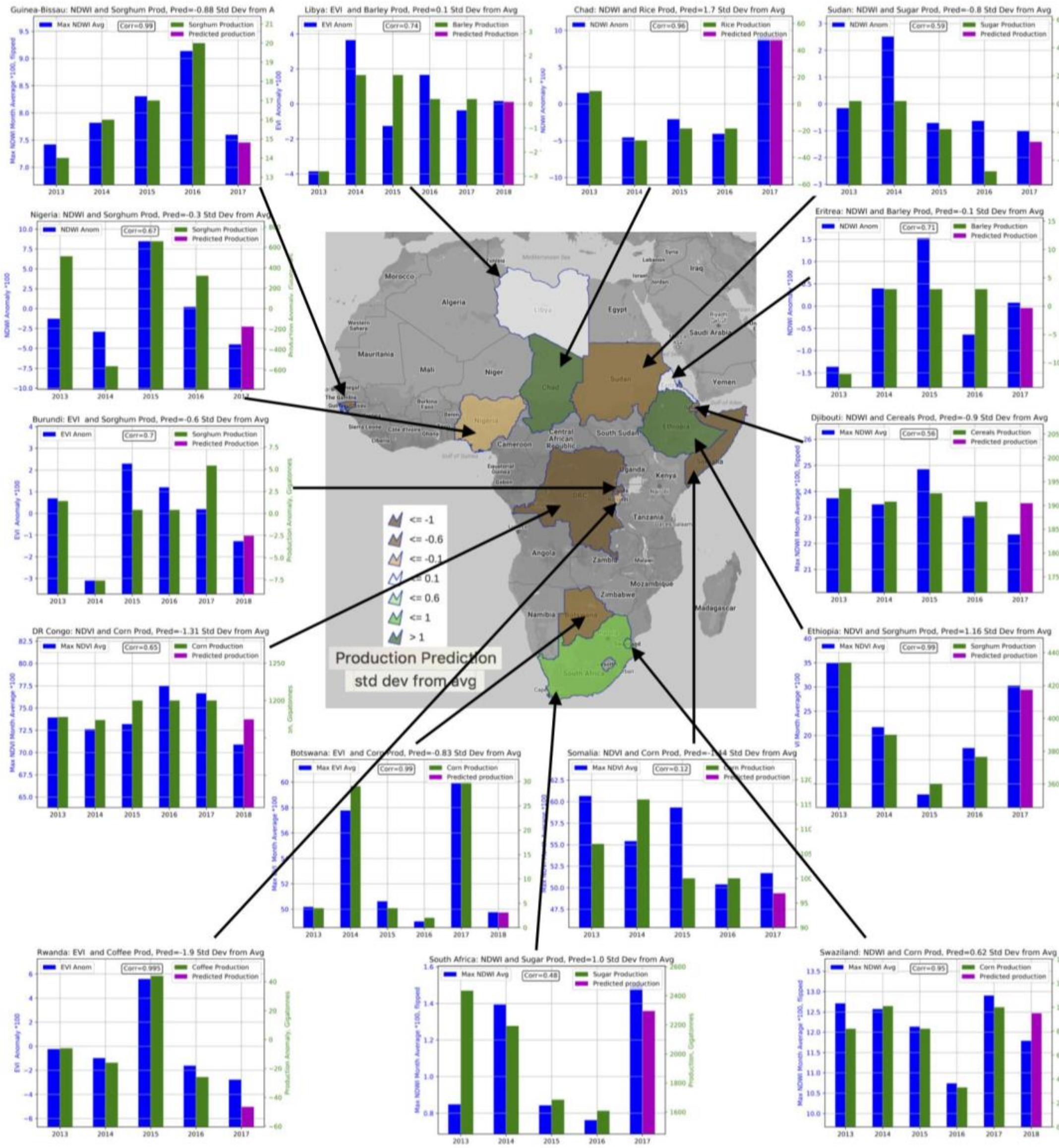

Figure 4. The map displaying the predicted production for every country currently in season (middle). Surrounding the map are plots showing each country's highest correlating crop and satellite index (green and blue) and predicted production (pink). All analysis, plots, and predictions are by the author.

2.2 Targeted Agricultural Development: Closing the Yield Gap

Satellite data analysis should be used to identify areas with low crop yields to optimize implementation of education and new technologies. The goal is to reduce the gap between current low yields and the potential yields of a particular soil and climate (Neumann et al. 2010).

