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# Real-time Prediction of Crop Yields from MODIS Relative Vegetation Health: A Continent-wide Analysis of Africa

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**Abstract:** Developing countries often have poor monitoring and reporting of weather and crop health, leading to slow responses to droughts and food shortages. Here I develop satellite analysis methods and software tools to predict crop yields two to four months before the harvest. This method measures relative vegetation health based on pixel-level monthly anomalies of NDVI, EVI and NDWI. Because no crop mask, tuning, or subnational ground truth data is required, this method can be applied to any location, crop, or climate, making it ideal for African countries with small fields and poor ground observations. Testing began in Illinois where there is reliable county-level crop data. Correlations were computed between corn, soybean, and sorghum yields and monthly vegetation health anomalies for every county and year. A multivariate regression using every index and month (up to 1600 values) produced a correlation of 0.86 with corn, 0.74 for soybeans, and 0.65 for sorghum, all with $p$-values less than $10^{-6}$. The high correlations in Illinois show that this model has good forecasting skill for crop yields. Next, the method was applied to every country in Africa for each country's main crops. Crop production was then predicted for the 2018 harvest and compared to actual production values. Twenty percent of the predictions had less than 2% error, and 40% had less than 5% error.

**Keywords:** Africa; satellite crop prediction; MODIS relative vegetation health; NDVI; EVI; NDWI

## 1. Introduction

In the United States, there is exceptional monitoring and reporting of weather and crop health, with thousands of weather stations and county-level crop yield data that has been recorded since 1910 [1,2]. With this substantial amount of publicly available data, crop yields may be predicted based on historical records. However, not all parts of the world have open, reliable data [3]. 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 a particularly important problem in developing countries where crop yields are less stable and droughts can lead to famines, death, government instability, and war.

Recent years have shown an advancement in strategies to obtain better data coverage in developing countries. For example, the World Bank implements national household panel surveys throughout Africa that include agricultural and household information [4]. These detailed surveys offer researchers insights into African agriculture. However, these methods require expensive ground-based surveys and remain difficult to scale across a large area. Other difficulties with these surveys include substantial self-reported yield error [5], an extremely low temporal resolution, presence only in select African countries, and a time lag of 1–2 years between collection and public dissemination of the data. Agriculture is one of the backbones of African economies and provides food, income, power, stability, and resilience to rural livelihoods [6]. Agricultural development is widely known to be crucial for poverty reduction and improved health; thus, there remains a major need to monitor crop health in the developing world [7,8].

Crop yields in developing countries do not benefit from the same level of agricultural technology as in the US. Therefore, these countries have much lower yields. Since 1970, corn yields have doubled in the US from 80

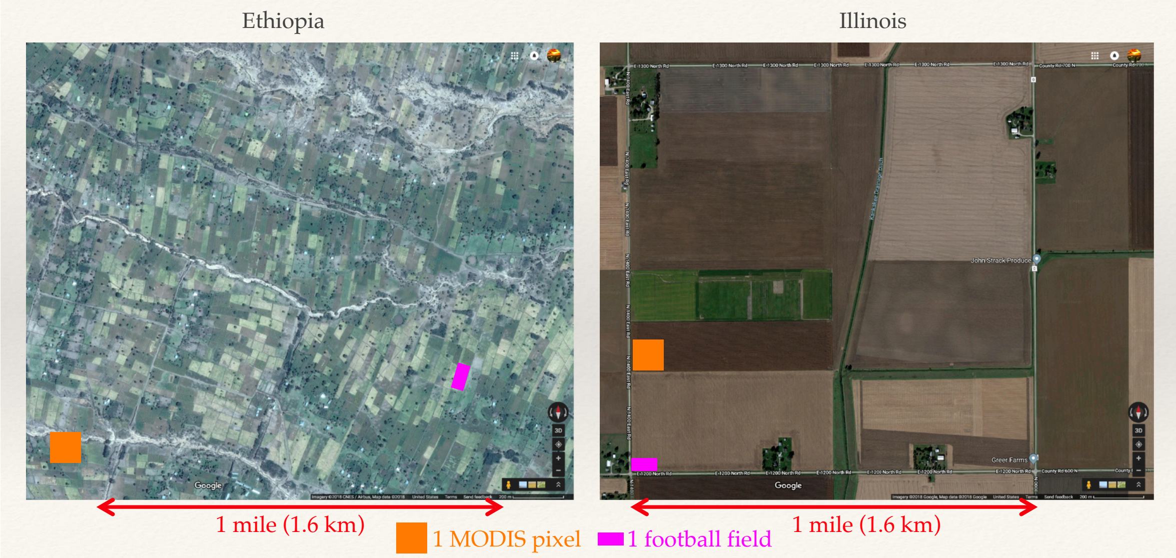



**Figure 1.** Farm fields by satellite in Ethiopia and Illinois at the same resolution. The small farm fields (smaller than a MODIS pixel) and poor ground truth data increase the difficulty of analyzing and predicting crop yields in Africa.

bu/acre to 160 bu/acre due to improvements in agricultural technology such as irrigation, pesticides, herbicides, fertilizers, and plant breeding. In developing countries, crop yields are both much lower and much more variable than in the US, both geographically and in time [9]. 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. Farmers in poor countries lack the financial resources and education to use the advanced technology in the American and European farm industries. Therefore, crop yields in African countries are much more susceptible to the dangers of heat waves and droughts.

Remote sensing has become an asset for detecting environmental changes that impact crop health since initial studies in the 1980s and 1990s [10–13]. Today satellite imagery costs less and is more easily accessible, making remote monitoring more broadly available to scientists and the general public. The majority of previous research on crop monitoring is in developed countries where there is an immense amount of yield and production data at high resolution. Such data significantly improves agricultural research, but it is only affordable by wealthier nations. The US also has large fields of a small number of individual crops: mainly corn, soybeans, and wheat (Figure 1). Becasue planting is so uniform, research can be specific to certain crops. For example, Johnson [14] developed algorithms to identify crops in the US from MODIS imagery and analyzed each crop individually. Gao *et al.* [15] utilized week-by-week plant growth data in Iowa to design a method to monitor the growth stages of corn and soybeans from satellite imagery.

Crop prediction is significantly more challenging in Africa due to minimal reporting of crop health and yields; farms consist of very small plots of varied crops interspersed with buildings (Figure 1); and the continent contains a vast number of different climates, growing seasons, and crops. Many small-holder farmers integrate inter-cropping methods, further complicating remote crop identification [16]. Recent GPS studies over four African countries suggest that 25% of the farms in Africa are less than half an acre and over half are less than one acre [17]. This compares to an average farm size of 444 acres in the US [18]. Researchers developing crop masks find that at the Landsat resolution of 30 meters, many African fields are covered by just a few pixels [19]. Pixels often contain multiple crops due to irregular field boundaries and heterogeneous landscapes. To more accurately predict yields at a higher spacial resolution, such as the household or community level, researchers shift to very high resolution imagery [19]. Yet high resolution imagery has many downsides, including cost, lack of a historical record, and the sheer amount of data and computation required. For example, the MODIS coverage obtained in this study just over Ethiopia would cost $320 million using Quickbird 65cm imagery and $23 million using RapidEye 6.5m imagery, one of the main products hosted on Planet [20]. The amount of imagery that must be processed for this scenario would require massive amounts of computational power. Additionally, many high resolution satellites have only been launched in the last couple years. For example, Sentinel-2 with a resolution of 10–20m was launched in 2017. Insufficient temporal duration of satellite observations reduces the accuracy of empirical data-based models. In short, it would be almost impossible to scale a crop health monitoring system using high-resolution imagery across a continent.

Low resolution imagery can offer insights into crop production on a larger scale without the drawbacks of higher resolution, and has also been shown to produce high correlations [21,22]. Much of the data from lower resolution satellites can be accessed for free and provides a substantial historical record. In addition, aggregate crop yields reported at the national level will be more accurate than municipality-level statistics.

Many studies have developed methods to monitor droughts in Africa (e.g. Gissila *et al.* [23], Tadesse *et al.* [24]) or forecast crop yields for early warning (e.g. Rembold *et al.* [25]). For example, Mann and Warner [9] use kebele (district) level economic and crop statistics collected by the Ethiopian government to estimate wheat output per hectare. This data would be useful for high-resolution crop predictions, but it is not generally available from the Ethiopian government. The lack of collection and free distribution of crop yields and other ground measurements severely hinders accurate predictions of crop health in developing countries.

A couple groups currently publish real-time forecasts of crop health. For example, the Group on Earth Observations Global Agricultural Monitoring Initiative (GEOGLAM) [26] and USDA Famine Early Warning System Network (FEWS NET) [27–29] each generate advance notice of impending food crises. These systems are comprised of large teams that incorporate data from remote sensing, on-the-ground monitoring, field reports, and agroclimate indicators such as rain, snow, and surface temperatures. These large models require an extensive budget. In contrast to this study, their predictions are also simplified into qualitative categories instead of numerical values.

The method presented here differs from previous work in the U.S. and Africa because it is an overall measure of relative vegetation health compared to the mean on a per-pixel basis. Unlike previous studies, it may be applied anywhere in the world—it does not depend on special tuning for the particular crop, region, or climate of interest. Crop masks are not used in this model to increase simplicity, versatility, and eliminate the complication of small field sizes, inter-cropping, and imperfect crop masks. Relatively low-resolution pixels of the Moderate Resolution Imaging Spectroradiometer (MODIS) decrease the amount of data that must be processed, making this system cheaper and more efficient. The method was created for developing countries where detailed monitoring on the ground simply does not exist and was successfully validated against extensive crop data in Illinois.

The goal of this study is to see how well crop yields may be predicted using extremely straightforward methods based on simple averages and differences of common indices and the resulting correlations. More complex models with crop masks and detailed tuning require a substantial staff and several years to develop and validate. This method, developed and tested by the author over the course of a couple months on a laptop computer, can produce reasonable forecasts of crop yields for the whole continent. In essence, this study shows that indices like NDVI, NDWI, and EVI are such strong indicators of crop health, that simple methods can capture much of the predictive skill of more complex models.

This paper is organized as follows. Methods are presented in section 2 and results in section 3. First, the results from the analysis in Illinois are explained, followed by the analysis in Africa, and ending with the predictions and accuracy of these predictions. The conclusions discuss the quality and limitations of this method compared to previous crop prediction systems.

## 2. Methods

The overall goal of this research is to create a predictive measure of crops computed from satellite data. Python code was written 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 county in Illinois, and then apply the same method to every country in Africa. The overall workflow is diagrammed in Figure 2 and described in detail in this section.

Moderate Resolution Imaging Spectroradiometer (MODIS) imagery was obtained from the Descartes Labs Satellite Platform (Figure 3a, 3b). MODIS, hosted on the satellites Aqua and Terra, has a revisit time of one day, giving almost continuous imagery across the entire earth since 2000. I interacted with the Descartes Labs Satellite

