The Effects of Climatic Patterns on Crop Yields In Africa and Asia

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Background

- Around the world, nations rely on agriculture for food and also their primary exports.
- This study is based around crop yield data, or the amount of a crop harvested per hectare of land.
- We will be using data for potatoes and beans, two crops crucial to these regions' food supplies.
- Particularly in Africa and Asia, oscillating climate anomalies are crucial factors in understanding crop yield variability.
- Studying which climatic patterns affect crop yields can help us understand how to better prepare for these uncertainties due to the fact that these climatic events can be predicted.

Rationale

- We can determine and identify the major climatic patterns responsible for the greatest effect on crop yields around the world.
- With this information, we may be able to predict weather phenomena in the future, allowing us to prepare our crops accordingly.

Methods

Collecting/Cleaning Data

We gathered crop yield data (beans and potatoes) from the FAOstat database of Asia and Africa, from 1961 - 2017 as an excel sheet. To clean the data, countries with many missing values were deleted. If a country was only missing a few values interpolating was done by finding the average of the year prior and the year after to insert into the missing slot.

Detrending Data

Our original crop yield data shows a clear positive linear trend over time. This trend is entirely due to advances in agricultural technology such as better fertilizers, etc. In order to isolate climate variables and their independent effects on crop yield, it was imperative that we detrended the time variable from our data. The detrended data no longer showed a linear trend, but instead illustrated the differences between yield values and their projected yearly averages.

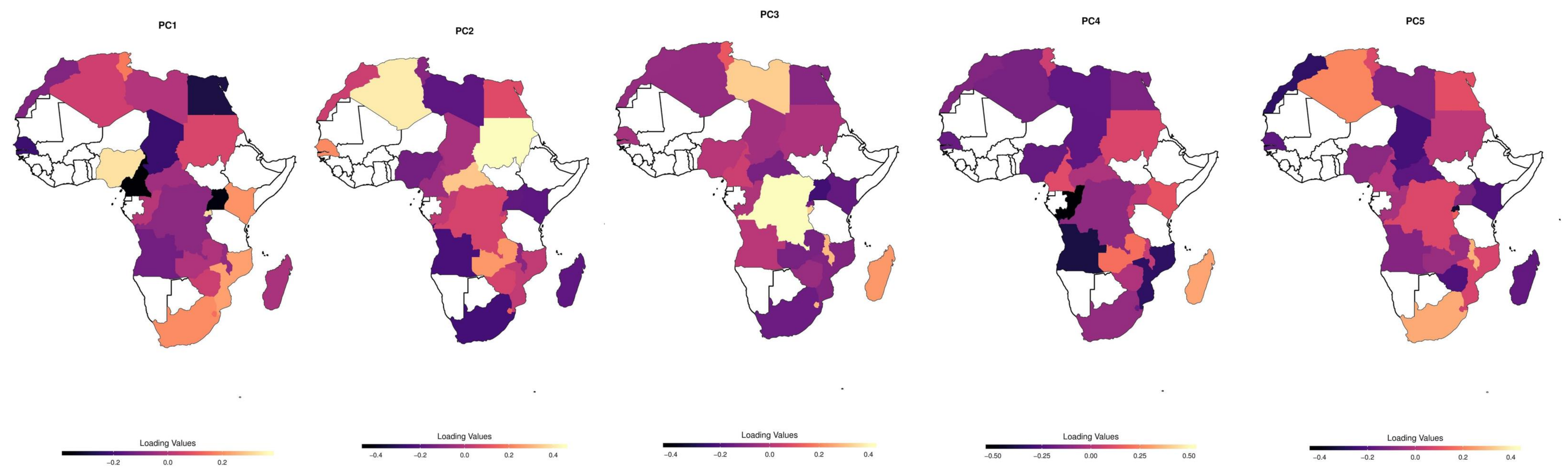
$$Y_t = \frac{y_t - \overline{y_{t-3:t+3}}}{\mathrm{std}(t_{t-3:t+3})}$$

