PAPER

Spatiotemporal monsoon characteristics and maize yields in West Africa

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Abstract

To assess the vulnerability of rainfed agriculture in West Africa (WA) to climate change, a detailed understanding of the relationship between food crop yields and seasonal rainfall characteristics is required. The highly seasonal rainfall in the region is expected to change characteristics such as seasonal timing, duration, intensity, and intermittency. The food crop yield response to changes in these characteristics needs greater understanding. We follow a data-driven approach based on historical yield and climate data. Such an approach complements model-based approaches. Previous data-driven studies use spatially and temporally averaged precipitation measures, which do not describe the high degree of spatial and temporal variability of the West African Monsoon (WAM), the primary source of water for agriculture in the region. This has led previous studies to find small or insignificant dependence of crop yields on precipitation amount. Here, we develop metrics that characterize important temporal features and variability in growing season precipitation, including total precipitation, onset and duration of the WAM, and number of non-precipitating days. For each temporal precipitation metric, we apply several unique spatial aggregation functions that allow us to assess how different patterns of high-resolution spatial variability are related to country-level maize yields. We develop correlation analyses between spatiotemporal precipitation metrics and detrended country-level maize yields based on findings that non-climatic factors, such as agricultural policy reform and increased investment, have driven the region’s long-term increase in maize yields. Results show that that the variability in the number of days without rain during the monsoon season and the lower bounds to the spatial rain pattern and end to the monsoon season are most strongly associated with maize yields. Our findings highlight the importance of considering spatial and temporal variability in precipitation when evaluating impacts on crop yields, providing a possible explanation for weak connections found in previous studies.

1. Introduction

Climate change may pose a major threat to West Africa’s (WA) agricultural systems and regional food security (Sultan and Gaetani 2016, Sultan et al 2019). While social, economic, and political factors, such as increased food crop demand and improvements to agricultural policy, have driven rapid production growth, the predominance of rainfed, low-input agriculture systems makes WA highly vulnerable to climatic change and variability (Hollinger and Staatz 2015, IPCC 2019). Maize is an important staple crop for food security in the region, and its demand for both human consumption and livestock is expected to grow in the coming decades (Elbehri et al 2013). However, maize is especially susceptible to drought (Fisher et al 2015). Abdoulaye et al (2012) estimates that drought affects 35% of maize growing in West and Central Africa, with farmers citing it as the greatest risk factor to maize yields. Important efforts like drought-tolerant maize varieties and early warning systems are
addressing drought vulnerability, but inconsistent adoption, data availability, policy implementation, and funding have limited the efficacy of these efforts (Genesio et al. 2011, Abdoulaye et al. 2012).

The primary source of water for agriculture in the WA maize belt is precipitation from the West African Monsoon (WAM), which is highly variable at seasonal, annual, and decadal time scales (Nicholson 2013, Xue et al. 2016). Rainfall in this region also exhibits high spatial variability. The dynamics of the WAM lead to a strong north-south gradient in rainfall totals, with average annual rainfall totals in the maize belt ranging from about 500 mm to 1500 mm. Therefore, a detailed understanding of the relationship between WAM characteristics and maize yields is necessary to develop climate adaptation strategies that ensure local food security.

While many studies have investigated the relationship between crop yields and precipitation, most data-driven studies use spatially and temporally aggregated precipitation measures such as total growing season precipitation. Schlenker and Lobell (2010) regressed average temperature and total precipitation on country-level crop yields in Sub-Saharan Africa (SSA), finding only a modest relationship between precipitation and yields. Other statistical crop-climate models have found both linear and non-linear relationships between total annual or monthly precipitation and crop yields at a global scale, though the relationships are not uniformly positive, often dominated by temperature impacts, and sometimes not statistically significant (Lobell et al. 2008, Lobell and Tebaldi 2014). More recently, global and SSA machine learning-based statistical models have been used to address aggregation bias, identify non-linear relationships, and explore a wider range of precipitation metrics, including both low and high extreme precipitation events (Hoffman et al. 2018, Vogel et al. 2019, Beillouin et al. 2020).

