Relationship Between West African Monsoon Precipitation Characteristics and Maize Yields Across Sub-Saharan West Africa

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Supervised by Dara Entekhabi and Sarah Fletcher

Abstract

Sub-Saharan Africa faces significant challenges to its food security in the coming decades as climate change and rapid population growth strains its agricultural systems. In a region where crops are near exclusively rainfed, precipitation from the West African Monsoon (WAM) plays a significant role in the region's food production. This study aims to add to the limited literature on the relationship between country-level maize yields and the WAM, particularly through the use of high resolution precipitation estimates to characterize the spatiotemporal variability of the monsoon. Multi-year annual precipitation characteristics of the monsoon such as total precipitation, number of non-precipitating days, and timing were derived and aggregated across the maize growing regions of West African countries. Aggregated precipitation metrics were linearly regressed against country-level maize yields that have undergone timeseries analysis to remove trends occurring independently of the WAM. The metrics most correlated with maize yields while maintaining statistically significant slopes were the minimum of total precipitation, standard deviation of the number of non-precipitating days, and the minimum monsoon end date. The strong positive correlations of the minimum of total precipitation and minimum monsoon end date metrics suggest that the worst performing areas in terms of total precipitation and monsoon end date drive down annual country-level maize yields. The positive correlation found using the standard deviation of the number of non-precipitating days is uninterpretable as an instance of Simpson's paradox, as the opposite relationship is discovered in analyses using individual countries. These results show the efficacy of analyzing maize yields against satellite mapped precipitation characteristics of the WAM.

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1 Introduction

1.1 Motivation

1.1.1 Agricultural Vulnerabilities in Sub-Saharan Africa

Sub-Saharan Africa (SSA) is home to one of the most challenged and vulnerable food production systems in the world. Having one of the world's fastest growing populations, expecting to double to 2.2 billion by 2050, the region faces significant strain on its food resources (Suzuki, 2019). While there can be many social, economic, geologic, and political causes for food insecurity, precipitation is considered one of the most important factors influencing the region's vegetation and food production (Hoscilo et al., 2015; Ray et al., 2015; Sassi, 2015). The region's food production is almost entirely rainfed, as only 1% of cultivated land is irrigated in SSA (Dixon et al., 2001). This poses significant vulnerabilities to the region's food security as climate change alters rainfall and growing temperatures in the coming decades (Blanc, 2012; Thornton et al., 2011; Waha et al., 2013). As such, an investigation into how crop yields relate to precipitation patterns in SSA can provide valuable insight into the region's food security for the coming decades.

1.1.2 Significance of Maize

Maize's drought sensitivity and significance to West Africa's food security makes it a prime subject for analysis. Compared to the global norm, maize is particularly important as a food staple for human consumption in SSA (Dixon et al., 2001; OECD & Nations, 2016). Cereal crops are critical to food security in SSA as they are the primary source of energy for more than 962 million people (OECD & Nations, 2016). By 2025, maize is expected to comprise 40% of cereal consumption in SSA, and 70% of total maize demand in the region is expected to be for food consumption (OECD & Nations, 2016). In West Africa, maize is grown in the cereal-root crop mixed system, which is a region particularly vulnerable to droughts and climate change, as the West African Monsoon (WAM) near exclusively supplies the region's water (CILSS, 2016; Dixon et al., 2001). Despite this, the region has the highest agricultural growth potentials in Africa due to its low population density and abundance of underutilized cultivated land (Dixon et al., 2001). Furthermore, compared to millet and sorghum grown in the region, maize is far more drought vulnerable, which makes it particularly sensitive to changes in the WAM (Brouwer et al., 1989). Together, these facts motivate the specific use of maize in this study's analysis.

1.1.3 Expanding on an Understudied Region

The relationship between crop yields and precipitation in SSA is not fully established in literature, providing motivation for this study. An early paper suggests using satellite data alongside ground measurements for developing an early famine warning in SSA (Hutchinson, 1991). However, the paper notes that nationally reported crop yields, satellite derived normalized vegetation index (NDVI), and crop models are limited in accuracy and data availability (Hutchinson, 1991). Meteorological satellites, proxy measurements for soil moisture, and on-ground rain measurements also have their limitations (Hutchinson, 1991). Advancements in data collection, modeling, and computing have reduced these limitations and allowed for further study into rainfall and crop yields, an example of which is seen in the release of Google Earth Engine, a service providing an accessible platform for retrieving and analyzing a diverse collection of spatial data (Gorelick et al., 2017). In Berg et al. (2010), climate forcing models were used to test the sensitivity of crop models to errors in rainfall datasets in SSA. To test the sensitivity of the crop models, 1° x 1° resolution climate forcing models for rainfall were constructed using a combination of NCEP/NCAR global meteorology reanalysis datasets and rain gauge data (Berg et al., 2010). The analysis used four West African countries and aggregated rainfall annually, which masked the data's drizzle bias in which the annual total precipitation is accurate but the distribution of rainfall contains more rainy days than occurs naturally (Berg et al., 2010). In a study that used validated crop models and a synthetic rainfall model, sorghum yields were found to be sensitive to rainfall frequency and intensity, with intensity being more beneficial to crop yields than frequency (Guan et al., 2015). In Hoscilo et al. (2015), 8 km resolution total annual rainfall and NDVI were used to analyze the relationship between rainfall and vegetation growth in SSA. While some spatial areas showed a relationship between increased rainfall and increased vegetation growth, other areas demonstrated the opposite relationship, even in neighboring countries (Hoscilo et al., 2015). Finally but not exhaustively, Rishmawi et al. (2016) used NDVI and 1° x 1° resolution NCEP/NCAR reanalysis data corrected for rainfall biases using rain gauge observations, finding that linear and multivariate regressions between total annual precipitation, total growing season precipitation, and seasonal precipitation variation were significantly related.

Similar to Hoscilo et al. (2015), the study did not establish significance across the entire analysis space, but found that growing season NDVI was positively related to total precipitation while negatively related to seasonal precipitation variation (Rishmawi et al., 2016).

While the aforementioned studies demonstrate the relationship between precipitation and crop growth, open questions regarding how reported historical crop yields relate to features of the WAM remain. While NDVI is a commonly used proxy for crop yields, it has its limitations in SSA due to the lack of on-ground crop statistics for verification and of high-resolution imagery required to capture small field sizes (Petersen, 2018). Otherwise, there is limited work that uses nationally reported yields gathered by the Food and Agriculture Organization of the United Nations (FAO), which could provide a more direct connection between precipitation and crop yields despite the country-size resolution and the shortcomings of its data collection methods (FAO, n.d., 2016). Schlenker and Lobell (2010) uses a panel of variables to model the impact of climate change on agriculture in SSA, including country-level crop yield data from the FAO, an 1^{o} x 1^{o} resolution NCEP/NCAR reanalysis recalibrated to a monthly observed precipitation dataset, and the monthly observed dataset itself. When the study measured the individual effect of total precipitation on crop yields for maize, total precipitation had little impact on yield (Schlenker & Lobell, 2010). The study included countries across SSA that can vary greatly in climate and agricultural practices, which may be why the study found total precipitation to have little impact on yields despite precipitation's importance to agriculture in the region (Hoscilo et al., 2015; Ray et al., 2015; Sassi, 2015; Schlenker & Lobell, 2010). In terms of using features of the seasonal rain pattern, there is a lot of work characterizing the dynamics of the WAM (Biasutti, 2019; Nicholson, 2013). However, studies combining precipitation and vegetal growth often do not consider monsoon dynamics that potentially impact agriculture, like duration and intensity. Such characteristics could provide valuable insight into crop yields and cannot be captured by total or average precipitation alone. Despite this, total and average precipitation is commonly if not exclusively used in studies of crop yields, often finding that total and average precipitation has an insignificant relationship with crop yields. Moreover, studies on monsoon dynamics have been limited by data availability and quality in addition to an overall decline in rain-gauge data for the region since 1990 (Biasutti, 2019; Climate Hazards Center, 2020a, 2020b; Nicholson, 2013). However, the current availability of high-resolution, daily precipitation data that limits drizzle bias and is well validated against on-ground measurements now motivates a detailed analysis of how precipitation characteristics of the WAM affect crop yields (Climate Hazards Center, 2020a; Gorelick et al., 2017).

1.2 Problem Statement

As discussed in the previous section, studies on the relationship between precipitation and crop yields in West Africa have been limited by data availability, data quality, and under acknowledgement of the underlying monsoon dynamics of the region. This study aims to address these gaps in the literature by analyzing the spatially distributed characteristics of the WAM against country-reported crop yields in West Africa. Furthermore, this study verifies the efficacy of using precipitation data with a high spatiotemporal resolution in a region where in-situ rain measurements are sparse and global data products are often less reliable.

1.3 Study Area

The WAM is a rainy season in West Africa that provides nearly all of the region's annual precipitation and plays an important role in the region's agriculture (Dixon et al., 2001). In the classical description for the WAM's dynamics, the Intertropical Convergence Zone (ITCZ) that is generally near the equator moves Northward with seasonal insolation, bringing moisture and precipitation to West Africa (Nicholson, 2013; Sultan & Janicot, 2003). At the end of the WAM, the ITCZ moves Southward, and the region undergoes a dry season (Nicholson, 2013; Sultan & Janicot, 2003). In a description of the WAM's dynamics that is more typical of monsoon systems, the WAM is caused by differential heating between the African continent and the Atlantic Ocean(Nicholson, 2013). When insolation is high during the summer, a low-pressure zone forms over the continent, drawing moist air from the Atlantic (Nicholson, 2013). When insolation decreases, the continent cools while the Atlantic retains its temperature, reversing the effect of the winds (Nicholson, 2013). In both schemes, the pattern of movement suggests that lower latitudes will experience an earlier monsoon onset, a longer monsoon season, and more precipitation over the season (Figure 1).

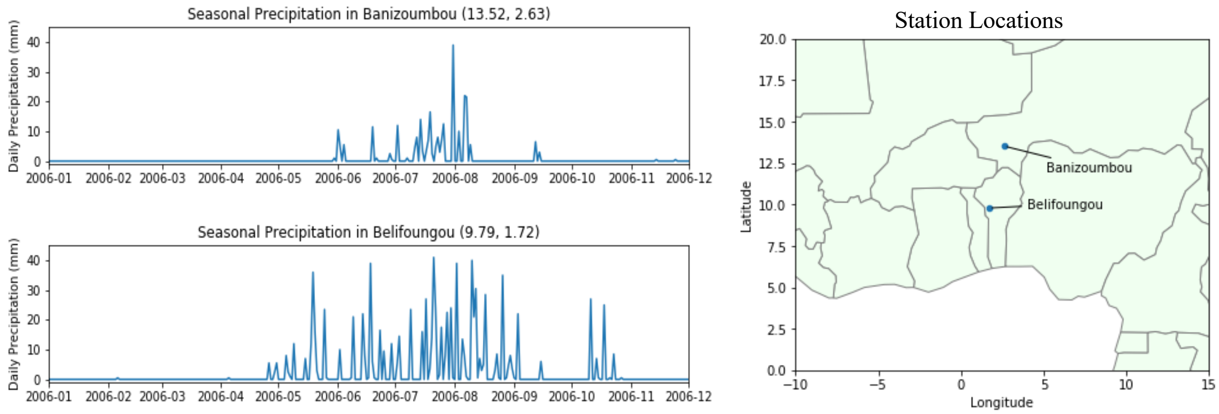


Figure 1: Plotting the daily precipitation logged by two AMMA automatic weather stations in 2006 demonstrates the seasonality of precipitation in the region due to the WAM. Belifoungou experiences more precipitation and an earlier onset date because it is located farther south than Banizoumbou.

