The Impacts of Climate Change on Agriculture in Sub-Saharan Africa: A Spatial Panel Data Approach

Citation for published version (APA):
Emediegwu, L., Wossink, G., & Hall, A. (Accepted/In press). The Impacts of Climate Change on Agriculture in Sub-Saharan Africa: A Spatial Panel Data Approach. *World Development*.

Published in:
World Development

The impacts of climate change on agriculture in sub-Saharan Africa: a spatial panel data approach

"*everything is related to everything else, but near things are more related than distant things*" Tobler (1970, p. 236) - Tobler's first law of Geography

Abstract

This paper reports estimates of the economic impact of changes in weather variables on sub-Saharan African pearl millet yield based on panel data for 1970 - 2016. We control for spatial effects in all the components of our *exposure-response* function, plus a *lag* in time of the covariates through spatio-temporal econometrics techniques. Our results indicate own-location weather variables have significant contemporaneous impacts on millet yield. Specifically, we find that vapor pressure deficit, wet day frequency and temperature are important determinants of millet yield. In addition, accounting for spatial and temporal spillovers exacerbates and attenuates wet day cumulative effect, respectively, and local crop production is affected by neighboring countries' production. The results are robust to several sensitivity checks, including accounting for adaptation using long-term averages, and are consistent across country-income groups. We also use our estimates to forecast how crop production would respond to climate change in the mid-future.

Keywords: Agriculture, precipitation, spatial econometrics, sub-Saharan Africa, temperature, vapor pressure deficit

1 Introduction

Given the consensus of a shift in earth's climatic status by the end of this century (IPCC, 2018), there are national, regional, and international concerns about the impacts of climate change on agriculture in the short-, medium-, and long-run. These concerns have led to a surge in empirical investigations into the nexus between climate change and agriculture. Most of the pioneering works in this respect are focused on the United States.[1] However, developing regions, such as sub-Saharan Africa (SSA), are more vulnerable to climatic shifts because of the agriculture-dependent structure of the economy, poverty, credit constraint, dearth of adaptive technology, and the *rain-fed* character of farm products (Allen et al., 2014). Burke et al. (2015b) differ in these respects by attributing the cause of economic loss emanating from climate change to the already hot condition of developing regions (including SSA). Whichever is the case, it is important to provide estimates of the impacts of climate change in these regions to aid policymakers comprehend the potential effects of climate variability, as well as to support them in making relevant decisions that will either alleviate its magnitude or stimulate adaptation.

One area that has not been explored in the SSA climate change-agriculture is how spatial influences affect crop production in a country. For example, spatial correlations occur due to incidental commonalities and agro-climatic conditions or geographical characteristics (Miao et al., 2015; Di Falco and Chavas, 2009). Moreover, significant spatial correlations arise due to the use of gridded weather datasets generated *via* extrapolation means (Auffhammer et al., 2013; Baylis et al., 2011). The impact of these spatial influences has not been addressed in previous studies focusing on climate change and Africa. Although Ward et al. (2013); Schlenker and Lobell (2010) make an attempt to correct for spatial correlation among the error terms, none use formal spatial panel methodology. This study intends to show evidence that adjusting for these potential spatial influences will affect the impact analysis of weather fluctuations on crop yield in sub-Saharan Africa.

This paper contributes to the existing literature on the SSA climate change-agriculture nexus in three major forms: methodology, weather measures and dataset.

In terms of methodology, we use a spatio-temporal panel data model to control for the effect of space and time. Specifically, our technique includes spatial lags of the dependent variable and regressors with errors clustered at location level to control for the possibility of spatial correlation of yields, weather measures and idiosyncratic shocks, respectively. Besides, temporal lags of the regressors are added since the effect of weather shocks may persist over time, a concept labeled in the literature as the *delayed effects* of weather shocks (see Hsiang (2016), for example). The importance of using such sophisticated tools is to disentangle local effects (impacts from own units) from spillover effects (impacts from neighboring units) (see e.g., Harari and Ferrara, 2018). Focusing on agricultural economics, Baylis et al. (2011) examine the importance of spatial influences in agricultural production by modifying the climate impact work of Schlenker et al. (2006) to account for spatial interactions. They find that estimates from spatial models differ from their non-spatial counterparts.

[1] See Mendelsohn and Neumann (1999) for a review of these earlier works. Recent empirical studies on the impact of climate change on the US economy include Yu et al. (2021); Rudebusch (2019); Hsiang et al. (2017), among others.

Part of the methodological contribution is to disentangle the effects of weather fluctuations on yields across country-level income class. Following Burke et al. (2015b); Dell et al. (2012), we examine whether the effect of weather shocks on crop yield is dissimilar across countries by country-income group, as well as whether the spatial and temporal effects are driven by spatial and temporal lags.

The empirical analysis is applied to pearl millet because of its economic importance. Millet is a major cereal for SSA and essential for food security (see e.g., Eriksson et al., 2018). Previous research has shown that millet possesses inherent properties that make it a good choice for adapting to climate change. For example, Wang et al. (2018) explain that the millet crop's nutritional requirements are minimal and require no fertilizer or irrigation, as it can adapt to various soil types. Moreover, it has good disease and pest resistant traits that reduce its proneness to disease and pests (Manners and van Etten, 2018; Goron and Raizada, 2015). The above properties are the basis for our choice of millet.

Our second contribution is in terms of the weather measures we use. We use wet day frequency rather than precipitation, which is the conventional rainfall measure. Wet day frequency is significant because it captures better the dynamics in within-growing season rainfall. Fishman (2016); Carleton and Hsiang (2016), for example, show that the impact of rainfall on economic activity in the same location will be similar for two different periods if their aggregate values are same; however, these impacts may differ significantly if the spread over time is considered. Another contribution of this work is the introduction of a new weather measure, vapor pressure deficit (VPD), into SSA studies. The inclusion of VPD is important to crop physiology as it denotes *drought sensitivity* of crops (Urban et al., 2015; Lobell et al., 2013; Roberts et al., 2012).

Our third contribution is regarding the geo-biophysical and temporal details, which are elaborated in turn. Whereas prior SSA panel studies use weather data averaged at country level, this study uses weather observations from each country's main production area (MPA, hereafter). This improvement is significant given that agricultural production does not occur in all parts of a country. If areas where most of the agricultural production takes place have farming-friendly weather, then aggregating with or averaging over hotter (or colder) areas would result in estimates that rise (or fall) when the total or mean weather measure increases. Furthermore, such spatial averaging can attenuate significant nonlinearities (Auffhammer and Schlenker, 2014).

Still on the geo-biophysical and temporal details, the growing season used here is specific to each country. The use of country-specific growing season is important because, unlike previous SSA studies that assume a uniform growing season across countries, we recognize that growing seasons differ across countries. For example, whereas the growing season for millet is November to June in Botswana (a country in the southern part of the region), it is July to November in Mauritania (a country in the North-Western part).

Lastly, this paper contributes to the existing literature on the SSA climate change-agriculture nexus by using the most recent millet yield and weather dataset (2016).[2] The updated dataset can be appreciated in light of noticeable rise in food insecurity and adverse weather shocks in the region over the last decade (FAO, IFAD, UNICEF, WFP & WHO, 2018). Although our analysis focuses on millet due to its economic importance, we, however, extended the analysis to other cereal crops. The results are available on requests from the authors.

Our empirical results provide evidence of a significant contemporaneous relationship between weather shocks and millet yield in SSA. Specifically, an increase in temperature and VPD is associated with yield loss, respectively. On the other hand, an increase in wet day frequency improves output. Further, the introduction of spatial and temporal lags only affects wet day frequency. However, local yield levels are affected by the millet yield production in neighboring regions. We also find that the effect of temperature on millet yield differs between poor and rich SSA countries, with poor countries at the receiving end of the adverse effects of weather shocks. We find no such differential effect for wet day frequency. Lastly, future projections of weather changes from an ensemble of climate models when integrated into our estimated model indicate that, for a temperature increase of 2.3°C in the region, millet yield will go down by an additional 20% if all other aspects of the state of the world persist to 2070.

Our work can be fitted into three branches of literature. First, this study relates to a new wave of overview papers (e.g., Hsiang, 2016; Dell et al., 2014) and recent empirical studies (e.g., Emediegwu, 2021; Harari and Ferrara, 2018; Burke et al., 2015b; Dell et al., 2012) that outline the importance of identifying the influence of past or neighbors' meteorological events. The argument is that the use of time-series identification of weather shocks necessitates accounting for these *ripple/delayed effects* in space and time so that a local transient impact is not misrepresented as a persistent response. These effects are not captured by a standard panel data model since it models a contemporaneous relationship with units of observations assumed to be spatially independent (Baltagi, 2011).

Regarding spatial effects, Kumar (2011) argues that the values of agricultural variables are, in reality, also defined by conditions in neighboring countries. For example, agricultural activities in a location can benefit from rainfall in neighboring locations if they share rivers, tributaries and dams, as evidenced in Zouabi and Peridy (2015). Moreover, the error terms could be serially correlated, which may bias the true variance-covariance matrix; hence standard inference procedures are invalid and robust methods must be used (Baltagi, 2011). Similarly, Dell et al. (2014) are of the view that neglecting such significant spillovers in a standard panel analysis could bias the resultant estimates, therefore accounting for such spillovers could be of *first-order* importance (see also, Nijkamp and Poot (2004)). Such spatial dependence can be captured econometrically *via* spatial panel

[2] Previous SSA studies such as Blanc (2012); Schlenker and Lobell (2010) use data up to 2002.

data models, as done in this paper.[3]

Second is the literature on climate change and crop yield in SSA. To further this literature, we employ a more disaggregated approach by identifying where these productions occur and isolating the weather components that matter for millet development in each location.

Finally, our paper relates to a sparse literature that considers the effect of water stress or drought on crop yield. Previous studies like Urban et al. (2015); Lobell et al. (2013); Roberts et al. (2012) have investigated these effects on maize yield in the United States. We add to their evidence by assessing these impacts on SSA millet yield because millet crops are more resistant to drought and water stress than maize (Wang et al., 2018; Manners and van Etten, 2018). This difference is appreciated if we consider that countries in SSA are already prone to warming, and investing in drought-resistant crops may be one policy response to climate change.

The rest of the paper is structured as follows. Some spatial concepts and processes are considered in the next section. Section 3 describes the data and specifies the estimation model. The main and robustness results are discussed in Section 4, climatic projections in Section 5, and finally, Section 6 summarizes the paper with some policy implications.

2 Spatial processes and mechanisms

Following the methodological contributions of Cliff and Ord (1973, 1981), spatial models became popular in specialized fields such as regional science, urban and real estate economics, economic geography, and related fields.[4] Further works by Anselin (2001); Polsky (2004); Baylis et al. (2011) popularize the application of spatial econometrics in standard fields of economics, such as development, agricultural and environmental economics.[5] It is important to state that the use of spatial models is necessitated if there are reasons to think that a location's agricultural production may be affected by its neighbor's activities.

Spatial interactions can occur in one or a combination of the following: error terms, regressors and dependent variables. For our analysis, we will be interested in all spatial interactions for a couple of reasons. First, we suspect the errors to be spatially correlated based on Miao et al. (2015); Di Falco and Chavas (2009), who give us reasons to believe that crop yields across countries can be spatially correlated in their disturbances if they share similar soil or geographic attributes. Carleton et al. (2020); Auffhammer and Schlenker (2014) also posit that such dependence could result from confounding variation

[3]Spatial panels, according to Elhorst (2003), refer to georeferenced point data over time of geographical units or (although less common) economic agents.

[4]See reviews in these fields from Paelinck and Klaassen (1979); Cliff and Ord (1981).

[5]Recent applications of spatial models in development and agricultural economics include Lim et al. (2021); Leiva et al. (2020); Ho et al. (2018).

in omitted climatic measures such as wind speed, solar irradiation, *etc.*

Second, Auffhammer et al. (2013) show that there exists significant spatial correlation of weather measures because of the underlying data generating process and the extrapolation methods employed in generating gridded weather datasets.[6] They further assert that spatial correlation of the regressors is problematic since most models cannot completely and correctly account for all relevant weather variables. In the same vein, Harari and Ferrara (2018) believe that the use of gridded weather dataset can introduce significant cross-grid spillovers. Also, certain natural/climatic occurrences could impact bordering countries. Hossain and Ahsan (2018) find that greater amount of rainfall in neighboring units has adverse effect on own-unit economic outcomes because patches of rainfall span several geographic units.

Moreover, rainfall could be channeled through rivers, tributaries and dams to impact positively or negatively (in the advent of flooding or drought) on agricultural activities in neighboring countries. For example, Frenken (1997) reveals that the Zambezi river[7] entering Zambia from Angola in the north has an annual discharge of 18km^3, doubling the volume needed to irrigate Angola. Hence, the amount of rainfall in the Zambezi basin affects the volume of water in the basin and, therefore, the water available to crops in the tributaries: Angola, Botswana, Malawi, Mozambique, Namibia, Tanzania, Zimbabwe and Zambia. In a similar twist, Zouabi and Peridy (2015) find that groundwater positively affects agricultural production for irrigated crops with interesting spillover effects with neighboring regions in Tunisia. A further climatic occurrence that travels spatially is related to temperature. There is evidence that heat travels horizontally from low to high latitudes due to pressure differences stemming from temperature disparities (Budyko, 1969).

Lastly, Hsiang (2016) reveals that crop yields could be displaced across space following meteorological events. In essence, weather conditions can affect economic activities in neighboring countries *via* price, trade (market) or conflict (Harari and Ferrara, 2018; Dell et al., 2014). For example, using panel data of over 20 years and from 271 districts, Kumar (2011) estimates the spatial effect of climate change on farm-level net revenue in India. The study finds a significant spatial autocorrelation between the dependent variables. More recently, Lim et al. (2021) find that farmers can adapt to changing environments due to interacting and learning from other farmers.

Given the preceding reasons, the standard model ought to be the general nesting spatial (GNS) model because it controls for spatial interactions in all the components of a *dose-response* function (see Table F2 in the Appendix for a brief description of the

[6]The use of gridded weather datasets has been popularized due to paucity of weather stations, especially in developing regions. There are two basic methods of obtaining gridded weather datasets: spatial extrapolation and data assimilation (see, Auffhammer et al. (2013) for better insight).

[7]The Zambezi basin ranks as the fourth largest basin in Africa, following Congo, Nile and Niger basins

several types of spatial models). However, Elhorst (2014) provides two reasons why this model is seldom used in applied research. One is the unavailability of a formal proof to obtain conditions under which the parameters are identified, hence GNS suffers from the well-known Manski reflection problem. The second reason is the problem of overfitting. Elhorst, on the other hand, argues that the parameters of the other specific spatial models, such as the spatial Durbin model (SDM), are identifiable and free from the problem of overfitting. Consequently, we follow Harari and Ferrara (2018) and Hossain and Ahsan (2018) by controlling for spatial correlation in the regressors and dependent variable using the spatial Durbin model (SDM) and accounting for spatial dependence in the residuals *via* clustering standard errors by MPAs.

According to Gibbons and Overman (2012), OLS provides consistent estimates of the parameters if the spatial correlation occurs only through the exogenous attributes (spatial lag of X (SLX) model); unbiased but inefficient estimates if the error terms are spatially correlated (spatial error model (SEM)); biased and inconsistent estimates in the presence of spatial dependencies in the dependent variable (spatial autoregressive (SAR) model). However, Lee and Yu (2010) prove that *bias-corrected* maximum likelihood (ML) estimation provides efficient estimators for all spatial models.[8] Consequently, we employ Lee and Yu's (2010) bias-corrected ML estimation strategy to estimate our model.

3 Data and model specification

3.1 Data description and sources

We use annual panel data from 1970 to 2016 for various millet-producing countries in SSA.[9] See Table F1 and Figure F1 of the Appendix for list of countries and locations, respectively.

Yield data

Data for our dependent variable, country-level millet average yield (ton/ha), come from FAOSTAT database (`http://www.fao.org/faostat/en/`). The Food and Agriculture Organization (FAO) obtained these figures from various sources: governments through national publications and FAO questionnaires (both paper and electronic); unofficial sources; national and international agencies or organizations. The original data from FAO online database are expressed in hectogram per hectare (hg/ha), but to keep with the standard unit in agricultural economics, we convert them to ton/ha by dividing the observations by 10000.

[8]The bias is a creation of the *incidental parameter* problem, which is briefly discussed in the Appendix, subsection B.

[9]For robustness and computational reasons, only countries with complete dataset are used because spatial panel models can only be estimated for balanced panel data.

Weather data

Our main variables of interest are **average temperature (TEMP)**, **wet day frequency (WDF)** and **vapor pressure deficit (VPD)**. The first two datasets are sourced from CRU TS v4.02, a dataset developed by the Climate Research Unit (CRU) of the University of East Anglia. This dataset (released 18th November 2018) provides gridded time series data for several monthly weather measures, including average temperature and wet day count for all land areas in the world (excluding Antarctica) at 0.5° resolution (approx. 56 km × 56 km across the equator) for the period January 1901 to December 2017.[10]

Although average temperature is appropriate for our work, agronomists have shown that crop development depends on cumulative heat exposure. Hence the use of degree units - cooling degree units (CDU), growing degree units (GDU) and killing degree units (KDU) - tends to be more appealing to climate scientists (Auffhammer and Schlenker, 2014; Lobell et al., 2011; Schlenker and Roberts, 2009). Degree unit (or day) calculates cumulative exposure to heat and is a better predictor of climate change impact than average temperature. GDU and KDU are the two complementary measures popularly used in agronomic studies, and of these two, the consensus among researchers is that KDU is a better predictor of climate change.[11,12] However, we are incapable of using it in this current study due to scanty KDU observations or little exposure to temperatures above 30 - 32°C in our data (see, Figure F2 of the Appendix).[13] For example, less than 1 percent of our millet data - a heat-tolerant cereal crop - reached the maximum

[10]See Harris et al. (2014) for a complete description of the dataset.