In WA specifically, most prior studies have either assessed the relationship between precipitation and yields using biophysical crop model simulations or remotely sensed landscape-scale vegetation productivity proxies like normalized difference vegetation index (NDVI). The impact of precipitation metrics on vegetation and agricultural growth has been well documented using crop models (Waha et al. 2013, Guan et al. 2015) and satellite based NDVI (Herrmann et al. 2005, Philippon et al. 2007, Hoscio et al. 2015, Rishmawi et al. 2016) in the region. However, crop models in this region are sensitive to uncertainty and biases in input data and model structure (Berg et al. 2010, Waha et al. 2015). Additionally, most studies using NDVI-based proxies for crop yields are limited in that they do not discriminate between natural vegetation and agricultural productivity. Mechiche-Alami and Abdi (2020) isolates agricultural productivity by using integrated NDVI (iNDVI) in identified cropland areas to explore the relationship between agricultural greening, climate, land surface phenology, and other external factors.

Our study explores the statistical relationship between crop yields using country-level yield data from the Food and Agriculture Organization of the United Nations (FAO) and new precipitation metrics that capture the spatial and temporal variability of the WAM. First, we develop temporal metrics of precipitation related to crop growth: monsoon onset, end, and duration; total growing season precipitation; and rain intermittency (measured using the number of zero-precipitation days). We then develop a set of spatial aggregation functions beyond just averages, such as the minimum value or standard deviation of each temporal metric across the maize belt in each country. For example, average country-level yields during drought years may be reduced by crop failures in the driest locations and therefore are more strongly correlated with the lowest precipitation across the region than the average precipitation. Finally, we apply each spatial aggregation function to each temporal precipitation metric to capture how spatiotemporal variability in precipitation is associated with country-level yields. We complement the statistical analysis with a qualitative review of socio-technological factors that have driven yield increases to motivate our detrending approach.

2. Materials and methods

2.1. Study area

WA’s maize belt is approximated at 7–13°N latitude where the cereal and root crop agricultural zone is defined by the FAO (Dixon and Gulliver 2001, Auricht et al. 2014). The WAM brings the intertropical convergence zone and associated high rainfall over WA starting in the spring and reaching the northern Sahel in August (Sultan and Janicot 2003). This short rainy season has variable start and end dates each year and has different volumes and timing of rainy days contained within it. The region is essentially dry and without rain during the remainder of the year. Such a singular and short-duration rainy season in a region dependent on local rain-fed agriculture poses a food security risk. The rain delivered during the WAM has a strong North-South gradient, with lower latitudes having a longer duration wet season and higher total precipitation. Our study includes Mali, Côte d’Ivoire, Burkina Faso, Ghana, Togo, Benin, Nigeria, Cameroon, Chad, and Central African Republic, where the maize belt regions have similar precipitation values; we have estimated approximate latitude bands representing the maize belt in each country, shown in figure 1. Despite the region’s drought vulnerability, maize yields have increased in the last three decades due to policy and economic reform, market incentives, and agricultural
intensification among other socioeconomic and political factors (OECD and Sahel and West Africa Club 2013, Hollinger and Staatz 2015, Resnick et al 2020).

2.2. Data
Deriving precipitation characteristics of the WAM requires accurate, daily, high resolution data. The Climate Hazards Group InfraRed Precipitation with Station data Version 2.0 (CHIRPS v2.0) provides a daily precipitation dataset from 1981 to the present spanning a 0.05° resolution grid between 50°S and 50°N latitude (Funk et al 2015). The Production of CHIRPS v2.0 data involves interpolating and regressing values from on-ground rain-gauge stations, satellite precipitation estimates, and physiographic characteristics, which helps temper biases from the complex terrain and lack of on-ground precipitation data in rural regions (Funk et al 2015). Most advantageously, the dataset avoids drizzle bias, a common feature of model-based precipitation products that distributes small amounts of rain across many days in the year rather than having isolated rainy days. Drizzle bias is particularly difficult to correct in SSA where the number of on-ground measuring stations has declined since 1990 (Symeonakis et al 2009, Funk et al 2015). Comparisons between CHIRPS v2.0, Modern-Era Retrospective for Research and Applications (MERRA) Version 2, and on-ground precipitation measurements from the African Monsoon Multidisciplinary Analysis verify that CHIRPS more closely matches in situ precipitation measurements (supplementary information available online at stacks.iop.org/ERC/3/125007/mmedia section 1).