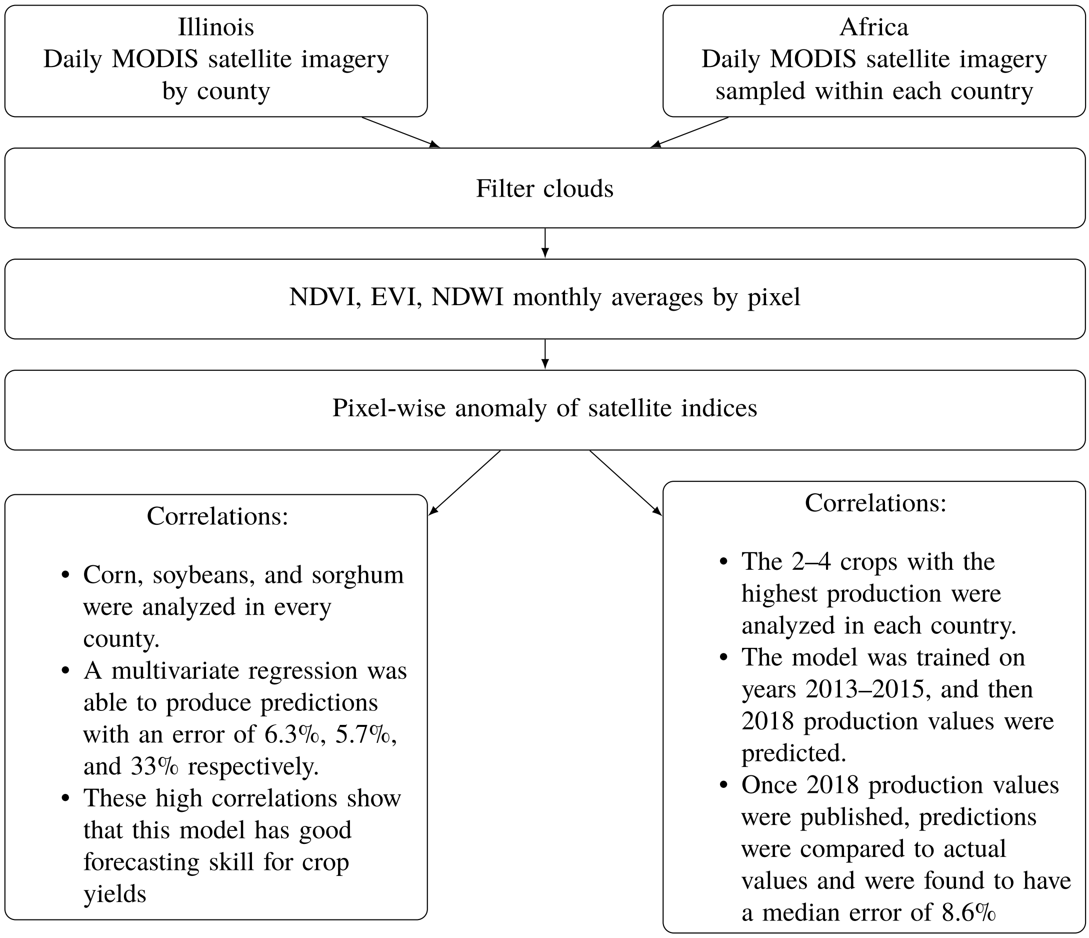



**Figure 2.** Workflow diagram.

Platform through a python console on a laptop computer. Data from MODIS has a nominal resolution of 250 m at the nadir of each swath. In the Descartes Platform, MOD09 Aqua and Terra surface reflectance data points with associated coordinates are interpolated onto a grid in the form of an image [30]. The python code then sends a request to the platform to retrieve a band over a certain area and satellite pass (e.g. green band over an Illinois county for 2017-01-01). The MODIS data was obtained in the first couple months of 2018. The rest of the analysis was done in the code, which is posted on github at https://github.com/lillianpetersen/CropPredictionFromSatellite2018.

Clouds and snow in images can disrupt data and distort values. In order to account for cloud contamination, a cloud mask was retrieved from the Descartes Platform. Pixels with clouds or snow were not included in monthly averages, and images with over 80% clouds were removed altogether (Figure 3c).

To measure the health of crops throughout the growing season, three indices were computed: Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI, Table 1). All three indices have served as crop monitoring tools in previous studies, and have been shown to resemble actual crop conditions [26,31,32]. All three indices range from -1 to 1. Areas containing dense vegetation show high NDVI and EVI values (between 0.4 and 0.8), desert sands will register at about zero, and snow and clouds are negative. NDVI is sensitive to chlorophyll, which absorbs visible light (0.4 to 0.7 μm) for use in photosynthesis. EVI detects canopy structural variations, including leaf area, canopy type, and canopy architecture [33]. NDWI detects water content. Each index performs better for certain conditions and climates. For example, EVI is best able to capture large negative anomalies in yield, and NDWI performs best in semi-arid regions [34].

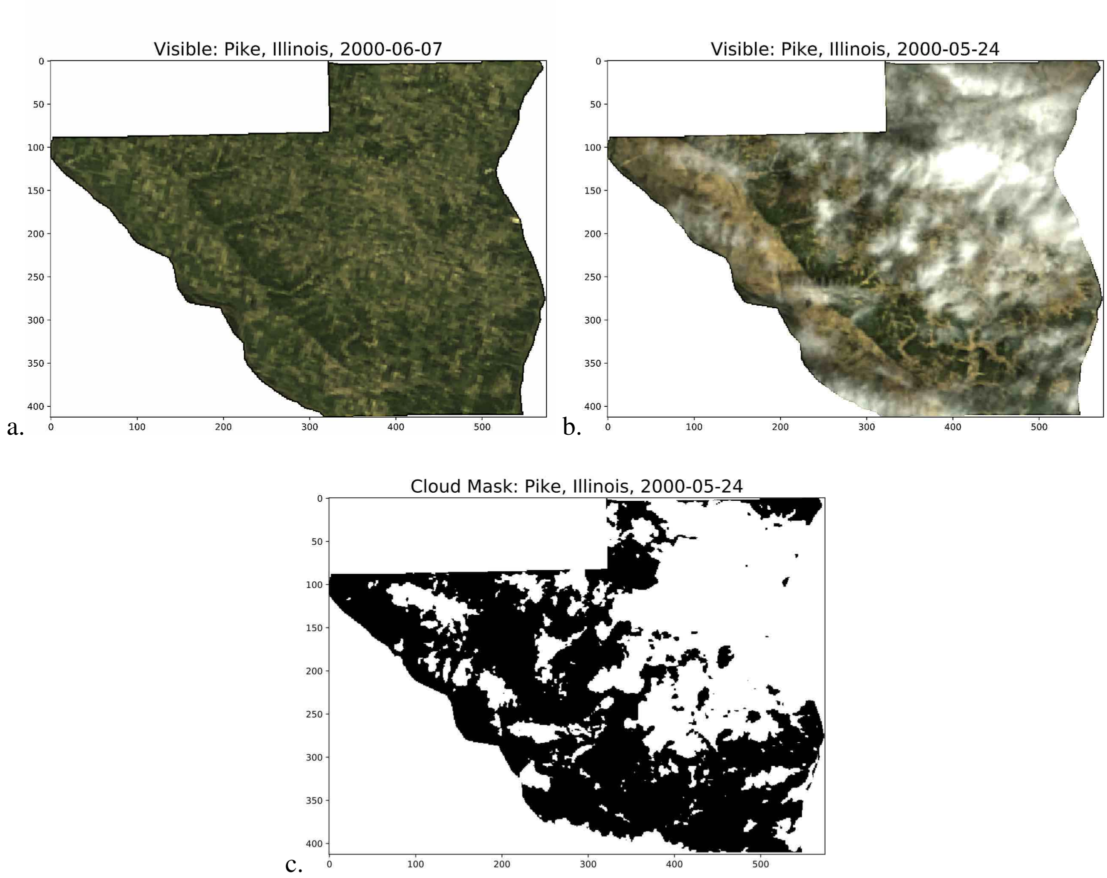



**Figure 3.** Snapshots of two MODIS satellite passes over Pike county, Illinois (a, b) and the cloud mask for the second image (c).

For every pixel in Illinois, the NDVI, EVI, and NDWI monthly averages and climatologies were computed. The climatology is defined as the average NDVI, EVI, or NDWI over years 2000 through 2016 for each month and pixel. Next, the monthly climatology was subtracted from the monthly average for every pixel, resulting in the monthly anomaly. The pixels in each county were then averaged together to find the monthly anomaly for NDVI, EVI, and NDWI. Monthly averaging was chosen for simplicity.

Illinois was chosen as a test site because the land is mostly agricultural and can provide a clear signal of crop health. Illinois also has very little irrigation: most counties irrigate less than 1% of their fields [35]. Similarly, 90% of staple food production in sub-Saharan Africa comes from rain-fed farming systems [36].

Annual crop yield data was downloaded for every county in Illinois for years 2000 through 2016 for three crops: corn, soybeans, and sorghum, from USDA county estimate reports available online through Quickstats [1]. These crops were chosen because they three of the largest food crops in Illinois with 4.5 million, 4.3 million, and 7.3 thousands hectares planted respectively [37–39]. Because each county has different growing conditions (soil quality, hills, proximity to large water bodies, etc.), the mean was subtracted out of each county's crop yield to find the yield anomaly. Correlations were found between each county's yield anomaly and the three satellite indices for five months, May–September. To find the highest possible correlation amongst these variables and months, a multivariate regression was fit to each month and index for a total of 15 variables.

To test the predictive ability of the model, the data was split into a training group of 90% and a testing group of the remaining 10%. The multivariate regression was then fit to the training data and asked to predict the testing set. To ensure randomness, this process was repeated 10 times for each crop.

After testing in Illinois was complete, the method was applied to three countries in Africa: Ethiopia, Tunisia, and Morocco. These countries were used as initial case studies because they have a recent history of relative agricultural and political stability and offer a range of climates and crops. In each country, the two

**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.

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

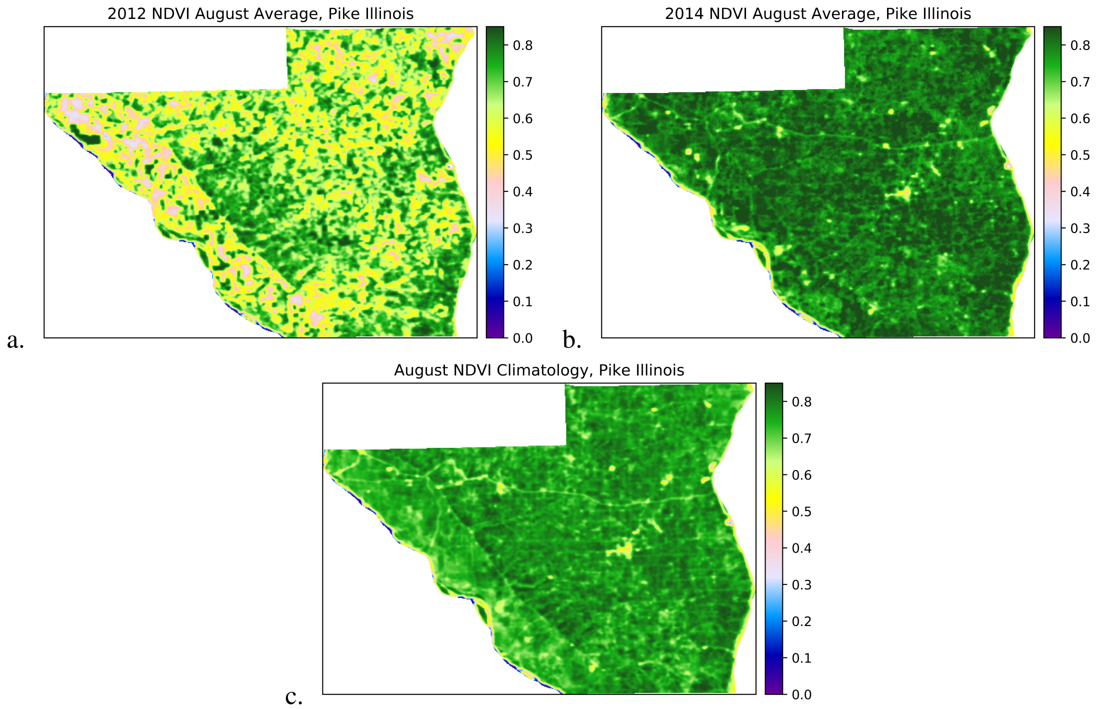



**Figure 4.** August average NDVI for a drought year (a) and a wet year (b), and the NDVI August climatology (c).

to four highest-producing crops were analyzed. African crop yields were downloaded from Index Mundi, a comprehensive data portal with country-level statistics compiled from multiple sources, but the production data was originally collected by the USDA Foreign Agricultural Service (FAS) [40].

In each country, a box was analyzed over a dense farming region (Figure 14) and was then correlated to national crop production data [40]. Subsections in each country were chosen based on sub-national crop production estimates from the Spatial Production Allocation Model (MAPSPAM), a global spatial crop allocation model [41]. Sample areas were selected rather than the entire country in order to limit the amount of data required. A continent-wide analysis would require significant data transfer and computational power, which is expensive and time consuming. Even with the smaller areas for analysis shown in Figure 14, the MODIS imagery over Africa totaled to 10 terabytes of data. This study provides a proof of concept that dense farming areas can serve as representative samples of larger regions, and shows that a single user with a personal computer can produce reasonable forecasts of crop yields for the whole continent.

The daily MODIS imagery over the selected boxes in each country was processed in a similar way to Illinois. First, the bands were retrieved from the Descartes Platform. NDVI, EVI, and NDWI were computed, and cloudy pixels were masked out. The climatology for each pixel was subtracted to gain monthly anomalies as well as averages of all three indices, resulting six variables for correlation analysis: NDVI average, NDVI anomaly, EVI average, EVI anomaly, NDWI average, and NDWI anomaly. Next, correlations were computed between the six indices of the month at the height of the growing season and the crop production. The height of the growing season is defined as the month in the growing season that the NDVI average peaks.