As discussed in Section 1.1.3, previous work characterizing the dynamics of the WAM have been limited by data availability. Nevertheless, there is substantial study characterizing the WAM, including its interannual variability and rainfall (Biasutti, 2019; Nicholson, 2013; Odoulami & Akinsanola, 2018; Zhang & Cook, 2014). Of particular importance in this study is the study of the WAM's onset date, which can vary greatly depending on the region of interest, data used, and definition for onset (Bombardi et al., 2019; Diaconescu et al., 2015; Dunning et al., 2016; Fitzpatrick et al., 2015; Marteau et al., 2009; Sultan & Janicot, 2003). Definitions of monsoon onset are further discussed in Section 2.2.1.1.

As introduced in Section 1.1.2, the cereal-root crop mixed system is an agriculturally significant region of West Africa (Dixon et al., 2001). It is an agricultural belt of SSA stretching from the West African coast to Central Africa in a classification by the FAO and the World Bank (Auricht et al., 2014; Dixon et al., 2001). As described previously, the region is vulnerable to droughts and climate change as a dry sub humid region that is dependent on the WAM for water (CILSS, 2016; Dixon et al., 2001). Maize, sorghum, millet, cassava, yams, legumes, and cattle are the main agricultural products cultivated in the system, many of which are staple crops in West Africa (Dixon et al., 2001). As this study focuses on analyzing the relationship between maize yields and precipitation characteristics of the WAM, the location of this region is hereafter referred to as the maize belt.

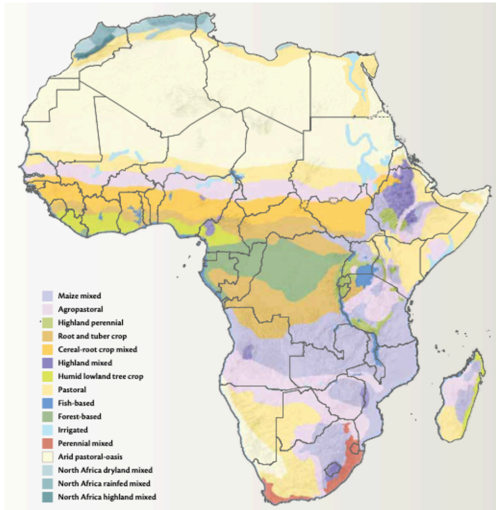


Figure 2: Map of farming systems in Africa (Auricht et al., 2014). The maize belt is a part of the cereal-root crop mixed system, which stretches from Guinea to South Sudan in orange (Auricht et al., 2014; Dixon et al., 2001).

2 Materials and Methods

2.1 Data

2.1.1 FAOSTAT

The FAOSTAT database publishes metrics on annual crop yields, crop production, and area harvested of 173 crops in over 254 countries (FAO, 2020). The FAO compiles information for the database through annual questionnaires and national publications (FAO, n.d.). For completeness, official data may be supplemented with data from various agencies, organizations, or unofficial sources (FAO, n.d.). Because self-reporting can result in inconsistent, erroneous, or missing data, the FAO has worked to validate, fill in, and revise data from 1991 onwards according to their most recent standards (FAO, 2016). According to the FAO, production data for maize in Sub-Saharan West Africa did not have a Relative Mean Absolute Revision exceeding 10%, which suggests that the impact of the FAO's revision process was low in the data of interest. Thus, maize yield data from FAOSTAT was selected for this study.

In preliminary analyses of maize yields in target countries, it is clear that maize yields have been increasing for the last three decades (Figure 3). In West Africa, the growth in maize yields comes mainly from changing cultivation intensity, crop variety selection, and other factors, not climatic causes (Hollinger & Staatz, 2015; NEPAD, 2013). To remove these extraneous variables from the yield data, the data needs to be detrended, which is described in further detail in Section 2.2.3.

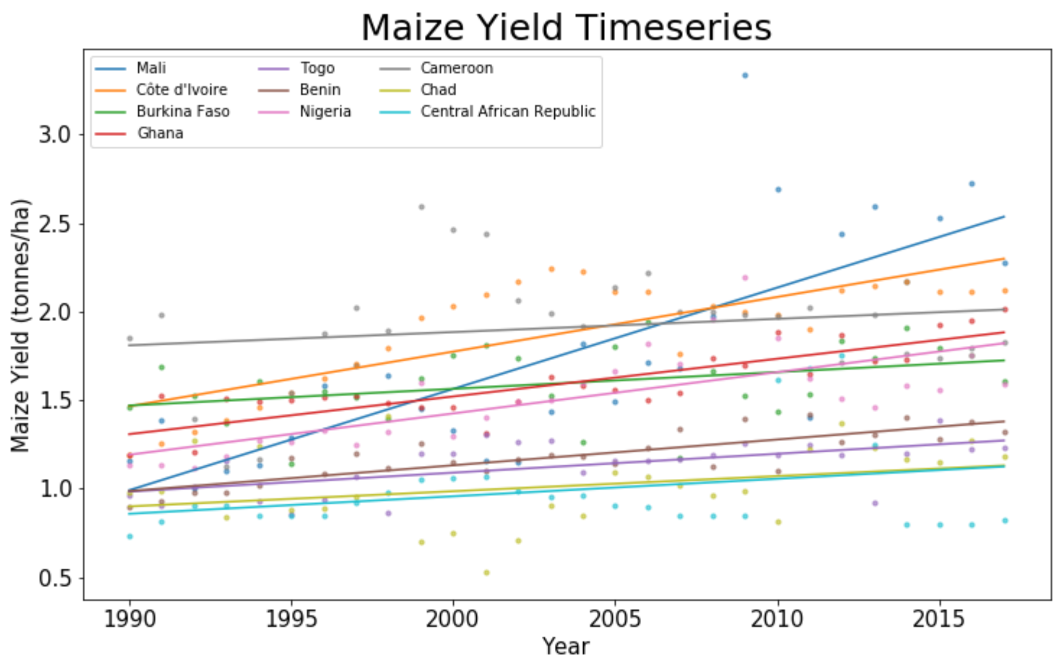


Figure 3: Maize Yields plotted for target countries from 1990-2017 show increasing yields in the last 3 decades for all countries. With the exception of Mali and Côte d'Ivoire, countries are generally increasing at the same rate. Plots for each country are included in Appendix A.

2.1.2 Climate Hazards Group InfraRed Precipitation with Station Data Version 2.0

Precipitation variability, onset, end, and annual totals are potential determinants of crop yield that require accurate, daily, high-resolution data to calculate. Publicly available data from the Climate Hazards Group InfraRed Precipitation with Station data Version 2.0 (CHIRPS v2.0) provides the necessary data for analyzing properties of precipitation in the WAM (Climate Hazards Center, 2018).

CHIRPS v2.0 is a daily, pentadal, and monthly precipitation dataset from 1981 to the present spanning a 0.05° resolution grid at all longitudes between 50°S and 50°N latitude (Funk et al., 2015). Production of CHIRPS v2.0 data involves interpolating and regressing values from on-ground rain-gauge stations, satellite precipitation estimates, and physiographic characteristics (Funk et al., 2015). The methodology addresses biases from satellite data that do not factor complex terrain in their precipitation models as well as biases from sparsity of on-ground precipitation data in rural regions (Funk et al., 2015). Additionally, the methodology prevents drizzle bias in daily, pentadal, and monthly time ranges by considering non-precipitating days in its aggregations and disaggregations of available precipitation data (Funk et al., 2015).

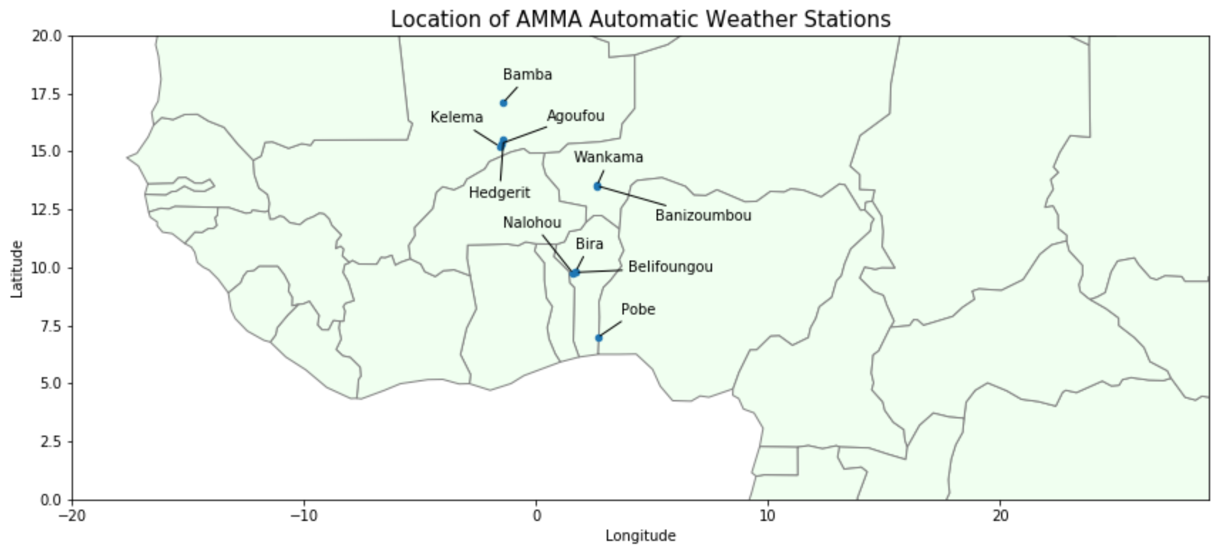


Figure 4: Location of automatic weather stations data provided by the AMMA project.

To further justify the use of CHIRPS v2.0, automatic weather station data provided by the African Monsoon Multidisciplinary Analysis (AMMA) project and gridded data from Modern-Era Retrospective for Research and Applications Version 2 (MERRA-2) were used for comparison. A limited dataset requested from the AMMA project yields data from 10 automatic weather stations measuring daily precipitation during the 2005-2007 monsoon seasons in West Africa (Figure 4) (NERC AMMA-UK & Parker, 2007). MERRA-2, like CHIRPS v2.0, has daily, high-resolution precipitation data spanning multiple decades with a 0.5°x0.66° resolution grid from 1979-2016 (Gelaro et al., 2017).