In Ethiopia, farmers often lack access to agricultural technology, especially in the rural areas farther away from major cities (Mann and Warner 2017b). Agricultural technology, defined as herbicides, pesticides, fertilizers, irrigation, and mechanical instruments, have the ability to tremendously increase crop production. For example, the US corn yields have more than tripled since 1970, from 80 to 180 bu/acre (Hamer et al. 2017, Petersen 2017). While Ethiopia's corn yields have also increased, it remains extremely low at 55 bu/acre (FAO 2018, Petersen 2018). From this, we can conclude that the yields in Ethiopia have substantial room for improvement which would help reduce risk of hunger and famine.

We know that NDVI values can help to estimate crop yield at a very local level (Swain et al. 2010). The crop health monitor described in the previous section has the power to observe which farms in a local area are consistently healthier than others. Satellite data can be used to observe which fields are most prone to diseases or low yields and estimate pesticide usage (Hall et al. 2014). Moisture indices can also signify irrigation (Salmon et al. 2015). Comparing the cross sections of this information with ground-truth data might quickly determine best local growing practices. Aid organizations could educate local farmers on recommended crops, when to fertilize, and irrigation procedures that produce the highest yields. Aid organizations could even detect real-time insect defoliation using the satellite index LAI (Leaf Area Index) and move quickly to reduce the loss of crop. This focused efforts can be applied in locations where results of increased yield will most greatly be seen both immediate and long term.

Additionally, continued satellite monitoring after implementing the new optimizing strategies could further fine-tune the recommended local practices, further increasing productivity over time (Seelan et al. 2003). Facilitating high yielding practices is a longer term solution than food aid because it will lead communities to be more self-dependent, ultimately raising people out of poverty and towards a developed society.

2.3 Preemptive Interventions According to Risk of Humanitarian Crises by Satellite Imagery

A third proposal uses satellite data to analyze poverty levels. Poverty is one of the driving factors of humanitarian crises, such as famine, conflict, and disease outbreaks. Although these events are usually seen as chaotic, the risks of them happening in certain locations can be calculated.

One-third of Ethiopia still lives in extreme poverty. However, very little is known about where the most impoverished populations are located or what needs they struggle to maintain. High-resolution poverty maps could provide invaluable information on which areas are most in need of aid. Satellite imagery indicators that suggest relative wealth, such as night lights, number of roads, distance to cities, and amount of farmland (Jean and Burke et al. 2016), can be used to predict the level of poverty in remote areas that would usually be inaccessible. Using satellite imagery, I hope to be able to build high-resolution poverty maps over Ethiopia in the next year.

Once international aid organizations have access to where poverty is most prevalent, they can calculate the different risks on those populations. Local communities with higher poverty rates are more likely to experience extreme conflict (Goodhand 2003, Tollefsen 2017). Risk of disease infection and famines are also much more substantial in poverty-ridden areas (Geerlings and Heffernan 2017).

Thus poverty maps would enable international aid organizations to optimize their budget and efforts on the most impoverished areas to decrease humanitarian risks. They would be able to better communicate with the local organizations and governments to negotiate solutions and take preemptive interventions in areas with the highest risk, such as negotiating treaties before conflicts can emerge, setting up health care facilities, or distributing vaccines. For example one-third of drinking water sources in Ethiopia come from unprotected springs or surface water (DHS 2016), so aid organizations could target these areas to improve sanitation and access to clean water, thus restricting the risk of diseases. This will reduce extreme poverty and increase living conditions, leading to a more sustainable society.

3 Conclusions and Discussion

When a drought or other crisis hits Ethiopia, there is little to no safety net to support the people most in need. An average rural family in Ethiopia engages in smallholder agriculture on farms usually smaller than two acres. People rely on their own production to feed themselves and have little access to international markets. For the greatest impact, interventions must reach the communities most isolated.

International aid organizations and local governments need real-time reliable information to optimize budgets and resources for the largest positive effect. Satellite monitoring is the answer. Satellites freely provide daily imagery covering almost every point on earth, meaning it sidesteps the need to put people on the ground or negotiate with local governments for access to data. The hope is that these remote monitoring systems would help aid organizations target the best ways and areas to decrease poverty, reducing dependence on foreign aid and leading to more sustainable futures.

It would be feasible for every person in Ethiopia to feel the impact of these solutions. Satellite monitoring can allow aid to be delivered to those most at risk and improve the food security of smallholder farmers. Additionally, raising the agricultural productivity of the lowest income bracket would give this group greater financial stability and discretionary income, which would in turn grow the economy and flow of goods. This reverberates throughout the economy, as service and manufacturing sectors have more business, leading to development and long term stability.

Protecting the most vulnerable members of society is beneficial for all. This holds true both within developing countries, and on a global scale. Satellite monitoring can allow international aid to better serve vulnerable communities across the globe.

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