After initial successes in Ethiopia, Tunisia, and Morocco, the method was expanded to every African country with the exceptions of Western Sahara due to lack of crops, and Equatorial Guinea and Gabon due to constant cloud cover. Satellite data was restricted in this study to 2013–2018 based on the limited download and compute time that is avaliable to a typical home user on a modern-day laptop. The satellite imagery processed in Africa totaled 10 terabytes even with only five years of data. Future production was then predicted for every African country with a harvest between December 2017 (e.g. Ethiopia) and June 2018 (e.g. Namibia). When the actual production values were published, the error of the predictions in every country and crop was computed.

## 3. Results

The method was first validated in Illinois and then applied in Africa.

### *3.1. Illinois*

Correlations were computed in Illinois between the anomalies of NDVI, EVI, and NDWI, and three crops: corn, soybeans, and sorghum; and all were found to have high correlations. The method was first tested with state-wide averages to show that results are significant when analyzing a large area. The correlations between state-wide corn yield and NDVI, EVI, and NDWI anomalies are extremely statistically significant at 0.90, 0.85, and −0.92 respectively (Figure 5). It was found that NDVI and EVI both have positive relationships to crop yields, while NDWI is inversely related. A possible theory for this relationship could be that NDWI senses evapotranspiration. Strong NDWI in critical growing stages could indicate insufficient evapotranspiration, which would lead to lower yields.

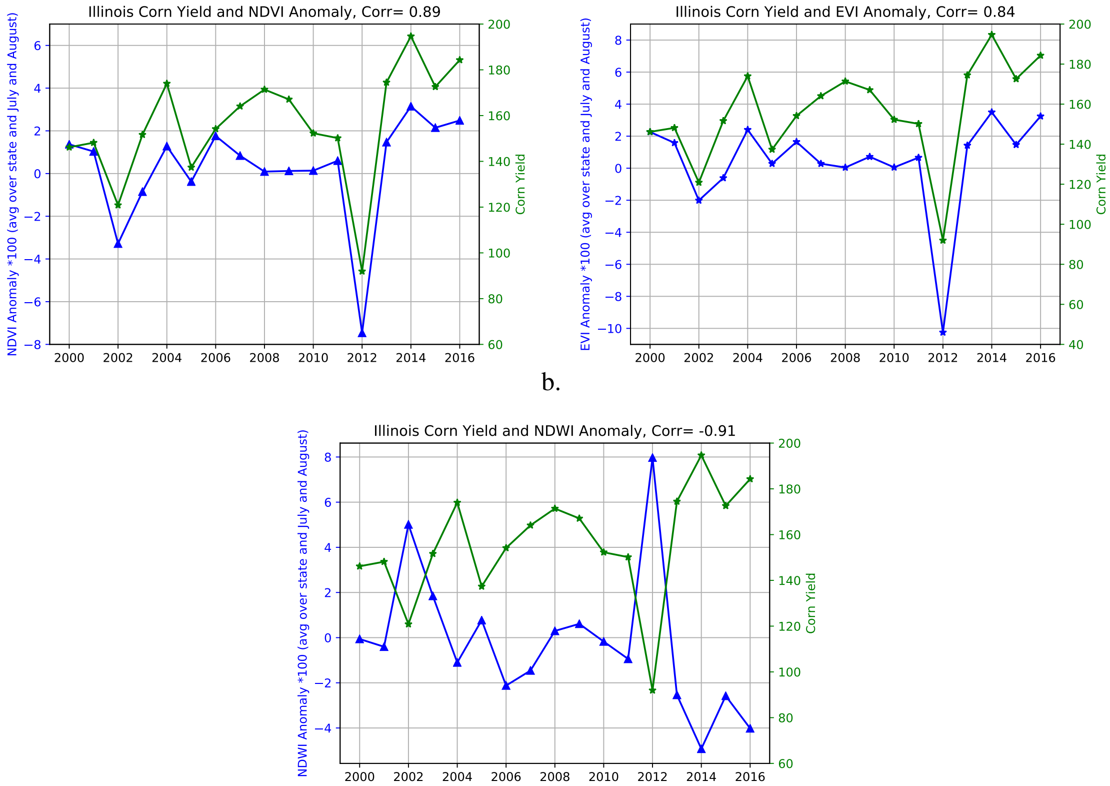
In 2012, the central United States was hit by a drought and Illinois had lower than average crop yields and a negative NDVI anomaly. Yields and NDVI anomalies in 2014 were significantly higher. These two years are used as examples to show corn yield and satellite anomalies at the county level (Figure 6).

Next, the relationships were examined at a higher resolution. The corn, soybean, and sorghum county yield data was plotted against NDVI, EVI, and NDWI anomalies for every month in the growing season for each county and every year since 2000, for a total of 1600 data points. August was found to have the highest correlation to all three crops, while July was just slightly lower (Figure 8). Corn had the strongest relation to the satellite indices with correlations of 0.7, 0.71, and −0.73 for EVI, NDVI, and NDWI respectively. Soybeans and sorghum had similar correlations to indices, both ranging from about 0.53 to 0.58. To see all of the correlations in more detail, refer to Figure 7. All of July's and August's correlations had a $p$-value less than $10^{-6}$ [42], meaning there is less than one in a million chance of them occurring through a random process.

Correlations for each crop have been computed with three indices (NDVI, EVI, and NDWI) and five months, for a total of fifteen independent variables. In order to create a single predictive measure of crop yields, a multivariate regression was fit to every index and every month using a Python machine learning library. Figure 9 shows an example of the multivariate regression for two of the variables and corn yield. The multivariate regression improved the individual correlations for all three crops to 0.86, 0.74, and 0.65 respectively (thick solid lines in Figure 8).

To test the predictive power of the model, the multivariate regression was trained on a random 90% of the data and then predicted the remaining 10%. This process was repeated ten times. The median errors of the predicted yields are 9.8 bu/acre (6.3%), 2.7 bu/acre (5.7%), and 9.1 bu/acre (33%) for corn, soybeans, and sorghum respectively (Figure 10). For both corn and soybeans, the model could predict the yield with minimal error based on only the anomalies of NDVI, EVI, and NDWI over the county throughout the growing season, demonstrating how this simple method is a good indicator of crop yields. The error for sorghum is higher, likely because it much less common in Illinois.

Corn, soybeans, and sorghum are planted on 11.2 million, 10.6 million, and 18 thousands acres in Illinois respectively [37–39]. While corn and soybeans each cover about 30% of the total land in Illinois, sorghum only covers 0.05%. Sorghum fields are therefore a very small minority of the satellite imagery processed over Illinois, yet the predictions are reasonably high. Sorghum in Illinois serves as a proof of concept that a crop can be moderately well predicted even if it only covers a small portion of land.




a. b. c.

**Figure 5.** Illinois mean corn yield since 2000 (green) correlated with the anomalies of NDVI (a, blue), EVI (b, blue) and NDWI (c, blue). Soybeans and sorghum performed similarly.

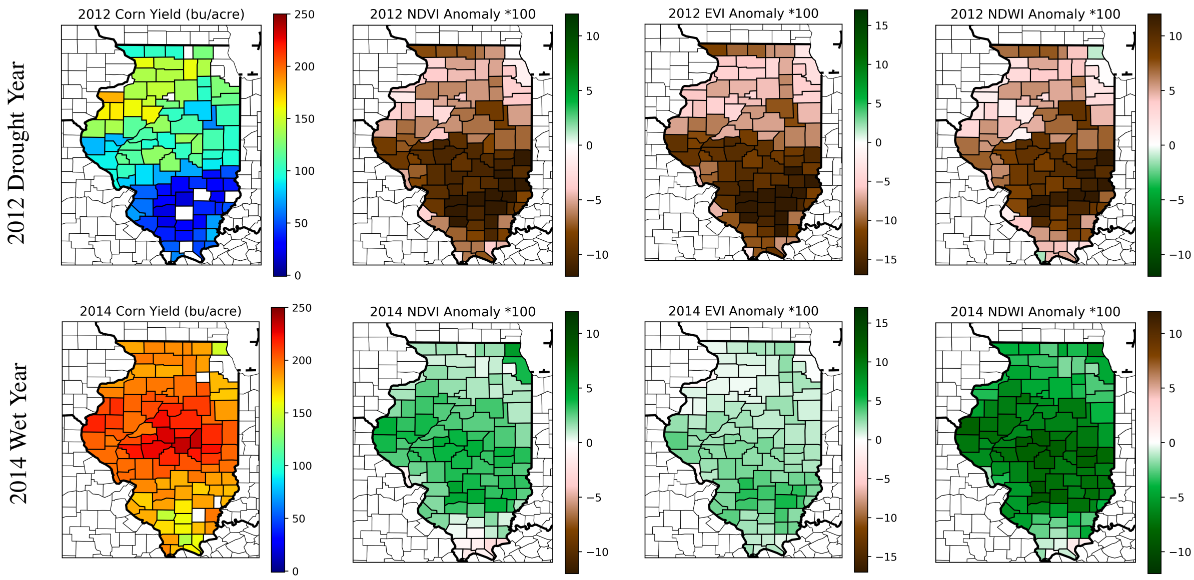



**Figure 6.** Corn yield (1st column), NDVI anomaly (2nd), EVI anomaly (3rd), and NDWI anomaly (4th) by county in Illinois for the drought year 2012 (top) and for the wet year 2014 (bottom). During the drought year, there are low yields, low NDVI anomalies, and high NDWI anomalies, while the wet year is opposite. Soybeans and sorghum performed similarly.

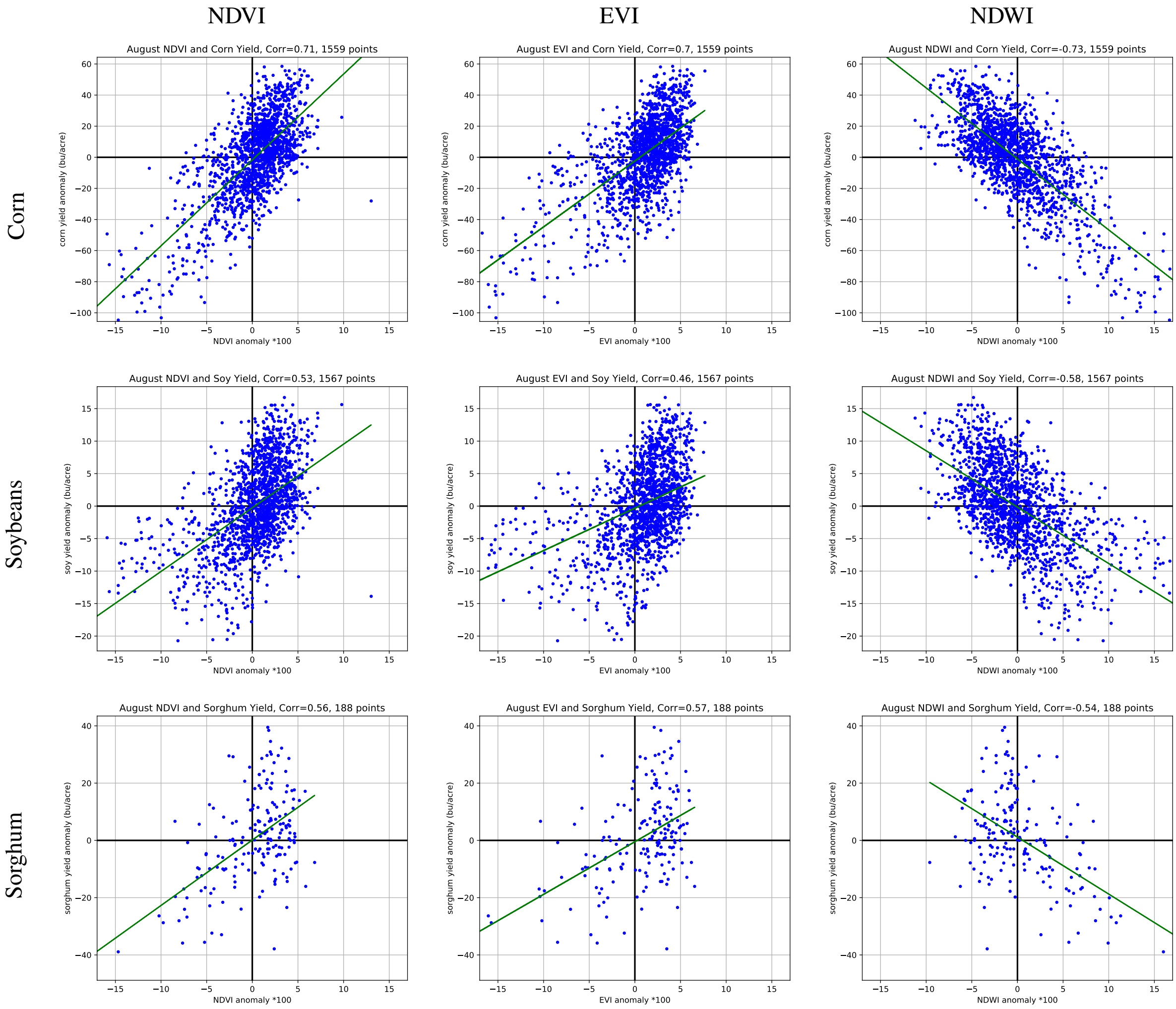
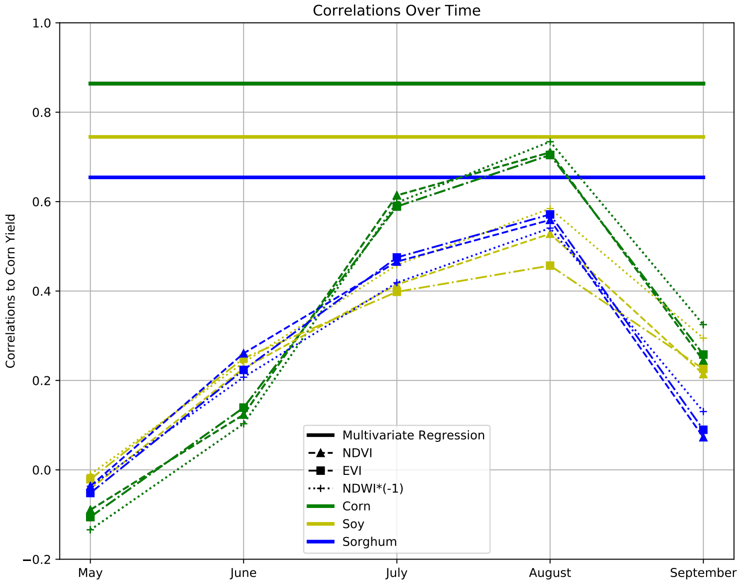