The in-situ data points from AMMA can be used to validate precipitation values at the equivalent location and time from CHIRPS v2.0 and MERRA-2. Plotting the matched precipitation measurements and their distributions, CHIRPS v2.0 more closely matches the in-situ values from AMMA. While neither CHIRPS v2.0 nor MERRA-2 are perfect matches with AMMA, CHIRPS v2.0 is more correlated with AMMA and has a lower mean squared error (Figure 5). CHIRPS v2.0 better captures the number of days with 0-10 mm of rain and the presence of heavy rain events with >40 mm rain (Figure 6). This conclusion is further strengthened when comparing the number of non-precipitating days at each station (Figure 7). Against AMMA's in-situ measurements, MERRA-2 appears to be unable to capture the number of non-precipitating days while CHIRPS v2.0 only slightly underestimates that value. Faithfully representing non-precipitating days is significant in the context of crop yields, as crops are almost exclusively rainfed in SSA and non-precipitating days can be a contributing factor to low crop yields (Dixon et al., 2001). Additionally, certain definitions of monsoon onset and end can be highly sensitive to non-precipitating days, so an accurate representation is crucial. As such, CHIRPS v2.0 is an appropriate choice for analyses between precipitation in the WAM and crop yields.

a. Correlation = 0.46, MSE = 49.51

b. Correlation = 0.18, MSE = 59.18

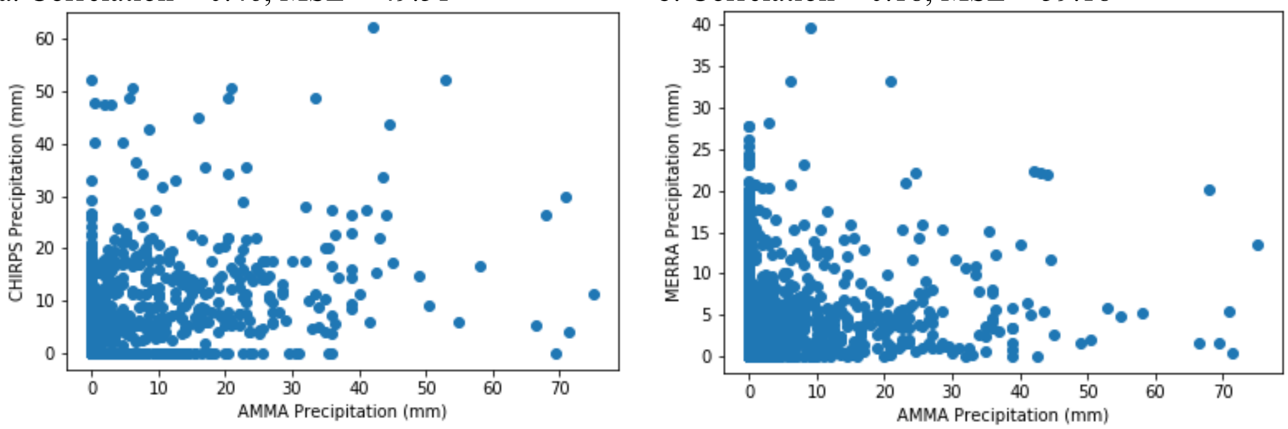


Figure 5: a.) Location and date-matched precipitation measurements between AMMA and CHIRPS v2.0. b. Location and date-matched precipitation measurements between AMMA and MERRA-2.

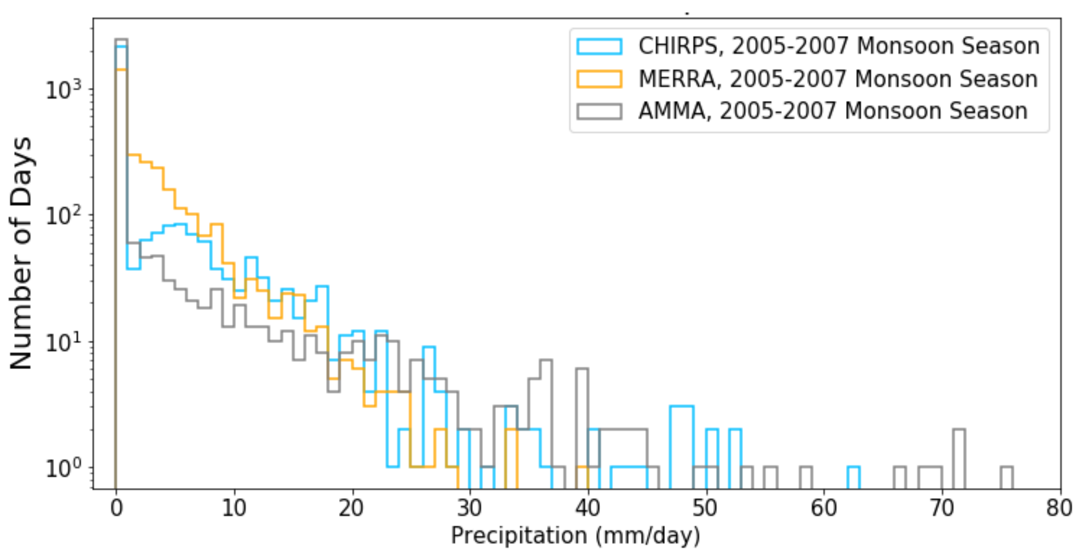


Figure 6: Distribution of location and date-matched monsoon-season precipitation values in AMMA, MERRA-2, and CHIRPS v2.0. CHIRPS v2.0's distribution is more similar to AMMA's distribution, particularly in capturing the number of days with 0-10 mm of rain and days with heavy rain exceeding 40 mm. This suggests that CHIRPS v2.0 is a better candidate for use of characterizing the monsoon dynamics of the region. The distributions for each of the 10 stations are included in Appendix B.

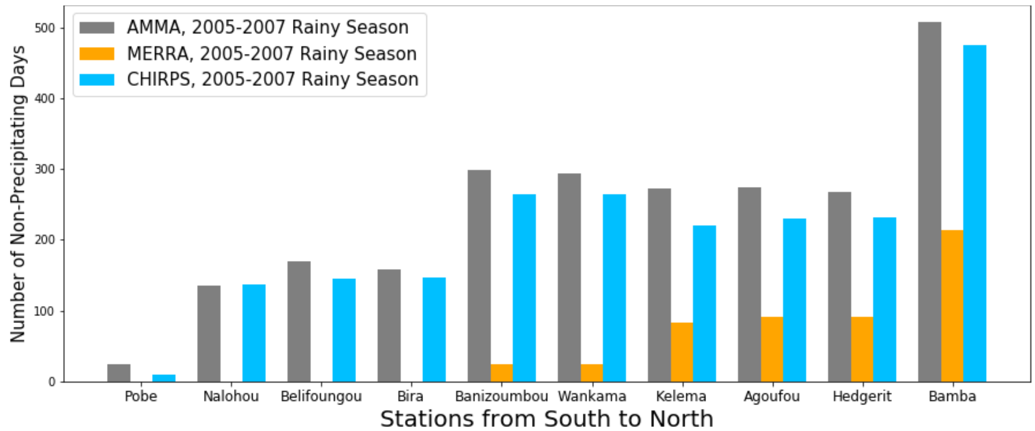


Figure 7: Number of non-precipitating days observed at each station for AMMA, MERRA-2, and CHIRPS v2.0 at matched locations and dates. AMMA and CHIRPS v2.0 have a similar number of non-precipitating days while MERRA-2 underestimates the number, suggesting that MERRA-2 data is sensitive to drizzle bias.

2.2 Analyses

2.2.1 Precipitation Metrics

Gridded daily precipitation values from 7°N-13°N latitude and 17°W-30°E longitude were used to calculate annual metrics of the WAM, producing a value per grid cell over West Africa from 1990-2017. These metrics are later aggregated and regressed against maize yields in Sections 2.2.2 and 2.2.3.

2.2.1.1 Monsoon Onset, End, and Duration

As farmers rely on the rainy season to water their crops, the timing of the WAM's onset, end, and duration can influence crop yields. As introduced in Section 1.3, there are many ways to define monsoon onset and end. For using precipitation data, onset can be defined using thresholds on precipitation amounts, values met at specific latitudes, or days of rain (Fitzpatrick et al., 2015). The thresholds and metrics for meeting these definitions have a level of subjectivity as these values can be chosen somewhat arbitrarily (Fitzpatrick et al., 2015). In definitions that are agriculturally significant, a minimum threshold for precipitation over a defined period of days can be used (Dunning et al., 2016; Marteau et al., 2009). However, a measure that can be generalized across regions with diverse hydroclimatology is preferred due to the high spatial variability of the monsoon's precipitation characteristics (Odoulami & Akinsanola, 2018). Bombardi et. al (2009) provides such a method in which the minimum and maximum of the cumulative precipitation anomaly are the onset and end dates respectively. Equation 1 calculates the cumulative anomaly S_{yt} for the date t at year y. In the equation, p_i is the daily precipitation at date i while $\bar{p}_y$ is the mean daily precipitation for year y. Subtracting $\bar{p}_y$ from p_i results in the daily anomaly at i, and summing the daily anomaly from January 1st up to day t produces the cumulative anomaly.

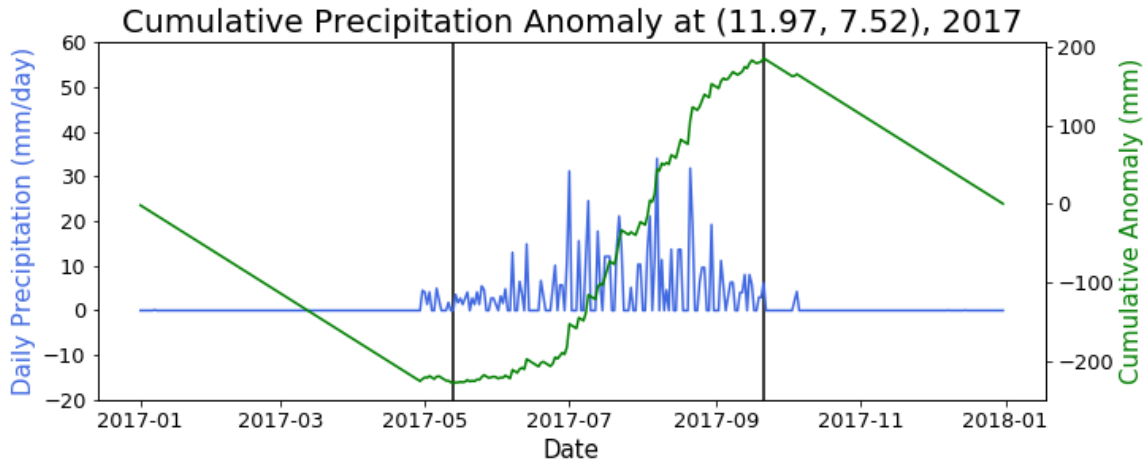
$$S_{yt} = \sum_{i=1}^{t} p_i - \bar{p}_y$$

Equation 1: Cumulative anomaly of precipitation.

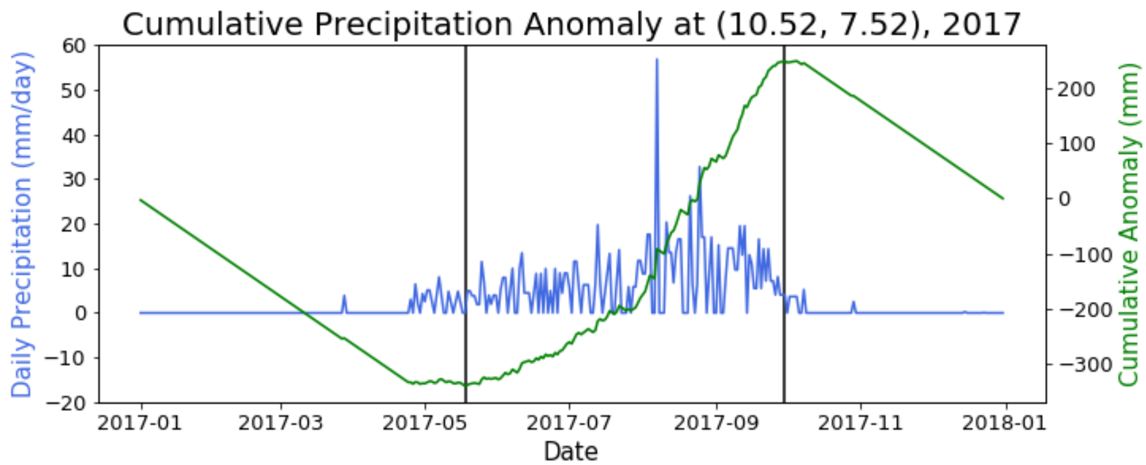
Once the cumulative anomaly for each day in a year is calculated, the day in which the minimum cumulative anomaly occurs is taken as the monsoon's start date while the day at which the maximum cumulative anomaly occurs is taken as the monsoon's end date. This effect occurs because over a year, cumulative anomaly decreases during the dry season until it begins increasing at the monsoon season. Cumulative anomaly subsequently decreases when the dry season returns. This produces a minimum when precipitation returns for the monsoon season and a maximum when precipitation ends. Because cumulative anomaly continues to increase or decrease according to the season, rain events during the dry season and non-precipitating days during the monsoon season, do not affect where the minimum or maximum occurs. Additionally, because cumulative anomaly does not change its slope unless there is a strong and prolonged change in precipitation between the seasons, the method avoids false starts and ends. Variations of this method have been used in multiple studies of monsoon onset (Bombardi et al., 2019; Diaconescu et al., 2015; Fitzpatrick et al., 2015).