Principal Component Analysis

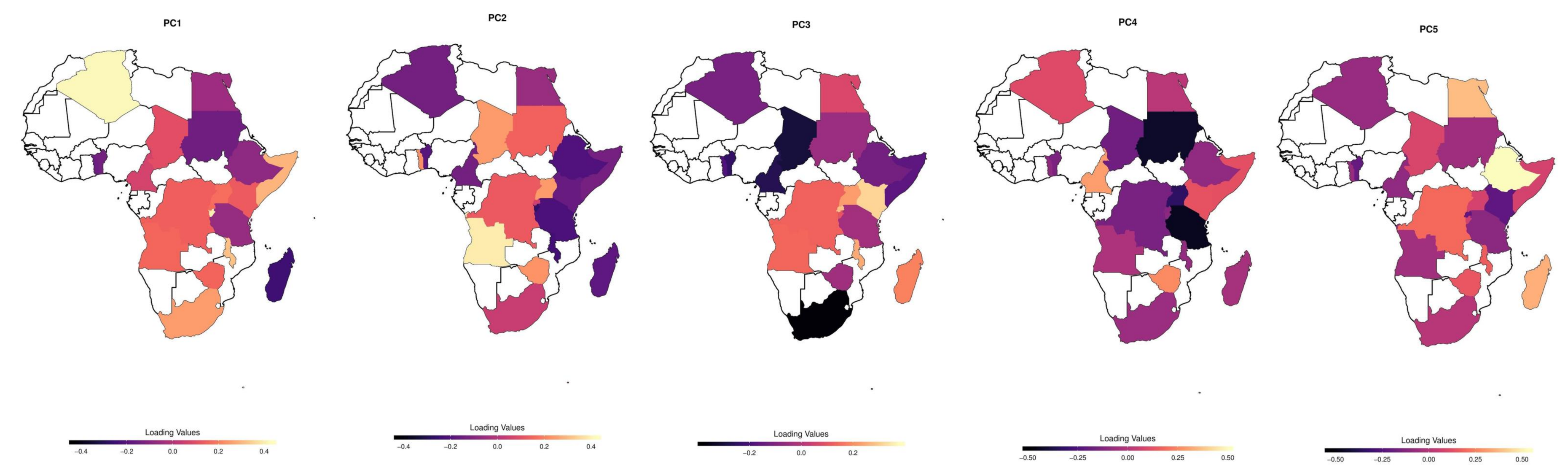
What is PCA? PCA (Principal Component Analysis) is a process of dimensionality reduction, where multiple variables are reduced to a single variable, based on their similarities. This allows data to be more clearly understood by condensing multiple dimensions into a format we can easily visualize. We used this method to merge countries and years, giving us a list of 5 major PCs that describe a majority of variance within the data. Our maps are based off of loading values, derived from comparing PCs against countries. Our correlation tables were created through the correlations between score values, calculated by comparing PCs against years, and 18 large-scale climatic variables.