**Figure 7.** The correlations between the August anomalies of NDVI (top), EVI (middle), and NDWI (bottom) with corn (left), soybeans (middle), and sorghum (right). Corn and soybeans have the best correlations, and sorghum is slightly worse, likely because it is grown much less in Illinois than the other crops. All correlations are extremely significant with $p$-values less than $10^{-6}$. August was the month with the highest correlations to yields.




a.

**Figure 8.** Correlations for each month between Illinois corn (green), soybeans (yellow), and sorghum (blue) yield and the anomalies of NDVI (dashed), EVI (dot-dashed), and NDWI$*(-1)$ (dotted). July and August have the highest predictive skill for all three crops. These crops are harvested in October, meaning there is a two to three month lead time on yield estimates. The thick solid lines show the correlations of the multivariate regression, which is higher than any individual month.

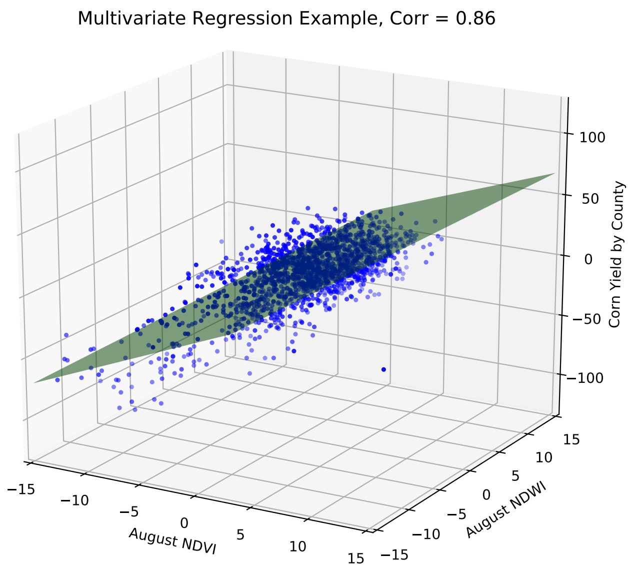



**Figure 9.** An example of the multivariate regression comprised of all three satellite indices and months, but here the corn yield is only plotted against August NDVI and NDWI for visualization purposes. The multivariate regression improved the individual correlations for corn to 0.86.

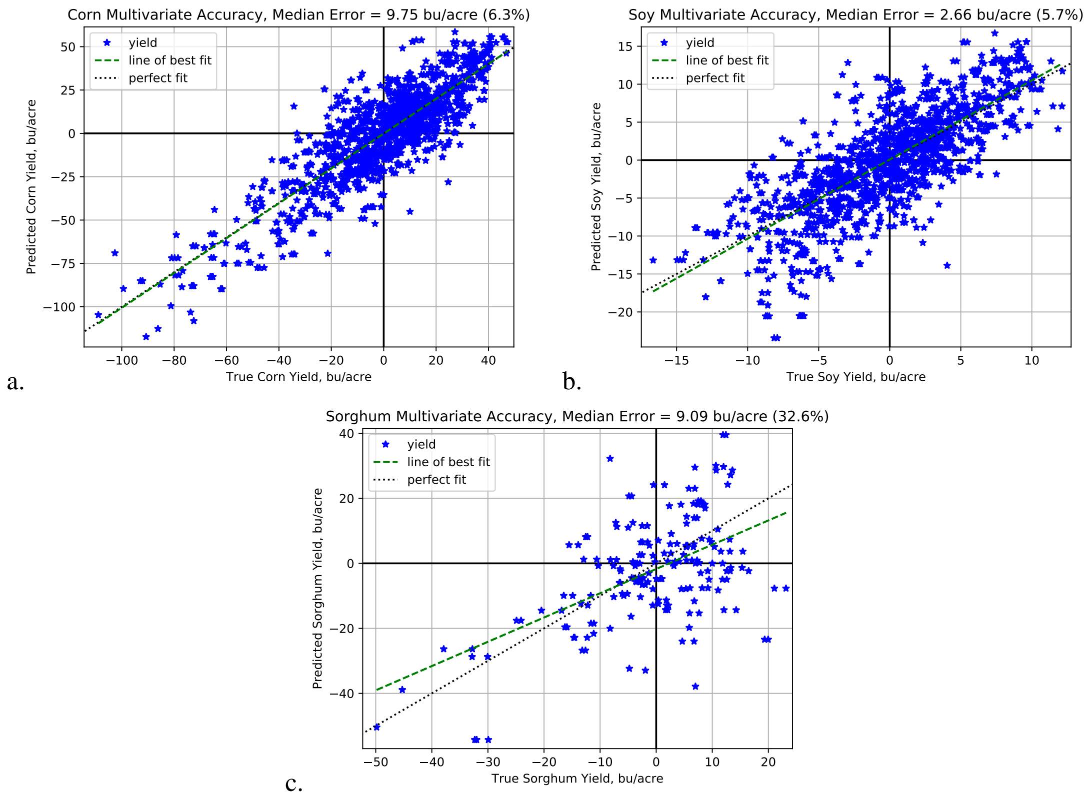



**Figure 10.** Accuracy of the multivariate regression predictions of yields in Illinois. The model was trained with a randomly selscted 90% of the data and then predicted the other 10%. This process was then repeated ten times to ensure randomness. The median error was lowest for soybeans with 5.7%, corn was similar at 6.3%, and sorghum had the worst error with 32.6%.

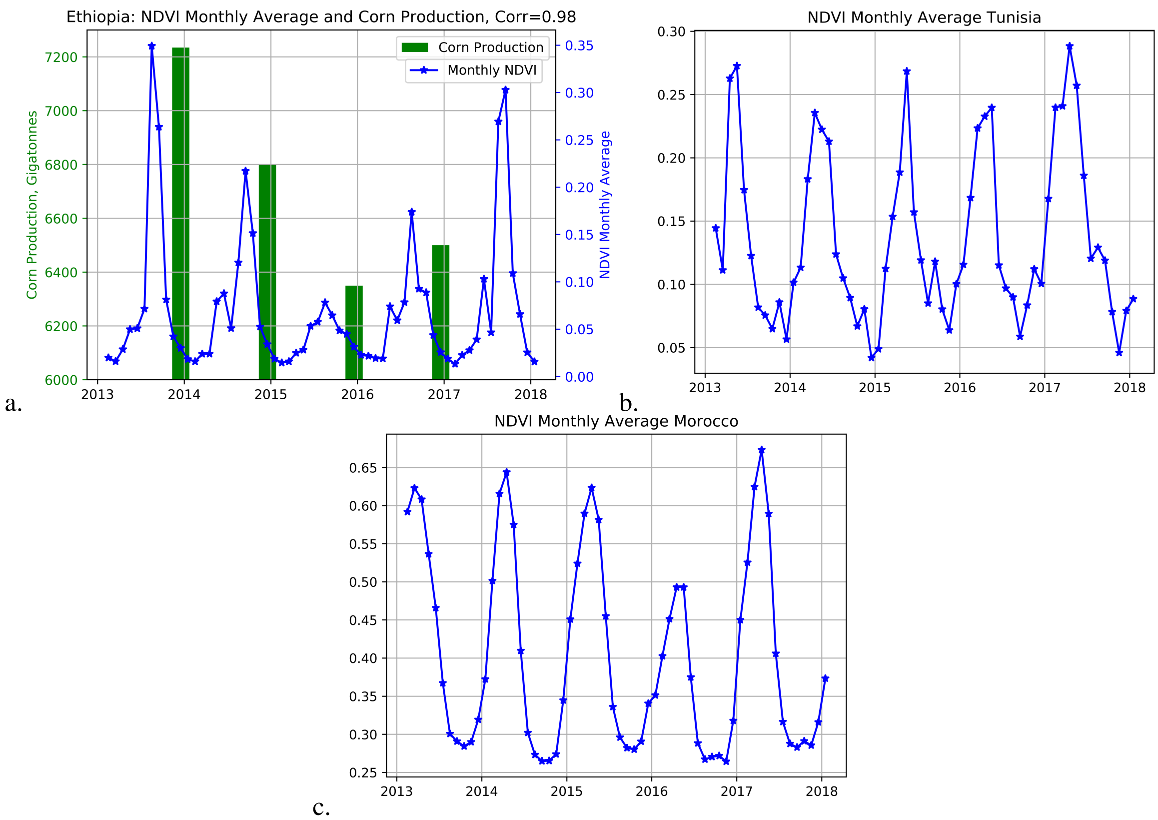



**Figure 11.** NDVI monthly average for Ethiopia (a), Tunisia (b), and Morocco (c). The annual rainy season produces high NDVI values and corresponds to the crop-growing months. Ethiopia includes the corn production as green bars, which has a very high correlation to maximum NDVI at 0.98.

### 3.2. Africa

The high correlations in Illinois show that this model has good forecasting skill for crop yields. Next, this method was applied to three countries in Africa: Ethiopia, Morocco, and Tunisia. For each country, a box within a major crop-growing region was analyzed (Figures 13a, 14).

Crop estimation in developing countries is vastly different than Illinois and the developed world. The greatest distinctions include the heterogeneity of the landscape, lack of agricultural technology, the spatial size of crop reports, and the accuracy of reported values. In Illinois, the ground is covered with large fields which grow a small number of crops: mostly corn and soybeans. In Africa, the landscape is highly diverse, with small family-owned farms neighboring villages, lakes, mountains, and forests, sometimes all within a couple pixels (Figure 1). These farms, usually smaller than an acre, lack much of agricultural technology found in the US, such as pesticides, herbicides, and fertilizers. This makes crops yields much more variable in Africa both seasonally and spatially. One of the largest difficulties of crop prediction in Africa is the area for which production numbers are reported. While the US reports crop data for every county, which range from 400 to 3000 square kilometers, African data is only easily available at the country level, which is 1.1 million square kilometers for a country like Ethiopia. Very rarely are yield or production values reported at the municipality or even state levels. Larger reporting areas average over more varied soil and climate conditions, which decreases correlations and ultimately reduces the accuracy of crop predictions.

In most places in Africa, there are wet and a dry seasons. For example, the wet season in Ethiopia spans from June to September, and crops are harvested in December. This is known as the Meher growing season. Ethiopia's core agriculture and food economy is comprised of five major cereals: corn, teff, wheat, sorghum, and barley. These cereals accounted for about three-quarters of total area cultivated and 29 percent of the agricultural GDP in 2005/06 [43].