The FAOSTAT database provides annual maize yields from 1990–2017 in our study area at a country-level resolution. While satellite-derived normalized vegetation index (NDVI) is a more commonly used proxy for crop yields, it requires land cover maps, especially in the highly fragmented landscapes of WA, and in situ crop yield data for accurate yield estimate. These are not widely available in WA (Vintrou et al 2012, Petersen 2018). The FAO compiles information through official questionnaires and national publications, which may be supplemented with data from various agencies, organizations, or unofficial sources for completeness (FAO 2020). FAO has worked to validate, add, and revise data from 1991 onwards according to their most recent standards, but this revision process has had a low impact on reported maize yields in WA (FAO 2020).

Note that we explored including temperature as another predictive variable in our analysis. Temperature and precipitation are correlated, and some studies have found that the relationship between precipitation and yields is smaller when controlled for temperature (Schlenker and Lobell 2010, Lobell and Tebaldi 2014). However, temperature data at the same high resolution with comparable accuracy as CHIRPS is not available. Because of the small number of weather stations in this region, reanalysis datasets often underestimate temporal and spatial variability by filling in data gaps with climatology. To verify this, we calculated the coefficient of variation (CV) for both annual precipitation from CHIRPS and growing degree days (GDD) using temperature data from ERA5-Land across the study region in 1990–2017 (Muñoz Sabater 2019). CV for precipitation is an order of magnitude higher than for temperature. Therefore, it is not suitable for our study, which focuses on assessing high resolution spatiotemporal variability and its implications for maize yields.

2.3. Temporal precipitation metrics
To capture the spatial and temporal variability of the WAM, daily precipitation data from CHIRPS v2.0 is used to derive spatially aggregated monsoon metrics for analysis of their relationship to maize yields. Each temporal precipitation metric is calculated within each grid cell of the study area within each year. The metrics are presented in table 1 and described below.

Total precipitation is defined as the sum of daily precipitation over a year in each grid point. Total precipitation allows for analysis of whether locations meet the cumulative water requirements of maize, which is
approximately 500–800 mm of water depending on climate (Brouwer et al 1989). Because of the region’s rainfed agriculture, it is expected that a greater or optimized amount of rain would result in higher maize yields, motivating the use of the spatial aggregation functions.

The monsoon onset, end, and duration can each have an impact on the region’s rainfed agriculture, as premature or delayed planting can impact crop yields (Fitzpatrick et al 2015, Ayanlade and Radeny 2020). Most agriculturally significant definitions of the WAM’s timing use an absolute precipitation threshold to define onset, but the choice of threshold must be tailored to the local hydro-climatology. A measure that can be generalized across our study region’s diverse hydro-climatology is preferred (Marteau et al 2009, Dunning et al 2016, Odoulami and Akinsanola 2018). We therefore define the WAM’s onset and end as the minimum and maximum of cumulative precipitation anomaly, as developed in Bombardi et al (2019). 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 $S_{yt}$:

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

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 for each grid point in the year (figure 2).

The number of non-precipitating days metric is defined as the number of days receiving 0 mm of rain during the year’s monsoon season. Because of the region’s rainfed agriculture, dry spells or an excess number of days without precipitation during the monsoon season could be detrimental to crop yields.