[11]This appeal, perhaps, comes from the econometric ability to capture possible nonlinear impacts of extreme heat using KDU.

[12]Formally, GDU is defined

$$GDU = \sum_d DU(t_d)$$

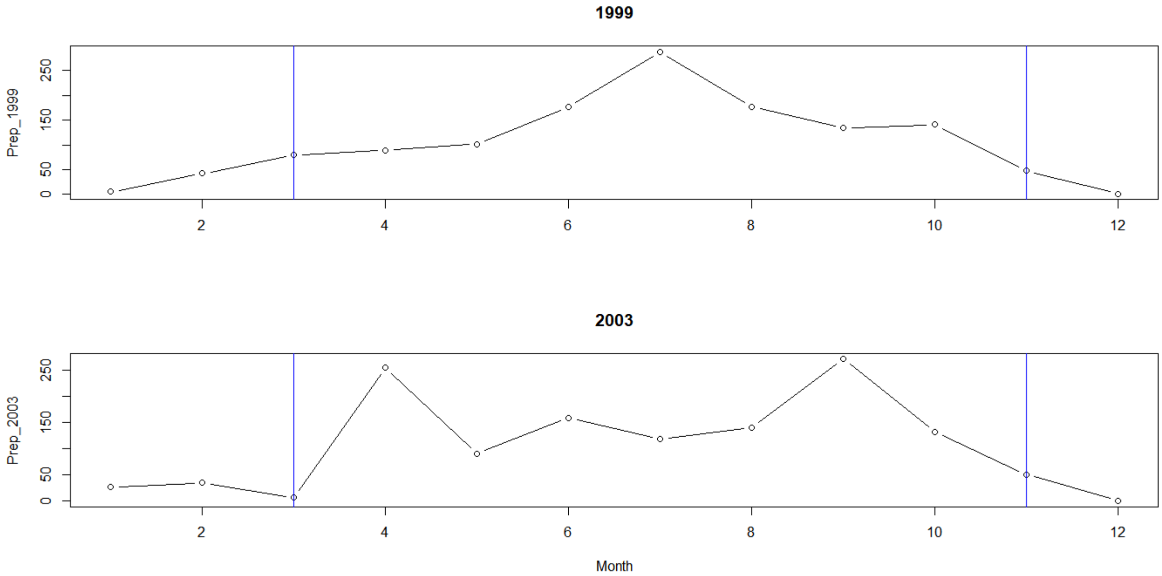
$$where\ DU(t_d) = \begin{cases} 0 & if\ t \leq \kappa_{low} \\ t - \kappa_{low} & if\ \kappa_{low} < t \leq \kappa_{high} \\ \kappa_{high} - \kappa_{low} & if\ \kappa_{high} < t \end{cases}$$

where t_d is average daily temperature in day d, κ_{low}, baseline temperature, but κ_{high} is the temperature ceiling beyond which crops are hurt. In the same vein,

$$KDU = \sum_d DU(t_d)$$

$$where\ DU(t_d) = \begin{cases} 0 & if\ t \leq \kappa_{high} \\ t - \kappa_{high} & if\ \kappa_{high} < t \end{cases}$$

[13]Earlier works by Miao et al. (2015); Lobell et al. (2011); Schlenker and Roberts (2009) volleyed harmful temperature for most cereals between 29°C and 32°C. However, they admitted that the bad temperature might be higher for climate-resilient crops like millet.



Note: The blue vertical lines show that the growing season for Millet MPA in Benin is from March (3rd month) to November (11th month). Precipitation is in mm/month.

Figure 1: Benin (Millet) MPA Monthly Precipitation for Two Years (1999 & 2003)

temperature. It is obvious, at sight, that most MPAs have very low numbers of KDU observations[14]. The scanty observations of KDU in the region are unsurprising given there is less variation in the tropics than in temperate regions from where the use of degree units was generated and mainly utilized (Auffhammer and Schlenker, 2014; Guiteras, 2009).[15] Consequently, in the absence of KDU observations, the second-best alternative is to use average temperature. One drawback of averaging temperature over time is that it masks nonlinearities; nevertheless, these can be recovered by the inclusion of a quadratic term which is the convention in the literature (Schlenker and Roberts, 2009).

The wet day frequency (or count) (WDF) dataset, likewise sourced from CRU TS v4.02, provides gridded time series data on the counts of days per month where precipitation is above 0.1mm for all land areas in the world (excluding Antarctica) at 0.5^{o} resolution for the period January 1901 to December 2017. Recent works like Lobell and Asseng (2017); Fishman (2016) have found WDF to be more relevant in predicting yield changes than the conventional aggregate precipitation used in existing SSA literature. For example, Figure 1 shows a country (Benin) with the same aggregate rainfall over the same growing season for millet (March - September) for two years but with differing distribution. Given the above example, Fishman (2016) argues that rainfall will produce

[14]This occurrence may first seem counter-intuitive given the hot nature of SSA; however, following works by the World Bank and FAO, Auffhammer and Schlenker (2014) affirm that developing countries (including SSA) have soils and climate that are conducive for agriculture.

[15]This may be why existing SSA studies use average temperature instead of degree units. An exception is Lobell et al. (2011), who use growing and harmful degree days to estimate the impact of weather on maize trials in SSA. However, Lobell et al. (2011) focused on areas where maize trials were done, which for most parts, are not where actual crop production takes place.

the same impact if modeled with the aggregate value but different effects for both years when distributional properties are taken into account. Furthermore, for optimal growth and development, water needs must be sustained over a period. For example, Brouwer et al. (1988) show that millet requires at least an assured precipitation of 450-650 mm annually. Using total rainfall does not account for when the rainfall occurs, which WDF remedies.

To our knowledge, vapor pressure deficit (VPD) is a new weather measure that we introduce into the empirical literature of climate change impacts in SSA.[16] VPD (in Kilopascal, kPa) drives water loss from plants *via* evapotranspiration. In essence, it is associated with daily temperature, cloud cover and precipitation; thus, it is a significant determinant of crop yields, as it measures the drought sensitivity of plants. Given the several weather measures related to VPD, it follows that it can impact crop yields in different directions. On the one hand, high VPD may reduce yields by increasing the water requirements of crops (Lobell et al., 2013). On the other hand, high VPD can also benefit plants since it is associated with less cloud cover allowing for much solar radiation, a *sine qua non* for crop growth *via* photosynthesis (Roberts et al., 2012). In sum, the overriding effect will be determined by the moisture content of the soil.[17] The VPD data were obtained from the TerraClimate monthly dataset of climate and climatic water balance for global terrestrial surfaces at a 0.05° spatial resolution (approx. 4 km $\times$ 4 km across the equator).[18]

We exploit this grid feature of our datasets to obtain historical weather observations of millet MPAs in all countries in our sample, thus weather data are unique to each MPA. We achieve this by taking a simple average of all the grid cells overlaying the MPAs. To account for heteroskedasticity, we weigh the weather data by the proportion of area harvested for each crop relative to the country's total land area. The choice of main producing area (MPA) for each country was based on information from the country's Ministry of Agriculture database, FAO (2018), and Monfreda et al. (2008), with the length of growing seasons taken from the various reports of FAO Global Information and Early Warning System (GIEWS)[19] and HarvestChoice (2018) (see, Table F1 of the Appendix for list of millet MPAs in each country, as well as the different growing seasons). One important observation from Figure F1 in the Appendix is the location of most MPAs - proximity to borders - making our assessment of spatial interactions relevant.

It is essential to state that each area is the largest producer (in tonnes) of millet crop in a country. Where there is more than one producing area in a country, we follow

[16]Also known as vapor pressure demand, thus indicating plant's water *demand*, while precipitation is likened to the *supply* side.

[17]It is equally important to state that previous studies such as Lobell et al. (2013) have found VPD to be a better predictor of cumulative evaporative demand than KDU, especially during the hottest months of the growing season.

[18]See, Abatzoglou et al. (2018) for dataset description

[19]`http://www.fao.org/giews/en/`

Table 1: Summary Statistics of Dataset for Millet Yield Model

Variables	**Mean**	**SD**	**Min**	**Max**
Millet Yield (ton/ha)	0.714	0.360	0.04	1.951
Average Temp (°C)	24.9	3.74	15.8	31.5
Average WDF	11.51	5.20	0.03	23.60
Average VPD (kPa)	1.286	0.619	0.392	3.307

Note: SD denotes standard deviation. All variables (except millet yield) are calculated over growing season. Observations = 1457; Countries = 31; Years = 47.

the advice of Moore et al. (2017) by choosing the area with the highest production of the associated cereal. Moreover, we admit that we cannot discountenance the possibility of a shift of main production areas over the period covered (1970-2016). Whereas we do not have any empirical proof to justify the non-occurrence of such displacements, several annual bulletins from FAO GIEWS do not indicate shift of MPAs over the period considered.

Countries in SSA are divided between North and South of the equator, as shown in Figure F1 of the Appendix; therefore, countries in the region do not experience similar seasons. The alternative favored in the literature (e.g., Dell et al., 2014) is growing seasons (the period from planting to harvesting). The use of growing season provides spatially disaggregated estimates that measure weather impacts during periods that are germane to plant growths. Growing seasons differ among countries: for example, although Nigeria and South Africa grow millet, they have different growing seasons. Ergo this study defines growing seasons by country (see Table F1 in the Appendix for a list of the growing seasons per country). This is the first SSA study to use such specific growing seasons as prior SSA studies use a generalized form of growing season across countries. It is important to note that in the event of more than one growing season, the primary growing season is selected.[20] Table 1 presents the summary statistics of the data used in this study, whereas Figure 2 shows a substantial variation in weather measures across the MPAs.

[20]Although there is evidence of change in planting season in some years, such changes are short-term (in response to weather events) rather than long-term (in response to climate). Our choice can, therefore, be likened to the modal growing season for each crop in the period under review.

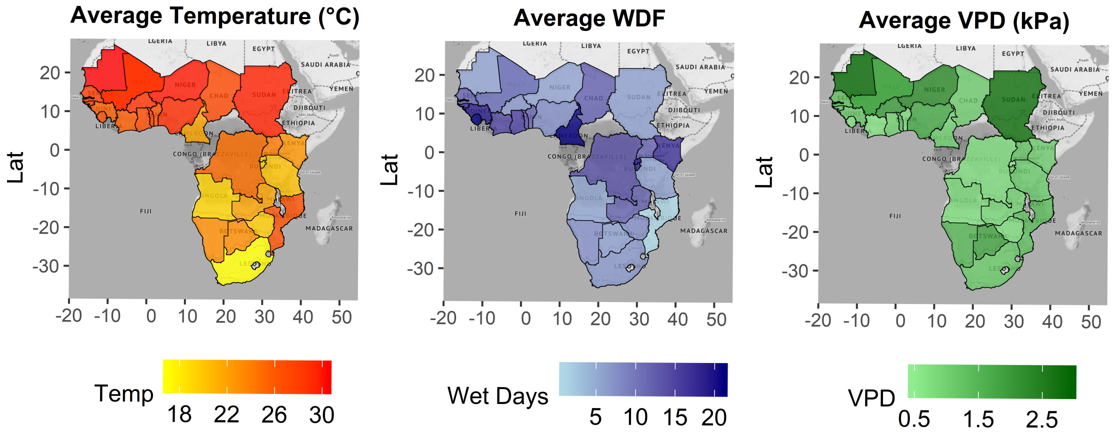


Figure 2: Spatial Variation of Average Weather Measures (1970 - 2016)

3.2 Model specification

Our dependent variable is country-specific millet average yield (tons/ha), y_{ct}, in country c and year t. Our baseline model contains weather measures specific to the MPA, their *spatial* and *temporal* lags, and the lag of the endogenous variable in space. The model is specified as

$$Y_t = WY_t\gamma + C_t\beta + WC_t\vartheta + R_t\omega + \rho + \varepsilon_t \tag{1}$$

where Y_t is an $N \times 1$ vector of (log of) millet yield observations in the cross-section of N countries at time t; C_t are $N \times K$ matrix of climatic variables; ε_t is an $N \times 1$ vector of unobservable random variables capturing the (idiosyncratic) errors. The time trend matrix R_t includes linear and squared terms to capture overall technological progress; ρ is an $N \times 1$ vector of country-level fixed effects which capture the influence of any unobserved, time-invariant country and agro-ecological zones (AEZ) features. The inclusion of the fixed effects implies that our estimates are identified from within-MPA variation in own weather measures and neighbor's from its long-term mean. In spatial econometric terms, W is an $N \times N$ matrix of spatial weights (or connectivity)[21], WY represents spatially autocorrelated outcomes, while WC represents spatial autocorrelation of the covariates (weather measures). In terms of parameter notations, $\boldsymbol{\beta}$, ω, $\boldsymbol{\gamma}$ and ϑ are vectors of parameters to be estimated, the last two being spatial parameters.[22]

The weather variables C in equation (1) includes **average temperature (TEMP)**, **wet day frequency (WDF)** and **vapor pressure deficit (VPD)** over growing season by MPA; the squared terms to capture the nonlinear effects of these weather variables on

[21] These weights can be different based on the spatial processes underlying the research.

[22] The introduction of spatially lagged variables makes our model specification similar to Baylis et al. (2011), except for the choice of location, agricultural outcome, weather variables, and spatial weights.

crop yield; temporal lags and monthly deviation in temperature to account for variability in temperature. Monthly deviation in temperature is calculated as the ratio of the standard deviation to the mean. Besides, we checked the effect of an alternative method, monthly maximum minus monthly minimum temperature, and find no significant difference.

We do not include the squared and temporal lag terms of VPD as we do not find any evidential reason to do so. Moreover, we do not include other controls for the following reasons. First, important edaphic factors such as soil quality are fixed over time and cannot be distinguished from country-specific effects.[23] Hsiang (2016) and Dell et al. (2014) further argue that the addition of more controls will not necessarily move the climate change impact estimate closer to its true value if the controls (such as GDP and institutional measures) are outcomes of climate. Rather, such addition will induce an "over-controlling problem". Consequently, the standard practice in climate change applied studies using panel data is to exclude other time-varying controls.[24]

In general, certain challenges confront the causal relationship in this setting. For a given MPA, meteorological conditions tend to trend throughout a growing season. Since crop output also trends, such temporal dependence may confound the estimated effect of weather fluctuations of millet yields with other determinants of crop outputs that are evolving gradually. Besides, several weather variables are strongly correlated, and these correlations can confound causal relationship if important weather variables are omitted. These potential challenges are addressed in this study by including time trend, country fixed effects, and several weather measures in the equation. Addressing these confounding challenges enables us to isolate the effect of random variation across our selected weather variables.

Concerning the choice of spatial weights, there is no unanimity in the literature on the most appropriate or a "one-fits-all" spatial weight (Anselin, 2001). In selecting spatial weights, we follow Ho et al. (2018) and Kumar (2011) in using inverse distance spatial weights matrix in the analysis with cutoff at 910 km. In essence, we assign the value *1* to MPAs within the cutoff distance from the centroid of the MPA of interest and *0* to others. The choice of the cutoff ensures that every MPA has at least one neighbor. It is important to note that LeSage and Pace (2009) emphasize that the true $\boldsymbol{W}$ is generally unknown, therefore, to further our analysis, we use a couple of other spatial weights

[23] Deschênes and Greenstone (2007); Schlenker et al. (2005) show that the effect of weather fluctuations on irrigated areas differs from nonirrigated areas. While we recognize that irrigation can be an important determinant of crop yield, we are limited by the lack of comprehensive irrigation data for SSA. Moreover, agriculture in SSA is mostly rain-fed with evidence of low capacity for crop management such as irrigation (FAO, IFAD, UNICEF, WFP & WHO, 2018; Dingkuhn et al., 2006).

[24] This conventional practice is evidenced in empirical studies like Hsiang and Meng (2015); Schlenker and Lobell (2010) (agricultural production); Emediegwu (2021); Deschênes and Greenstone (2011) (mortality); Kalkuhl and Wenz (2020); Dell et al. (2012) (economic growth), and Hsiang et al. (2013, 2011) (conflict).

matrix to check for robustness of results. Specifically, we re-estimate the model using *4-nearest* and spatial weights based on the prevailing economic network. To create these weights matrices, we construct shapefiles from the ArcGIS 10.3 software.[25] Thereafter, we cascade the shapefile into Anselin et al. (2006) GeoDa 1.10 software to create any spatial weights matrix of our choice.[26] For ease of interpretation, spatial matrices based on inverse distance are usually not row-normalized (Anselin, 1988): however, we row-normalize other spatial weight matrices used in our robustness analysis. More explanation on spatial weight matrices can be found in the Appendix, Section A.

Our baseline specification corrects for spatial interactions in the dependent and independent variables *via* spatial weight matrices, resulting in a so-called spatial Durbin model (SDM) (Elhorst, 2014). Spatially-dependent errors are accounted for through clustering at MPA level. We present the likelihood of the SDM in Section B of the Appendix. Following Elhorst (2014) and Anselin et al. (2008), we implement maximum likelihood estimation (MLE) using a package in R developed by Millo and Piras (2012), known as *splm* to estimate the attendant spatial models.[27] However, for comparative purposes, we will be contrasting estimates from our baseline spatial model with those from a non-spatial (NS, hereafter) model by excluding the spatial effects mentioned above, that is, by estimating equation (1) with $\boldsymbol{\gamma}$ and ϑ in equation (1) set to zero.

In addition to the baseline estimation, we employ different strategies to (1) ascertain the robustness of our estimates, and (2) account for adaptation possibilities. For sensitivity analysis, we re-estimate equation (1) with alternative time trends; more time lags; exclusion of outlier country; different spatial weight. We also use long differences approach developed in Burke and Emerick (2016) and flexible long differences approach by Yu et al. (2021) to check whether or not SSA countries adapted to changing climate within our sample period.[28]

4 Results and discussion

4.1 Baseline estimates

Let us begin by looking at the broad outline of the results in Table 2. The existence of spatial dependence in our model specification is ascertained *via* the classical Lagrange multiplier (LM) test by Anselin (1988) and its robust version developed in Anselin et al. (1996). The results in Table 2 show that the LM test and robustness are significant at

[25]The ArcGIS is a geographic information system (GIS) for working with maps and geographic information developed by the Environmental Systems Research Institute (ESRI).