Figure 8 visualizes the precipitation, cumulative anomaly, and resulting monsoon start and end dates. Because the WAM travels from South to North and North to South during the monsoon season, lower latitudes tend to have two rainy peaks that the cumulative anomaly method cannot distinguish. However, locations a. (11.97, 7.52) b.(10.52, 7.52) and c.(9.02, 7.52) in Figure 8 form a longitudinal transect through the range of the maize belt and each show one overall peak. Consequently, the cumulative anomaly method requires no adjustments to account for two peaks.

a.



b.



c.

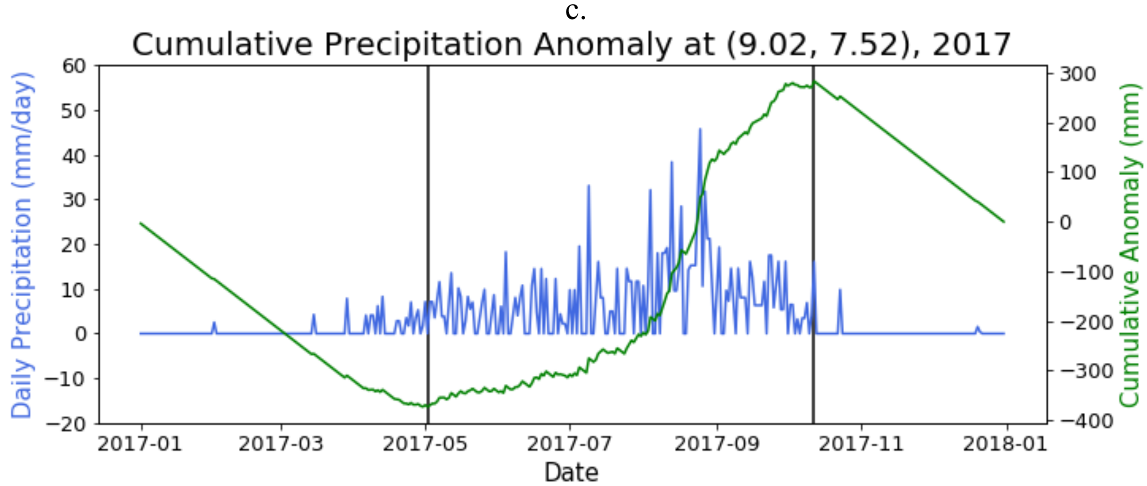


Figure 8: Cumulative precipitation anomaly plotted over daily precipitation in 2017 at locations: a. (11.97, 7.52) b. (10.52, 7.52) and c. (9.02, 7.52). Black horizontal lines indicate the minimum and maximum of cumulative anomaly, which correspond to the monsoon start and end dates respectively. At lower latitudes, the monsoon season begins earlier and ends later, as the WAM moves from South to North at the beginning of the season and North to South at the end. There is only one precipitation peak in our region of analysis, which points to the propriety of using this definition of monsoon onset and end.

2.2.1.2 Non-Precipitation Days

The non-precipitation days metric is defined as the number of days during each year's monsoon season that have 0 mm of rain. The monsoon season is defined as the days between monsoon onset and end as calculated in Section 2.2.1.1. Because farmers rely on rain to water their crops, days without rain can be detrimental for production (Dixon et al., 2001). Calculating the number of non-precipitation days over the monsoon season is a measure of this effect.

2.2.1.3 Total Precipitation

In each grid cell, total precipitation is defined as the sum of daily precipitation over a year. Total precipitation allows analysis of whether grid points meet the water requirements of maize, which is approximately 500-800 mm of water per growing season depending on climate (Brouwer & Heibloem, 1986). While farmers rely on the monsoon's onset to plant their crops, planting schedules do not necessarily occur at the onset date defined in this study. Some rain occurs before the monsoon onset and little rain occurs during the dry season. Thus, total precipitation over an entire year, rather than over the defined monsoon season, is calculated as a precipitation metric.

2.2.2 Aggregating to Timeseries

With precipitation metrics for each grid cell and year calculated, metrics need to be aggregated to one value per country per year to match annual country-level maize yield values. For each year, grid cells within the borders of each country and the approximated maize belt (see Table 1 and Figure 9 for latitude bounds of the maize belt for each country) were aggregated with a panel of functions: standard deviation, mean, median, minimum, maximum, and range. The total precipitation metric was aggregated by three additional functions based on the water needs of maize, the proportion of grid points within the boundaries that have a total precipitation: >1200mm, >800mm, and 500-800mm. Figure 10b plots one such example of an aggregated metric in which the standard deviation of the number of non-precipitating days across a country's grid cells was calculated for each year. While using the spatial average of precipitation metrics is typical when analyzing precipitation's relationship with crop yields, this study hypothesizes that spatial variation and extremes in precipitation metrics are also related to crop yields. For example, by taking the minimum of total precipitation among the grid points of a country's maize belt, it is expected that all other grid points have at least that much rain, which may or may not meet the water needs of maize as a representation of the worst performing regions. As a result, the minimum of total precipitation can be related to maize yield in a way that cannot be captured by the average total precipitation.

	Maize Belt Lower Latitude	Maize Belt Upper Latitude
Benin	8.4	11.4
Togo	8.5	11.2
Cameroon	7.1	9.6
Mali	10.0	12.7
Ghana	8.5	11.3
Burkina Faso	9.3	11.5
Nigeria	8.1	11.4
Guinea	9.3	10.8
Côte d'Ivoire	8.6	10.8
Central African Republic	7.2	10.2
Chad	7.3	10.6
Senegal	12.0	13.0
Guinea-Bissau	10.8	12.8
Sierra Leone	9.4	10.1

Table 1: Latitude extents of the maize belt estimated from Auricht et al. (2014) seen in Figure 2.

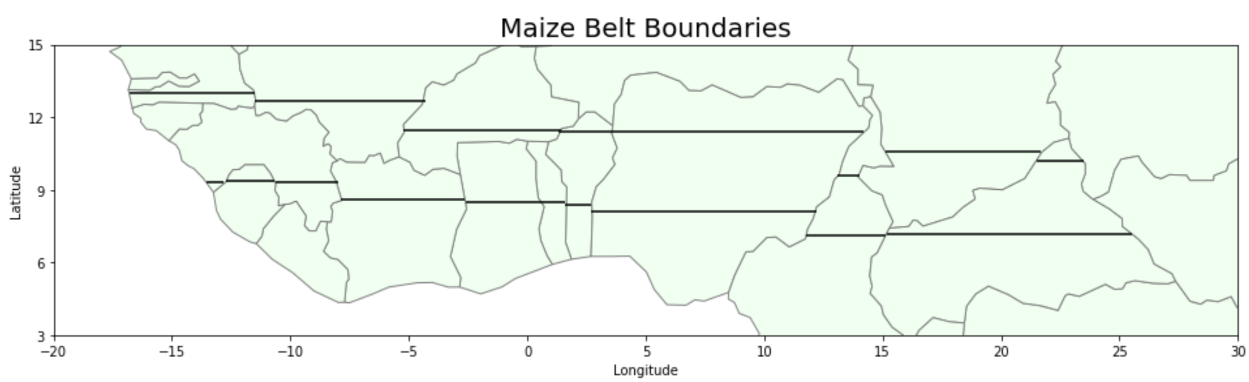


Figure 9: Estimated maize belt boundaries for each country plotted according to Table 1.

2.2.3 Timeseries and Regression Analyses

As discussed in Section 2.1.1, preprocessing of the maize yield timeseries for each country is necessary to remove the increase in yields occurring independently of climatic changes from the last three decades. Thus, an ordinary least squares regression line was fit to and subtracted from the maize yield timeseries for each country, which can be alternatively described as finding the residuals of a linear model of maize yield. To maintain interpretable units in the residuals, the mean annual maize yield of each country was added back to the residuals. Ultimately, this preprocessing produced linearly detrended maize yields for each country.

Equipped with an annual timeseries of linearly detrended maize yield and aggregated precipitation metrics for each country, the two sets of values (Figure 10 a and b) are merged and correlated against each other (Figure 10c).

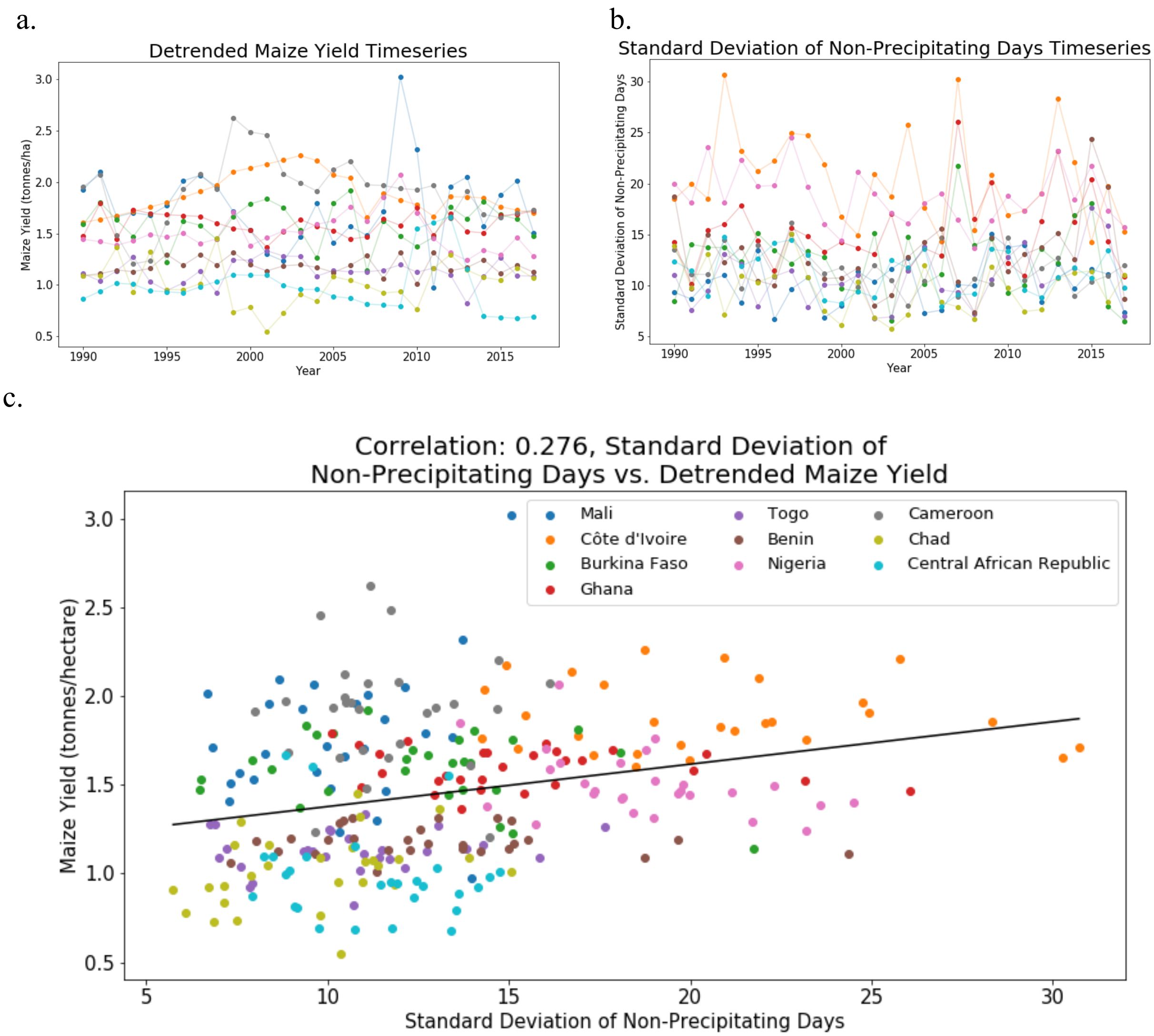
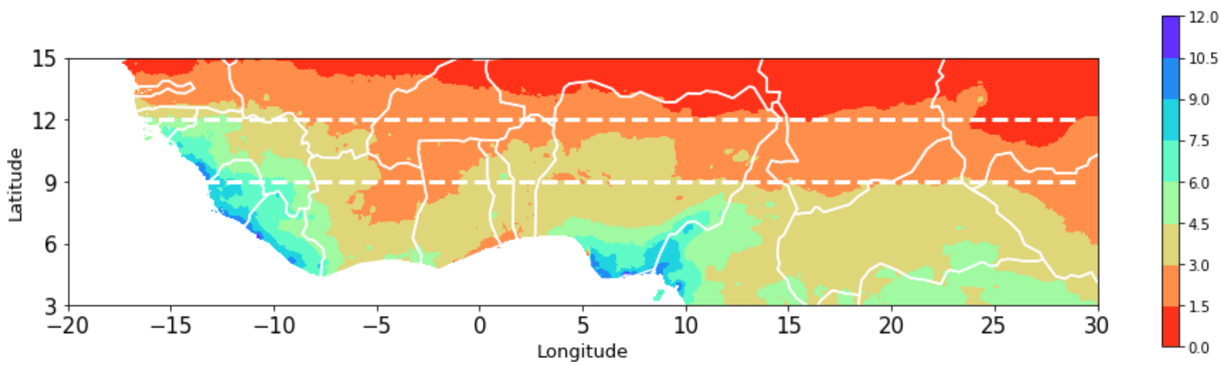