2.4. Spatial aggregation functions

Spatial aggregation functions—median, standard deviation, maximum, minimum, and the proportion of points meeting total precipitation thresholds—reduce the dimensions of the gridded precipitation metrics to match that of the FAO’s annual country-level maize yields. The borders of each country’s maize belt are approximated by a fixed mapping of the cereal-root crop system defined by the FAO (Dixon and Gulliver 2001, Auricht et al 2014). Thus, each spatial aggregation function is applied to the precipitation metric grid points within each country’s maize belt, resulting in a spatially aggregated precipitation metric for each country and year between 1990–2017. Spatial aggregation functions additionally serve to describe the spatial characteristics of precipitation and monsoon conditions occurring within each country. To represent the area meeting the water needs of maize in a growing season, the proportion of points in the country’s borders with >800 mm or 500–800 mm of rain are each used to characterize the spatial variability within each spatial aggregation region. We additionally used >1200 mm of rain as a threshold, which is approximately the average total precipitation in our study area across all years. These and other spatial aggregation precipitation metrics provide new

\[\text{Figure 2. Cumulative anomaly (green) plotted over daily precipitation (blue) in 2017 at 10.52°N, 7.5°S. The maximum and minimum of the cumulative anomaly (black horizontal lines) correspond to the monsoon start and end dates respectively. The monsoon duration is the number of days between the start and end dates.}\]
agriculturally relevant measures of precipitation, allowing for detailed analysis of the relationship between the WAM’s precipitation characteristics and maize yields (table 1).

### 2.5. Correlation analysis

We apply ordinary least squares regression and Pearson correlation analysis between each spatially aggregated precipitation metric and country-level annual maize yields. The maize yields time series has an upward trend, increasing an average of 1.7%–5.5% annually between 1990 and 2017 across countries in our study area (FAO 2020). A review of the literature on agricultural growth in WA suggests that maize yield’s time trend is largely driven by non-climatic factors, such as agricultural intensification, market forces, and improved economic and agricultural policy (see the discussion section for further analysis of this literature) (OECD and Sahel and West Africa Club 2013, Hollinger and Staatz 2015, Resnick et al 2020). Thus, we linearly detrend maize yields in time before performing correlation analysis with climate variables. Mean annual yields for each country were added back to the residuals to maintain interpretable units and to recognize the production differences between countries. The monsoon metrics were also tested for time-trends, were found to be statistically stationary during the period of record, and thus did not require detrending (supplementary information section 2).

To assess the validity of a linear correlation model, we evaluate the normality and heteroskedasticity of the regression’s residuals (supplementary information section 3). We find that the residuals are uncorrelated. Smaller maize-producing countries such as the Central African Republic, Benin, Chad, and Togo result in some small deviations from normality, but this is expected given the sample size. We conclude there is no strong reason to introduce more complicated, nonlinear models with a higher number of parameters. Such complicated and parameterized models require more observations than are available to be fit in a robust manner.

### 3. Results

We first define metrics of seasonal rainfall to characterize detailed monsoon characteristics related to timing, intensity, and intermittency. We analyze these metrics against historical maize yield data to understand which characteristics of seasonal regional rainfall have the largest impact on yields. Shifts in these characteristics due to climate change would effect food security in the region.

#### 3.1. Temporal precipitation metrics

First, we present each of the temporal precipitation metrics in table 1 in figures 3–5. For each metric, we show the mean, standard deviation, and coefficient of variation across the date range of our analysis, 1990 to 2017. Total precipitation in the region (figure 3) shows a strong latitudinal gradient in accumulated precipitation due to the seasonal northward migration and retreat of the WAM from its equatorial origins. The standard deviation and coefficient of variance show that there can be substantial interannual variability relative to the mean across the region. Within the maize belt region, almost no areas have precipitation under 500 mm while most areas have annual precipitation between 800 and 1200 mm. Combined with our analysis that, against maize yields, the 500–800 mm aggregated precipitation metric is negatively correlated, the >800 mm metric is positively