[26]GeoDa is a free software program developed by Anselin and his team that acts as an introduction to spatial analysis.

[27]We use the *spml* command in R package "splm" with options for robust inferential statistics, bias correction and spatial diagnostics.

[28]Thanks to an anonymous referee that directed us to these approaches.

5% level, indicating the presence of neglected spatial effects in our model specification.

By way of comparison, Table 2 shows that the non-spatial (NS) specifications' coefficient estimates have the same sign and statistical significance as the SDM for all weather measures. Generally, the signs of the weather estimates follow *a priori* expectations and are statistically significant in both models. The estimates on temperature and WDF are shown to be negatively and positively related to yield, respectively. In contrast, the estimate on temperature deviation is insignificant in all the models, which is unsurprising given the small within variation in temperature over the growing period. Temperatures in the tropics exhibit similar values across growing season resulting in little within variation in temperature (Auffhammer and Schlenker, 2014; Guiteras, 2009), thereby leading to insignificant estimates. The squared term for WDF is negative and significant across specifications, whereas the quadratic term for temperature is positive and significant in all models, ergo reflecting the nonlinear relationship between weather changes and crop outputs.

VPD is significantly and negatively related to millet yield signifying that millet yield can be affected by water loss from the crops. Besides, the time trend and its squared term are positive, as expected, showing technological and agronomic progress over time.

4.1.1 Spatial lag effects

Caution must be exercised in an attempt to compare the estimates from spatial models (SDM, for example) to non-spatial models (NS), as the coefficients from the spatial models do not represent marginal effects, unlike its non-spatial companion. In terms of interpretation, the estimates of NS models represent direct and total effects, as NS models do not produce spillover effects by construction. Hence, using point estimates to inform comparative or inferential judgments tend to be erroneous (Elhorst, 2014). On the other hand, the (non)existence of spatial spillovers in an SDM should be ascertained from the estimated indirect effects of the regressors, rather than the coefficient estimates (and standard errors) of the spatially lagged regressors. Said differently, the statistical significance of the estimated coefficient of a spatially lagged explanatory variable can differ from its estimated indirect effect. To achieve this aim, we use the *impacts* command in R package "splm" to derive the direct, spillover (indirect) and total effects and report them in Table 3.[29]

The existence of spatial interactions has vital economic implications. Any change in spatially lagged variables has both direct and indirect consequences to which we now focus attention. Whereas the estimates of NS models represent direct and total effects, the estimates of the SDM can be split into direct and indirect effects. Table 3 shows that the direct effects of the spatial specification differ from those of the NS specification. For

[29]In the face of significant spillovers, it is expected that the direct effects of the explanatory variables differ from their estimated coefficients.

Table 2: Model Comparison of the Estimation Results of Millet Yield (Yield is in log)

	NS	**SDM**
TEMP	-0.2034***	-0.2177***
	(0.0904)	(0.0521)
WDF	0.0227***	0.0201***
	(0.0023)	(0.0016)
VPD	-0.2704***	-0.1968***
	(0.1082)	(0.0311)
TEMPsq	0.0107***	0.0035**
	(0.0036)	(0.0016)
WDFsq	-0.0031***	-0.0007***
	(0.0009)	(0.0002)
TEMP. dev.	-0.0131	-0.0071
	(0.0101)	(0.0065)
Time trend	0.0114***	0.0144***
	(0.0031)	(0.0033)
Time trend squared	0.0001***	0.0001***
	(0.0000)	(0.0000)
W*TEMP		-0.0086
		(0.0092)
W*WDF		0.0063**
		(0.0026)
W*VPD		0.0083
		(0.0112)
W*TEMPsq		-0.0021
		(0.0033)
W*WDFsq		0.0004
		(0.0051)
$TEMP_{t-1}$	-0.0028*	-0.0020
	(0.0014)	(0.0008)
$TEMP_{t-2}$	0.0052	0.0015
	(0.0036)	(0.0040)
WDF_{t-1}	-0.0026**	-0.0026**
	(0.0010)	(0.0011)
WDF_{t-2}	0.0073	0.0007
	(0.0061)	(0.0064)
Gamma		-0.0419***
		(0.0052)
LM spatial lag	13.67***	
Robust LM spatial lag	4.18**	
R^2	0.21	0.60

Notes: Standard errors (in parentheses) are clustered at MPA level. W = inverse distance matrix, cutoff = 910 km. ***p<0.01, **p<0.05, *p<0.1.

example, the direct effect of VPD is -0.21 in the SDM and -0.27 in the NS specification. On the other hand, only the estimate of the indirect effect WDF appears to be moderately significant. However, the estimate of the indirect effects are relatively small compared to those of the direct effects, reinforcing the notion that most of the effects emanate from the home country, thus are local effects. Furthermore, the indirect effects associated with the temperature variables and VPD are statistically insignificant in our spatial models, however, we included them in our models to have a full specification with lagged exogenous variables.

In all, the respective estimated total effects of temperature and WDF are negative and positive for the NS models, although these effects increase marginally when we correct for spatial influences. We also find that the signs of the total (direct plus indirect) effects of TEMPsq and WDFsq are significantly negative and positive, respectively. As a result, the overall total effect of temperature depend on the level of temperature itself, and the overall total effect of WDF depend on the level of WDF. When calculated at their respective means, the overall total effect of temperature is -0.158, while that of WDF is 0.023. Therefore, a temperature rise is associated with a fall in millet yield. On the other hand, millet yield changes in the same direction as WDF in SSA. Overall, our result suggests that controlling for spatial effects provides larger estimates of the impacts of temperature and WDF on millet yield than those of non-spatial effects. This result is in line with earlier findings by Hossain and Ahsan (2018); Kumar (2011) that rainfall patches span longer periods and travel as underground water and through river channels to positively affect agricultural production in neighboring units.

The estimation results in Table 3 further show that VPD is negatively related to millet yield. This finding, supported by plant physiological understanding and previous empirical studies (Lobell et al., 2013; Barnabás et al., 2008), signifies that water loss or high water demand can be disastrous for plant development. Further, the strong adverse effect of VPD depicts that our model is more sensitive to heat than water gain, which is consistent with previous studies such as Urban et al. (2015); Lobell et al. (2013); Roberts et al. (2012). However, these impacts are entirely local as we find no evidence of any spatial effect arising from VPD, as the estimated indirect impacts are minimal and insignificant.

Spatial lag of millet yield (*gamma* in Table 3) is negative and significant for the spatial model. This means that reduction in millet production in one country would induce a rise in output in the surrounding countries. The implication of this finding is in tandem with previous empirical studies (e.g., Cai et al., 2016; Bohra-Mishra et al., 2014; Gray and Mueller, 2012) that find that households use migration as a risk management strategy against climatic shocks.

In summary, it is clear that the direct effects stochastically dominate the indirect effects in our model since the direct effect of WDF is several times higher than its in-

Table 3: Direct and Spillover Effects based on the Models' Estimates from Table 2

	NS	**SDM**
Direct Effect[a]		
TEMP	-0.2034***	-0.2187***
	(0.0904)	(0.0533)
WDF	0.0227***	0.0210***
	(0.0023)	(0.0058)
VPD	-0.2704***	-0.2106***
	(0.1082)	(0.0336)
TEMPsq	0.0107***	0.0031**
	(0.0036)	(0.0016)
WDFsq	-0.0031***	-0.0007***
	(0.0009)	(0.0001)
Indirect Effect[a]		
TEMP		-0.0041
		(0.0055)
WDF		0.0069**
		(0.0028)
VPD		0.0042
		(0.0096)
TEMPsq		-0.0018
		(0.0040)
WDFsq		0.0005
		(0.0053)
Total Effect[a]		
TEMP	-0.2034***	-0.2228***
	(0.1096)	(0.0436)
WDF	0.0227***	0.0279***
	(0.0023)	(0.0011)
VPD	-0.2704***	-0.2064***
	(0.1082)	(0.0412)
TEMPsq	0.0107***	0.0013**
	(0.0036)	(0.0006)
WDFsq	-0.0031***	-0.0002***
	(0.0009)	(0.0000)
Gamma		-0.0419***
		(0.0047)

Notes: [a]The overall effects with respect temperature depend on the figures reported here for TEMP and TEMPsq, and the overall effects with respect to WDF depend on the figures reported here for WDF and WDFsq; see text. Standard errors (in parentheses) are clustered at MPA level. W = inverse distance matrix, cutoff 910 km. ***p<0.01, **p<0.05, *p<0.1.

Table 4: Total Effect of Temporal Lags based on the Models' Estimates from Table 3

Dependent Variable log (yield)	**NS**	**SDM**
$\text{TEMP}_{t\text{-}1}$	-0.0028*	-0.0035
	(0.0014)	(0.0024)
$\text{TEMP}_{t\text{-}2}$	0.0052	0.0032
	(0.0036)	(0.0041)
$\text{WDF}_{t\text{-}1}$	-0.0026**	-0.0029**
	(0.0010)	(0.0014)
$\text{WDF}_{t\text{-}2}$	0.0073	0.0019
	(0.0061)	(0.0011)

Notes: Standard errors (in parentheses) are clustered at MPA level. W = inverse distance matrix, cutoff = 910 km. ***p<0.01, **p<0.05, *p<0.1.

direct counterpart. Nevertheless, regardless of how small the indirect effect may seem in magnitude, it is not negligible, signifying that changes in one country's parameters, especially WDF, translate to small but significant changes in nearby countries. Therefore, their inclusion in statistical analysis is of first-order importance, as Dell et al. (2014) suggested.

4.1.2 Temporal lag effects

The results in Table 4 indicate that the impacts of time lags are dissimilar in the NS and the SDM model. From the NS model, high temperature values reduce millet output marginally in the following year, but not the year after: however, this weak effect becomes insignificant when spatial influences are accounted for. This weak effect implies that the impact of a hot year does not persist into the following year. On the flip side, one-year lag of WDF is negatively related to yield, but such persistence fades away in the second year. This sustained effect is unsurprising as a very wet year may lead to flooding, the impact of which may spill over to the next year, thus bringing on an adverse effect on crop development the following growing season.[30] The findings here differ with the use of precipitation instead of WDF, as explained in section C of the Appendix.

The above results reflect the *delayed* effect or *temporal* persistence of weather shocks cited in several studies (Hsiang, 2016; Burke et al., 2015b; Dell et al., 2012). Accounting for these *ripple* effects is significant if economic activities, such as agriculture, still catch up or degenerate further after contemporaneous impacts. In sum, for WDF, the impact of weather shocks continues into the next time period but fizzles out in the third time

[30] Most SSA countries are already susceptible to flooding (see, `http://floodlist.com/africa`) due to natural and anthropogenic causes such as prolonged and heavy rainfall, deforestation, improper waste disposal, lack of crop management procedures, *etc.*

period. However, these delayed effects attenuate rather than dominate contemporaneous effects.

4.2 Sensitivity analysis

We employ different strategies to check the robustness of our baseline estimates. The results of the robustness checks are presented in Table 5. We truncate the results due to space by presenting only estimates for direct and spillover effects and the total effects of one-period temporal lags of the weather measures. Put another way, we exclude the estimates of the quadratic terms, the spatial lag of Y, the second-period temporal lags, and time trend with its square.

Column 2 in Table 5 shows that including only linear time trend produces analogous estimated spatial effects of the weather variables, both in spatial and temporal terms. In like manner, column 3, which utilizes no time trend produces similar results, although at the expense of a marginal decrease in the coefficients in some cases. Removing outlier country, South Africa, which reports high millet yield, does not change our benchmark estimates, as seen in column 4, implying that outliers do not drive our results. Introducing more time lags (using three lags instead of two) does not significantly alter the baseline estimates, as seen in column 5, although some weather estimates like temperature reduced in significance.[31]

We also confirm whether our results are robust to different weighting schemes by using another spatial weight matrix, *k-nearest neighbor* where $k = 4$, and weight "1" is assigned to the four nearest MPAs to MPA i, and "0" to others. In the spirit of LeSage (2014), we do not expect a properly specified spatial model to be sensitive to the choice of spatial weight. It is possible that the spillover effects do not emanate from just the border countries but distant countries as well. The results presented in column 6 show that the direct and indirect effects' estimates are not significantly different from those following the inverse distance matrix in baseline estimates, except that the indirect effect of temperature became slightly significant. Summarily, we evidence that our baseline estimates are broadly similar across a range of empirical specifications.

4.3 Disaggregating the impacts

Do poor and rich countries react similarly to weather changes? This debate has been ongoing in the last few years. On the one hand, Dell et al. (2012) find no difference in climate response between rich and poor countries, concluding that countries are affected adversely by temperature increase because they are already hot and not due to poverty. On the other hand, Burke et al. (2015b) argue that poor and rich countries respond

[31] Additionally, we also checked whether using levels (instead of logs) of yields will affect the results considerably and find it not to.

Table 5: Main Estimates and Robustness Results

	(1) Baseline	(2) Linear Time	(3) No Trend	(4) No ZAF	(5) 3 Lags	(6) *4-NN*
Direct effects						
TEMP	-0.2187***	-0.1923***	-0.2170***	-0.2258***	-0.1224*	0.2281***
	(0.0533)	(0.0512)	(0.0531)	(0.0651)	(0.0930)	(0.0555)
WDF	0.0210***	0.0205***	0.0227***	0.0244***	0.0108***	0.0270***
	(0.0058)	(0.0078)	(0.0057)	(0.0077)	(0.0066)	(0.0061)
VPD	-0.2106***	-0.226***	-0.2380***	-0.2032***	-0.2451***	0.2079***
	(0.0336)	(0.0466)	(0.0316)	(0.0433)	(0.0270)	(0.0321)
Indirect effects						
TEMP	-0.0041	-0.0031	-0.0036	-0.0014	-0.0020	-0.0026*
	(0.0055)	(0.0073)	(0.0072)	(0.0083)	(0.0114)	(0.0012)
WDF	0.0069**	0.0063**	0.0063**	0.0059**	0.0030*	0.0046**
	(0.0028)	(0.0030)	(0.0032)	(0.0027)	(0.0014)	(0.0020)
VPD	0.0042	0.0047	0.0051	0.0032	0.0054	0.0061
	(0.0096)	(0.0055)	(0.0050)	(0.0027)	(0.0061)	(0.0063)
Temporal Effects						
$TEMP_{t-1}$	-0.0035	-0.0024	-0.0026	-0.0030	-0.0011	-0.0032
	(0.0024)	(0.0047)	(0.0047)	(0.0035)	(0.0053)	(0.0046)
WDF_{t-1}	-0.0029**	-0.0025*	-0.0025*	-0.0031**	-0.0019	-0.0047**
	(0.0014)	(0.0013)	(0.0013)	(0.0014)	(0.0015)	(0.0020)
R^2	0.60	0.59	0.60	0.58	0.40	0.61

Except stated, all models include time trend and its quadratic term, spatial weight is inverse distance, with errors clustered at the MPA level. Temperature is measured in ^{o}C and VPD in kPa. Columns: (1) baseline specification from Table 2, (2) as in column 1 but only linear time trend, (3) as in column 1 but no time trend, (4) as in column 1 but dropping South Africa, (5) as in column 1 but adding 3 temporal lags of TEMP and WDF, (6) as in column 1 but using *4-NN* as spatial weights.

***p<0.01, **p<0.05, *p<0.1.

Table 6: Effects by Income Classification of SSA Countries

	(1) Baseline	(2) TEMP	(3) WDF
Direct Effect			
TEMP	-0.2187***	-0.1942***	-0.2103***
	(0.0533)	(0.0484)	(0.0510)
WDF	0.0210***	0.0207***	0.0197***
	(0.0058)	(0.0051)	(0.0060)
VPD	-0.2106***	-0.2209***	-0.1918***
	(0.0336)	(0.0340)	(0.0342)
Indirect Effect			
WDF	0.0069**	0.0057**	0.0059*
	(0.0028)	(0.0023)	(0.0030)
Gamma	-0.0419***	-0.0415***	-0.0418***
	(0.0047)	(0.0046)	(0.0046)
Temporal Effect			
TEMP$_{t-1}$	-0.0035	-0.0023	-0.0031
	(0.0024)	(0.0048)	(0.0071)
WDF$_{t-1}$	-0.0029**	-0.0027*	-0.0031*
	(0.0014)	(0.0015)	(0.0016)
Interaction Effect			
TEMP*Poor		-0.0008*	
		(0.0004)	
WDF*Poor			-0.0006
			(0.0009)
R^2	0.60	0.61	0.61

Notes: Except stated, all models include time trend and its square, spatial weight as inverse distance, with errors clustered at the MPA level. Column 2 (3) includes an interaction term for temperature (WDF) and poor countries into the baseline equation. Temperature is measured in ^{O}C and VPD in kPa. For space sake, we do not include temporal lags and quadratic terms of TEMP and WDF. A country is termed "poor" if it is classified as low income by the World Bank; otherwise, it is termed "rich". ***p<0.01, **p<0.05, *p<0.1.

differently to weather shocks when nonlinearities in weather measures are included. We want to contribute to the debate by ascertaining whether our lags' estimates will differ on account of income differentiation. We examine the impact of weather shocks on millet yield while controlling for each country's income class. Using the income classification of SSA countries from World Development Indicators, we interact poor countries with temperature and WDF separately, where a country is labeled as 'poor' if it falls in the low-income category as of 2018 (see, Figure F4 of the Appendix for income classification of countries).

The results in Table 6 show that the main variables maintained their signs and significance, but the spatial and temporal lags' effects reduced in significance. For example, Column 3 shows that the indirect and temporal lag effects of WDF decreased significantly. Moreover, similar to the findings of Burke et al. (2015b), temperature increase would adversely affect poor countries more than rich countries, although the significance is weak. On the contrary, we find no such effect on interacting with WDF.