Results and Visualizations

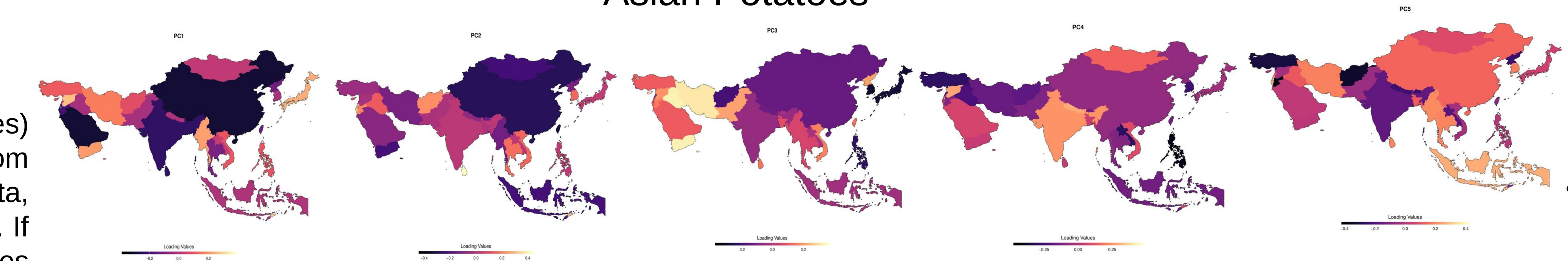
African Potatoes



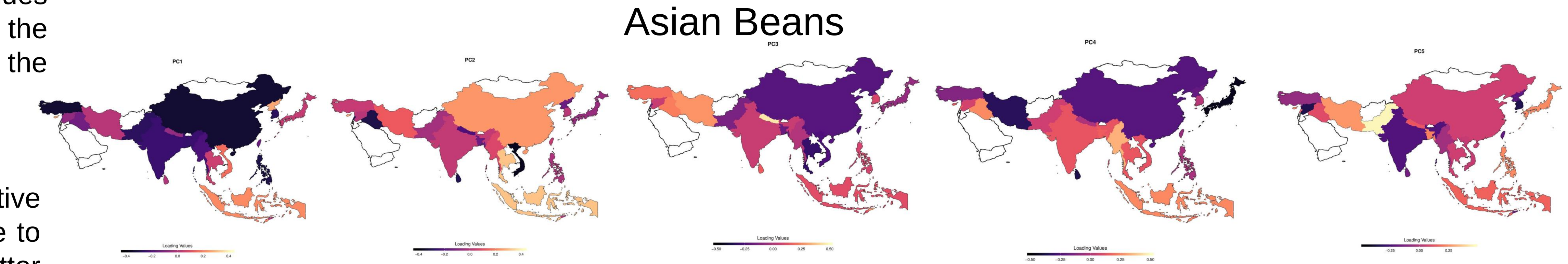
African Beans



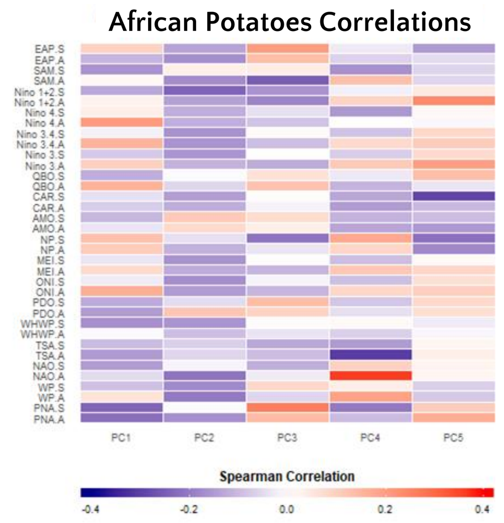
Asian Potatoes



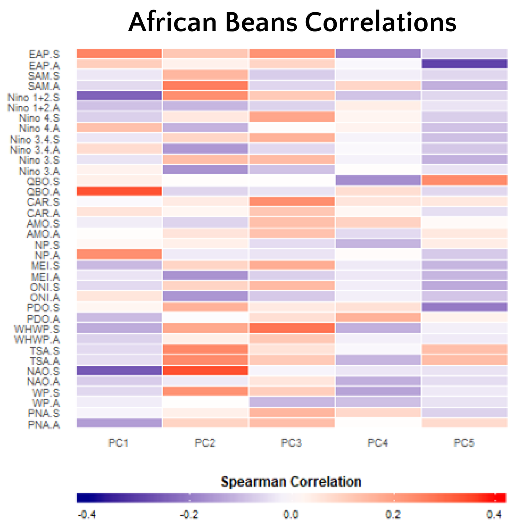
Asian Beans



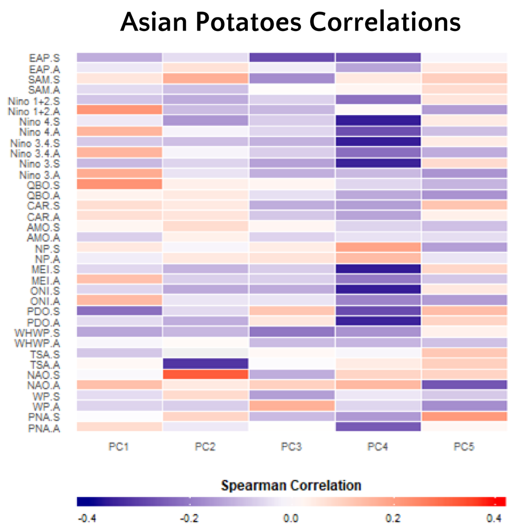
African Potatoes Correlations



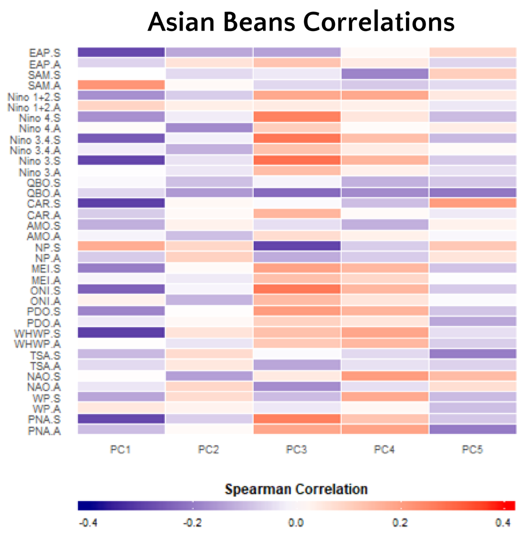
African Beans Correlations



Asian Potatoes Correlations



Asian Beans Correlations



Conclusion

The effect of climatic variables differs depending on location. For example, most of the variation in Asian countries is highly correlated with indices of the El Niño Southern Oscillation (ENSO), an anomaly regarding sea surface temperatures in the Pacific Ocean. This corroborates the idea that crop yield variance is affected by ENSO in Asia. African yield variation was highly correlated with the North Atlantic Oscillation (NAO). This information is very important in understanding how food security varies in these specific regions. Knowing which climatic patterns affect which areas can help us better identify and prepare for potentially devastating events. This could reduce food insecurity in particular areas by predicting possible climatic occurrences. Then we can see how this cycle affects the crop yields using our research and focus on the specific areas which are negatively affected and come up with a solution to further improve on people's well being regarding food security.

Discussion