Figure 10: a. Detrended FAO maize yield timeseries for each country of interest from 1990-2017. The data requires detrending to remove the effect of activities increasing maize yields that are independent of precipitation. b. An example calculation of the standard deviation of non-precipitating days within the borders of each country across time. c. After matching the aggregated metric and maize yield by country and year, the two variables were linearly regressed. The resulting correlation and regression line are plotted.

2.2.4 Country and Latitude Range Choice

The region of study is the overlap between the WAM and the maize belt. While CHIRPS v2.0 has data available from 1981-present, data was constrained to 1990-2017, as CHIRPS v2.0 data from the 1980s is heavily interpolated while crop yield data from the FAO after 2017 is unavailable. Mapping the mean and standard deviation of daily precipitation from 1990-2018 shows the structure of precipitation in West Africa (Figure 11). The latitudes bordering the maize belt were visually estimated for each country in the cereal-root crop system (Table 1 and Figure 2), and the approximate mean of those latitudes outlines the maize belt in Figure 11. Overall, the mean and standard deviation of precipitation are homogenous throughout the maize belt with the exception of the West coast where the mean and standard deviation of precipitation is higher. Consequently, countries on the West coast were excluded from the analysis. The production per capita for each country is calculated to confirm that a requisite amount of maize is produced per country. Sierra Leone produces little maize per capita compared to other West African countries and has already been excluded from further analysis for being on the West coast. As such, 10 countries were used for further analysis.

a.



b.

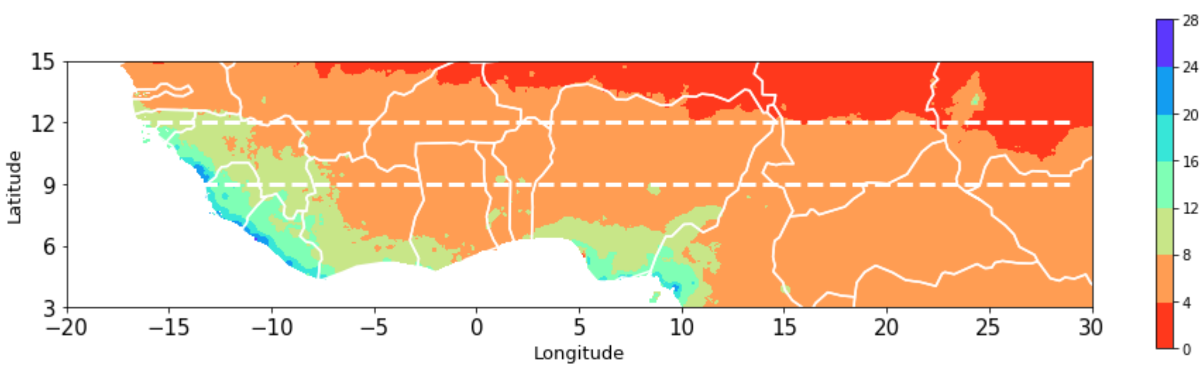


Figure 11: a. Mean daily precipitation from 1990-2018. The white dashed lines are the estimated latitude extents of the maize belt. b. Standard deviation of precipitation from 1990-2018. The white dashed lines are the estimated latitude extents of the maize belt.

	Production Quantity (thousands of tonnes)	Population Size (millions)	Production per Capita (tonnes/person)
Benin *	870	7.8	0.11
Togo *	540	5.5	0.095
Cameroon *	1100	17	0.062
Mali *	880	13	0.060
Ghana *	1300	21	0.059
Burkina Faso *	770	13	0.054
Nigeria *	6900	140	0.051
Guinea	430	9.0	0.045
Côte d'Ivoire *	630	18	0.036
Central African Republic *	100	3.8	0.027
Chad *	190	10.	0.017
Senegal	190	11	0.017
Guinea-Bissau	17	1.3	0.013
Sierra Leone	21	5.5	0.0037
United States of America	280000	290	0.95

Table 2: Mean maize production per capita from 1990-2017 of countries intersecting the maize belt. Starred countries are ultimately used in analyses of precipitation and crop yields.

3 Results and Discussion

After completing the timeseries and regression analyses between maize yields and aggregated precipitation metrics described in Section 2.2.3, the correlations and p-values associated with each aggregated precipitation metric were tabulated (Table 3 a and b). Scaled from -1 to 1, a higher absolute value of correlation suggests a stronger relationship between the aggregated precipitation metric and maize yields. Additionally, the r-squared value, calculated by squaring the correlation, demonstrates the percent of variability in maize yields described by the aggregated precipitation metric in the regression. P-values associated with the slope of the regression expresses the likelihood that the slope is equal to zero. Thus, a p-value less than 0.05 suggests that the slope of the regression line is statistically significant at the 5% statistical confidence level and that the aggregated precipitation metric is a meaningful variable in the regression model. Table 3 a and b are the correlation and p-value tables for all the countries while Appendix C has the country breakdown. Generally, the correlation and p-values in the tables using all countries are lower due to greater data availability and greater diversity of agricultural practices and economic resources between the countries. Conversely, the correlation and p-value for each individual country have higher values due to lower sample size and fewer extraneous variables between countries.

a. Correlations of Aggregated Precipitation Metrics Against Detrended Maize Yields for All Countries

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.062				
Proportion of Points >800mm	0.168				
Proportion of Points 500-800mm	-0.168				
Standard Deviation	0.156	0.276	0.167	-0.041	0.136
Mean	0.163	0.136	-0.006	0.040	0.024
Median	0.143	0.140	-0.004	0.010	-0.019
Minimum	0.209	-0.031	-0.054	0.288	-0.030
Maximum	0.042	0.153	0.108	0.061	0.058
Range	-0.034	0.181	0.119	-0.195	0.064

b. P-values of Slope Between Aggregated Precipitation Metrics Against Detrended Maize Yields for All Countries

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.3038				
Proportion of Points >800mm	0.0048				
Proportion of Points 500-800mm	0.0048				
Standard Deviation	0.0088	0.0000	0.0051	0.4904	0.0232
Mean	0.0064	0.0226	0.9146	0.5096	0.6833
Median	0.0165	0.0190	0.9446	0.8728	0.7556
Minimum	0.0004	0.6060	0.3724	0.0000	0.6152
Maximum	0.4795	0.0105	0.0710	0.3105	0.3361
Range	0.5689	0.0024	0.0467	0.0010	0.2839

Table 3: a. Linear correlations between the aggregated precipitation metric indicated in the table and detrended maize yields. The blue shades for each cell represent the strength of the correlation. The analysis includes all countries and years from 1991-2017. The columns are the precipitation metrics and the rows are the aggregating functions used on the yearly gridded precipitation metrics within the maize belt of each country. The visual representation of this analysis between maize yields and the standard deviation of the number of zero precipitation days is in Figure 10. b. Using the same regression analysis in Table 3a, this table represents the p-values of the slope in the linear regression between the aggregated precipitation metric indicated in the table and detrended maize yields. The trend indicated by a positive or negative correlation value is considered statistically significant when the p-value of the slope is less than 0.05 which is indicated in black. P-values whose values are greater than 0.05 are colored in red.

Three aggregated precipitation metrics have particularly high correlation values and significant p-values when analyzing all countries together: minimum total precipitation, standard deviation of the number of non-precipitating days, and the minimum monsoon end date. While more investigation is necessary to determine the causal relationship between these aggregated precipitation metrics, there are some possibilities to consider.

For the minimum total precipitation and the minimum monsoon end date metrics, their relationship with maize yield may stem from agriculture's near exclusive reliance on precipitation in West Africa. The crop production in the region is rain-fed, and irrigation is not generally applied (Dixon et al., 2001). For minimum total precipitation, all grid points within the bounds of each country's maize belt have as much if not more rain than the minimum aggregated value. When the minimum total precipitation is high, the likelihood of meeting maize's watering requirements across most of the region is higher; and when the minimum total precipitation is low, the grid points facing the most water insecurity reduces the total production. Thus, maize yield's relationship with minimum total precipitation is positive and stronger than that of other aggregated precipitation metrics. For the minimum monsoon end date metric, an earlier end date results in a shorter growing season and less crop maturity. While one would expect that the minimum monsoon duration and maximum monsoon onset date metrics would have the same level of correlation as the minimum monsoon end date, the calculated onset dates and duration do not necessarily correspond to on-ground sowing schedules while the calculated end date marks when precipitation tapers to its end. Thus, the minimum monsoon end date, which occurs when the agriculture ceases, is more strongly correlated with maize yields. For these metrics, the worst performing locations drive variability in yield production such that yields are lower when the minimum total precipitation is low, and the minimum monsoon end date is early.