4.4 Accounting for adaptation

The most critical challenge of panel model analysis is adaptation. In particular, the use of country fixed effects and time-trends absorbs long-run atmospheric conditions, which are important for understanding how agents adapt to climate change. Said differently, the panel data model assumes that the relationship modeled remains unchanged or *stationary*, even in the face of climate change. Hence it rules out the possibility of farmers taking adaptive measures (such as use of weather-resistant cultivars) to alleviate the adverse effects of climate change, thus presenting a pessimistic view of its impacts.[32] Different methods have been proposed to take account of the possibility of adaptation to climate change within a panel data setting. For example, Burke and Emerick (2016) use estimates based on a long differences (LD) approach to identify how US farmers adapt to climate change.

More recently, Yu et al. (2021) extend the LD approach by developing a flexible long differences (FLD) technique to estimate the responsiveness of crop yields to gradual changes in climate. Unlike the LD approach, the FLD technique allows for time-varying agricultural adaptation between two periods by interacting a period dummy with climate variables. The parameter estimates from these methods can be argued to provide a better basis for predictions of the impact of future climate changes on yields because the estimates take account of adaptations by farmers to past climate changes. This argument is premised on the assumption that there has been sufficient variation in climate variables in the estimation sample for adaptation to be adequately captured.

Here, we employ both models to check whether adaptation occurred within the period of our estimation. We only present the results here, the construction of the associated model is given in Section D in the Appendix. The results of both models are summarized in Table 7. We compare the results from the LD and FLD approaches to the non-spatial analogue of equation (1) for two reasons. One is for ease of identifying the presence or otherwise of adaptation using the LD and FLD approaches devoid of spatial complications. The second is following the *specific-to-general* modeling procedure, where we only proceed to a more complex model if we find evidence of adaptation in the non-spatial model. The results from Columns 2 - 3 in the Table 7 show that the estimates are insignificant across all model specifications. Consequently, this study does not find evidence that millet yield in SSA is affected by changes in 5-year and 10-year average weather conditions.

Furthermore, previous studies like Burke et al. (2015b); Dell et al. (2012) find no evidence that SSA countries adapt during the period under review, either by way of technological advancement or knowledge accumulation. Summarily, neither the LD nor the FLD approach provides evidence of adaptation in SSA countries over the period considered in this study. The scope of this result could differ if a more disaggregated dataset (e.g., household or farm level) is considered. For example, using farm-level dataset,

[32] Auffhammer and Schlenker (2014) attenuate this claim by suggesting that the introduction of non-linear weather measures introduces cross-sectional variation in climate, hence the estimated parameters, at least, partially captures long-run adaptation. However, the extent to which the adaptation effect is captured is still a subject for debate as it depends on the size of the cross-sectional variation *vis-a-vis* location-specific weather variation (see, Carter et al. (2018) for more intuition).

Table 7: Alternative Estimation Procedures

	1 (Baseline)	2a (LD)	2b (LD)	3a (FLD)	3b (FLD)
TEMP	-0.2034^{***}	-0.1422	-0.1770	-0.1401	-0.1572
	(0.0904)	(0.1121)	(0.2941)	(0.1226)	(0.2031)
WDF	0.0227^{***}	0.0165	0.0096	0.0131	0.0104
	(0.0023)	(0.0318)	(0.0167)	(0.0364)	(0.0177)
VPD	-0.2704^{***}	-0.1153	-0.1539	-0.1271	-0.1321
	(0.1082)	(0.2012)	(0.2331)	(0.1952)	(0.1962)
$D_b \times TEMP$				0.0631	0.0472
				(0.0724)	(0.0532)
$D_b \times WDF$				-0.0091	-0.0025
				(0.0138)	(0.0109)
$D_b \times VPD$				0.0818	0.0596
				(0.1749)	(0.0839)

Notes: Column (1) is the results of the non-spatial version of equation (1). Columns (2a) and (2b) are long differences model estimates of the impact of a change in 5-year (1970-1974 and 2012-2016) and 10-year (1970-1979 and 2007-2016) average weather conditions on millet yield. Columns (3a) and (3b) are flexible long differences model estimates of the impact of a change in 5-year (1970-1974 and 2012-2016) and 10-year (1970-1979 and 2007-2016) average weather conditions on millet yield. Temperature is measured in ^{o}C and VPD in kPa.
***p<0.01, **p<0.05, *p<0.1.

Di Falco et al. (2020); Di Falco (2014) find that local farmers adapt to climate change in some parts of SSA. Consequently, our result here should not be interpreted to imply the absence of adaptation to climate change in SSA but, rather, should be interpreted cautiously with the observational unit in mind.

4.5 Trade mechanism

Weather shocks in an MPA can affect other MPAs' yields if free trading exists among contiguous MPAs. Earlier studies have highlighted that where free trade exists among countries, the principle of comparative advantage could re-align countries to focus on products where they are more efficient and import those products where they are less efficient.[33] Weather is one of the factors that determine which crop a country is (in)efficient at, thus such country can (dis)invest in such crop at which it is (in)efficient. Alternatively, where crop production takes place at border areas (which is the case for many MPAs as seen in Figure F1 in the Appendix) and given that most SSA countries' borders are porous, countries with much harvest tend to attract resources (including potential farm labor) away from neighboring countries.

We re-examine our baseline equation using spatial weights to account for free trade.[34] As outlined in Corrado and Fingleton (2012); Ullah (1998), spatial weight matrices can be created to reflect spatial interactions based on economic (or regional market) network. To create this special spatial weights matrix, we subdivide the entire SSA region into seven economic blocs as specified by the United Nations Economic Commission for Africa (UNECA) (see, Table F3 of the Appendix for the list of these blocs and the constituent countries). Among the aims of these blocs is free movement of persons and goods among member states. Free trade might be made easier given that most of the MPAs are at border areas, in addition to the porous nature of these borders. We proceed by assigning the value *1* to MPAs within the same economic bloc and *0* to others.

The results are displayed in Table 8. Since we are interested in the spatial effects, the results are truncated to exclude temporal lags. A look at the weather variables in column 2 shows a qualitative similarity to our baseline estimates in column 1, although some weather coefficients change noticeably. For instance, the indirect effect of WDF gained significance, while the indirect impact of temperature rose marginally. Additionally, the impact of spatial lag of yields became stronger in the new spatial model. The result is expected as the spatial weights matrix used for our baseline analysis may group MPAs who do not trade freely.

[33] Earlier studies on comparative advantage, free trade and non-agricultural sector include Doku and Di Falco (2012); Redding (1999); Leamer and Levinsohn (1995); Krugman (1987), among others; while works such as Matsuyama (1992); Goldin (1990) discussed the agricultural sector.

[34] We would have preferred to use trade indicators such as price, import or export indices, but they are either unavailable or incomplete.

Table 8: Direct and Spillover Effects using Economic Networks as Spatial Weights

	1 (Baseline)	2 (Economic network)
Direct Effect		
TEMP	-0.2187***	-0.1919***
	(0.0533)	(0.0431)
WDF	0.0210***	0.0258***
	(0.0058)	(0.0012)
VPD	-0.2106***	-0.2581***
	(0.0336)	(0.0476)
Indirect Effect		
TEMP	-0.0041	-0.0025*
	(0.0055)	(0.0014)
WDF	0.0069**	0.0076**
	(0.0028)	(0.0030)
Total Effect		
TEMP	-0.2228***	-0.1944***
	(0.0436)	(0.0457)
WDF	0.0279***	0.0334***
	(0.0011)	(0.0041)
Gamma	-0.0419***	-0.0580***
	(0.0047)	(0.0037)
R^2	0.60	0.62

Notes: Except stated otherwise, all models include time trend and its quadratic term, spatial weight is inverse distance, with errors clustered at the MPA level. Temperature is measured in ^{O}C and VPD in kPa. Models: (1) estimates from baseline specification, (9) as in model 1 but using economic networks (blocs) as spatial weights.
***p<0.01, **p<0.05, *p<0.1.

5 Mid-future climate projections (2040 - 2069)

This section considers the contemporaneous, spillover, and temporal effects of millet yield to future changes in SSA climatic events. The conventional method of estimating the potential impacts is to combine the regression estimates from the baseline model with forecasted climatic changes derived from global climate models (GCMs). However, this method, which is the norm for previous African studies (with exception of Schlenker and Lobell (2010)) produces point estimates that neglect two crucial sources of uncertainty - climate and statistical sources. Two exercises are essential to incorporating these uncertainties - derive projected changes in relevant weather variables under three climate change models and re-calibrate the baseline model with inputs from bootstrapped runs.

5.1 Global climate models (GCMs)

To tackle the first exercise, we use projected daily weather measures from the following global climate models (GCMs) at a 0.5° spatial resolution belonging to the CMIP5[35]: the Canadian Center for Climate (CCC) model (Flato et al., 2000), the Center for Climate Systems Research (CCSR) model (Sakamoto et al., 2004) and the Parallel Climate Model (PCM) (Washington et al., 2000). The choice of these GCMs against the use of a single model or multi-model predictions is predicated on two factors. One, the selected GCMs predict a varied range of outcomes, which is in tandem with the expectations for the sub-Saharan African region as documented in African climate literature.[36] These heterogeneous outcomes amplify the number of potential scenarios typical of the region under study. The second and perhaps most important reason for using several GCMs is to capture climate uncertainty to some degree. Given that there are no perfect or best models, the use of a single GCM introduces significant uncertainty in climate forecast since we do not know for sure what the future state of the world will be. Although several studies (Moore et al., 2017; Auffhammer and Schlenker, 2014; Knutti, 2010) have promoted the use of CMIP5 average against the use of a single model because predictions from this multi-model approach have been consistently shown to outperform those from individual models, Knutti (2010) notes that this method may smoothen out important heterogeneity in individual models, thereby leading to loss of important information. In spirit of Burke et al. (2015a), we employ individual forecasts from the three GCMs, rather than a single GCM or multi-model average.[37]

Also, we employ the business-as-usual scenario (RCP 8.5) from the GCMs. The decision to use the RCP8.5 scenario is justified by previous studies like Burke et al. (2015b); Dell et al. (2012) that find no evidence that SSA countries adapt during the period under review, either by way of technological advancement or knowledge accumulation. Moreover, Figure F5 of the Appendix finds little variation in the weather measures-yield relationship between 1970 - 2000 and 2001 - 2017.

We derive the change in weather variables at the end of a future period (2040-2069, in our case) by differencing the GCMs projected average weather measures over 2040 to 2069 for a given grid cell over that of a relevant historical (baseline) period (1981 - 2010). This downscaling method helps to remove the bias introduced by global climate models

[35]The fifth phase of the Coupled Model Intercomparison Project (CMIP5) is an umbrella that contains multi-model datasets. In lieu of presenting detailed description of the simulation processes of these global climate models (GCMs), readers are referred to Taylor et al. (2012), whereas the dataset can be retrieved from the CMIP5 website `https://pcmdi.llnl.gov/?cmip5`.

[36]Examples of papers on African agriculture and climate change that use a combination of these GCMs are Kurukulasuriya and Rosenthal (2013); Blanc (2012); Schlenker and Lobell (2010); Mendelsohn and Dinar (2009).

[37]In principle, climate uncertainty cannot be totally eliminated, no matter the number of GCMs used, because the influence of climate on aerosols is complex (Hawkins and Sutton, 2009). At best, uncertainty can be reduced by using forecasts from several GCMs.

Table 9: Summary Statistics of Projected Climate Change

Variables	Baseline (1981-2010)	(1) PCM	(2) CCSR	(3) CCC
Average Temperature (°C)	25.7	26.2	27.5	28.3
Average WDF	15.6	17.43	14.9	12.14
Average VPD (kPa)	1.431	1.451	1.521	1.586

Notes: All variables are calculated over growing season. The entries in columns 2 - 4 reflect projections from the GCMs under RCP8.5 scenario for 2040-2069.

(GCMs) for current climate in some locations.[38] We recognise that averaging these GCMs tends to smooth out heterogeneous spatial patterns.

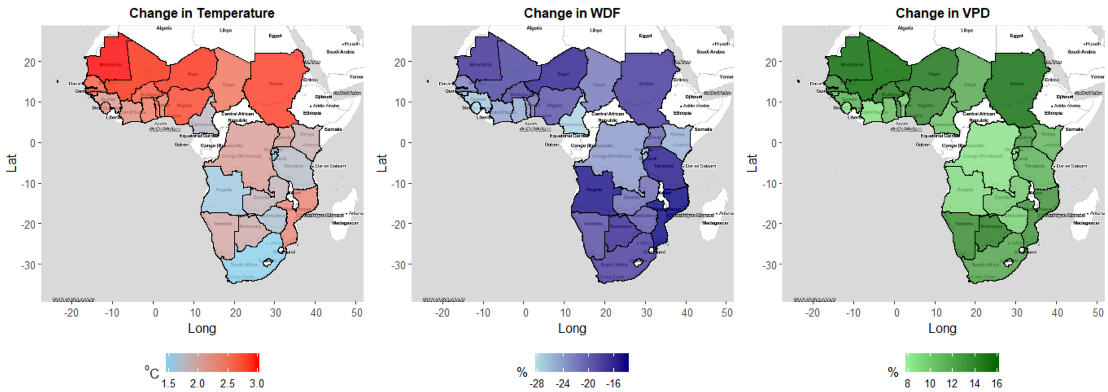
We use MPA-level daily mean precipitation forecasts from the respective GCMs to construct our projected WDF values for each MPA, where WDF is the number of days with rainfall above 0.1 mm. For projected future VPD changes, we obtain daily MPA-level maximum temperature (T_h) and minimum temperature (T_l) and thereafter derive VPD using the conventional formula from Roberts et al. (2012)

$$VPD = 0.6107(e^{(\frac{17.269T_h}{227.2+T_h})} - e^{(\frac{17.269T_l}{227.2+T_l})}) \quad (2)$$

Given the already hot nature of SSA, there is a high prospect of regional warming, making it unlikely to obtain a positive effect on yield from the current projection trend. In like manner, VPD follows the warming trend because both maximum and minimum temperatures are projected to increase over time if future socio-economic conditions mimic past conditions. On the contrary, there is no unanimity on the future trend of rainfall (wet day). For example, Allen et al. (2014) show that for A1B scenario, projected rainfall change across the West African coast by 2090 ranges from -9% to 13% for different GCMs. However, temperature change is anticipated to eclipse rainfall changes (Lobell and Asseng, 2017; Lobell et al., 2013). Notwithstanding, there is a decline in regional WDF on average. It is significant to note that one key assumption in the use of climate models for future predictions is the *ceteris paribus* assumption, plus the belief that climate will continue to affect agriculture in the future.

The summary statistics for the projected values of our weather measures are found in Table 9, and Figure 3 shows the spatial variation of the predicted changes in weather measures. Suggestively, there is evidence of future regional warming from the GCMs, although CCC seems to predict the highest increase by 2069. The trend in predicted WDF varies across the GCMs. While PCM predicts an increase in wet day frequency,

[38]Using observed data against climate model's historical data for the same period will introduce bias into our predicted estimates because both data may have dissimilar observations. For more on this form of bias, see Burke et al. (2015a); Auffhammer et al. (2013).



Note: Predicted changes are from the average of the three GCMs (CCC, CCSR, PCM) for 2040 - 2069 under RCP8.5 scenario. Changes are relative to a 1981 - 2010 baseline.

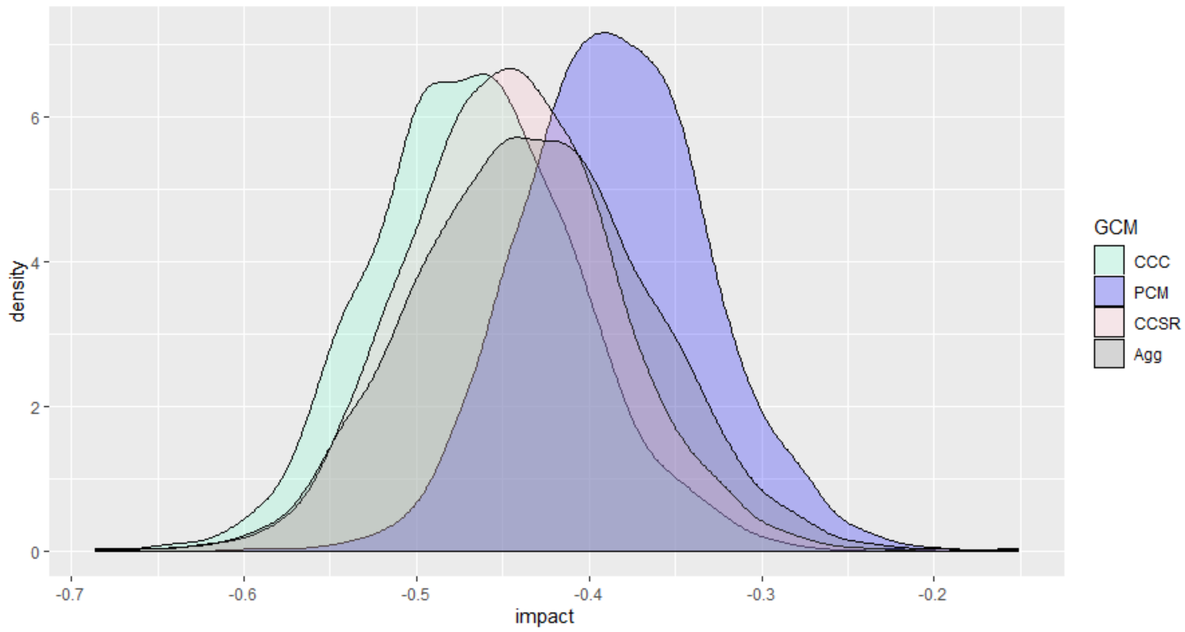
Figure 3: Spatial Variation in Projected Climate Change

others report a decrease in WDF.