### Table 1. Summary of the spatial aggregation functions applied to annual precipitation metrics from the WAM.

| Spatial Aggregation Functions | Total Precipitation | Monsoon Onset, End, and Duration | Non-Precipitating Days |
|------------------------------|---------------------|----------------------------------|------------------------|
| Median                       | Measure of the median performance in a country’s maize growing region. |
| Standard Deviation           | Measure of the spatial variation and diversity of rain conditions in a country’s maize growing region. |
| Maximum                      | Measure of the best and worst performing grid points in a country’s maize growing region. |
| Minimum                      | Measure of the proportion of points in each country that meets maize’s water needs. |
| Proportion of Points >1200 mm | Measure of the proportion of points in each country that meets maize’s water needs. |
| Proportion of Points >800 mm  | Measure of the proportion of points in each country that meets maize’s water needs. |
| Proportion of Points 500–800 mm | Measure of the proportion of points in each country that meets maize’s water needs. |
correlated, and the >1200 mm metric has no significant correlation (table 2), the ideal precipitation amount for maize growth in West Africa is between 800–1200 mm rather than the expected 500–800 mm.

The WAM duration also shows a strong latitudinal gradient due to the migration of the WAM (figure 4). The monsoon can be as short as three months on average in the north of the WA region and extend as much as six months in the more tropical south. Interannual variability in the monsoon duration can be a substantial fraction of the average monsoon duration.

The number of non-precipitating days during our defined WAM does not show a latitudinal gradient (figure 5). Rather, there are areas in Côte d’Ivoire, Burkina Faso, Ghana, Togo, Benin, and Nigeria where over half of the days during the WAM have no rain while others have more consistent rainfall. Comparison of the mean and interannual variability of this metric suggest that there is strong climate variability from year-to-year.
in this characteristic of the WAM. For each of these precipitation metrics, the strong interannual variability may be a challenge to the region’s rainfed agriculture, as farmers must predict and plan accordingly for each year’s growing conditions.

### 3.2. Monsoon variability and yields

Correlation and regression analyses demonstrate particularly high correlation and significant p-values between detrended maize yields and three spatially aggregated precipitation metrics: minimum total precipitation, standard deviation of the number of non-precipitating days, and the minimum monsoon end date (table 2). The standard deviation of total precipitation and proportion of points with a total precipitation >800 mm and 500–800 mm also show some correlation with detrended maize yields, but to a lesser extent and smaller

| Pixel-Wise Precipitation Metric for Characterizing the West African Monsoon |
|-------------------------------|----------------|----------------|----------------|----------------|
| Spatial Aggregation Function  | Total Precipitation | Non-Precipitating Days | Monsoon Onset | Monsoon End |
| Median                        | 0.143 *          | 0.140 *          | -0.004        | 0.01         | -0.019       |
| Standard Deviation            | 0.156 **         | 0.276 ***        | 0.167 **      | -0.041       | 0.136 *      |
| Maximum                       | 0.042            | 0.153 *          | 0.108         | 0.061        | 0.058        |
| Minimum                       | 0.209 ***        | -0.031           | -0.054        | 0.288 ***    | -0.03        |

| Additional Spatial Aggregations for the Total Annual Precipitation Metric |
|-------------------------------|----------------|
| Proportion of Points >1200mm  | 0.062          |
| Proportion of Points >800mm   | 0.168 **       |
| Proportion of Points 500-800mm| -0.168 **      |
significance level. See supplementary information section 4 for linear regression plots between each precipitation metric and detrended maize yields.

Strong associations between maize yields and the minimum total precipitation and monsoon end date metrics reflect the predominance of rainfed agriculture in WA. Minimum total precipitation represents the lower bound of total precipitation among each country’s grid point values. Therefore, maize’s watering requirements are met across a larger fraction of the study area when the minimum total precipitation is high. The grid cells facing the most water insecurity reduce total production when the minimum total precipitation is low.