For the standard deviation of the number of non-precipitating days metric and the non-precipitating days metric overall, the positive values of the correlations suggest a positive trend between the metric and maize yield. These results are opposite of what is expected: that greater spatial variation in the number of non-precipitating days would lead to decreased maize yields as precipitation becomes less consistent and predictable over space. However, these results could be an instance of Simpson's paradox in which a trend occurs for the data overall but not for the data's subgroups. In the country breakdown of correlation tables in Appendix C, there is disagreement over whether the relationship between the non-precipitating metric and maize yields is positive or negative for each of the aggregating functions. Six out of the ten countries analyzed show a negative trend rather than the positive trend observed when all countries are organized together. This effect is plotted in Figure 12. However, with the exception of Nigeria whose slope is negative, the individual slopes for each country's metric regressed against maize yield is not statistically significant. Consequently, speculative proposals for why the standard deviation of non-precipitating days is related to maize yields cannot be made.

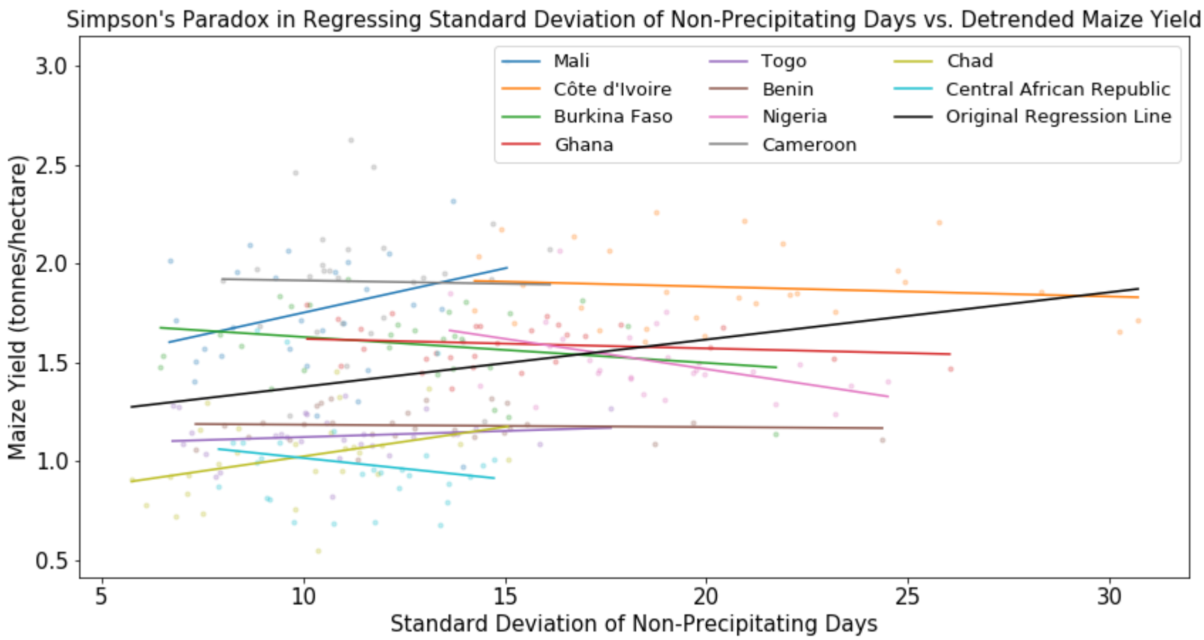


Figure 12: Same as the plot in Figure 10, the standard deviation of non-precipitating days is plotted against detrended maize yields. The regression line for data including all countries shows a positive trend between the metric and maize yields. However, when plotting individual regression lines for each country, six out of ten countries have a negative trend between the two variables. This suggests that Simpson's paradox is in play, in which the data's overall trend is different from trends seen in the data's subgroups.

Performing the same regression analyses by country yields higher correlations and fewer statistically significant p-values for slope (Appendix C). Correlations as high as -0.593 from regressing the median number of non-precipitation days in Togo against its yearly maize yields are achieved with a p-value of 0.001 for the slope. All correlations with an absolute value greater than or equal to 0.374 have a statistically significant slope, and 36 out of 330 regressions meet these values. A reason why many slopes are not statistically significant could be due to small sample sizes; for each country, a datapoint for maize yield and an aggregated precipitation metric exists for every year between 1990-2017. While there are approximately four decades of CHIRPS v2.0 data for precipitation and FAO data for maize yield, data from before 1990 is effectively lower in resolution and quality due to heavy interpolation of satellite data and lack of maize yield validation. Thus, sample sizes will remain small until future data is available.

On a different note, each country has unique significant correlations and p-values. For example, multiple aggregations of total precipitation and the number of non-precipitating days had high correlations and statistically significant slopes when regressed against maize yields in Nigeria. For Central African Republic, only some aggregations of total precipitation, monsoon onset, and monsoon duration were highly correlated and had statistically significant slopes. Differences in agricultural, economic, geographic, and social factors may be the cause for these discrepancies. Notably, because data from the FAO are calculated and reported by the originating country, there may be differences in data quality and data gathering ability between countries. Nevertheless, with the available data, fairly high correlations can be achieved on the country scale.

4 Conclusion

In this study, features of the WAM were regressed against maize yields in West Africa. CHIRPS v2.0, a high spatiotemporal resolution precipitation model, was used to derive features of the WAM while the FAO provided self-reported maize yields from each country.

This study demonstrated the advantages of using precipitation data with high spatiotemporal resolution. The data's high resolution and quality enabled extraction of features that are uniquely relevant to the region's climate and agricultural practices. West Africa in particular is a region where agriculture near exclusively relies on rain from the WAM. The WAM's features can be highly variable depending on location, which highlighted the need to extract features based on the total precipitation, the number of non-precipitating days during the season, and the monsoon's timing across space.

This study explored the relationship between precipitation characteristics of the WAM and maize yields using linear regression models. Minimum total precipitation and the earliest date when seasonal precipitation ends over each country and in each year was positively correlated with maize yields to a significant degree. When separating the data for analysis by country, each country had unique sets of aggregated precipitation metrics that were highly correlated with maize yields. Additionally, correlations increased while the statistical significance of the regressions' slopes decreased. These results point to a possible disadvantage of using self-reported yield data, as some countries may have provided higher quality data than others, leading to inconsistent correlations between countries. Other variables related to agricultural practices, climate, economics, and social factors outside the scope of this study may have also been at play.

Overall, this project added to the limited study between precipitation and crop yields in West Africa through the use of novel precipitation models with high spatiotemporal resolution.

5 Future Research

This study points to several potential avenues for future research. Firstly, applying the methods of this study to other datasets will be crucial in verifying that the results of this study are not spurious correlations. Potential sources of data for verification include modeled crop data, remote sensing measurements, alternative models for precipitation, and rain gauge data. Additionally, as maize was the main focus of this study, these methodologies may be expanded to other important crops in the region, like sorghum or millet. However, improvements in crop yield data may be necessary, as data from the FAO may be unreliable between countries. Next, the aggregated precipitation metrics used in this study are not exhaustive. Subjective definitions of monsoon onset and end date can be designed to be closely related to on-ground agricultural practices, which has the potential to produce stronger results. With enough computing power, such definitions could be tuned to produce the strongest result. The set of aggregated precipitation metrics can also be expanded to definitions such as the longest consecutive rainy spell and longest consecutive dry spell. Lastly, multivariate regression may be applicable using combinations of aggregated precipitation metrics or with the addition of other climatic variables like temperature, producing models that capture a more complex picture of how the WAM influences crop yields in West Africa.

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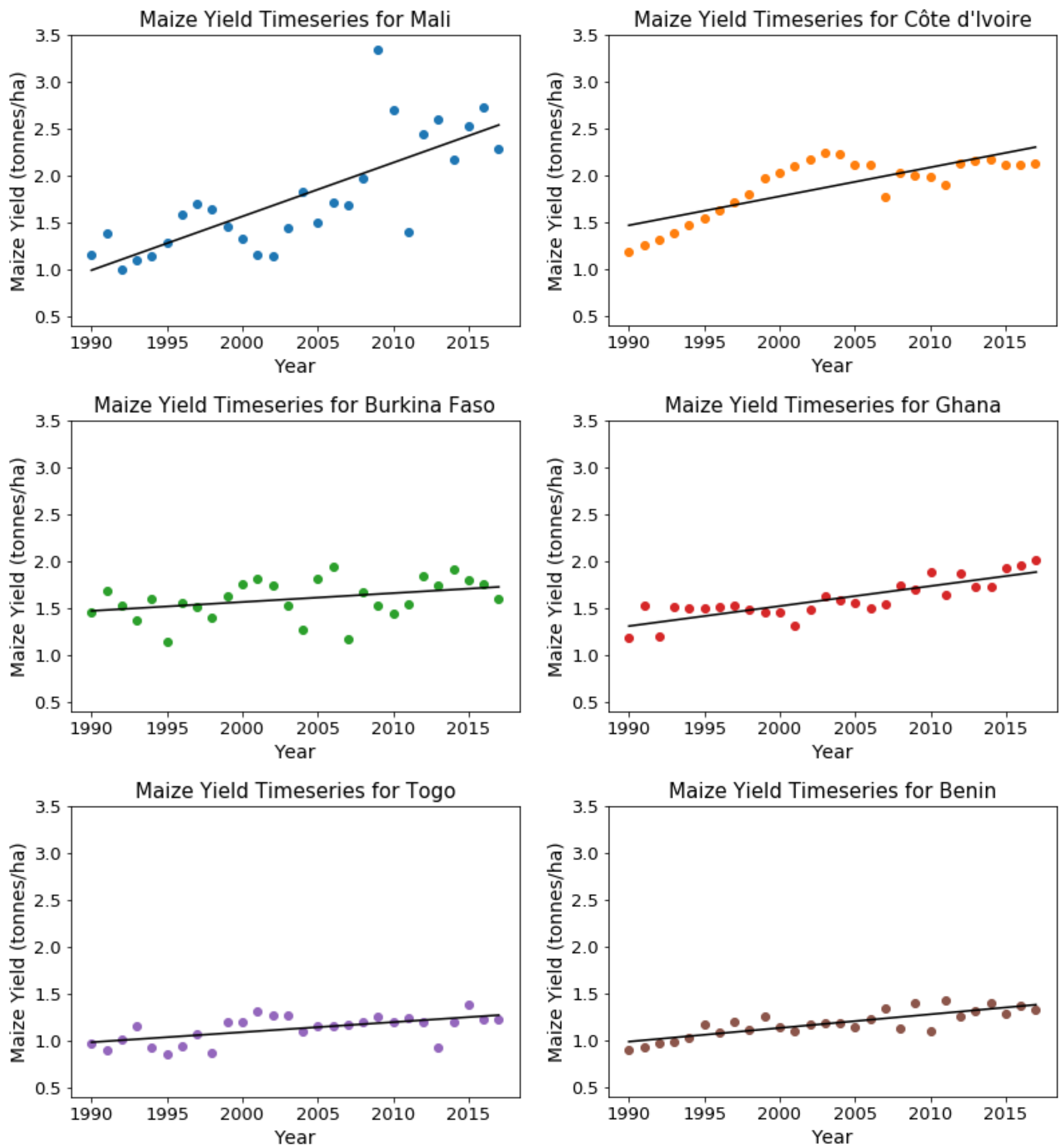
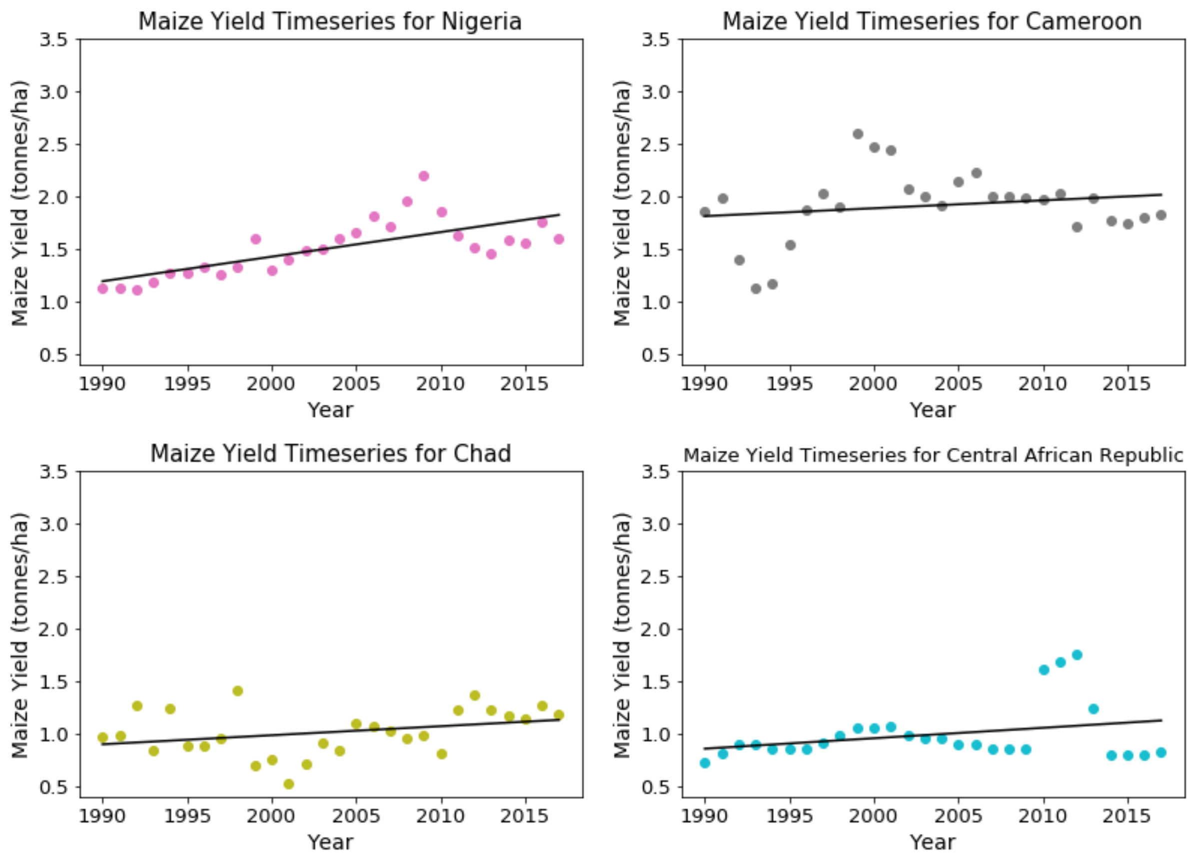
8 Appendix A