5.2 Predicted impact from climate change projections

To fulfill the second exercise, we have to integrate the predicted climatic changes into the response function from equation (1) while controlling for statistical (or regression) uncertainty as noted by Burke et al. (2015a). To sidestep statistical (or regression) uncertainty, we re-estimate equation (1) using data from bootstrapped predicted yields from 1000 bootstrapped residuals and historical climate data to generate bootstrapped coefficients (this is to control for regression uncertainty). After that, we obtain bootstrapped estimates of average predicted impact by varying climate. Finally, a bootstrapped prediction interval with 95% of projected estimates will be constructed from the 2.5th and 97.5th percentiles: hence, distributions are for 3000 (1000 bootstrapped runs $\times$ 3 GCMs) predicted impacts. The construction of the bootstrapped prediction interval is detailed in Section E of the Appendix.

The distributions of predicted impacts from the GCMs' scenarios spanning 2040-2069 are displayed in Figure 4. Assuming that present socio-economic conditions persist, Figure 4 reveals that the median impacts under the baseline specification are -0.46, -0.43, -0.37, and -0.44 for the CCC, the CCSR, the PCM and aggregated models, respectively. Unsurprisingly, the effect from the CCC model is more severe, given it has the highest temperature rise among the selected GCMs. The 2.5th percentile, which images a worst-case scenario, shows dire losses in regional millet yields, ranging between 48% to 55% for all climate models by the middle of the Century. These figures signify an additional 26% to the estimates derived from observational data.



Note: Each density plot represents projected impacts obtained from individual (and aggregate) GCMs with RCP8.5 scenario corrected for both climate and regression uncertainties. The gray plot represents impact from aggregated climate models with inputs from the three GCMs used for projections - CCC, PCM and CCSR. While the impact projections from the individual GCMs plots represent regression uncertainty, the aggregated plot combines both climate and regression sources of uncertainty.

Figure 4: Projections of Climate Change Effects on Millet Yields across GCMs under RCP8.5 Scenario by Mid-Century (2040 - 2069), Relative to a 1981 - 2010 Baseline

Overall, unless there is a positive change in carbon emission trajectory, SSA might experience an overall negative impact in millet output given the amplified damage from warming and the diminished benefits from reduced rainfall in the near future. However, accounting for adaptation possibilities and the beneficial effect of CO_2 on crop fertilization will likely dampen this negative impact.

6 Summary

This paper uses a formal spatio-temporal panel data model to estimate the effect of annual weather fluctuations on millet yield in sub-Saharan Africa (SSA) for 1970-2016. In addition to using updated data, this paper is the first to utilize region-specific weather realizations from major production areas of millet producing countries to analyze the impact of weather variation on millet yields in SSA. Generally, in tandem with weather-agronomic studies for the region, we find that a rise in regional warming reduces millet yield, which is not unexpected since warming increases plant's respiration leading to an increase in carbon metabolism and resulting in a decrease in yields. On the other hand, wet day's increase improves millet output. Our work contributes to African climate studies by revealing that weather changes can indirectly affect cereal production in bordering countries. The omission of such spatial effects could bias the impact of climate change on agriculture in SSA.

By way of comparison, we showed that the estimates from the spatial models differ significantly from those of non-spatial models. For example, accounting for spatial effects amplifies the effect of wet day frequency. The finding is not unexpected since spatial models have both direct effect within the country, as well as spillovers coming from the spatially lagged covariates, thereby moderating or aggravating the direct effect. On the other hand, we find no such indirect effect for temperature and vapor pressure deficit. Furthermore, the effect of wet day frequency on millet yield spills over time, unlike temperature. Although VPD has no transferred effect, either in time or space, the significant contemporaneous relationship suggests that water demand is vital for crop development, and ignoring this weather measure could bias the estimated impact. This finding is robust to a several alternative empirical specification such as use of more lags, different weight matrix, *etc.* Further, we do not find any evidence of adaptation to gradual change in climate over the period considered using national data and long differences approaches. Consequently, there is a call for nations within the region to put efforts together to mitigate and adapt to the harsh effects of climate change on agriculture.

Furthermore, accounting for temporal effects of weather measures is necessary for generating a better estimate of the impact of climate change on agriculture in SSA. Given that several SSA countries are prone to flooding, many wet days tend to have an adverse spillover effect in next year's millet yield. Consequently, national governments must intensify their efforts in the fight against flooding by, among others, facilitating land use planning measures that reduce predisposition to future flooding, educating citizens on the causes, consequences, and effective means of checkmating flooding.

The findings in this paper also reinforce the need for international research and policy coordination in the fight against climate change. Such collaborations are pertinent to overcoming climate change since weather outcomes in a location can affect economic activities in near-by countries. In addition to forging inter-continental partnerships to tackle such a global challenge, Africa needs effective local think-tanks to develop and drive Africa-centric mitigation and adaptation actions and policies. For example, an analogue of the European's Union's research and innovation program, Horizon Europe (2021-2027), which proposes mission areas on adaptation to climate change, including societal transformation, should be founded and funded by African Union (AU) leaders. Collaborative programs of this sort will help maximize the impact of the AU's support to research and innovation in climate change science and demonstrate its relevance for the African society and citizens. Such regional institutions would also address the problems of data availability, accessibility, and quality that have bedeviled the study of climate change impact analysis in SSA.

Finally, if future socio-economic conditions mimic past experiences in the mid-century, unmitigated warming will likely prevail, and yield will go down by an additional 26% (assuming land use remains the same). This drop in millet production accompanied by a projected increase in the region's future population necessitates urgent attention in SSA.[39]

Some caveats are noteworthy in this study: first, we did not account for the beneficial effect of CO_2 on crop fertilization which will likely attenuate this negative impact. However, the non-inclusion of CO_2 might not significantly impact our results as CO_2 fertilization effect might not be that important for millet (see, McGrath and Lobell (2013)). Second, the processes involved in the computation of GCMs leave much to be desired as there is no unanimity on the trajectory path weather measures will follow in the future. For example, while some GCMs project a future increase in rainfall on the West African coasts, others forecast a decrease, and even the extent of the change differs massively. Summarily, in utilizing the interpretation of results generated from uncertain models, caution must be exercised. Regardless of how cautious the results may be, efforts must be combined at different government strata to adapt to and mitigate these climatic influences. One strong proposal, among others, is to increase the production area of tolerant cereal crops such as millet.

References

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., and Hegewisch, K. C. (2018). Terraclimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data*, 5:170191.

Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Church, J. A., Clarke, L., Dahe, Q., Dasgupta, P., Dubash, N. K., et al. (2014). IPCC fifth assessment synthesis report-climate change 2014 synthesis report. *Intergovernmental Panel on Climate Change (IPCC)*.

Anselin, L. (1988). Model validation in spatial econometrics: A review and evaluation of alternative approaches. *International Regional Science Review*, 11(3):279–316.

Anselin, L. (2001). Spatial econometrics. *A Companion to Theoretical Econometrics*, pages 310–330.

Anselin, L., Bera, A. K., Florax, R., and Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, 26(1):77–104.

Anselin, L. and Hudak, S. (1992). Spatial econometrics in practice: A review of software options. *Regional Science and Urban Economics*, 22(3):509–536.

[39] UN (2015) projects SSA population to increase by over 20 percent by 2050 from its 2015 figures.

Anselin, L., Le Gallo, J., and Jayet, H. (2008). Spatial panel econometrics. In *The Econometrics of Panel Data*, pages 625–660. Springer, Berlin.

Anselin, L., Syabri, I., and Kho, Y. (2006). Geoda: An introduction to spatial data analysis. *Geographical Analysis*, 38(1):5–22.

Arbia, G. (2014). *A primer for spatial econometrics: With applications in R*. Palgrave, New York.

Auffhammer, M., Hsiang, S. M., Schlenker, W., and Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, 7(2):181–198.

Auffhammer, M. and Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, 46:555–561.

Baltagi, B. H. (2011). *Spatial Panels*. Chapman and Hall, Taylor and Francis Group Boca Raton, Florida.

Barnabás, B., Jäger, K., and Fehér, A. (2008). The effect of drought and heat stress on reproductive processes in cereals. *Plant, Cell & Environment*, 31(1):11–38.

Baylis, K., Paulson, N. D., and Piras, G. (2011). Spatial approaches to panel data in agricultural economics: A climate change application. *Journal of Agricultural and Applied Economics*, 43(3):325–338.

Belotti, F., Hughes, G., and Piano Mortari, A. (2017). *XSMLE: Stata module for spatial panel data models estimation*. Boston College Department of Economics.

Blanc, É. (2012). The impact of climate change on crop yields in Sub-Saharan Africa. *American Journal of Climate Change*, 1(1):1–13.

Bohra-Mishra, P., Oppenheimer, M., and Hsiang, S. M. (2014). Nonlinear permanent migration response to climatic variations but minimal response to disasters. *Proceedings of the National Academy of Sciences*, 111(27):9780–9785.

Brouwer, C., Prins, K., Kay, M., and Heibloem, M. (1988). *Irrigation water management: irrigation methods*, volume 9. FAO, Rome.

Budyko, M. I. (1969). The effect of solar radiation variations on the climate of the earth. *tellus*, 21(5):611–619.

Burke, M., Dykema, J., Lobell, D. B., Miguel, E., and Satyanath, S. (2015a). Incorporating climate uncertainty into estimates of climate change impacts. *Review of Economics and Statistics*, 97(2):461–471.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, 8(3):106–40.

Burke, M., Hsiang, S. M., and Miguel, E. (2015b). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235.

Cai, R., Feng, S., Oppenheimer, M., and Pytlikova, M. (2016). Climate variability and international migration: The importance of the agricultural linkage. *Journal of Environmental Economics and Management*, 79:135–151.

Carleton, T., Cornetet, J., Huybers, P., Meng, K. C., and Proctor, J. (2020). Global evidence for ultraviolet radiation decreasing covid-19 growth rates. *Proceedings of the National Academy of Sciences*, 118(1).

Carleton, T. A. and Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, 353(6304).

Carter, C., Cui, X., Ghanem, D., and Mérel, P. (2018). Identifying the economic impacts of climate change on agriculture. *Annual Review of Resource Economics*, 10:361–380.

Cliff, A. and Ord, J. (1973). *Spatial Autocorrelation.* Pion, London.

Cliff, A. D. and Ord, J. K. (1981). *Spatial Processes: Models & Applications.* Taylor & Francis, London.

Corrado, L. and Fingleton, B. (2012). Where is the economics in spatial econometrics? *Journal of Regional Science*, 52(2):210–239.

Davidson, R. and MacKinnon, J. G. (1993). *Estimation and Inference in Econometrics.* Oxford University Press, Oxford.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, 52(3):740–98.

Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1):354–385.

Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, 3(4):152–85.

Di Falco, S. (2014). Adaptation to climate change in Sub-Saharan agriculture: Assessing the evidence and rethinking the drivers. *European Review of Agricultural Economics*, 41(3):405–430.

Di Falco, S. and Chavas, J.-P. (2009). On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia. *American Journal of Agricultural Economics*, 91(3):599–611.

Di Falco, S., Doku, A., and Mahajan, A. (2020). Peer effects and the choice of adaptation strategies. *Agricultural Economics*, 51(1):17–30.

Dingkuhn, M., Singh, B., Clerget, B., Chantereau, J., and Sultan, B. (2006). Past, present and future criteria to breed crops for water-limited environments in West Africa. *Agricultural Water Management*, 80(1-3):241–261.

Doku, A. and Di Falco, S. (2012). Biofuels in developing countries: Are comparative advantages enough? *Energy Policy*, 44:101–117.

Elhorst, J. P. (2003). Specification and estimation of spatial panel data models. *International Regional Science Review*, 26(3):244–268.

Elhorst, J. P. (2010). Applied spatial econometrics: Raising the bar. *Spatial Economic Analysis*, 5(1):9–28.

Elhorst, J. P. (2014). *Spatial Econometrics: From Cross-sectional Data to Spatial Panel.* Springer, New York.

Emediegwu, L. E. (2021). Health impacts of daily weather fluctuations: Empirical evidence from COVID-19 in US counties. *Journal of Environmental Management*, 291:112662.

Eriksson, D., Akoroda, M., Azmach, G., Labuschagne, M., Mahungu, N., and Ortiz, R. (2018). Measuring the impact of plant breeding on sub-saharan african staple crops. *Outlook on Agriculture*, 47(3):163–180.

FAO (2018). Global Information and Early Warning System (GIEWS).

FAO, IFAD, UNICEF, WFP & WHO (2018). *The State of Food Security and Nutrition in the World 2018: Building climate resilience for food security and nutrition.* FAO Rome.

Fishman, R. (2016). More uneven distributions overturn benefits of higher precipitation for crop yields. *Environmental Research Letters*, 11(2):024004.

Flato, G., Boer, G., Lee, W., McFarlane, N., Ramsden, D., Reader, M., and Weaver, A. (2000). The Canadian Centre for Climate Modelling and Analysis global coupled model and its climate. *Climate Dynamics*, 16(6):451–467.

Frenken, K. (1997). *Irrigation potential in Africa: A basin approach*, volume 4. Food & Agriculture Org., Rome.

Gibbons, S. and Overman, H. G. (2012). Mostly pointless spatial econometrics? *Journal of Regional Science*, 52(2):172–191.

Goldin, I. (1990). *Comparative Advantage: Theory and Application to Developing Country Agriculture*. OECD, Paris.

Goron, T. L. and Raizada, M. N. (2015). Genetic diversity and genomic resources available for the small millet crops to accelerate a new green revolution. *Frontiers in Plant Science*, 6:157.

Gray, C. and Mueller, V. (2012). Drought and population mobility in rural ethiopia. *World development*, 40(1):134–145.

Guiteras, R. (2009). The impact of climate change on Indian agriculture. *Manuscript, Department of Economics, University of Maryland, College Park, Maryland.*

Harari, M. and Ferrara, E. L. (2018). Conflict, climate, and cells: a disaggregated analysis. *Review of Economics and Statistics*, 100(4):594–608.

Harris, I., Jones, P., Osborn, T., and Lister, D. (2014). Updated high-resolution grids of monthly climatic observations–the CRU TS 3.10 Dataset. *International Journal of Climatology*, 34(3):623–642.

HarvestChoice (2018). CELL5M: A Multidisciplinary Geospatial Database for Africa South of the Sahara.

Hawkins, E. and Sutton, R. (2009). The potential to narrow uncertainty in regional climate predictions. *Bulletin of the American Meteorological Society*, 90(8):1095–1108.

Ho, C.-Y., Wang, W., and Yu, J. (2018). International knowledge spillover through trade: A time-varying spatial panel data approach. *Economics Letters*, 162:30–33.

Hossain, F. and Ahsan, R. (2018). When it rains, it pours: Estimating the spatial spillover effect of rainfall. *Available at SSRN 3267074*.

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, 8:43–75.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D., Muir-Wood, R., Wilson, P., Oppenheimer, M., et al. (2017). Estimating economic damage from climate change in the United States. *Science*, 356(6345):1362–1369.

Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367.

Hsiang, S. M. and Meng, K. C. (2015). Tropical Economics. *American Economic Review*, 105(5):257–61.

Hsiang, S. M., Meng, K. C., and Cane, M. A. (2011). Civil conflicts are associated with the global climate. *Nature*, 476(7361):438.

IPCC (2018). GLOBAL WARMING OF 1.5 ^{o}C an IPCC special report on the impacts of global warming of 1.5 ^{o}C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.

Kalkuhl, M. and Wenz, L. (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management*, 103:102360.

Kapoor, M., Kelejian, H. H., and Prucha, I. R. (2007). Panel data models with spatially correlated error components. *Journal of Econometrics*, 140(1):97–130.

Kelejian, H. H. and Prucha, I. R. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The Journal of Real Estate Finance and Economics*, 17(1):99–121.

Kelejian, H. H. and Prucha, I. R. (1999). A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review*, 40(2):509–533.

Knutti, R. (2010). The end of model democracy? *Climatic Change*, 3(102):395–404.

Krugman, P. R. (1987). Is free trade passé? *Journal of Economic Perspectives*, 1(2):131–144.

Kumar, K. K. (2011). Climate sensitivity of Indian agriculture: Do spatial effects matter? *Cambridge Journal of Regions, Economy and Society*, 4(2):221–235.

Kurukulasuriya, P. and Rosenthal, S. (2013). *Climate Change and Agriculture: A Review of Impacts and Adaptations.* World Bank, Washington, DC.

Leamer, E. E. and Levinsohn, J. (1995). International trade theory: the evidence. *Handbook of International Economics*, 3:1339–1394.

Lee, L. and Yu, J. (2010). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics*, 154(2):165–185.

Leiva, M., Vasquez-Lavín, F., and Oliva, R. D. P. (2020). Do immigrants increase crime? spatial analysis in a middle-income country. *World Development*, 126:104728.

LeSage, J. (2014). What regional scientists need to know about spatial econometrics. *The Review of Regional Studies*, 44(1):13–32.

LeSage, J. P. and Pace, R. K. (2009). *Introduction to Spatial Econometrics (Statistics, textbooks and monographs)*. CRC Press, Florida.

Lim, K., Wichmann, B., and Luckert, M. (2021). Adaptation, spatial effects, and targeting: Evidence from Africa and Asia. *World Development*, 139:105230.

Lobell, D. B. and Asseng, S. (2017). Comparing estimates of climate change impacts from process-based and statistical crop models. *Environmental Research Letters*, 12(1):015001.

Lobell, D. B., Bänziger, M., Magorokosho, C., and Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature Climate Change*, 1(1):42.

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., and Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change*, 3(5):497.

Manners, R. and van Etten, J. (2018). Are agricultural researchers working on the right crops to enable food and nutrition security under future climates? *Global Environmental Change*, 53:182–194.

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory*, 58(2):317–334.