In a similar spatial framework as the minimum total precipitation metric, an earlier monsoon end date results in a shorter growing season and less crop maturity. Of the precipitation metrics used, the minimum monsoon end date metric is most strongly correlated to maize yields. The maximum monsoon onset date and minimum monsoon duration metrics do not have as strong of a correlation to maize yields, which suggests that our calculated onset date is not a suitable proxy for on-ground planting schedules. A contributing factor may be the use of post-hoc calculation for the monsoon onset, while farmers use a combination of in-moment observations, past experience, climate forecasts, and traditional practices in their decision-making (Ingram et al 2002, Tarchiani et al 2017, Guido et al 2020). Thus, farmers planting schedules may be very different from our calculated onset date. In contrast, harvesting time is physiologically constrained by the time when precipitation begins approaching zero, which enables our calculated monsoon end date to be a closer proxy for the end of the growing season on-ground. Based on the high correlation and the significance of its least-squares regression against yield, locations with the earliest monsoon end date drive variability in yield production when non-climatic factors are accounted for. The standard deviation of the number of non-precipitating days metric exhibited a strong positive correlation with maize yields, which is the 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 spotty and intermittent over the region. However, these results may be due to Simpson’s paradox in which a trend occurs for the data overall but not for the data’s subgroups. In correlation analyses between each country’s yields and the aggregated precipitation metric, there is disagreement over whether the relationship between the precipitation metric and maize yields is positive or negative (figure 6). Six out of the ten countries show a negative trend rather than the positive trend observed when all countries’ data are analyzed together. Furthermore, with the exception of Nigeria whose trend is negative, the individual slopes for each country’s metric regressed against maize yield is not statistically significant. Therefore, we cannot confidently interpret a relationship between the standard deviation of non-precipitating days and detrended maize yields.

Figure 6. The standard deviation of non-precipitating days is plotted against detrended maize yields. The regression line for data including all countries (black) 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.
The relationships between monsoon characteristics and end of season maize yields demonstrate the sensitivity of rainfed agriculture to the spatial and temporal features of the singular rainy season. Because we used historical yield reports instead of modeled yields in this study, we must acknowledge the other climatic and non-climatic factors that have contributed to yield values in the last two decades. We attribute the long-term growth in yields to non-climatic factors by detrending the yield data before determining correlations with monsoon characteristics. To provide support for this assumption that maize yield growth is driven by non-climatic factors, we supplement quantitative checks of our correlation analysis design with literature review and analysis of the region’s economic, agricultural, and demographic shifts below. We additionally discuss the results of our study and potential future explorations of the relationship between yields and other climatic features like aridity.

4.1. Non-climatic factors to maize yield growth

Between 1990 and 2017, maize yields have increased an average of 1.7%–5.5% per year in WA, which is higher than most other staple crops grown in the region (Hollinger and Staatz 2015, FAO 2020). This trend is removed from our data before our correlation analyses to effectively remove the effect of non-climatic factors. Previous research analyzing the causes of agricultural production growth in SSA argued that production increases have occurred in the past irrespective of rainfall conditions (Resnick et al 2020). An alternative approach using the significance of the relationship between iNDVI and the climate variables precipitation, temperature, and solar radiation to determine whether climate or non-climatic factors drive trends in iNDVI found that our study area experienced a non-climatic browning trend from 2000–2018 (Mechiche-Alami and Abdi 2020). This is consistent with the expansion of agricultural land for maize and other agricultural products because agricultural land has a lower NDVI than land with natural vegetation (Louise et al 2014, Hollinger and Staatz 2015, Santpoort 2020).

A variety of non-climatic potential drivers exist for this yield growth. Hollinger and Staatz (2015) attribute WA’s yield growth to increased use of fertilizers and improved varietals. However, Resnick et al (2020) argues that fertilizer use remains low and could be better-targeted to local needs, which limits its impact on yields. Instead, current policy reforms and improved economic governance in the region has allowed the region’s production to take advantage of opportune rain and market conditions (Resnick et al 2020). Another perspective suggests that maize production is transitioning from being subsistence-driven to market-driven in WA, creating economic incentives that drive yield increases (OECD and Sahel and West Africa Club 2013).