The wet and dry seasons are evident in the monthly NDVI values for all three countries (Figure 11). During the wet season, the crops green and the NDVI values spike. During the harvest, the values drop. The crops with the highest production in each country were evaluated for this study. Table 2 in the appendix shows the crops examined in each country and the correlation with each satellite index. It was found that Ethiopia and Morocco have the best correlation to the maximum NDVI value of the growing season, while Tunisia has the highest correlations to NDWI.

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 13). The anomalies are especially evident in the Rift Valley where farming is most dense.

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 (Figures 11a, 12a). That is an almost perfect correlation between the crop production harvested in December and satellite imagery four months earlier. Tunisia has a correlation of 0.97 and Morocco has a correlation of 0.73 for wheat (Figure 12b, 12c), showing high predictive skill of satellite indices in all three countries.

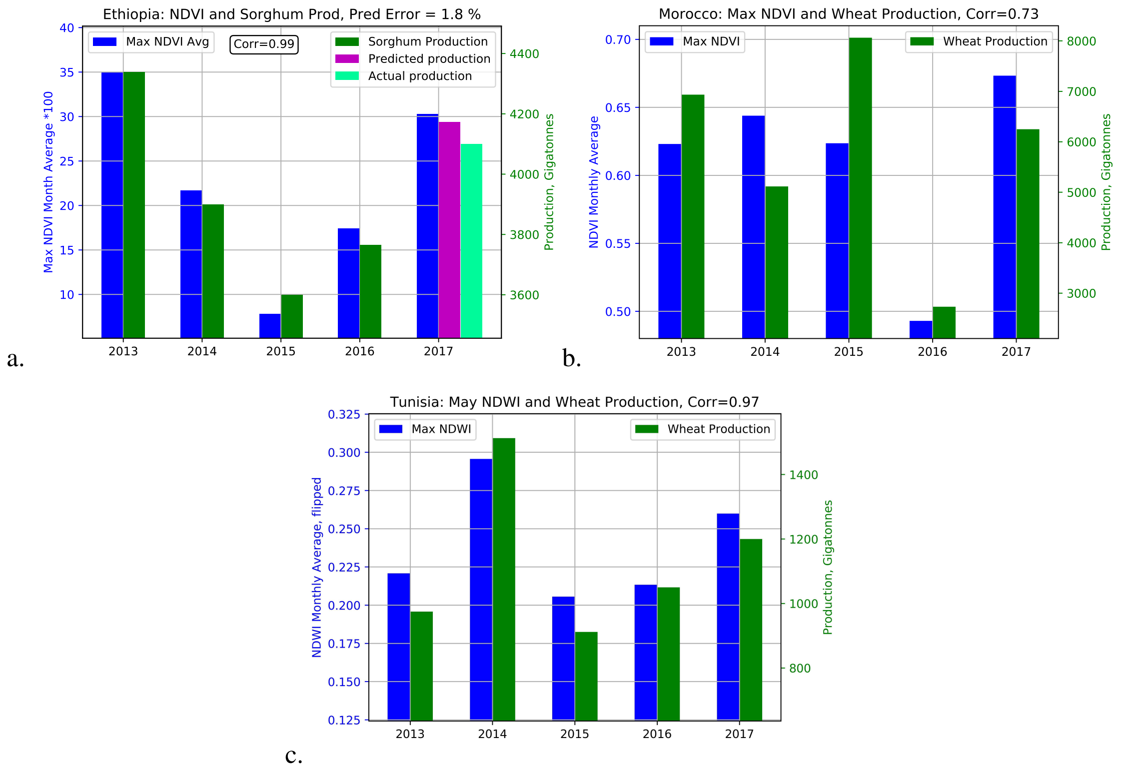



**Figure 12.** Maximum NDVI value of the growing season (green) with crop production (blue). All countries have significant correlations ranging from 0.99 to 0.73. In Ethiopia, the 2018 crop production was predicted based on the historical regression (pink) and was later compared to reported crop production (light green). The error is very low at 1.8%.

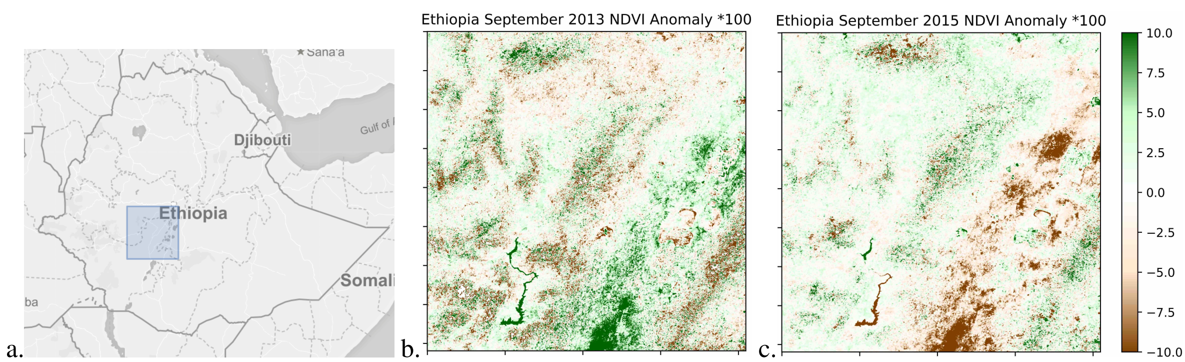



**Figure 13.** The box examined in Ethiopia (a) and its September NDVI anomalies during a wet year (b) and a dry year (c). The NDVI anomalies are especially high in the Rift Valley, where farming is the most dense.

### *3.3. Africa: Prediction of Future Crop Production*

Satellite imagery was processed for every African country. First, a box in an agricultural region was selected in every African country and a total of 10 terabytes of daily satellite imagery was processed according to the method above. Correlations and linear regressions were computed in every country for their 2–4 highest producing crops. Difficulties in finding accurate correlations could include:

- false reporting of production in some countries due to lack of resources, poor oversight, or corruption (e.g. DR Congo, Eritrea, Libya). In severe cases, one could simply use the NDVI anomaly as a proxy for production rather than computing a correlation with reported crop yields.
- multiple growing seasons in specific central countries (Rwanda, Somalia);
- growing seasons split across the December–January year boundary (Tanzania, Botswana);
- clouds every day for months at a time in central African countries (Gabon, Cameroon);
- time delays and misclassification of harvests in October–December, where production is incorrectly reported in the following calendar year (Nigeria, Sudan).

In every African country, correlations were computed between six indices (NDVI, EVI, NDWI, averages and anomalies) and every crop. A full listing of all correlations can be found in Table 2 in the appendix. Next, the historical regressions were used to predict crop production for 2018 harvests. Every country that reported production values for their harvest in 2018 before the publication of this article was examined. This mainly includes harvests ranging from December 2017 (e.g. Ethiopia) through June 2018 (e.g. Namibia), and included a total of 21 countries, about half of Africa.

A 2018 crop production value was predicted for every country, crop, and index (NDVI, EVI, NDWI averages and anomalies), and a publically viewable interactive map displaying these predictions was posted online [44]. Once the actual production values for 2018 were published, the predictions were compared to the reported values (Figure 16).

In Ethiopia, the model predicted the 2018 harvests to yield 7055 gigatonnes (GT) of corn and 4174 GT of sorghum. The actual production was 7100 GT and 4100 GT respectively, for an error of 0.6% and 1.8%. These minimal errors show how this simple model can predict yields very accurately, even with only a few years of historical relationships.

Small errors in predictions were common across Africa. The histogram in Figure 15 displays the percent error for every country, crop, and index. The median error was 8.6%. Twenty-one percent of the predictions had a relative error below 2%, and 40% had errors below 5%.

One of the countries with a very high error was Botswana. Botswana's production of corn and sorghum is very low at only an average of 14 GT, as opposed to Ethiopia's 4000 GT. In addition, they had a very bad drought year in 2018. With the combination of low production values and a severe drought, the linear regression predicted a negative production. This example displays a drawback of a linear model: In real life, the relationship flattens as yields approach zero, as production cannot actually be negative. However, negative predictions, although not accurate, would still signal alarm in an operational forecast system. In retrospect, flagging Botswana as at risk would have been justified this past year, as they did end up with very low crop production.


**Figure 14.** A box was chosen in the densest agricultural region for each country in Africa.

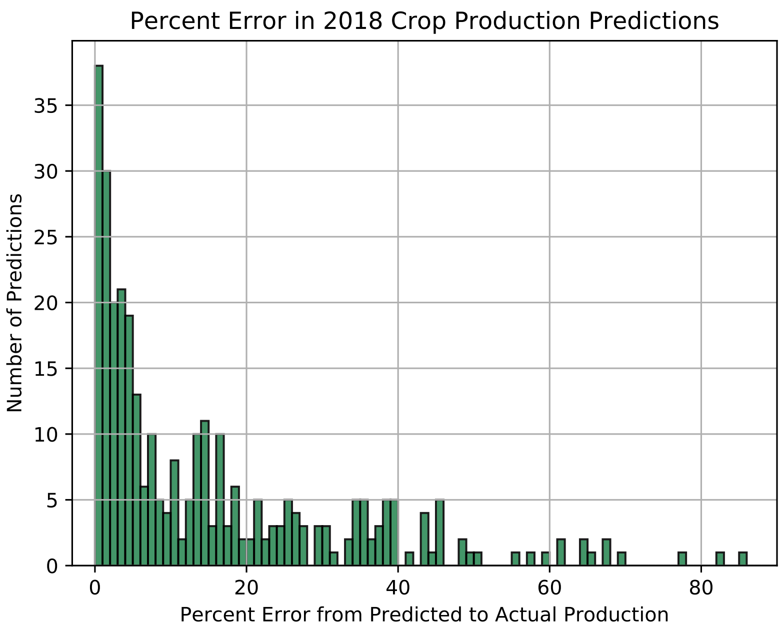



**Figure 15.** The the percent error for the 2018 predictions of every crop in every country. Forty percent of the predictions are under 5% error, and over half are below 10%.

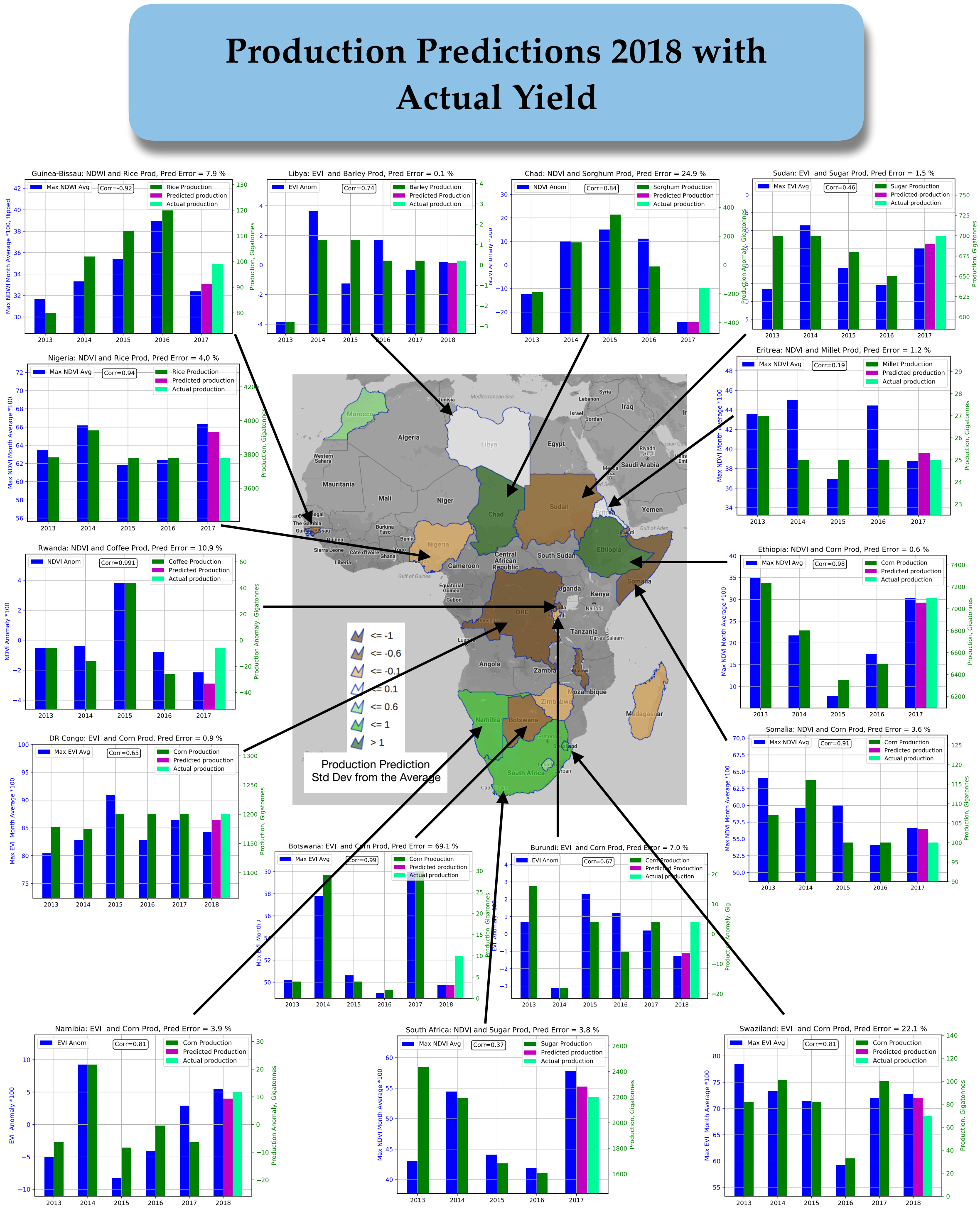



**Figure 16.** The map in the center displays the predicted crop production for African countries with harvests between December 2017 and June 2018 in standard deviations from the average. Surrounding the map are bar charts of satellite indices (blue), historical crop production (dark green), predicted 2018 crop production (pink), and actual 2018 production (light green). To view the accuracy of predictions for all crops and countries predicted, see Table 2.