McGrath, J. M. and Lobell, D. B. (2013). Regional disparities in the co2 fertilization effect and implications for crop yields. *Environmental Research Letters*, 8(1):014054.

Mendelsohn, R. and Neumann, J. E., editors (1999). *The Impact of Climate Change on the United States Economy*. Cambridge University Press, Cambridge.

Mendelsohn, R. O. and Dinar, A. (2009). *Climate Change and Agriculture: An Economic Analysis of Global Impacts, Adaptation and Distributional effects*. Edward Elgar Publishing, Cheltenham.

Miao, R., Khanna, M., and Huang, H. (2015). Responsiveness of crop yield and acreage to prices and climate. *American Journal of Agricultural Economics*, 98(1):191–211.

Millo, G. and Piras, G. (2012). splm: Spatial panel data models in R. *Journal of Statistical Software*, 47(1):1–38.

Monfreda, C., Ramankutty, N., and Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, 22(1).

Moore, F. C., Baldos, U. L. C., and Hertel, T. (2017). Economic impacts of climate change on agriculture: a comparison of process-based and statistical yield models. *Environmental Research Letters*, 12(6):065008.

Nijkamp, P. and Poot, J. (2004). Meta-analysis of the effect of fiscal policies on long-run growth. *European Journal of Political Economy*, 20(1):91–124.

Paelinck, J. H. P. and Klaassen, L. L. H. (1979). *Spatial Econometrics*, volume 1. Saxon House, Farnborough.

Polsky, C. (2004). Putting space and time in Ricardian climate change impact studies: Agriculture in the US Great Plains, 1969–1992. *Annals of the Association of American Geographers*, 94(3):549–564.

Redding, S. (1999). Dynamic comparative advantage and the welfare effects of trade. *Oxford Economic Papers*, 51(1):15–39.

Roberts, M. J., Schlenker, W., and Eyer, J. (2012). Agronomic weather measures in econometric models of crop yield with implications for climate change. *American Journal of Agricultural Economics*, 95(2):236–243.

Rudebusch, G. D. (2019). Climate change and the Federal Reserve. *FRBSF Economic Letter*, 9.

Sakamoto, T. T., Sumi, A., Emori, S., Nishimura, T., Hasumi, H., Suzuki, T., and Kimoto, M. (2004). Far-reaching effects of the Hawaiian Islands in the CCSR/NIES/FRCGC high-resolution climate model. *Geophysical Research Letters*, 31(17).

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2005). Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. *American Economic Review*, 95(1):395–406.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2006). The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions. *Review of Economics and Statistics*, 88(1):113–125.

Schlenker, W. and Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*, 5(1):1–8.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37):15594–15598.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, 93(4):485–498.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46(sup1):234–240.

Ullah, A., editor (1998). *Handbook of Applied Economic Statistics*. CRC Press, Boca Raton.

UN (2015). World population prospects: The 2015 revision. *United Nations Econ Soc Aff*, 33(2):1–66.

Urban, D. W., Sheffield, J., and Lobell, D. B. (2015). The impacts of future climate and carbon dioxide changes on the average and variability of US maize yields under two emission scenarios. *Environmental Research Letters*, 10(4):045003.

Vicente-Serrano, S. M., Van der Schrier, G., Beguería, S., Azorin-Molina, C., and Lopez-Moreno, J.-I. (2015). Contribution of precipitation and reference evapotranspiration to drought indices under different climates. *Journal of Hydrology*, 526:42–54.

Wang, J., Vanga, S., Saxena, R., Orsat, V., and Raghavan, V. (2018). Effect of climate change on the yield of cereal crops: A review. *Climate*, 6(2):41.

Ward, P. S., Florax, R. J., and Flores-Lagunes, A. (2013). Climate change and agricultural productivity in Sub-Saharan Africa: A spatial sample selection model. *European Review of Agricultural Economics*, 41(2):199–226.

Washington, W., Weatherly, J., Meehl, G., Semtner Jr, A., Bettge, T., Craig, A., Strand Jr, W., Arblaster, J., Wayland, V., James, R., and Zang, Y. (2000). Parallel climate model (PCM) control and transient simulations. *Climate Dynamics*, 16(10-11):755–774.

Yu, C., Miao, R., and Khanna, M. (2021). Maladaptation of US corn and soybeans to a changing climate. *Scientific Reports*, 11(1):1–12.

Zouabi, O. and Peridy, N. (2015). Direct and indirect effects of climate on agriculture: An application of a spatial panel data analysis to Tunisia. *Climatic Change*, 133(2):301–320.

A Spatial neighbours and weights

The spatial dependence structure among spatial units in a sample of size N is formalized using a nonnegative $N \times N$ spatial weights matrix, $\boldsymbol{W}$. The matrix provides information on how locations in a sample affect a given spatial unit. The weight matrix is mainly determined by the definition of a neighborhood set for each unit. The conventional mode of forming this matrix is to select for each unit i (as the row) the neighbors (as the columns) corresponding to nonzero elements $w_{i,j}$ as illustrated below[40];

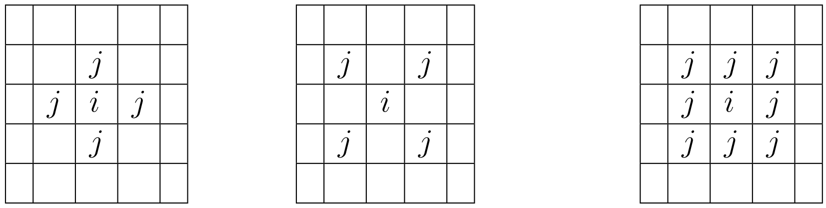
$$W = \begin{bmatrix} 0 & w_{1,2} & \cdots & w_{1,n-1} & w_{1,n} \\ w_{2,1} & 0 & \cdots & w_{2,n-1} & w_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ w_{n-1,1} & w_{n-1,2} & \cdots & 0 & w_{n-1,n} \\ w_{n,1} & w_{n,2} & \cdots & w_{n,n-1} & 0 \end{bmatrix}$$

where the element, $w_{\mathrm{i,j}}$ expresses the interaction intensity between spatial unit i and neighbor, j. In terms of interpretation, the elements of j^{th}column reflect the effect of j^{th} unit on all other units, whereas the elements of i^{th}row reflect impact of all other units on unit i. For further explanation, suppose there are observations of a variable y in N spatial locations, thereby forming an $N \times 1$ vector where the i^{th}element is the value of y in location i, then the $N \times N$ matrix W can be multiplied by vector y to produce a *spatial lag* vector, *Wy,* which can be interpreted as a simple average of observations from neighboring units.

$$Wy = \begin{bmatrix} 0 & w_{1,2} & \cdots & w_{1,n-1} & w_{1,n} \\ w_{2,1} & 0 & \cdots & w_{2,n-1} & w_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ w_{n-1,1} & w_{n-1,2} & \cdots & 0 & w_{n-1,n} \\ w_{n,1} & w_{n,2} & \cdots & w_{n,n-1} & 0 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{n-1} \\ y_n \end{bmatrix}$$

It is important to note that the definition of what constitutes a neighbor varies. LeSage and Pace (2009) list two sources of geographical information that are generally exploited. First, the knowledge and shape of spatial units define what a neighbor is. The simplest classification in this category is *p-order binary contiguity*, where p refers

[40]This condition only holds for $i \neq j$, hence the diagonal elements, $w_{i,i} = 0$, because a location is never a neighbor of itself.



Rook (*common side*) *Bishop* (*common vertex*) *Queen* (*common edge or vertex*)

Figure A1: Contiguity on a Regular Lattice

to the order of contiguity. Specifically, two units are considered as neighbors if they share borders: if p=1, only immediate neighbors are considered, if p=2, both immediate neighbors and neighbors of immediate neighbors are considered, and so on.[41] Additionally, what is regarded as a border varies. For example, Figure A1 illustrates how contiguity is subdivided based on border location. Neighborhood can be considered on the basis of common side (rook contiguity), common vertex (bishop contiguity), or both (queen contiguity), with the cells labeled j as contiguous.[42]

The second source of geographical information commonly exploited in defining what constitutes a neighbor is the use of centroids (or geometric centers) in the Cartesian space to compute distances between locations. One of the classes here is the *k-nearest neighbor* (k-NN) to unit i, where k is a positive integer. For example, *3*-NN implies that only the three closest locations from the centroid of unit i will be considered as neighbors, thus the entire locations in the sample will have the same number of neighbors, *three* in this instance. Other classes are *inverse distance* matrix ($w_{i,j} = \frac{1}{d_{i,j}}$) and the *inverse squared-distance* matrix ($w_{i,j} = \frac{1}{d^2_{i,j}}$), where $d_{i,j}$ is an approximated spatial distance (with or without a cut-off point) between the centroids of spatial units i and j. The *inverse distance* matrix assumes a linear relationship whose strength varies proportionally to the distance, whereas the *inverse squared-distance* matrix is a nonlinear relation whose strength declines with distance.

We decided to opt for distance-based matrix rather than a contiguity-based one because the former specifies the exact locations of the MPAs in the Cartesian plane, while the latter is based on border proximity which is of little practical relevance because some MPAs are not situated at the border. In other words, specifying a weight that includes only boundaries may pick up spatial relationships that are not typical of the MPAs.

For ease of interpretation, spatial weights matrix elements are generally row-normalized, such that for each row, i, $\sum_{j=1}^{n} w_{i,j} = 1$. This transformation alters the symmetric nature of the spatial weights matrix.[43] Since the elements of the weights matrix are based on

[41] Anselin (1988) remarks that the assumption of the existence of a map, from which boundaries can be discerned, is key to the definition of contiguity.

[42] Since maps are not really regular lattices, the most preferred contiguity-based weighting scheme used is queen.

[43] Anselin (1988) argues that the *inverse distance* matrix becomes problematic in the face of row-

some spatial arrangement or contiguity, Anselin (2001) argues that they are, therefore, nonstochastic and exogenous. It is important to state that the weights considered so far are purely cross-sectional. However, extending them to cover panel setting requires the assumption that weights are fixed over time.[44] In addition, the spatial weights matrix is specified as $W_{NT} = I_T \otimes W_N$, where W_{NT} is the $NT \times NT$ panel weights matrix, W_N is an $N \times N$ cross-sectional weights matrix, and I_{T} is an identity matrix of dimension T.

B Estimation of spatial panel models

LeSage and Pace (2009) show that in the presence of a spatially lagged dependent variable, OLS estimates of the coefficients are inefficient, and inferences based on the conventional OLS estimator of the standard errors are biased. To obtain consistent estimates, therefore, several alternative econometric methods have been proposed in the literature - maximum likelihood (ML) (Elhorst, 2003; Anselin, 1988), quasi-maximum likelihood (QML) (Lee and Yu, 2010), generalized method of moments (GMM)/instrumental variable (IV) (Kapoor et al., 2007; Kelejian and Prucha, 1999, 1998).

Our study employs the ML approach since it is the most commonly used estimation technique, and inferences are based on an asymptotic variance matrix (Anselin et al., 2008). However, the major weakness of the ML method, according to Arbia (2014), is the computational difficulties associated with manipulating $N \times N$ matrices, which is remedied in the IV/GMM approach since it has no Jacobian term.[45] Moreover, unlike the ML estimator, the IV/GMM estimators are well-suited for spatial models when more than one endogenous regressor needs to be instrumented. Nevertheless, where this is not the case, the ML estimator is preferred since the IV/GMM estimation method can end up with spatial coefficients that lie outside its restricted space; in the ML estimator, these coefficients are restricted in the Jacobian term in the log-likelihood function (Elhorst, 2014). Besides, the use of the ML is conditioned on the assumption that the errors are normally distributed, a position assumed in our analysis.

Spatial panel models can be estimated using either fixed or random effects approach. In random effects approach, the locational effects (ρ in equation (3)) are uncorrelated with the explanatory variables. However, we will focus on fixed effects estimation since that is the approach our model follows. With recourse to the objective of our analysis, we discuss in what follows the ML estimation process of SDM assuming fixed effects. We also assume that the $\boldsymbol{W}$ is fixed and the panel is balanced.[46]

---

standardization since the asymmetric nature of the matrix invalidates its economic interpretation in terms of distance decay.

[44] Anselin et al. (2008), however, note that weights can be allowed to vary, given that the parameters are fixed, although this is less tractable. They further argue that although it is possible to let both the weights and parameters vary, this will result in identification and interpretation problems.

[45] Advances in computing technology have remedied this difficulty (LeSage and Pace, 2009).

[46] A general approach for estimating unbalanced panel due to missing observations is not available,

B.1 Fixed effects spatial Durbin model (SDM)

This model controls for spatial correlation in both the dependent variable and the regressors. The SDM and the associated data generation process (DGP) are shown in (3) and (4), respectively

$$Y_t = WY_t\gamma + X_t\beta + \rho + \varepsilon_t \tag{3}$$

$$\begin{aligned} Y_t &= (I_N - \gamma W)^{-1}(X_t\beta + \rho + \varepsilon_t) \\ \varepsilon|X &\sim N(0, \sigma^2 I_N) \end{aligned} \tag{4}$$

where Y is an $N \times 1$ vector of dependent variables, W is a positive $N \times N$ spatial weights matrix, WY is an $N \times 1$ vector that represents the endogenous interaction effects among the outcome variables, X is an $N \times K$ matrix of K regressors. For the sake of being concise, we assume that spatial lags of the regressors are included in the matrix X. γ is the spatial autoregressive coefficient, β denotes $K \times 1$ vector of fixed but unknown parameters to be estimated, ρ is an $N \times 1$ vector of location-specific fixed effects that absorb time-invariant spatial attributes, ε is the vector of disturbances that are assumed to be independent and identically distributed (*iid*), and I_N is an identity matrix of dimension N. We can equally express (4) in stacked form as represented in (5)

$$Y = \gamma(I_T \otimes W_N)Y + X\beta + (\iota_T \otimes I_N)\rho + \varepsilon \tag{5}$$

where $Y = \begin{bmatrix} Y_1', & Y_2', & Y_3', & \cdots, & Y_T' \end{bmatrix}'$ is an $NT \times 1$ vector of dependent variables, X is an $NT \times K$ matrix of observations on K explanatory variables (including spatially lagged covariates), ι_T is a $T \times 1$ vector of ones, I_T is an identity matrix of dimension T, $\otimes$ is known as Kronecker product, ε is an $NT \times 1$ vector spatially-corrected innovations, all other terms are as defined in (3) and (4). Two complications immediately arise in equation (3). First is the endogeneity bias due to the lagged dependent variable, WY_t, which violates the standard regression exogeneity assumption, resulting in biased and inconsistent estimates if the model is analyzed *via* OLS. The second is a less general problem that depends on N and T. According to Lee and Yu (2010), the fixed effects estimation may be affected because of the existence of spatial dependence among spatial units at each point in time.

The ML estimator is derived to treat the problem of endogeneity in equation (3).

hence statistical software such as R, Matlab and recently, Stata and GeoDa find such estimation process problematic.

Assuming that the group-level effect is fixed, the log-likelihood function of equation (4) can be expressed as

$$lnL = -\frac{NT}{2}ln(2\pi\sigma^2) + Tln \mid I_N - \gamma W_N \mid - \frac{NT}{2\sigma^2}(e(\psi) - \rho)'(e(\psi) - \rho) \tag{6}$$

where $e(\psi) = Y - \gamma(I_T \otimes W_N)Y - X\beta$, $\psi = (\gamma, \beta')$ and $|I_N - \gamma W_N|$ is an $N \times N$ matrix representing the Jacobian term of transformation from ε to Y which is the most cumbersome part of the estimation procedure (Anselin et al., 2008). In the remaining part, we follow Elhorst's (2014) estimation method, an empirical extension of Anselin (1988) estimation technique for cross-sectional spatial models. Given ψ, it is straightforward to show, by taking the partial derivatives of equation (6) with respect to ρ, that the ML estimator of ρ is given as

$$\widehat{\rho} = \frac{1}{T}(\iota_T' \otimes I_N)e(\psi) \tag{7}$$

The presence of individual fixed effects in a small panel where T is fixed and $N \to \infty$ generates what is popularly known in panel data literature as the *incidental parameter* problem, a situation where the number of unknown parameters increases in direct proportion to the number of observations (for a précis of this problem, and the remedies, see next subsection). Substituting *closed form solution* from equation (7) into (6) and rearranging the terms will produce the *concentrated* log-likelihood function with respect to the remaining parameters[47]

$$lnL = -\frac{NT}{2}ln(2\pi\sigma^2) + Tln \mid I_N - \gamma W_N \mid - \frac{NT}{2\sigma^2}\hat{e}(\psi)'\hat{e}(\psi) \tag{8}$$

where *hat* denotes temporal demeaning by spatial unit and $\hat{e}(\psi) = \hat{Y} - \gamma(I_T \otimes W_N)\hat{Y} - \hat{X}\beta$.[48] Functions like equation (8) boil down to a repetition of a typical cross-sectional model in T cross-sections, thus successive T cross-sections are arranged in a stacked form to get $NT \times 1$ vectors of $\hat{Y}$ and $(I_T \otimes W_N)\hat{Y}$, and an $NT \times K$ matrix for $\hat{X}$. Next, regress $\hat{Y}$ and $(I_T \otimes W_N)\hat{Y}$ on $\hat{X}$ successively, and store estimates of the regression coefficients as $\boldsymbol{\varphi}_0$ and $\boldsymbol{\varphi}_1$, and let $\check{\boldsymbol{\eta}}_0$ and $\check{\boldsymbol{\eta}}_1$ be the associated residuals. Therefore, γ can be estimated by maximizing the concentrated log-likelihood function

$$lnL(\gamma) = H + Tln \mid I_N - \gamma W_N \mid - \frac{NT}{2}ln(R(\gamma)) \tag{9}$$

[47] Davidson and MacKinnon (1993) provided evidence that ML estimates from the concentrated log-likelihood function are similar to those from the full log-likelihood. However, LeSage and Pace (2009) argues that the simplification of the optimization problem by reducing multivariate optimization problem to a univariate one is the primary motivation for the preference of concentrated log-likelihood function.