To gain insight into the possible role of management practices on yields, we examine the recent historical records on yields in the context of concurring socioeconomic conditions as well as any known trends in agricultural management. In table 3, we collect demographic, socioeconomic, and agricultural statistics from the FAO and World Bank. We develop annual time-series for each country in our study area and explore statistical relations between maize yield growth rates (far left column) and non-climatic agricultural growth drivers identified in our literature review (other columns) for each country. The number in each cell reflects the change or percent change between 1990 and 2017 of each variable in each country and are color coded with the value’s magnitude for easy comparison against maize yield growth from 1990–2017. Beyond the agricultural and

### Table 3. Compilation of socioeconomic and agricultural growth in study region countries from 1990–2017. The red and blue color coding represents the magnitude of growth for each socioeconomic and agricultural variable (The World Bank 2020, FAO 2020).

| Country | Agricultural | Economic | Demographic | Infrastructure |
|---------|--------------|----------|-------------|----------------|
|         | Maize Yield (tons/ha) Growth 1 | Percent Change in Cropland (ha) Growth 1 | Fertilizer Use (kg/ha) Growth 1 | Pesticide Use (kg/ha) Growth 1 | GDP per cap (US$ per cap) Growth 1 | Growth in Foreign Development Aid to Agriculture per cap (US$ per cap) | % Change in Population Size | Rural Population (% of total) Growth 1 | % Employment in Agriculture Growth 1 | % Literacy Access Growth 1 |
| Mali    | 0.011 | 20.3% | 0.001 | 4.002 | 25.203 | 0.964 | 199% | -5.1% | -9.39% | 1.8% |
| Cape Verde | 0.031 | 34.9% | 0.246 | 0.062 | 41.258 | 6.116 | 135% | -0.4% | -0.32% | 1.1% |
| Nigeria | 0.023 | 26.3% | -0.006 | 100.992 | 0.971 | 106% | -2.0% | -0.8% | 0.9% |
| Ghana  | 0.021 | 76.2% | 0.061 | 0.062 | 76.553 | 0.041 | 97% | -0.7% | -0.78% | 2.1% |
| Sierra  | 0.015 | 97.7% | -0.399 | 35.328 | 0.510 | 124% | -0.4% | -0.3% | 1.1% |
| Togo   | 0.011 | 28.8% | 0.012 | 0.006 | 12.088 | 0.115 | 104% | -0.4% | -0.4% | 1.8% |
| Central African Republic | 0.010 | -6.3% | -0.007 | 0.0063 | 3.317 | 0.021 | 64% | -0.1% | -0.09% | 0.0% |
| Burkina Faso | 0.009 | 76.6% | 0.415 | 0.0056 | 22.917 | 0.779 | 118% | -0.6% | -2.9% | 0.5% |
| Chad   | 0.009 | 58.7% | 0.0061 | 32.197 | 0.099 | 152% | -0.9% | -0.28% | 0.0% |
| Cameroon | 0.007 | 8.1% | 0.234 | 0.0035 | 26.682 | 0.177 | 199% | -0.6% | -2.98% | 1.1% |
socioeconomic factors discussed previously, demographic and developmental factors such as population size, rural population size, agricultural employment, and electricity access may play a role in yield growth. Urbanization, where population size has increased while rural population and agricultural employment has decreased, has contributed to the consolidation of small-scale farms to medium-scale farms, which are more able to invest in mechanization and agricultural inputs (Jayne et al 2019). Furthermore, urbanization has increased the need for farmers to produce a surplus to meet urban food demands and has strengthened food distribution networks through the development of small towns between urban and rural areas (Allen 2015). Other infrastructure improvements, such as increasing electricity access, enables farmers to profit from shipping surplus product to urban areas (Hollinger and Staatz 2015).