- By cross-referencing our maps with the correlation tables, we were able to discern which climatic anomalies accounted for the greatest variation in crop yield, and which areas experienced the most change.
- The most impactful anomalies, shown by the darker boxes in the below correlation tables, all conform to a substantial pattern.
- The anomalies with the highest correlations to crop yield appear to be related to the El Nino Southern Oscillation (ENSO) in the tropical Pacific. Indices such as Nino 3 or the Oceanic Niño Index (ONI), as well as related effects such as the Western Hemisphere Warm Pool (WHWP), are all highly correlated with yield values.
- In addition, the North Atlantic Oscillation (NAO) and the Quasi-Biennial Oscillation (QBO) anomalies also have strong positive correlations with yield variation.
- Conversely, precipitation anomalies such as The East Asia-Pacific (EAP) teleconnection pattern have smaller or even negative correlations to crop yield variations.

Future Studies

- In order to account for more specific variance, we should analyze local-scale variables such as temperature, precipitation and soil moisture, instead of exclusively global-scale oscillation patterns.
- To ensure the accuracy of our calculations, we should cross-reference our Principal Component Analysis results with those from a Multiple Linear Regression method.
- It is imperative we apply this data, and find ways to prepare for and protect nations whose food supplies could be decimated by weather phenomena.

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