[48] $\hat{Y} = D_{NT}Y$ and $\hat{X} = D_{NT}X$ where $D_{NT} = I_{NT} - (\iota_T\iota_T'/T \otimes I_N)$ is a popular $NT \times NT$ matrix in the conventional panel data literature.

$$R(\gamma) = (\check{\boldsymbol{\eta}}_0 - \gamma\check{\boldsymbol{\eta}}_1)'(\check{\boldsymbol{\eta}}_0 - \gamma\check{\boldsymbol{\eta}}_1)$$

where H is a constant that is independent of the parameter γ. According to Elhorst (2003), the non-existence of a closed-form solution means the optimization problem necessitates a numerical solution. Anselin and Hudak (1992) show that a unique numerical solution exists because the concentrated log-likelihood function is concave in γ[49]. Finally, given the numerical estimate of γ, the ML estimates of β and σ^2 are computed

$$\beta = \boldsymbol{\varphi}_0 - \gamma\boldsymbol{\varphi}_1 = (\hat{X}'\hat{X})^{-1}\hat{X}'[\hat{Y} - \gamma(I_T \otimes W_N)\hat{Y}] \tag{10}$$

$$\sigma^2 = \frac{1}{NT}(R(\gamma)) \tag{11}$$

B.2 The *incidental parameter* problem

A less general problem emanates from the asymptotic properties of the sample size of (7). According to Lee and Yu (2010), for short panels, where T is fixed and $N \to \infty$, consistent estimation of the individual fixed effect is impracticable because of the classical *incidental parameter* problem - a situation where the number of unknown parameters increases with the sample size. The problem is inconsequential if the individual fixed effects are not the coefficients of interest, which is the case in this study as it is in most empirical studies, as argued by Elhorst (2014).[50] Nevertheless, Lee and Yu (2010) use thorough asymptotic evidence to establish that the variance parameter, σ^2 is inconsistent for finite T. Consequently, they propose two alternative solutions to deal with the problem of inconsistency.

The first approach is the *transformation* method that eliminates the individual fixed effects by taking the deviation from time average for each spatial unit. This transformation has the net effect of reducing the sample size by one observation for each unit in the sample, from NT to *N(T-1)* sample size. The second approach proposed by Lee and Yu is a *bias correction* process of the variance parameter estimated *via* the direct approach.[51] Hence, the true (bias-corrected) parameter, $\widehat{\sigma}^2_{bc} = \frac{T}{T-1}\widehat{\sigma}^2$, where $\widehat{\sigma}^2$ is the estimated variance parameter using direct approach. Moreover, since the correction affects the variance parameters, the standard errors and t-values of the parameter estimates will also be affected. Nevertheless, Lee and Yu (2010) show that the correction does not affect the asymptotic variance matrices of the parameters of the spatial model (see, Theorems 2

[49] There are R commands and Matlab routines dedicated to such estimation.

[50] This is possible since $\beta \neq f(\rho_i)$, therefore any inconsistency in the individual fixed effects will not be relayed to the parameters of other regressors.

[51] Lee and Yu labeled the conventional demeaning procedure for estimating fixed effects panel data model as "direct approach".

and 4 in Lee and Yu (2010) for formal proofs). Finally, both approaches produce numerically equivalent estimates, thus the variance estimate of the bias corrected ML is that of transformed approach. This study adopts the former (bias-correction) approach.[52]

B.3

C Alternative weather measures

C.1 Precipitation

One of this paper's contributions is the use of WDF in SSA climate change studies, as against aggregate precipitation (PREP) used in previous studies (refer to Sections 1 and 3 for an extensive discussion on why we prefer WDF to PREP). Our monthly precipitation dataset was obtained from the same source as the WDF dataset, CRU TS v4.02, and we aggregate over growing season by MPA. For estimation purposes, we replaced WDF variable with PREP in our benchmark equation (1). While we expect our estimates to vary in size, since we are using a different dataset, we do not expect a broad change in the signs and significance because of the positive and significant correlation between WDF and PREP, calculated as 0.70.

The results are presented in Table C1, but for brevity sake, we did not include estimates of quadratic terms, time trend, and the spatial lag of VPD. The results compare our baseline (column 1) estimates (using WDF) with the estimates from column 2 (using PREP) and find marginal differences. While the indirect effect of temperature gained slight significance, it reduced in magnitude. On the other hand, there is an increase in the direct effect. Besides, the significance of temporal lag for precipitation disappeared, with a reduction in the overall fit of the new model, whereas VPD increases sharply in magnitude. These results reveal that the choice of weather measures matters in terms of estimation. Using aggregate precipitation, which does not account for intra-periodic fluctuations in rainfall, increases the negative impact of millet yield *vis-a-vis* temperature effect while using a more accountable measure of rainfall, like WDF, attenuates this effect.

C.2 Standardized precipitation evapotranspiration index (SPEI)

As an add-on exercise, we examined the (contemporaneous, spatial and temporal) effect of extreme weather conditions, such as drought, on millet yield in SSA. Although an earlier study in this regard has been done by Blanc (2012) using standardized precipitation index (SPI), we, in spirit of Harari and Ferrara (2018), use a more robust measure that accounts for temperature - standardized precipitation evapotranspiration index (SPEI).

[52] Spatial econometrics software such as R and Matlab have "bias correction" option.

Table C1: Model Comparison using Alternative Weather Measure - Precipitation

	(1) (WDF)	(2) (PREP)
Direct Effect		
TEMP	-0.2187***	-0.2663***
	(0.0533)	(0.0481)
WDF/PREP	0.0210***	0.0027***
	(0.0058)	(0.0004)
VPD	-0.2106***	-0.2893***
	(0.0336)	(0.0366)
Indirect Effect		
TEMP	-0.0041	-0.0012
	(0.0055)	(0.0008)
WDF/PREP	0.0069**	0.0009*
	(0.0028)	(0.0005)
Gamma	-0.0419***	-0.0503***
	(0.0047)	(0.0042)
Temporal Effect		
$\text{TEMP}_{t\text{-}1}$	-0.0035	-0.0035
	(0.0024)	(0.0030)
$\text{WDF}_{t\text{-}1}/\text{PREP}_{t\text{-}1}$	-0.0029**	-0.0000
	(0.0014)	(0.0000)
R^2	0.60	0.58

Except stated, all models include time trend and its square, spatial weight as inverse distance, with errors clustered at the MPA level. Temperature is measured in ^{O}C , VPD in kPa and precipitation in mm. For space sake, we do not include the estimates of the quadratic terms of TEMP, WDF, and PREP. Columns: (1) main specification estimates, (2) as in column 1, but aggregate precipitation replaces wet day frequency.
***p<0.01, **p<0.05, *p<0.1.

In addition, we control for spatial and temporal correlations, which are absent in Blanc (2012). The SPEI was developed by Vicente-Serrano et al. (2015) using temperature and precipitation data from CRU TS3.0 as inputs and has been found to outperform other measures of extreme weather events such as self-calibrated Palmer Drought Severity Index (sc-PDSI) and SPI in quantifying extreme weather impacts (Harari and Ferrara, 2018).[53]

Table C2: Model Comparison using Alternative Weather Measure - SPEI

	SPEI
Direct Effect	0.0237***
	(0.0038)
Indirect Effect	0.0029
	(0.0102)
SPEI^2	-0.0299*
	(0.0172)
$\text{SPEI}_{t\text{-}1}$	-0.0024
	(0.0091)
$\text{SPEI}_{t\text{-}2}$	-0.0007
	(0.0169)
Gamma	-0.0521***
	(0.0110)
R^2	0.24

Except stated, all models include time trend and its square, spatial weight as inverse distance, with errors clustered at the MPA level.
***p<0.01, **p<0.05, *p<0.1.

The results presented in Table C2 suggest that a point increase in SPEI (indicating less drought) will benefit millet yield. This indication can be seen from the trend in Figure F3 of the Appendix, as, on average, all MPAs are drifting away from the mean value towards dry conditions.[54] Therefore an increase in the SPEI value will be restoring weather conditions to the mean value. Besides, the quadratic term is significant, showing that the marginal effect will change to negative as one moves away from the mean. This result is sensible given the understanding that the lower values of SPEI denote conditions, while the above mean values indicate flooding (see, Table C3). In terms of spatial and temporal lags effects because we find no significant effects from both lags. For temporal

[53]The SPEI is a standardized variable with a mean value and standard deviation of 0 and 1, respectively, fitted to different time scales such as 2, 4, 8, 12 months, *etc.* For our analysis, we use SPEI at a 12-month scale since the growing seasons in the various MPAs are of different duration.

[54]The trend from Figure F3 in the Appendix also suggests the MPAs are not experiencing extreme weather events such as flooding or drought, confirming the submission of Auffhammer and Schlenker (2014) that most of the growing areas in developing regions have weather conditions that are conducive for agriculture. In a similar twist, this also explains why most MPAs have very scant KDU observations.

Table C3: Extreme Weather Classification of SPEI

SPEI Value	**Moisture Category**
≥ 2.00	Extremely wet (flood)
1.50 - 1.99	Severely wet
1.00 - 1.49	Moderately wet
0.50 - 0.99	Slightly wet
-0.49 - 0.49	Near normal
-0.99 - -0.50	Mild dry
-1.49 - -1.00	Moderately dry
-1.99 - -1.50	Severely dry
≤ -2.00	Extremely dry

lags, this implies that high (positive or negative) values of SPEI, indicating drought or flooding, may not have a carry-over effect on millet. This result further reinforces the position of millet as a drought-resistant cereal crop.

D Construction of long differences (LD) and flexible long differences (FLD)

One of the most critical shortcomings of the standard panel model is the absence of adaptive response; hence, crop yields' response to climate change might be overestimated. To address this challenge, several methods have been proposed in the climate econometrics literature, among which are long difference approach by Burke and Emerick (2016) and flexible long difference method by Yu et al. (2021). We describe how we construct the differences in relation to the non-spatial analogue of our model in turn.[55]

D.1 Long differences (LD) approach

We start with a reminder of the baseline model in (12),

$$Y_t = WY_t\gamma + C_t\boldsymbol{\beta} + WC_t\vartheta + \rho + \varepsilon_t \tag{12}$$

where Y_t is an $N \times 1$ vector of (log of) millet yield observations at time t; C_t are $N \times K$ matrix of climatic variables; ε_t is an $N \times 1$ vector of unobservable random variables. The time trend matrix R_t includes linear and squared terms; ρ is an $N \times 1$ vector of country-level fixed effects. W is an $N \times N$ matrix of spatial weights (or connectivity),

[55] The reasons for considering the non-spatial rather than the spatial model have been explained in the main text.

WY represents spatially autocorrelated outcomes, while WC represents spatial autocorrelation of the covariates (weather measures). In terms of parameter notations, $\boldsymbol{\beta}$, ω, $\boldsymbol{\gamma}$ and ϑ are vectors of parameters to be estimated, the last two being spatial parameters.

Our sample period is 1970-2016, so spanning 47 years. Let period a consist of *(n=5)* years {1970, 1971, 1972, 1973, 1974}, and period b consist of *(n=5)* years {2012, 2013, 2014, 2015, 2016}. For each period, we construct a period average of each variable. Since there are two lags of $Temp_{i,t}$ and $WDF_{i,t}$ included in the main specification, this means we need these variables for 1968 and 1969. The notional dates of periods a and b are taken as the mid-points of 1972 and 2014. In subsequent analysis, we consider a longer average of ten years *(n=10)*: period a as 1970 - 1979 and period b as 2007 - 2016.

Given the estimated specification:

$$
\begin{aligned}
C_t^{(i,\bullet)} = (&Temp_{i,t}, WDF_{i,t}, VPD_{i,t}, TempDev_{i,t}, Temp_{i,t}^2, WDF_{i,t}^2, \\
&TEMP_{i,t-1}, TEMP_{i,t-2}, WDF_{i,t-1}, WDF_{i,t-2})
\end{aligned}
$$

Let $\bar{Y}_{i,a} = \sum_{t\in a} Y_{i,t}/n, \bar{Y}_{i,b} = \sum_{t\in b} Y_{i,t}/n, \bar{Y}_a = \sum_{t\in a} Y_t/n, \bar{Y}_b = \sum_{t\in b} Y_t/n,$ *etc.* It then follows from equation (1) that

$$\bar{Y}_{i,a} = \gamma W_{i,\bullet}\bar{Y}_a + \bar{C}_{i,a}\beta + W_{i,\bullet}\bar{C}_a^{(\bullet,1:3)}\vartheta + \bar{R}_a\omega + \rho_i + \bar{\varepsilon}_{i,a} \tag{13}$$

$$\bar{Y}_{i,b} = \gamma W_{i,\bullet}\bar{Y}_b + \bar{C}_{i,b}\beta + W_{i,\bullet}\bar{C}_b^{(\bullet,1:3)}\vartheta + \bar{R}_b\omega + \rho_i + \bar{\varepsilon}_{i,b} \tag{14}$$

where $C^{(\bar{\bullet},1:3)}$ denotes the $N \times 3$ matrix consisting of the first three columns of C. Subtracting (13) from (14), zero-constraining $\boldsymbol{\gamma}$ and ϑ, and stacking the resulting non-spatial equation yields

$$\Delta_{b,a}\bar{Y} = \Delta_{b,a}\bar{C}\beta + \Delta_{b,a}\bar{R}\omega + \Delta_{b,a}\bar{\varepsilon} \tag{15}$$

where $\Delta_{b,a}\bar{Y} = \bar{Y}_b - \bar{Y}_a$, *etc.* Equation (15) is a cross-sectional model with the resulting OLS estimates as $\{\bar{\beta}, \bar{\omega}\}$.

D.2 Flexible long differences (FLD) approach

Define D_τ to be a dummy variable that indicates the period as follows: $D_\tau = 0$ if $\tau = a$ and $D_\tau = 1$ if $\tau = b$. Interacting the period dummy with the climate variables in the respective period yields the flexible long differences (FLD) model. Hence, the FLD approach applied to our model is:

$$\bar{Y}_{i,\tau} = \gamma W_{i,\bullet}\bar{Y}_\tau + \bar{C}_{i,\tau}\beta + W_{i,\bullet}\bar{C}_\tau^{(\bullet,1:3)}\vartheta + \delta W_{i,\bullet}D_\tau\bar{Y}_\tau + \bar{C}_{i,\tau}D_\tau\eta$$
$$+W_{i,\bullet}D_\tau\bar{C}_\tau^{(\bullet,1:3)}\phi + \bar{R}_\tau\omega + \rho_i + \bar{\varepsilon}_{i,\tau} \quad (16)$$

Taking difference between $\tau = b$ and $\tau = a$ to eliminate the fixed effect and setting $\boldsymbol{\gamma} = \vartheta = \delta = \phi = 0$ yield the model

$$\Delta_{b,a}\bar{Y} = \Delta_{b,a}\bar{C}\beta + \bar{C}_b\eta + \Delta_{b,a}\bar{R}\omega + \Delta_{b,a}\bar{\varepsilon} \quad (17)$$

where $\Delta_{b,a}\bar{Y} = \bar{Y}_b - \bar{Y}_a$, *etc.* Equation (17) is a cross-sectional model with the resulting OLS estimates as $\{\bar{\beta}, \bar{\eta}, \bar{\omega}\}$.

The difference between equations (15) and (17) is the presence of the interaction term $(\bar{C}_b)$ differentiating the effect of climate on crop yields across the two periods, thereby representing time-varying agricultural adaptation. Consequently, where the estimate of the interaction term, η, is not significantly different from zero, the FLD approach is (17) collapses into the LD approach in (15).

E Bootstrapping the prediction interval

To sidestep statistical (or regression) uncertainty, we need a prediction interval. Following the description in subsection 5.1 in the main text, let $C_{CCP} = C_{PP} - C_{HIST}$, where *CCP* is climate change projection, *HIST* stands for a relevant historical period (1981 - 2010, in our case), and *PP* stands for a projected period (2040 - 2069, in our case). Predicted impact is, therefore, given as

$$\Lambda = E[Y_t|C_t = C_{PP}] - E[Y_t|C_t = C_{HIST}] = (I_N - \gamma_0 W)^{-1}(C_{CCP}\beta_0 + WC_{CCP}\vartheta_0)$$

where Λ is an $N \times 1$ vector by definition, and

$$\hat{\Lambda} = (I_N - \hat{\gamma}W)^{-1}(C_{CCP}\hat{\beta} + WC_{CCP}\hat{\theta})$$

with I_N as an identity matrix of dimension *N,* and other variables already defined in equation (1).

The bootstrapped prediction interval for Λ is calculated as follows where $\hat{\delta} = (\hat{\beta}', \hat{\vartheta}', \hat{\omega}', \hat{\gamma}, \sigma^2)' = (\hat{\theta}', \hat{\gamma}, \sigma^2)' = (\hat{\zeta}', \sigma^2)'$ and $\hat{\rho}$ are the maximum likelihood estimates from equation (1), and $Z = [C_t, WC_t, R_t]$:

1. Construct the residuals from original data: $\{\hat{\varepsilon}_t(\hat{\delta}, \hat{\rho})\}_{t=1}^T$

2. For $b = 1, 2, \ldots, B = 1000$

(a) obtain bootstrap residuals, $\{\hat{\varepsilon}_t^{(b)}\}_{t=1}^T$ from the empirical distribution of the sample residuals from (i)

(b) construct bootstrap yields, $\{Y_t^{(b)}\}_{t=1}^T$ *via*

$$Y_t^{(b)} = (I_N - \hat{\gamma}W)^{-1}(Z_t\hat{\theta} + \hat{\rho} + \hat{\varepsilon}_t^{(b)})$$

(c) re-estimate equation (1) *via* ML based on $\{Y_t^{(b)}, Z_t\}_{t=1}^T$ to generate bootstrap ML estimates $\hat{\delta}^{(b)}$ and $\hat{\rho}^{(b)}$

(d) construct bootstrap estimates of Λ

$$\hat{\Lambda}^{(b)} = (I_N - \hat{\gamma}^{(b)}W)^{-1}(C_{CCP}\hat{\beta}^{(b)} + WC_{CCP}\hat{\theta}^{(b)})$$

3. Construct a 95% equal tailed bootstrap prediction interval for Λ from the 2.5th and 97.5th percentiles.

4. Aggregate $\hat{\Lambda}^{(b)}$ from the three GCMs (1000 bootstrapped runs $\times$ 3 GCMs) to produce 3000 distributions, and repeat step (iii).