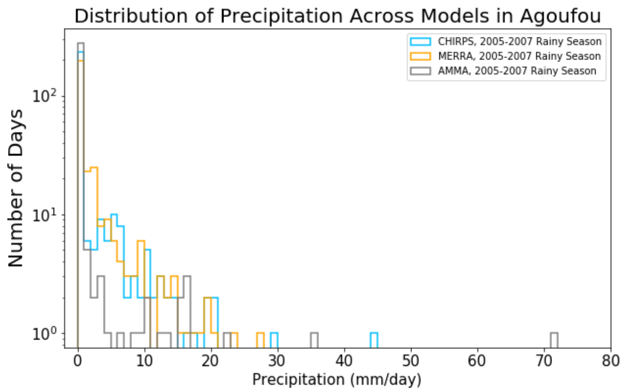
Plotted maize yields for each target country with a linear regression line demonstrate that most countries have increasing yields over time. The values of the lines are subtracted from each point to linearly detrend the data. To preserve the units, the mean maize yield for each country is added back to their respective points.

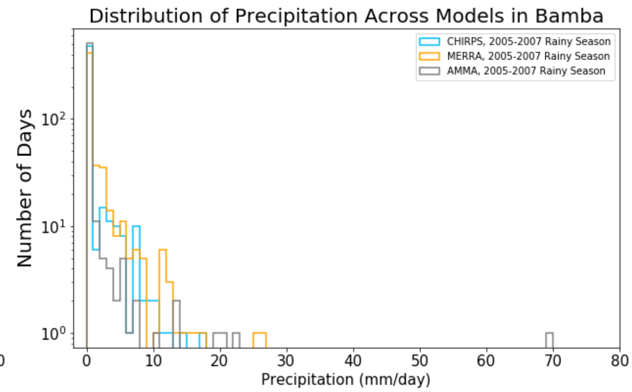


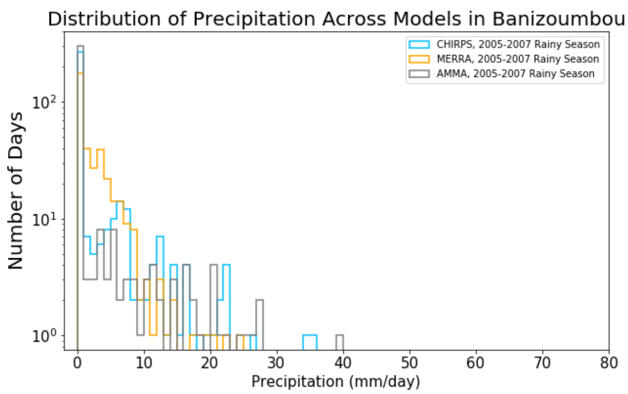

Maize Yield Timeseries for Nigeria
Maize Yield Timeseries for Cameroon
Maize Yield Timeseries for Chad
Maize Yield Timeseries for Central African Republic
Maize Yield (tonnes/ha)
Year
3.5
3.0
2.5
2.0
1.5
1.0
0.5
1990
1995
2000
2005
2010
2015

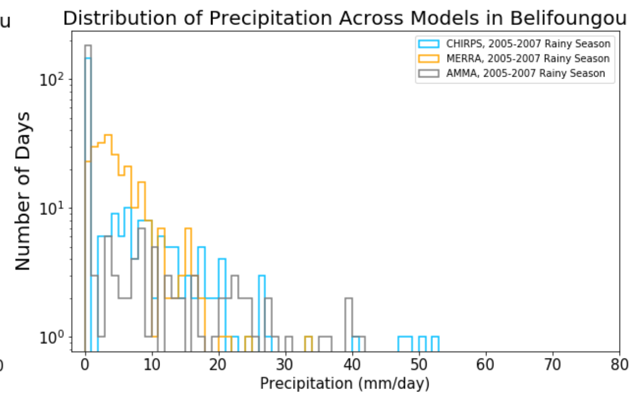
9 Appendix B

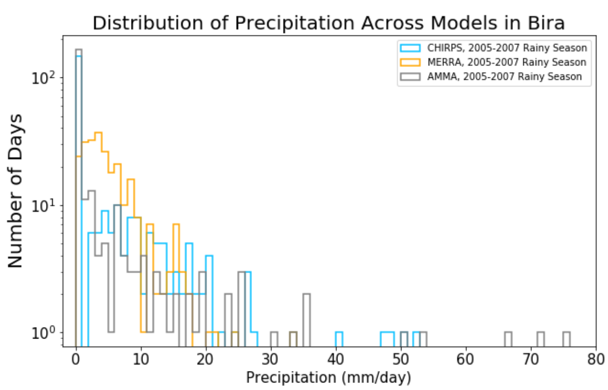
Distribution of location and date matched AMMA, MERRA-2, and CHIRPS v2.0 precipitation measurements for each of the 10 AMMA automatic weather stations.

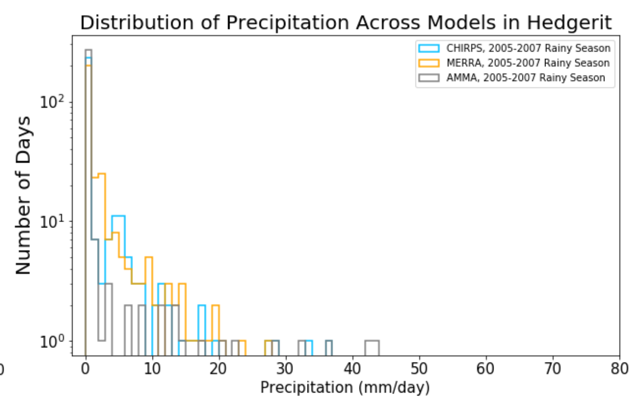


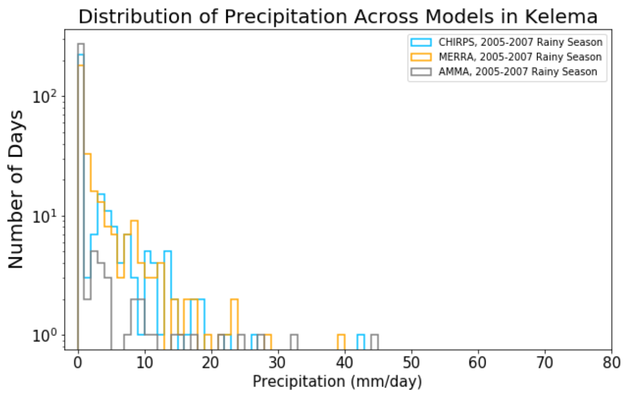


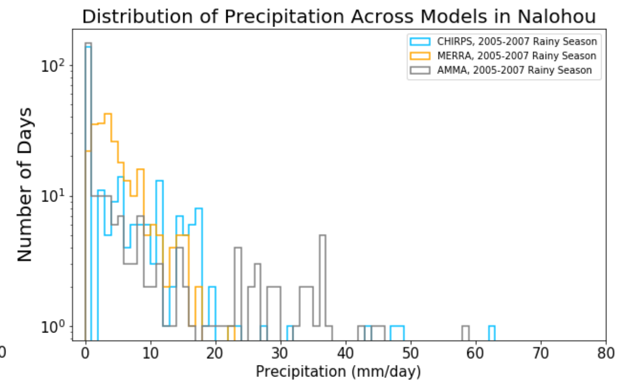


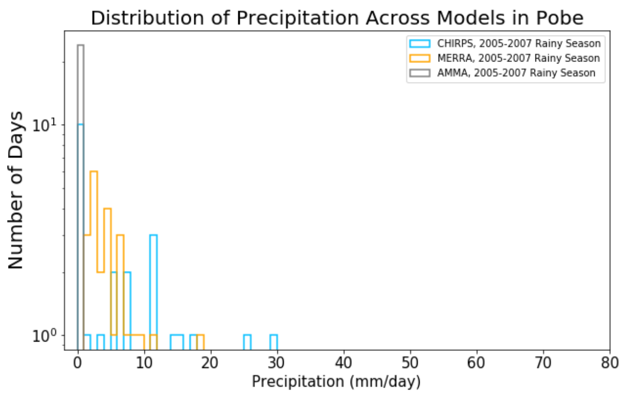


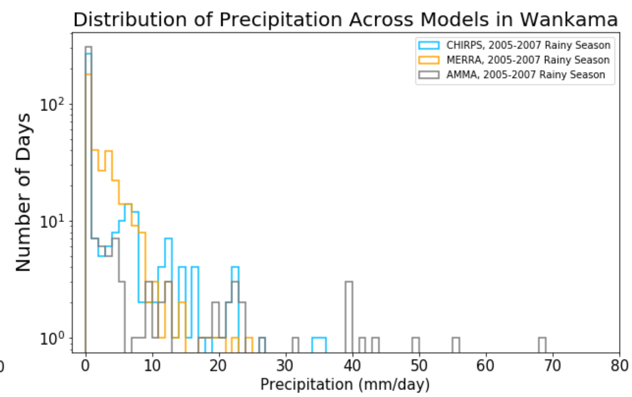





Distribution of Precipitation Across Models in Kelema
CHIRPS, 2005-2007 Rainy Season
MERRA, 2005-2007 Rainy Season
AMMA, 2005-2007 Rainy Season
Number of Days
Precipitation (mm/day)


Distribution of Precipitation Across Models in Nalohou
CHIRPS, 2005-2007 Rainy Season
MERRA, 2005-2007 Rainy Season
AMMA, 2005-2007 Rainy Season
Number of Days
Precipitation (mm/day)


Distribution of Precipitation Across Models in Pobe
CHIRPS, 2005-2007 Rainy Season
MERRA, 2005-2007 Rainy Season
AMMA, 2005-2007 Rainy Season
Number of Days
Precipitation (mm/day)


Distribution of Precipitation Across Models in Wankama
CHIRPS, 2005-2007 Rainy Season
MERRA, 2005-2007 Rainy Season
AMMA, 2005-2007 Rainy Season
Number of Days
Precipitation (mm/day)

10 Appendix C

Tabulated linear correlations and slope p-values between the aggregated precipitation metric indicated in the table and detrended maize yields for each target country. The blue shades for each cell in the correlation tables represent the strength of the correlation. The trend indicated by a positive or negative correlation value is considered statistically significant when the p-value of the slope is less than 0.05, which is indicated in black in the p-value tables. P-values whose values are greater than 0.05 are colored in red. The analysis includes all countries and years from 1991-2017. The columns are the precipitation metrics and the rows are the aggregating functions used on the yearly gridded precipitation metrics within the maize belt of each country.

