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

Lotanna E. Emediegwu [a,b,*], Ada Wossink [b], Alastair Hall [b]

[a] Manchester Metropolitan University, UK
[b] University of Manchester, UK

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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.

1. Introduction

"*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.

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, Hsiang, and Miguel (2015) 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 to 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, Khanna, & Huang, 2015; Di Falco & Chavas, 2009). Moreover, significant spatial correlations arise due to the use of gridded weather datasets generated *via* extrapolation means (Auffhammer, Hsiang, Schlenker, & Sobel, 2013; Baylis, Paulson, & Piras, 2011). The impact of these spatial influences has not been addressed in previous studies focusing on climate change and Africa. Although Ward, Florax, and Flores-Lagunes (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.

* Corresponding author at: Department of Economics, Policy and International Business, Business School Building, Manchester Metropolitan University, M15 6BH Manchester, UK.

E-mail address: l.emediegwu@mmu.ac.uk (L.E. Emediegwu).

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

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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 & 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, Hanemann, and Fisher (2006) to account for spatial interactions. They find that estimates from spatial models differ from their non-spatial counterparts.

Part of the methodological contribution is to disentangle the effects of weather fluctuations on yields across country-level income class. Following Burke et al. (2015), Dell, Jones, and Olken (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, Vanga, Saxena, Orsat, and Raghavan (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 & van Etten, 2018; Goron & 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, Sheffield, & Lobell, 2015; Lobell et al., 2013; Roberts, Schlenker, & Eyer, 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 & 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, Jones, & Olken, 2014) and recent empirical studies (e.g., Emediegwu, 2021; Harari & Ferrara, 2018; Burke et al., 2015; 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 & Poot (2004)). Such spatial dependence can be captured econometrically *via* spatial panel 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

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

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

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 & 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), Cliff and Ord (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, 2004, 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, Cornetet, Huybers, Meng, and Proctor (2020), Auffhammer and Schlenker (2014) also posit that such dependence could result from confounding variation 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 18 km^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 & Ferrara, 2018; Dell et al., 2014). For example, using panel data of over 20 years 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 with 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 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 the GNS model suffers from the well-known Manski reflection problem. The second reason is the problem of overfitting. Elhorst (2014), 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.

[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, Wichmann, and Luckert (2021), Leiva, Vasquez-Lavín, and Oliva (2020), Ho, Wang, and Yu (2018).

[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

[8] The bias is a creation of the *incidental parameter* problem, which is briefly discussed in the Appendix, subsection B.2.

[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.

3.1.1. 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.

3.1.2. 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^o resolution (approx. 56 km $\times$ 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 & Schlenker, 2014; Lobell, Bänziger, Magorokosho, & Vivek, 2011; Schlenker & 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 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 & 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 & 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 0.1 mm 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, Fig. 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 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, Prins, Kay, and Heibloem (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^o spatial resolution (approx. 4 km $\times$ 4 km across the equator).[18]

We exploit the 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

[10] See Harris, Jones, Osborn, and Lister (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

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

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

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,

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

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

[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.

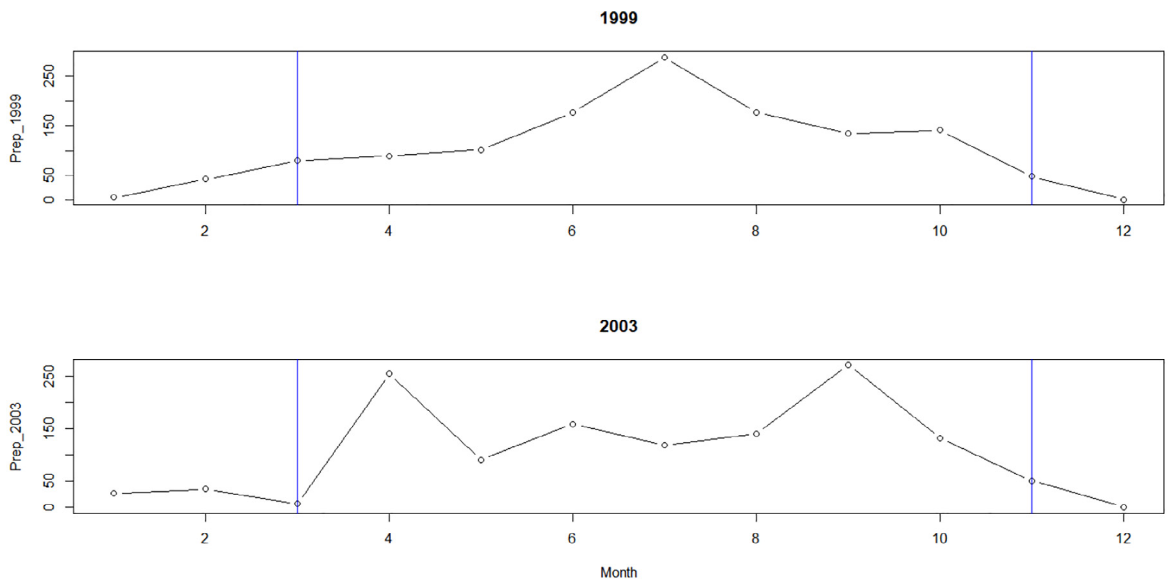
[14] This occurrence may first seem counter-intuitive given the hot nature of SSA; however, following works by the World Bank and FAO, Auffhammer and Schlenker (2014) affirm that developing countries (including SSA) have soils and climate that are conducive for agriculture.