F Tables and Figures

Table F1: Main-Producing Areas (MPAs) used in the Study and their respective Growing Seasons

Country	**MPA**	**Growing Season**
Angola	Huila	November-June
Benin	Borgou	May-November
Botswana	Ghanzi	November-June
Burkina Faso	Bam	May-December
Burundi	Bururi	September-February
Central African Republic	Bamingui-Bangora	May-October
Cameroon	Bamenda	March-November
Chad	Moyen-Chari	May-October
Democratic Republic of Congo	Haut-Congo	April-November
Cote d'Ivoire	Seguela	May-November
Gambia	Upper River	June-November
Ghana	Zabzugu	May-November
Guinea	Kindia	May-November
Guinea Bissau	Bafata	May-October
Kenya	Nyanza	March-November
Mali	Segou	May-November
Mauritania	Assaba	July-November
Mozambique	Zambezi	November-June
Namibia	Kavango	December-June
Niger	Diffa	June-October
Nigeria	Maiduguri	June-October
Rwanda	Byumba	September-February
Senegal	Kaolack	July-November
Sierra Leone	Moyamba	May-November
South Africa	Free State	September-July
Sudan	South Darfur	March-August
Tanzania	Singida	March-August
Togo	Savanes	May-November
Uganda	Gulu	September-January
Zambia	Mbala	December-July
Zimbabwe	Mashonaland East	November-June
Total	**31**	

Table F2: Classes of Spatial Models

Spatial Model	**Interaction Effects**
Spatial lag model (SLM) or spatial autoregressive model (SAR)[a]	Endogenous interaction effects (Y)
Spatial error model (SEM)	Error terms interaction effects (u)
Spatial lag of X model (SLX)	Exogenous interaction effects (X)
Spatial autoregressive combined (SAC)[b]	Endogenous and error terms interaction effects (Y, u)
Spatial Durbin model (SDM)[c]	Endogenous and exogenous interaction effects (Y, X)
Spatial Durbin error model (SDEM)	Exogenous and error terms interaction effects (X, u)
General nesting spatial model (GNS)	All interactions

[a] Anselin (1988) terms it "mixed regressive spatial autoregressive" model.

[b] Elhorst (2010) names it after its pioneers, the "Kelejian-Prucha" model. Other names used for this model are spatial autoregressive with spatially autocorrelated errors (SARAR) or Cliff-Ord models.

[c] The model can be generalized by employing different spatial weights structure for the endogenous variable and the spatially weighted regressors or by using explanatory variables that differ from the spatially weighted regressors (Belotti et al., 2017).

Table F3: Economic Blocs in SSA and Member Countries

Economic Community	**Member States**
ECOWAS[a,b]	Benin, Burkina Faso, Cape Verde, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo
SADC	Angola, Botswana, DR Congo, Lesotho, Madagascar, Malawi, Mozambique, Namibia, South Africa, eSwatini, Tanzania, Zambia, Zimbabwe
EAC	Burundi, Kenya, Rwanda, Uganda, Sudan, Tanzania
ECCAS	Angola, Burundi, Cameroon, Central Africa Republic, Chad, DR Congo, Congo, Gabon, Rwanda
COMESA	Burundi, DR Congo, Kenya, Madagascar, Malawi, Rwanda, Sudan, eSwatini, Uganda, Zambia, Zimbabwe
CEN-SAD	Benin, Burkina Faso, Cape Verde, Central Africa Republic, Chad, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Somalia, Sudan, Togo
IGAD	Kenya, Somalia, Sudan, Uganda

[a]ECOWAS = Economic Community of West African States; SADC = Southern African Development Community; EAC = East African Community; ECCAS = Economic Community of Central African States; COMESA = Common Market for Eastern and Southern Africa; CEN-SAD = The Community of Sahel-Saharan States; IGAD = Intergovernmental Authority on Development

[b]Information obtained from UNECA website, `http://www.un.org/en/africa/osaa/peace/recs.shtml`

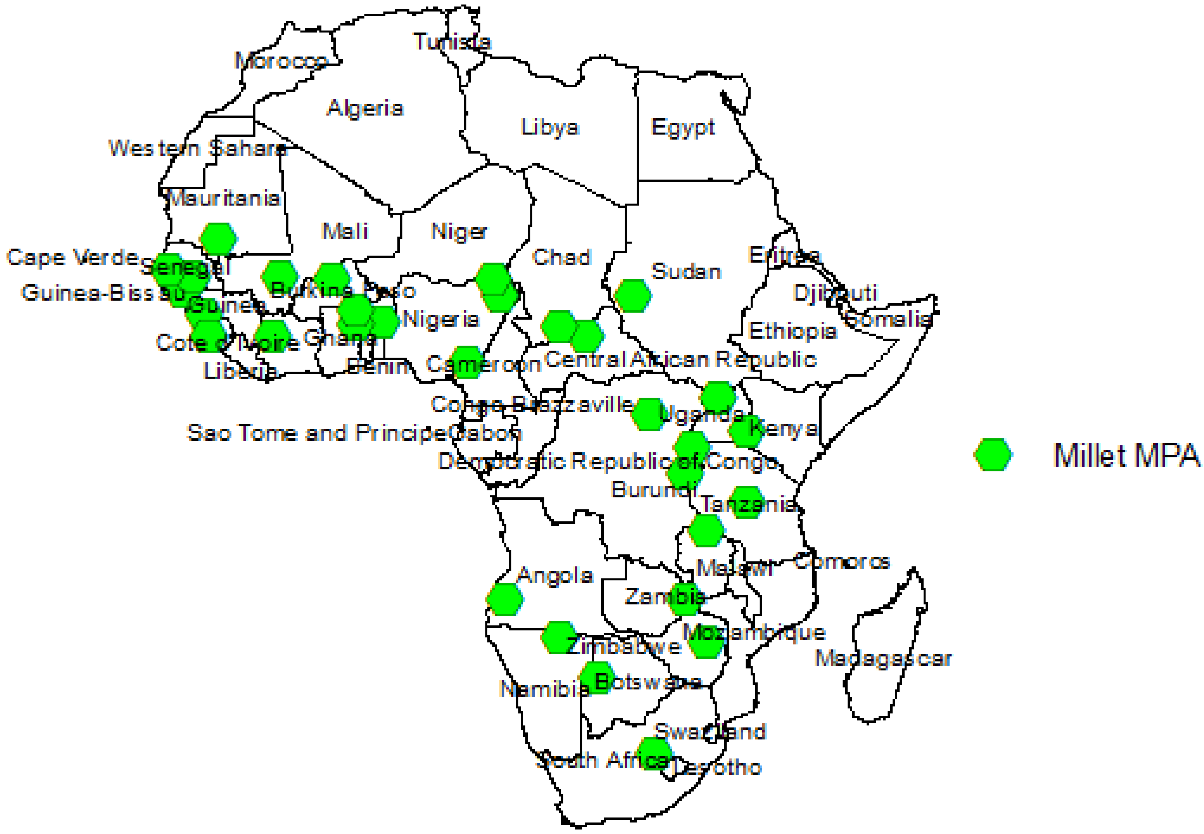


Figure F1: Millet MPAs Locations in SSA Countries

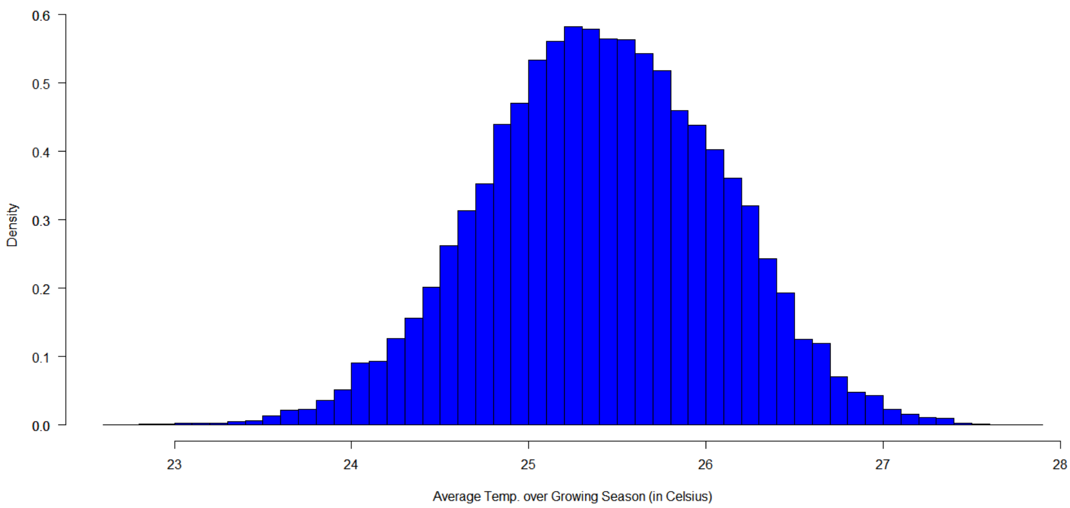


Figure F2: Average Temperature Distribution across MPAs

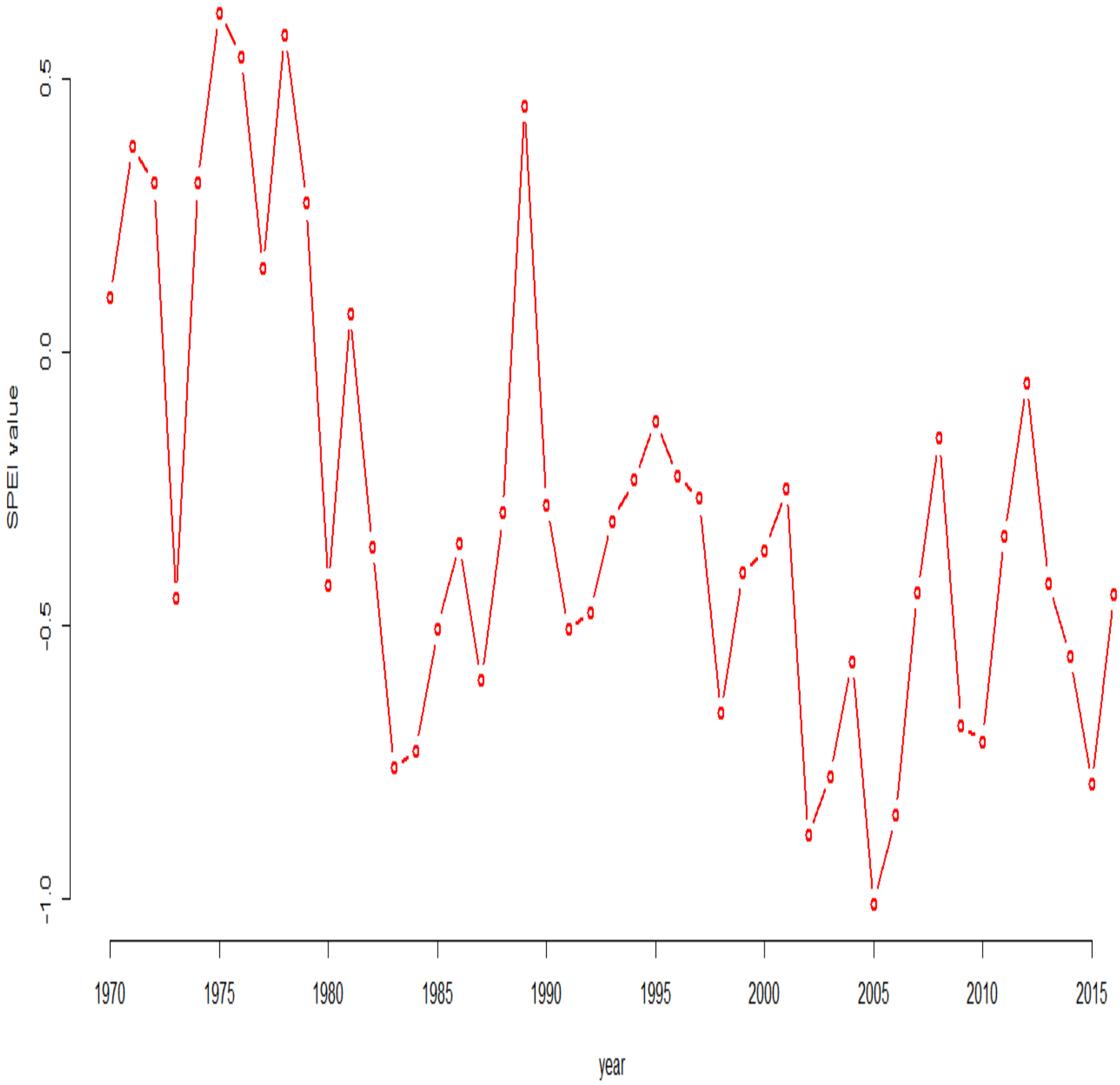
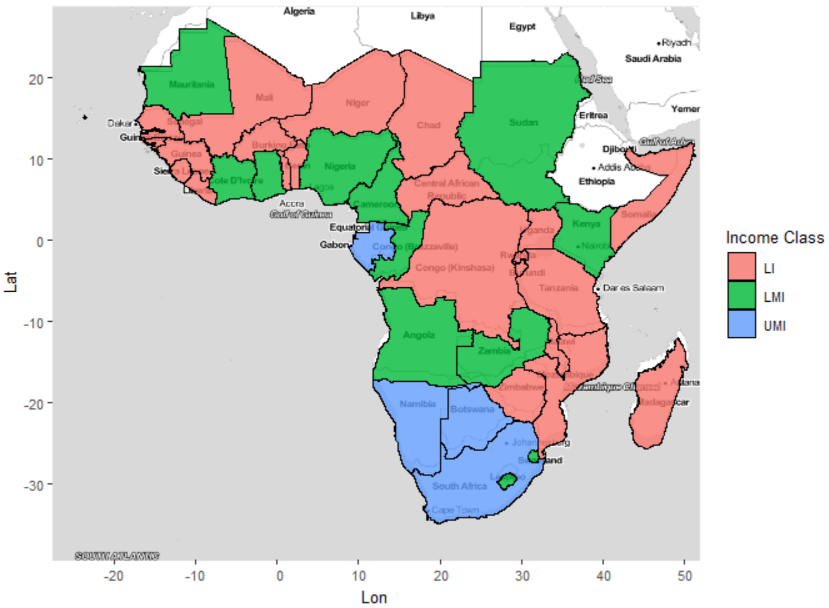


Figure F3: Trend of SPEI for SSA (by MPA)



Note: LI = low-income countries, LMI = lower middle income countries, UMI = upper middle income countries. This income classification is from World Development Indicators (2018). We merged LMI and UMI countries as rich countries, while LMI countries are labeled as poor. SSA has no high-income country.

Figure F4: Classification of SSA Countries by Income Class

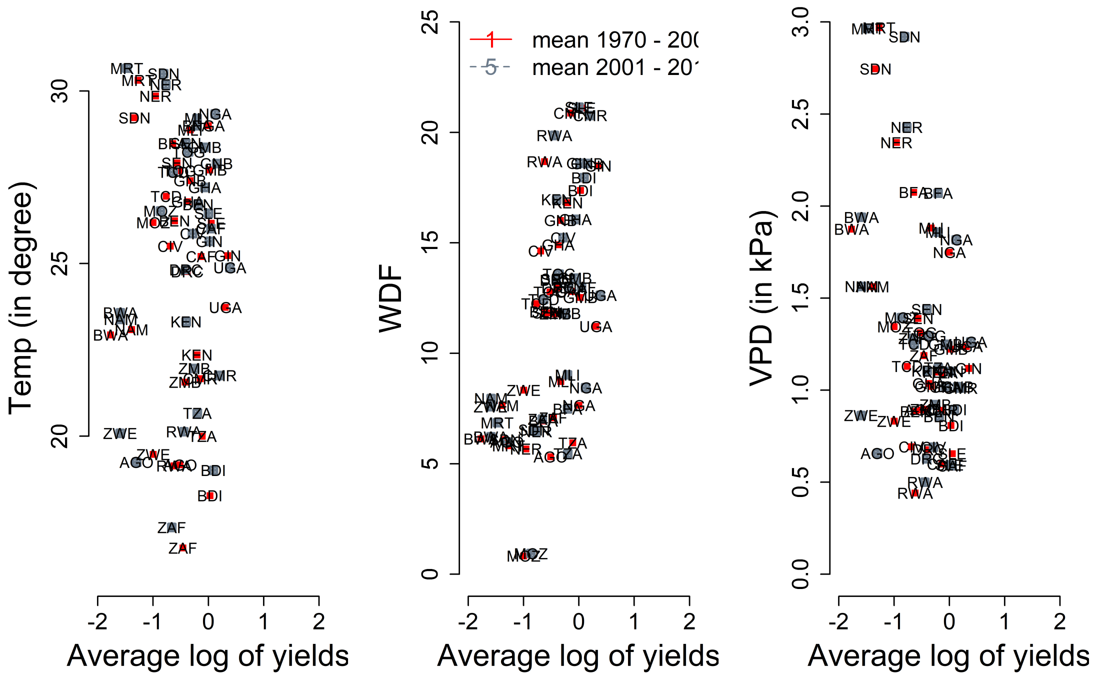


Figure F5: Scatterplots of the Weather Measures and Millet Yield (in Logs) for Two Separate Periods: 1970 - 2000 & 2001 - 2016