Mali

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.285				
Proportion of Points >800mm	0.495				
Proportion of Points 500-800mm	-0.495				
Standard Deviation	-0.069	0.265	0.366	0.254	0.309
Mean	0.350	0.043	-0.003	0.358	0.218
Median	0.297	-0.022	-0.139	0.412	0.232
Minimum	0.330	-0.163	0.146	0.218	-0.119
Maximum	0.333	0.120	0.352	0.373	0.068
Range	0.166	0.209	0.140	0.019	0.148

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.141				
Proportion of Points >800mm	0.007				
Proportion of Points 500-800mm	0.007				
Standard Deviation	0.728	0.173	0.056	0.193	0.109
Mean	0.067	0.828	0.987	0.061	0.265
Median	0.125	0.912	0.481	0.029	0.235
Minimum	0.087	0.407	0.459	0.264	0.546
Maximum	0.084	0.544	0.067	0.051	0.732
Range	0.398	0.286	0.477	0.923	0.453

Côte d'Ivoire

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.259				
Proportion of Points >800mm	0.156				
Proportion of Points 500-800mm	-0.156				
Standard Deviation	0.013	-0.117	-0.041	0.007	-0.069
Mean	0.223	0.011	0.122	-0.135	-0.189
Median	0.312	0.025	0.200	-0.146	-0.264
Minimum	0.147	0.024	0.227	0.148	0.034
Maximum	0.084	-0.030	-0.152	-0.056	-0.254
Range	-0.011	-0.035	-0.224	-0.135	-0.163

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.184				
Proportion of Points >800mm	0.429				
Proportion of Points 500-800mm	0.429				
Standard Deviation	0.947	0.554	0.837	0.971	0.729
Mean	0.254	0.955	0.536	0.494	0.335
Median	0.106	0.901	0.307	0.458	0.175
Minimum	0.457	0.903	0.246	0.453	0.864
Maximum	0.670	0.880	0.441	0.777	0.192
Range	0.957	0.859	0.252	0.492	0.407

Burkina Faso

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.012				
Proportion of Points >800mm	-0.019				
Proportion of Points 500-800mm	0.019				
Standard Deviation	0.196	-0.234	-0.053	-0.238	-0.183
Mean	0.081	-0.136	0.260	0.266	-0.134
Median	0.129	-0.122	0.237	0.125	-0.127
Minimum	0.019	0.264	0.016	0.181	0.298
Maximum	-0.049	-0.083	-0.095	-0.184	-0.165
Range	-0.086	-0.281	-0.094	-0.248	-0.338

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.952				
Proportion of Points >800mm	0.923				
Proportion of Points 500-800mm	0.923				
Standard Deviation	0.316	0.230	0.788	0.223	0.352
Mean	0.684	0.491	0.181	0.171	0.497
Median	0.514	0.536	0.225	0.527	0.521
Minimum	0.923	0.175	0.935	0.357	0.124
Maximum	0.804	0.673	0.632	0.348	0.402
Range	0.665	0.147	0.633	0.203	0.079

Ghana

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.449				
Proportion of Points >800mm	0.047				
Proportion of Points 500-800mm	-0.047				
Standard Deviation	0.401	-0.163	-0.187	0.080	-0.196
Mean	0.431	-0.118	0.197	0.241	-0.014
Median	0.417	-0.136	0.206	0.256	-0.104
Minimum	0.326	-0.060	0.017	-0.106	-0.004
Maximum	0.413	0.038	-0.031	0.047	0.097
Range	0.331	0.071	-0.031	0.119	0.052

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.017				
Proportion of Points >800mm	0.811				
Proportion of Points 500-800mm	0.811				
Standard Deviation	0.035	0.408	0.340	0.686	0.319
Mean	0.022	0.550	0.315	0.217	0.944
Median	0.027	0.491	0.293	0.189	0.599
Minimum	0.091	0.762	0.933	0.590	0.982
Maximum	0.029	0.846	0.877	0.811	0.624
Range	0.085	0.720	0.876	0.545	0.792

Togo

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	-0.122				
Proportion of Points >800mm	-0.138				
Proportion of Points 500-800mm	0.138				
Standard Deviation	-0.068	0.144	0.162	-0.047	0.192
Mean	-0.060	-0.575	0.443	-0.242	-0.484
Median	-0.053	-0.593	0.436	-0.152	-0.470
Minimum	-0.062	-0.374	0.432	0.071	-0.178
Maximum	-0.087	-0.441	0.079	-0.278	-0.483
Range	-0.075	-0.095	-0.217	-0.240	-0.196

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.535				
Proportion of Points >800mm	0.485				
Proportion of Points 500-800mm	0.485				
Standard Deviation	0.729	0.464	0.409	0.811	0.329
Mean	0.763	0.001	0.018	0.215	0.009
Median	0.787	0.001	0.020	0.441	0.012
Minimum	0.755	0.050	0.022	0.718	0.364
Maximum	0.661	0.019	0.688	0.152	0.009
Range	0.706	0.630	0.268	0.218	0.317

Benin

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.076				
Proportion of Points >800mm	0.149				
Proportion of Points 500-800mm	-0.149				
Standard Deviation	0.142	-0.056	0.010	0.195	0.017
Mean	0.069	-0.131	0.192	0.121	-0.106
Median	0.029	-0.189	0.315	-0.057	-0.179
Minimum	0.030	-0.062	-0.045	0.046	-0.057
Maximum	0.174	-0.026	-0.057	0.381	0.203
Range	0.185	0.013	-0.019	0.217	0.177

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.702				
Proportion of Points >800mm	0.450				
Proportion of Points 500-800mm	0.450				
Standard Deviation	0.470	0.778	0.958	0.321	0.932
Mean	0.727	0.505	0.328	0.541	0.591
Median	0.884	0.336	0.103	0.773	0.362
Minimum	0.878	0.755	0.821	0.817	0.775
Maximum	0.376	0.896	0.773	0.046	0.301
Range	0.347	0.949	0.923	0.267	0.366

Nigeria

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.457				
Proportion of Points >800mm	0.228				
Proportion of Points 500-800mm	-0.227				
Standard Deviation	0.296	-0.450	-0.185	0.208	-0.148
Mean	0.444	-0.386	0.404	0.327	-0.208
Median	0.480	-0.308	0.362	0.341	-0.147
Minimum	0.144	-0.075	0.325	-0.031	-0.162
Maximum	0.333	-0.437	-0.068	0.225	-0.295
Range	0.232	-0.433	-0.215	0.161	-0.109

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.015				
Proportion of Points >800mm	0.244				
Proportion of Points 500-800mm	0.244				
Standard Deviation	0.126	0.016	0.345	0.289	0.452
Mean	0.018	0.043	0.033	0.089	0.289
Median	0.010	0.111	0.058	0.075	0.456
Minimum	0.464	0.705	0.092	0.876	0.409
Maximum	0.083	0.020	0.732	0.251	0.127
Range	0.236	0.021	0.273	0.414	0.582

Cameroon

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	-0.003				
Proportion of Points >800mm	0.091				
Proportion of Points 500-800mm	-0.091				
Standard Deviation	-0.185	-0.020	0.036	-0.312	-0.105
Mean	-0.088	0.072	0.141	0.267	0.037
Median	-0.086	0.096	0.149	0.328	0.058
Minimum	0.165	0.098	0.230	0.264	-0.171
Maximum	-0.090	-0.192	0.298	-0.131	-0.211
Range	-0.181	-0.267	0.085	-0.252	-0.044

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.988				
Proportion of Points >800mm	0.646				
Proportion of Points 500-800mm	0.646				
Standard Deviation	0.345	0.920	0.857	0.106	0.595
Mean	0.656	0.714	0.474	0.169	0.854
Median	0.663	0.627	0.450	0.088	0.768
Minimum	0.401	0.621	0.239	0.174	0.385
Maximum	0.650	0.328	0.123	0.506	0.281
Range	0.357	0.169	0.667	0.195	0.825

Chad

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.068				
Proportion of Points >800mm	0.206				
Proportion of Points 500-800mm	-0.206				
Standard Deviation	0.249	0.352	0.145	0.417	0.343
Mean	0.167	0.004	-0.154	-0.229	0.029
Median	0.143	0.026	-0.365	-0.272	0.170
Minimum	0.155	-0.392	-0.044	-0.073	-0.374
Maximum	0.222	0.246	0.181	0.206	0.119
Range	0.156	0.456	0.192	0.142	0.311

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.730				
Proportion of Points >800mm	0.292				
Proportion of Points 500-800mm	0.292				
Standard Deviation	0.201	0.066	0.461	0.027	0.074
Mean	0.396	0.985	0.435	0.241	0.885
Median	0.467	0.895	0.056	0.162	0.388
Minimum	0.431	0.039	0.823	0.713	0.050
Maximum	0.257	0.208	0.356	0.293	0.548
Range	0.429	0.015	0.328	0.472	0.107

Central African Republic

	Total Precipitation	Non-Precipitating Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.501				
Proportion of Points >800mm	0.337				
Proportion of Points 500-800mm	-0.337				
Standard Deviation	0.180	-0.180	-0.234	-0.341	-0.405
Mean	0.540	-0.272	0.471	0.315	-0.202
Median	0.569	-0.290	0.448	0.100	-0.358
Minimum	0.274	-0.062	0.371	0.097	0.271
Maximum	0.279	-0.257	0.191	-0.029	-0.276
Range	0.140	-0.235	-0.201	-0.096	-0.316

	Total Precipitation	Zero Precipitation Days	Monsoon Onset	Monsoon End	Monsoon Duration
Proportion of Points >1200mm	0.007				
Proportion of Points >800mm	0.079				
Proportion of Points 500-800mm	0.079				
Standard Deviation	0.359	0.360	0.231	0.076	0.032
Mean	0.003	0.161	0.011	0.102	0.303
Median	0.002	0.134	0.017	0.612	0.062
Minimum	0.158	0.754	0.052	0.624	0.163
Maximum	0.150	0.187	0.331	0.883	0.154
Range	0.476	0.228	0.305	0.627	0.102