The agriculture-related variables are positively or weakly related to crop yield growth. Increased land under cultivation and fertilizer use are generally positively correlated with yield growth but have weak correspondences. Pesticide use intensity does not appear to be a contributing factor. Economic indicators such as gross domestic product per capita and growth in international development aid appear to consistently track the maize yield growths. The demographic and infrastructure factors have the strongest and most consistent correlations across all countries. They indicate a consistently growing population concentrated in urban areas. Even though the region’s population has been urbanizing, a larger, higher yielding land area is under crop production.

4.2. Significance of results and potential future explorations
Food security in the region is a function of how changes in the monsoon affect crop yields and how agricultural management practices and interventions can mitigate any negative impacts of climate change on yields. Our results show that spatiotemporal characteristics of the WAM, such as the timing of the end of the monsoon and the amount of rain received by the driest areas, has an impact on maize yields. This advances our understanding of how precipitation affects maize yields in SSA beyond total growing precipitation, which has been a commonly used measure for precipitation in this region with mixed results.

Future explorations on how yields are affected by additional climate variables in combination with the WAM precipitation metrics examined in this study can provide further insight. For example, we observed that the median and maximum number of non-precipitating days during the WAM had a significant relationship with yields, although the relationship was not as strong as the metrics we discussed more specifically. The non-precipitating days metric can be improved by also analyzing the temperature and number of consecutive dry days to measure heat stress and aridity during a growing season. Using general circulation models, Lickley and Solomon (2018) found that SSA is one of the most vulnerable regions in the world to climate change driven aridity, which emphasizes the need to do further research in this area. Recognizing that non-climatic factors have had a large impact on yield in SSA, continued study of how climatic factors impact yields can help inform the future goals of agricultural management and climate resilience in the region.

5. Conclusions
Our study explored the relationship between crop yields and new spatiotemporal characteristics of the WAM by leveraging a new, high resolution, and high accuracy precipitation dataset. We found that the spatiotemporal metrics most strongly correlated with country-level crop yields are the spatial minimum of total precipitation and the spatial minimum of monsoon end date. This finding makes important contributions to our understanding of the relationship between precipitation and crop yields. First, using spatial aggregation functions that capture the spatial variability in precipitation instead of spatial measures of central tendency like median and mean can provide better information about yields at the country-scale. This is especially important in regions like WA where smallholder agricultural landscapes are highly heterogenous—climate at the average farm is a poor indicator of climate across the region. The minimum precipitation farm, however, provides a lower bound on water available for crops across the region. A higher lower bound on potential crop yields across the region means higher average crop yields at the country-scale. Similarly, our results highlight that while total precipitation across the growing season is an important metric, other temporal features like the timing of the monsoon season are important to capture.

Our analysis has some limitations due to the availability of data. While linear detrending of crop yields is well supported by quantitative checks on the residuals as well as a qualitative review and discussion of non-climatic drivers that are likely to contribute to linear yield growth, it is an influential assumption. Additionally, we limit the analysis to precipitation and do not include other influential climatic variables like temperature. This choice was made due to a lack of a comparably high resolution and high accuracy temperature dataset. It is further supported by analysis of GDD in the region, which showed both an order of magnitude lower coefficient variation than precipitation and values consistently above estimates of GDD needed for maize to reach full...
maturity. However, it is still likely that, due to correlation between precipitation and temperature, some of the correlation we find between precipitation and yields is driven by temperature. Our correlation estimates should therefore be interpreted as upper bounds on the relationship between precipitation and yields.

This study provides a complement to many studies on yields in SSA focused on using in situ farm-scale yield data or satellite-based estimates of farm-scale yields. While this is an important and rapidly growing area of research, data limitations prevent the development of long-time series of yields as is available from FAO country-level estimates, posing a challenge to data-driven approaches assessing climate-crop relationships. Our contribution allows for analysis of data-driven climate crop analysis. By doing so in a way that leverages high spatial resolution precipitation data, we find stronger support for significant relationships between precipitation and crop yields than previous studies. These findings have the potential to inform climate adaptation planning in this important, rainfed agricultural region as well as to guide future research to better understand the relationship between precipitation and crop yields.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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