## 4. Conclusions

In this research, I developed a method to use three measures of crop health computed from daily MODIS satellite imagery as a predictive tool for crop yields 2–4 months before the harvest. The model was first validated in Illinois where there is high-resolution yield data by computing the linear fit between harvest yields in October [45] and the satellite indices in July and August. When a split sample validation was applied to a multivariate regression with all months of the growing season and all three indices, the model could predict the crop yields within an accuracy of 6.3%, 5.7%, and 33% for corn, soybeans, and sorghum respectively. Next, the method was applied to three countries in Africa (Ethiopia, Tunisia, Morocco), all with different climates and crops. High correlations between maximum satellite indices and crop production were calculated in all three countries, with Ethiopia the highest at 0.99 to sorghum. After this success, satellite imagery was analyzed in every African country, and productions for the 2018 harvests were predicted 2–4 months before the harvest. Once 2018 harvests were published, the prediction accuracy was tested against the reported values. Forty percent of the predictions were found to have less than a 5% error.

The main objective of this study was to show how a very simple method can serve as an early warning system to predict crop yields in every African country. This method relies solely on NDVI, EVI, and NDWI anomalies calculated over specific subsections of the countries, without the use of crop masks, subnational yield statistics, or special tuning for location or climate. Even with these many simplifications, the model was still able to produce predictions with minimal error over Illinois and throughout Africa.

The model was found to perform best in countries with a relatively large agricultural sector and recent political stability. Some countries with relatively poor correlations include Sudan, Somalia and DR Congo, which are all currently in a state of conflict. Because of the political instability, it can be assumed that agricultural reports in those countries could have lower accuracy, and farming as a whole could be of a lower priority. A limitation of this model is that it relies on published yield data, so it will not predict as reliably in countries that lack reporting accuracy. In these places, the NDVI anomaly could be used as a proxy for relative crop yields compared to a mean. The model also only predicts yields at the national level and has no subnational component. However, it has the ability to predict yields sub-nationally in the future when sub-national crop data is supplied.

The model developed here may be compared to the existing early-warning systems of GEOGLAM and FEWS NET. Both systems can most likely be said to have predictions with better accuracy than the one presented here, which can be traced back to a couple reasons. Primarily, both are run under large budgets by an extensive team of people with partnerships around the globe. Their systems include ground observations, remotely sensed data, agroclimate indicators, field reports, and communications with national and regional experts. In contrast, this method can be run by a single user on a modern laptop computer. It was developed over the course of a couple months, and is practically free. This model is also able to predict a numerical value of crop production, while GEOGLAM and FEWS NET present their results as a qualitative measure: conditions are compacted into five categories of crop conditions or food insecurity phases.

The power of the method developed here is that can be applied to any crop, location, or climate to produce reasonable real-time forecasts of crop yields. It is unique because of its versatility and easy to apply due to its simplicity.

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## 6. Appendix: Summary of Results

**Table 2.** The predictions for select African countries for every crop and satellite index. All the countries that had harvests between December 2017 and June 2018 are displayed. Forty percent of the predictions had an error of less than 10% from the actual production. The fourth column is correlation between the index and reported crop production from 2013 to 2017.

| Country | Crop | Index | Correlation | 2018 Predicted (GT) | 2018 Actual (GT) | % Error |
|---|---|---|---|---|---|---|
| Botswana | Corn | NDVI Avg | 0.984 | 4 | 10 | 61.7 |
| Botswana | Corn | EVI Avg | 0.989 | 3 | 10 | 69.1 |
| Botswana | Corn | NDWI Avg | -0.879 | 0 | 10 | 104.9 |
| Botswana | Corn | NDVI Anom | 0.893 | 0 | 10 | 100.0 |
| Botswana | Corn | EVI Anom | 0.783 | 0 | 10 | 100.0 |
| Botswana | Corn | NDWI Anom | -0.661 | 0 | 10 | 100.0 |
| Botswana | Sorghum | NDVI Avg | 0.813 | 5 | 8 | 33.7 |
| Botswana | Sorghum | EVI Avg | 0.896 | 4 | 8 | 48.2 |
| Botswana | Sorghum | NDWI Avg | -0.664 | 3 | 8 | 59.0 |
| Botswana | Sorghum | NDVI Anom | 0.712 | 0 | 8 | 100.0 |
| Botswana | Sorghum | EVI Anom | 0.691 | 0 | 8 | 100.0 |
| Botswana | Sorghum | NDWI Anom | -0.446 | 0 | 8 | 100.0 |
| Burundi | Coffee | NDVI Avg | 0.398 | 172 | 200 | 14.1 |
| Burundi | Coffee | EVI Avg | -0.512 | 226 | 200 | 12.8 |
| Burundi | Coffee | NDWI Avg | 0.775 | 202 | 200 | 1.2 |
| Burundi | Coffee | NDVI Anom | -0.819 | 267 | 200 | 33.5 |
| Burundi | Coffee | EVI Anom | 0.08 | 202 | 200 | 1.0 |
| Burundi | Coffee | NDWI Anom | 0.919 | 210 | 200 | 4.8 |
| Burundi | Corn | NDVI Avg | -0.78 | 170 | 150 | 13.2 |
| Burundi | Corn | EVI Avg | 0.116 | 144 | 150 | 3.9 |
| Burundi | Corn | NDWI Avg | 0.083 | 146 | 150 | 2.7 |
| Burundi | Corn | NDVI Anom | -0.46 | 159 | 150 | 6.2 |
| Burundi | Corn | EVI Anom | 0.673 | 139 | 150 | 7.0 |
| Burundi | Corn | NDWI Anom | 0.404 | 147 | 150 | 2.1 |
| Burundi | Sorghum | NDVI Avg | -0.594 | 36 | 35 | 3.8 |
| Burundi | Sorghum | EVI Avg | -0.069 | 30 | 35 | 14.3 |
| Burundi | Sorghum | NDWI Avg | -0.033 | 30 | 35 | 15.4 |
| Burundi | Sorghum | NDVI Anom | -0.508 | 35 | 35 | 0.2 |
| Burundi | Sorghum | EVI Anom | 0.703 | 27 | 35 | 22.6 |
| Burundi | Sorghum | NDWI Anom | 0.296 | 30 | 35 | 14.7 |
| Chad | Corn | NDVI Avg | 0.533 | 457 | 450 | 1.5 |
| Chad | Corn | EVI Avg | 0.779 | 437 | 450 | 2.8 |
| Chad | Corn | NDWI Avg | -0.037 | 398 | 450 | 11.6 |
| Chad | Corn | NDVI Anom | 0.738 | 284 | 450 | 37.0 |
| Chad | Corn | EVI Anom | 0.78 | 275 | 450 | 38.8 |
| Chad | Corn | NDWI Anom | -0.713 | 254 | 450 | 43.6 |
| Chad | Millet | NDVI Avg | 0.416 | 705 | 700 | 0.8 |
| Chad | Millet | EVI Avg | 0.315 | 680 | 700 | 2.9 |
| Chad | Millet | NDWI Avg | -0.297 | 690 | 700 | 1.4 |
| Chad | Millet | NDVI Anom | -0.307 | 703 | 700 | 0.5 |
| Chad | Millet | EVI Anom | -0.241 | 696 | 700 | 0.6 |
| Chad | Millet | NDWI Anom | 0.261 | 708 | 700 | 1.1 |
| Chad | Rice | NDVI Avg | 0.087 | 161 | 154 | 4.8 |
| Chad | Rice | EVI Avg | -0.251 | 155 | 154 | 0.7 |
| Chad | Rice | NDWI Avg | -0.414 | 170 | 154 | 10.2 |
| Chad | Rice | NDVI Anom | -0.919 | 195 | 154 | 26.5 |
| Chad | Rice | EVI Anom | -0.882 | 194 | 154 | 26.0 |
| Chad | Rice | NDWI Anom | 0.8 | 200 | 154 | 29.9 |
| Chad | Sorghum | NDVI Avg | 0.562 | 1433 | 950 | 50.8 |
| Chad | Sorghum | EVI Avg | 0.735 | 1340 | 950 | 41.0 |
| Chad | Sorghum | NDWI Avg | -0.314 | 1307 | 950 | 37.5 |
| Chad | Sorghum | NDVI Anom | 0.842 | 714 | 950 | 24.9 |
| Chad | Sorghum | EVI Anom | 0.854 | 699 | 950 | 26.5 |
| Chad | Sorghum | NDWI Anom | -0.959 | 480 | 950 | 49.5 |

| Country | Crop | Index | Correlation | 2018 Predicted (GT) | 2018 Actual (GT) | % Error |
|---|---|---|---|---|---|---|
| Djibouti | Cereals | NDVI Avg | -0.206 | 19185 | 19079 | 0.6 |
| Djibouti | Cereals | EVI Avg | -0.622 | 18929 | 19079 | 0.8 |
| Djibouti | Cereals | NDWI Avg | -0.568 | 19036 | 19079 | 0.2 |
| Djibouti | Cereals | NDVI Anom | -0.647 | 18972 | 19079 | 0.6 |
| Djibouti | Cereals | EVI Anom | -0.668 | 18926 | 19079 | 0.8 |
| Djibouti | Cereals | NDWI Anom | 0.624 | 19056 | 19079 | 0.1 |
| DR Congo | Coffee | NDVI Avg | -0.454 | 235 | 220 | 6.7 |
| DR Congo | Coffee | EVI Avg | -0.453 | 228 | 220 | 3.8 |
| DR Congo | Coffee | NDWI Avg | 0.447 | 232 | 220 | 5.5 |
| DR Congo | Coffee | NDVI Anom | -0.188 | 230 | 220 | 4.7 |
| DR Congo | Coffee | EVI Anom | -0.478 | 201 | 220 | 8.4 |
| DR Congo | Coffee | NDWI Anom | 0.33 | 231 | 220 | 5.2 |
| DR Congo | Corn | NDVI Avg | 0.654 | 1175 | 1200 | 2.1 |
| DR Congo | Corn | EVI Avg | 0.652 | 1190 | 1200 | 0.9 |
| DR Congo | Corn | NDWI Avg | -0.522 | 1183 | 1200 | 1.4 |
| DR Congo | Corn | NDVI Anom | 0.325 | 1184 | 1200 | 1.3 |
| DR Congo | Corn | EVI Anom | 0.348 | 1221 | 1200 | 1.8 |
| DR Congo | Corn | NDWI Anom | -0.434 | 1183 | 1200 | 1.4 |
| Eritrea | Barley | NDVI Avg | -0.191 | 63 | 65 | 3.6 |
| Eritrea | Barley | EVI Avg | -0.252 | 64 | 65 | 2.0 |
| Eritrea | Barley | NDWI Avg | 0.142 | 62 | 65 | 4.1 |
| Eritrea | Barley | NDVI Anom | -0.197 | 63 | 65 | 3.6 |
| Eritrea | Barley | EVI Anom | -0.255 | 64 | 65 | 2.1 |
| Eritrea | Barley | NDWI Anom | 0.149 | 62 | 65 | 4.1 |
| Eritrea | Millet | NDVI Avg | 0.191 | 25 | 25 | 1.3 |
| Eritrea | Millet | EVI Avg | 0.252 | 25 | 25 | 0.7 |
| Eritrea | Millet | NDWI Avg | -0.142 | 25 | 25 | 1.4 |
| Eritrea | Millet | NDVI Anom | 0.197 | 25 | 25 | 1.3 |
| Eritrea | Millet | EVI Anom | 0.255 | 25 | 25 | 0.7 |
| Eritrea | Millet | NDWI Anom | -0.149 | 25 | 25 | 1.4 |
| Ethiopia | Corn | NDVI Avg | 0.979 | 7055 | 7100 | 0.6 |
| Ethiopia | Corn | EVI Avg | 0.972 | 7157 | 7100 | 0.8 |
| Ethiopia | Corn | NDWI Avg | -0.983 | 7045 | 7100 | 0.8 |
| Ethiopia | Corn | NDVI Anom | 0.812 | 6294 | 7100 | 11.4 |
| Ethiopia | Corn | EVI Anom | 0.263 | 6805 | 7100 | 4.2 |
| Ethiopia | Corn | NDWI Anom | -0.845 | 6160 | 7100 | 13.2 |
| Ethiopia | Sorghum | NDVI Avg | 0.987 | 4174 | 4100 | 1.8 |
| Ethiopia | Sorghum | EVI Avg | 0.98 | 4257 | 4100 | 3.8 |
| Ethiopia | Sorghum | NDWI Avg | -0.974 | 4161 | 4100 | 1.5 |
| Ethiopia | Sorghum | NDVI Anom | 0.883 | 3524 | 4100 | 14.1 |
| Ethiopia | Sorghum | EVI Anom | 0.402 | 4005 | 4100 | 2.3 |
| Ethiopia | Sorghum | NDWI Anom | -0.909 | 3411 | 4100 | 16.8 |
| Guinea-Bissau | Rice | NDVI Avg | 0.897 | 100 | 99 | 1.2 |
| Guinea-Bissau | Rice | EVI Avg | 0.578 | 147 | 99 | 48.9 |
| Guinea-Bissau | Rice | NDWI Avg | -0.919 | 91 | 99 | 7.9 |
| Guinea-Bissau | Rice | NDVI Anom | 0.95 | 88 | 99 | 11.0 |
| Guinea-Bissau | Rice | EVI Anom | -0.446 | 103 | 99 | 3.9 |
| Guinea-Bissau | Rice | NDWI Anom | -0.943 | 85 | 99 | 13.8 |
| Guinea-Bissau | Sorghum | NDVI Avg | 0.987 | 16 | 20 | 18.9 |
| Guinea-Bissau | Sorghum | EVI Avg | 0.521 | 22 | 20 | 12.3 |
| Guinea-Bissau | Sorghum | NDWI Avg | -0.992 | 15 | 20 | 25.9 |
| Guinea-Bissau | Sorghum | NDVI Anom | 0.973 | 14 | 20 | 27.6 |
| Guinea-Bissau | Sorghum | EVI Anom | -0.71 | 17 | 20 | 17.0 |
| Guinea-Bissau | Sorghum | NDWI Anom | -0.989 | 14 | 20 | 30.0 |
| Lesotho | Corn | NDVI Avg | 0.611 | 125 | 100 | 24.7 |
| Lesotho | Corn | EVI Avg | 0.636 | 121 | 100 | 20.7 |
| Lesotho | Corn | NDWI Avg | -0.652 | 106 | 100 | 5.9 |
| Lesotho | Corn | NDVI Anom | 0.535 | 101 | 100 | 1.1 |
| Lesotho | Corn | EVI Anom | 0.534 | 99 | 100 | 1.2 |
| Lesotho | Corn | NDWI Anom | -0.66 | 72 | 100 | 28.0 |

| Country | Crop | Index | Correlation | 2018 Predicted (GT) | 2018 Actual (GT) | % Error |
|---|---|---|---|---|---|---|
| Lesotho | Wheat | NDVI Avg | 0.713 | 12 | 12 | 0.3 |
| Lesotho | Wheat | EVI Avg | 0.829 | 12 | 12 | 1.0 |
| Lesotho | Wheat | NDWI Avg | -0.619 | 10 | 12 | 13.2 |
| Lesotho | Wheat | NDVI Anom | 0.667 | 10 | 12 | 14.8 |
| Lesotho | Wheat | EVI Anom | 0.733 | 10 | 12 | 16.1 |
| Lesotho | Wheat | NDWI Anom | -0.646 | 8 | 12 | 30.8 |
| Libya | Barley | NDVI Avg | 0.454 | 100 | 100 | 0.0 |
| Libya | Barley | EVI Avg | 0.736 | 100 | 100 | 0.1 |
| Libya | Barley | NDWI Avg | -0.538 | 100 | 100 | 0.3 |
| Libya | Barley | NDVI Anom | 0.624 | 100 | 100 | 0.1 |
| Libya | Barley | EVI Anom | 0.741 | 100 | 100 | 0.1 |
| Libya | Barley | NDWI Anom | -0.618 | 100 | 100 | 0.4 |
| Libya | Olive Oil | NDVI Avg | -0.86 | 17 | 18 | 5.7 |
| Libya | Olive Oil | EVI Avg | -0.85 | 17 | 18 | 4.7 |
| Libya | Olive Oil | NDWI Avg | 0.799 | 17 | 18 | 3.7 |
| Libya | Olive Oil | NDVI Anom | -0.791 | 17 | 18 | 4.9 |
| Libya | Olive Oil | EVI Anom | -0.859 | 17 | 18 | 4.8 |
| Libya | Olive Oil | NDWI Anom | 0.776 | 17 | 18 | 3.4 |
| Madagascar | Coffee | NDVI Avg | 0.244 | 392 | 300 | 30.9 |
| Madagascar | Coffee | EVI Avg | 0.241 | 403 | 300 | 34.5 |
| Madagascar | Coffee | NDWI Avg | -0.467 | 412 | 300 | 37.6 |
| Madagascar | Coffee | NDVI Anom | -0.16 | 465 | 300 | 55.1 |
| Madagascar | Coffee | EVI Anom | 0.046 | 416 | 300 | 38.9 |
| Madagascar | Coffee | NDWI Anom | -0.216 | 406 | 300 | 35.5 |
| Madagascar | Corn | NDVI Avg | -0.18 | 347 | 300 | 15.8 |
| Madagascar | Corn | EVI Avg | 0.175 | 339 | 300 | 13.0 |
| Madagascar | Corn | NDWI Avg | 0.036 | 342 | 300 | 14.2 |
| Madagascar | Corn | NDVI Anom | -0.678 | 378 | 300 | 26.2 |
| Madagascar | Corn | EVI Anom | 0.004 | 342 | 300 | 14.1 |
| Madagascar | Corn | NDWI Anom | 0.393 | 349 | 300 | 16.5 |
| Madagascar | Rice | NDVI Avg | 0.622 | 2234 | 2304 | 3.0 |
| Madagascar | Rice | EVI Avg | 0.73 | 2257 | 2304 | 2.0 |
| Madagascar | Rice | NDWI Avg | -0.652 | 2322 | 2304 | 0.8 |
| Madagascar | Rice | NDVI Anom | 0.03 | 2335 | 2304 | 1.4 |
| Madagascar | Rice | EVI Anom | 0.579 | 2206 | 2304 | 4.2 |
| Madagascar | Rice | NDWI Anom | -0.176 | 2325 | 2304 | 0.9 |
| Madagascar | Sugar | NDVI Avg | 0.647 | 90 | 90 | 0.5 |
| Madagascar | Sugar | EVI Avg | 0.447 | 93 | 90 | 3.8 |
| Madagascar | Sugar | NDWI Avg | -0.836 | 94 | 90 | 5.1 |
| Madagascar | Sugar | NDVI Anom | 0.262 | 91 | 90 | 1.9 |
| Madagascar | Sugar | EVI Anom | 0.265 | 93 | 90 | 3.3 |
| Madagascar | Sugar | NDWI Anom | -0.587 | 92 | 90 | 3.1 |
| Malawi | Corn | NDVI Avg | -0.206 | 3309 | 3000 | 10.3 |
| Malawi | Corn | EVI Avg | 0.848 | 2362 | 3000 | 21.3 |
| Malawi | Corn | NDWI Avg | 0.496 | 3275 | 3000 | 9.2 |
| Malawi | Corn | NDVI Anom | -0.206 | 3309 | 3000 | 10.3 |
| Malawi | Corn | EVI Anom | 0.848 | 2363 | 3000 | 21.2 |
| Malawi | Corn | NDWI Anom | 0.496 | 3275 | 3000 | 9.2 |
| Malawi | Cotton | NDVI Avg | 0.06 | 121 | 90 | 34.6 |
| Malawi | Cotton | EVI Avg | 0.474 | 81 | 90 | 9.5 |
| Malawi | Cotton | NDWI Avg | 0.107 | 122 | 90 | 35.6 |
| Malawi | Cotton | NDVI Anom | 0.061 | 121 | 90 | 34.6 |
| Malawi | Cotton | EVI Anom | 0.474 | 81 | 90 | 9.5 |
| Malawi | Cotton | NDWI Anom | 0.107 | 122 | 90 | 35.6 |
| Malawi | Peanut Oilseed | NDVI Avg | 0.395 | 292 | 325 | 10.1 |
| Malawi | Peanut Oilseed | EVI Avg | -0.028 | 299 | 325 | 7.8 |
| Malawi | Peanut Oilseed | NDWI Avg | -0.375 | 297 | 325 | 8.5 |
| Malawi | Peanut Oilseed | NDVI Anom | 0.395 | 292 | 325 | 10.1 |
| Malawi | Peanut Oilseed | EVI Anom | -0.028 | 299 | 325 | 7.8 |
| Malawi | Peanut Oilseed | NDWI Anom | -0.375 | 297 | 325 | 8.5 |

| Country | Crop | Index | Correlation | 2018 Predicted (GT) | 2018 Actual (GT) | % Error |
|---|---|---|---|---|---|---|
| Morocco | Barley | NDVI Avg | 0.524 | 2014 | 2500 | 19.5 |
| Morocco | Barley | EVI Avg | 0.473 | 2496 | 2500 | 0.1 |
| Morocco | Barley | NDWI Avg | -0.494 | 2051 | 2500 | 18.0 |
| Morocco | Barley | NDVI Anom | 0.504 | 1851 | 2500 | 26.0 |
| Morocco | Barley | EVI Anom | 0.534 | 2430 | 2500 | 2.8 |
| Morocco | Barley | NDWI Anom | -0.471 | 1894 | 2500 | 24.2 |
| Morocco | Wheat | NDVI Avg | 0.669 | 5666 | 8200 | 30.9 |
| Morocco | Wheat | EVI Avg | 0.623 | 6879 | 8200 | 16.1 |
| Morocco | Wheat | NDWI Avg | -0.642 | 5757 | 8200 | 29.8 |
| Morocco | Wheat | NDVI Anom | 0.641 | 5270 | 8200 | 35.7 |
| Morocco | Wheat | EVI Anom | 0.667 | 6666 | 8200 | 18.7 |
| Morocco | Wheat | NDWI Anom | -0.606 | 5371 | 8200 | 34.5 |
| Namibia | Corn | NDVI Avg | 0.643 | 50 | 58 | 14.4 |
| Namibia | Corn | EVI Avg | 0.642 | 48 | 58 | 18.0 |
| Namibia | Corn | NDWI Avg | -0.581 | 48 | 58 | 18.0 |
| Namibia | Corn | NDVI Anom | 0.808 | 54 | 58 | 6.6 |
| Namibia | Corn | EVI Anom | 0.811 | 56 | 58 | 3.9 |
| Namibia | Corn | NDWI Anom | -0.727 | 48 | 58 | 16.8 |
| Nigeria | Corn | NDVI Avg | -0.89 | 9628 | 11000 | 12.5 |
| Nigeria | Corn | EVI Avg | 0.276 | 11440 | 11000 | 4.0 |
| Nigeria | Corn | NDWI Avg | 0.983 | 9498 | 11000 | 13.7 |
| Nigeria | Corn | NDVI Anom | 0.16 | 10178 | 11000 | 7.5 |
| Nigeria | Corn | EVI Anom | 0.147 | 10355 | 11000 | 5.9 |
| Nigeria | Corn | NDWI Anom | 0.217 | 10363 | 11000 | 5.8 |
| Nigeria | Rice | NDVI Avg | 0.939 | 3932 | 3780 | 4.0 |
| Nigeria | Rice | EVI Avg | -0.226 | 3704 | 3780 | 2.0 |
| Nigeria | Rice | NDWI Avg | -0.961 | 3941 | 3780 | 4.3 |
| Nigeria | Rice | NDVI Anom | -0.343 | 3885 | 3780 | 2.8 |
| Nigeria | Rice | EVI Anom | -0.365 | 3835 | 3780 | 1.5 |
| Nigeria | Rice | NDWI Anom | -0.175 | 3824 | 3780 | 1.2 |
| Nigeria | Sorghum | NDVI Avg | -0.93 | 5708 | 6800 | 16.1 |
| Nigeria | Sorghum | EVI Avg | 0.397 | 7866 | 6800 | 15.7 |
| Nigeria | Sorghum | NDWI Avg | 0.95 | 5647 | 6800 | 17.0 |
| Nigeria | Sorghum | NDVI Anom | 0.095 | 6339 | 6800 | 6.8 |
| Nigeria | Sorghum | EVI Anom | 0.132 | 6425 | 6800 | 5.5 |
| Nigeria | Sorghum | NDWI Anom | 0.341 | 6411 | 6800 | 5.7 |
| Rwanda | Coffee | NDVI Avg | -0.539 | 254 | 250 | 1.5 |
| Rwanda | Coffee | EVI Avg | 0.743 | 253 | 250 | 1.3 |
| Rwanda | Coffee | NDWI Avg | -0.762 | 311 | 250 | 24.3 |
| Rwanda | Coffee | NDVI Anom | 0.991 | 223 | 250 | 10.9 |
| Rwanda | Coffee | EVI Anom | 0.744 | 253 | 250 | 1.3 |
| Rwanda | Coffee | NDWI Anom | 0.063 | 254 | 250 | 1.7 |
| Rwanda | Corn | NDVI Avg | -0.44 | 576 | 400 | 43.9 |
| Rwanda | Corn | EVI Avg | 0.425 | 556 | 400 | 39.1 |
| Rwanda | Corn | NDWI Avg | -0.411 | 574 | 400 | 43.5 |
| Rwanda | Corn | NDVI Anom | -0.473 | 556 | 400 | 39.0 |
| Rwanda | Corn | EVI Anom | 0.424 | 556 | 400 | 39.1 |
| Rwanda | Corn | NDWI Anom | 0.951 | 551 | 400 | 37.8 |
| Rwanda | Sorghum | NDVI Avg | -0.226 | 146 | 145 | 1.0 |
| Rwanda | Sorghum | EVI Avg | -0.541 | 144 | 145 | 0.6 |
| Rwanda | Sorghum | NDWI Avg | 0.521 | 142 | 145 | 2.4 |
| Rwanda | Sorghum | NDVI Anom | 0.318 | 143 | 145 | 1.2 |
| Rwanda | Sorghum | EVI Anom | -0.541 | 144 | 145 | 0.6 |
| Rwanda | Sorghum | NDWI Anom | -0.981 | 145 | 145 | 0.2 |
| Somalia | Corn | NDVI Avg | 0.91 | 104 | 100 | 3.6 |
| Somalia | Corn | EVI Avg | 0.243 | 105 | 100 | 4.6 |
| Somalia | Corn | NDWI Avg | -0.365 | 121 | 100 | 21.0 |
| Somalia | Corn | NDVI Anom | 0.385 | 103 | 100 | 3.5 |
| Somalia | Corn | EVI Anom | 0.243 | 105 | 100 | 4.6 |
| Somalia | Corn | NDWI Anom | -0.42 | 103 | 100 | 3.3 |

| Country | Crop | Index | Correlation | 2018 Predicted (GT) | 2018 Actual (GT) | % Error |
|---|---|---|---|---|---|---|
| Somalia | Sorghum | NDVI Avg | 0.432 | 116 | 130 | 10.7 |
| Somalia | Sorghum | EVI Avg | 0.196 | 122 | 130 | 6.0 |
| Somalia | Sorghum | NDWI Avg | -0.128 | 148 | 130 | 14.2 |
| Somalia | Sorghum | NDVI Anom | -0.474 | 190 | 130 | 45.9 |
| Somalia | Sorghum | EVI Anom | 0.195 | 122 | 130 | 6.0 |
| Somalia | Sorghum | NDWI Anom | -0.115 | 123 | 130 | 5.2 |
| South Africa | Corn | NDVI Avg | -0.592 | 7392 | 13500 | 45.2 |
| South Africa | Corn | EVI Avg | -0.673 | 5684 | 13500 | 57.9 |
| South Africa | Corn | NDWI Avg | 0.651 | 7471 | 13500 | 44.7 |
| South Africa | Corn | NDVI Anom | -0.848 | 2343 | 13500 | 82.6 |
| South Africa | Corn | EVI Anom | -0.859 | 1967 | 13500 | 85.4 |
| South Africa | Corn | NDWI Anom | 0.902 | 3006 | 13500 | 77.7 |
| South Africa | Sugar | NDVI Avg | 0.366 | 2283 | 2200 | 3.8 |
| South Africa | Sugar | EVI Avg | 0.467 | 2439 | 2200 | 10.9 |
| South Africa | Sugar | NDWI Avg | -0.43 | 2297 | 2200 | 4.4 |
| South Africa | Sugar | NDVI Anom | 0.343 | 2384 | 2200 | 8.4 |
| South Africa | Sugar | EVI Anom | 0.292 | 2333 | 2200 | 6.1 |
| South Africa | Sugar | NDWI Anom | -0.396 | 2391 | 2200 | 8.7 |
| South Africa | Wheat | NDVI Avg | -0.746 | 1383 | 1800 | 23.1 |
| South Africa | Wheat | EVI Avg | -0.778 | 1310 | 1800 | 27.2 |
| South Africa | Wheat | NDWI Avg | 0.775 | 1405 | 1800 | 21.9 |
| South Africa | Wheat | NDVI Anom | -0.984 | 1114 | 1800 | 38.1 |
| South Africa | Wheat | EVI Anom | -0.998 | 1091 | 1800 | 39.4 |
| South Africa | Wheat | NDWI Anom | 0.995 | 1179 | 1800 | 34.5 |
| Sudan | Cotton | NDVI Avg | -0.849 | 178 | 500 | 64.5 |
| Sudan | Cotton | EVI Avg | -0.776 | 162 | 500 | 67.5 |
| Sudan | Cotton | NDWI Avg | 0.971 | 193 | 500 | 61.3 |
| Sudan | Cotton | NDVI Anom | -0.748 | 172 | 500 | 65.7 |
| Sudan | Cotton | EVI Anom | -0.754 | 161 | 500 | 67.8 |
| Sudan | Cotton | NDWI Anom | 0.804 | 175 | 500 | 65.0 |
| Sudan | Millet | NDVI Avg | -0.565 | 1018 | 1000 | 1.8 |
| Sudan | Millet | EVI Avg | -0.515 | 835 | 1000 | 16.5 |
| Sudan | Millet | NDWI Avg | 0.478 | 1150 | 1000 | 15.0 |
| Sudan | Millet | NDVI Anom | -0.548 | 941 | 1000 | 5.9 |
| Sudan | Millet | EVI Anom | -0.51 | 820 | 1000 | 18.0 |
| Sudan | Millet | NDWI Anom | 0.455 | 989 | 1000 | 1.1 |
| Sudan | Sorghum | NDVI Avg | -0.875 | 4945 | 4000 | 23.6 |
| Sudan | Sorghum | EVI Avg | -0.837 | 3802 | 4000 | 4.9 |
| Sudan | Sorghum | NDWI Avg | 0.798 | 5811 | 4000 | 45.3 |
| Sudan | Sorghum | NDVI Anom | -0.851 | 4482 | 4000 | 12.1 |
| Sudan | Sorghum | EVI Anom | -0.83 | 3704 | 4000 | 7.4 |
| Sudan | Sorghum | NDWI Anom | 0.804 | 4773 | 4000 | 19.3 |
| Sudan | Sugar | NDVI Avg | 0.34 | 682 | 700 | 2.6 |
| Sudan | Sugar | EVI Avg | 0.457 | 690 | 700 | 1.5 |
| Sudan | Sugar | NDWI Avg | -0.025 | 682 | 700 | 2.6 |
| Sudan | Sugar | NDVI Anom | 0.484 | 685 | 700 | 2.2 |
| Sudan | Sugar | EVI Anom | 0.486 | 691 | 700 | 1.3 |
| Sudan | Sugar | NDWI Anom | -0.425 | 682 | 700 | 2.5 |
| Sudan | Wheat | NDVI Avg | 0.239 | 455 | 400 | 13.7 |
| Sudan | Wheat | EVI Avg | 0.341 | 464 | 400 | 16.1 |
| Sudan | Wheat | NDWI Avg | -0.083 | 454 | 400 | 13.4 |
| Sudan | Wheat | NDVI Anom | 0.33 | 458 | 400 | 14.6 |
| Sudan | Wheat | EVI Anom | 0.359 | 466 | 400 | 16.5 |
| Sudan | Wheat | NDWI Anom | -0.364 | 456 | 400 | 14.0 |
| Swaziland | Corn | NDVI Avg | 0.917 | 89 | 70 | 27.0 |
| Swaziland | Corn | EVI Avg | 0.811 | 85 | 70 | 22.1 |
| Swaziland | Corn | NDWI Avg | -0.95 | 95 | 70 | 36.1 |
| Swaziland | Corn | NDVI Anom | 0.826 | 83 | 70 | 18.9 |
| Swaziland | Corn | EVI Anom | 0.72 | 85 | 70 | 21.1 |
| Swaziland | Corn | NDWI Anom | -0.853 | 88 | 70 | 25.1 |

| Country | Crop | Index | Correlation | 2018 Predicted (GT) | 2018 Actual (GT) | % Error |
|---|---|---|---|---|---|---|
| Swaziland | Sugar | NDVI Avg | -0.383 | 659 | 690 | 4.5 |
| Swaziland | Sugar | EVI Avg | -0.214 | 663 | 690 | 4.0 |
| Swaziland | Sugar | NDWI Avg | 0.569 | 650 | 690 | 5.8 |
| Swaziland | Sugar | NDVI Anom | -0.278 | 663 | 690 | 3.9 |
| Swaziland | Sugar | EVI Anom | -0.175 | 663 | 690 | 3.9 |
| Swaziland | Sugar | NDWI Anom | 0.449 | 658 | 690 | 4.6 |
| Zimbabwe | Corn | NDVI Avg | 0.725 | 931 | 1700 | 45.3 |
| Zimbabwe | Corn | EVI Avg | -0.618 | 1347 | 1700 | 20.8 |
| Zimbabwe | Corn | NDWI Avg | -0.816 | 1022 | 1700 | 39.9 |
| Zimbabwe | Corn | NDVI Anom | 0.729 | 934 | 1700 | 45.1 |
| Zimbabwe | Corn | EVI Anom | 0.212 | 1268 | 1700 | 25.4 |
| Zimbabwe | Corn | NDWI Anom | -0.759 | 956 | 1700 | 43.8 |
| Zimbabwe | Cotton | NDVI Avg | 0.897 | 142 | 230 | 38.4 |
| Zimbabwe | Cotton | EVI Avg | -0.029 | 176 | 230 | 23.7 |
| Zimbabwe | Cotton | NDWI Avg | -0.873 | 158 | 230 | 31.2 |
| Zimbabwe | Cotton | NDVI Anom | 0.898 | 142 | 230 | 38.1 |
| Zimbabwe | Cotton | EVI Anom | 0.346 | 199 | 230 | 13.4 |
| Zimbabwe | Cotton | NDWI Anom | -0.872 | 148 | 230 | 35.8 |
| Zimbabwe | Sugar | NDVI Avg | 0.496 | 448 | 460 | 2.6 |
| Zimbabwe | Sugar | EVI Avg | 0.236 | 451 | 460 | 1.9 |
| Zimbabwe | Sugar | NDWI Avg | -0.466 | 452 | 460 | 1.8 |
| Zimbabwe | Sugar | NDVI Anom | 0.493 | 448 | 460 | 2.5 |
| Zimbabwe | Sugar | EVI Anom | -0.055 | 453 | 460 | 1.5 |
| Zimbabwe | Sugar | NDWI Anom | -0.517 | 449 | 460 | 2.4 |