[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.

[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, Dobrowski, Parks, and Hegewisch (2018) for dataset description



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.

Fig. 1. Benin (Millet) MPA Monthly Precipitation for Two Years (1999 & 2003).

Agriculture database, FAO (2018), Monfreda, Ramankutty, and Foley (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 the advice of Moore, Baldos, and Hertel (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). To the best of our knowledge, 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 Fig. 2 shows a substantial variation in weather measures across the MPAs.

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 zone (AEZ) features. The inclusion of 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, β, ω, γ and ϑ are vectors of parameters to be estimated, the last two being spatial parameters.[22]

The weather variables C in Eq. (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 crop yield; temporal lags; and monthly deviation in temperature to account for variability in temperature. Monthly deviation in tem-

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

[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.

[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.

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.

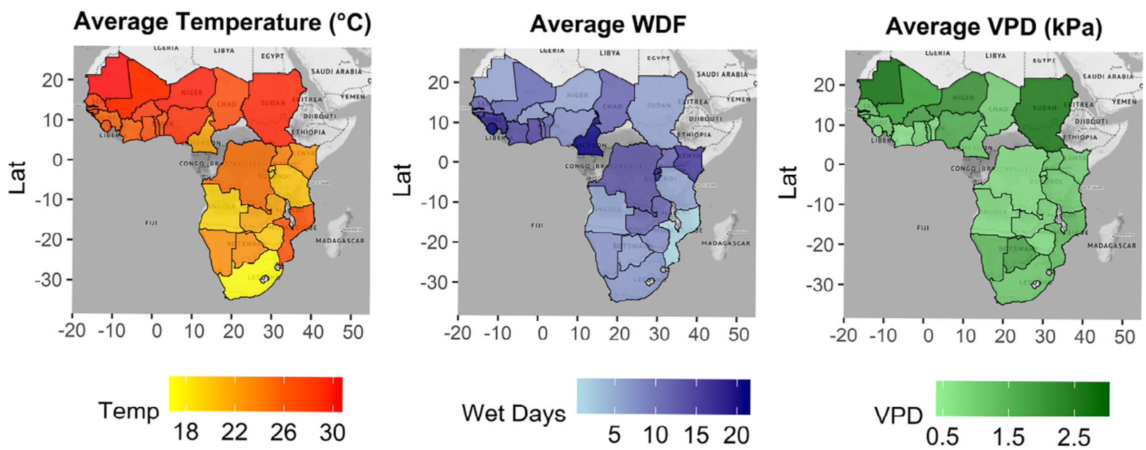


Fig. 2. Spatial Variation of Average Weather Measures (1970–2016).

perature 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 the 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 *W* is generally unknown, therefore, to further our analysis, we use a couple of other spatial weights matrix to check the robustness of results. Specifically, we re-estimate the model using *4-nearest neighbor (4-NN)* spatial weights and spatial weights based on the prevailing economic network. To create these weight matrices, we construct shapefiles from the ArcGIS 10.3 software.[25] Thereafter, we cascade the shapefile into Anselin, Syabri, and Kho (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 supplementary section (Appendix A).

Our baseline specification corrects for spatial interactions in the dependent and independent variables *via* spatial weight matrices,

[23] Deschênes and Greenstone (2007), Schlenker, Hanemann, and Fisher (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, Singh, Clerget, Chantereau, & Sultan, 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, Burke, and Miguel (2013), Hsiang, Meng, and Cane (2011) (conflict).

[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.

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, Le Gallo, and Jayet (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 Eq. (1) with γ and ϑ in Eq. (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 Eq. (1) with alternative time trends; additional 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, Bera, Florax, and Yoon (1996). The results in Table 2 show that the LM test and robustness are significant at 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 seasons resulting in little within variation in temperature (Auffhammer & 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 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 and VPD variables 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 largely negative 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 depends on the level of temperature itself, and the overall total effect of WDF depends on the level of WDF. When calculated at their

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

	NS	SDM
TEMP	−0.2034*** (0.0904)	−0.2177*** (0.0521)
WDF	0.0227*** (0.0023)	0.0201*** (0.0016)
VPD	−0.2704*** (0.1082)	−0.1968*** (0.0311)
TEMPsq	0.0107*** (0.0036)	0.0035** (0.0016)
WDFsq	−0.0031*** (0.0009)	−0.0007*** (0.0002)
TEMP. dev.	−0.0131 (0.0101)	−0.0071 (0.0065)
Time trend	0.0114*** (0.0031)	0.0144*** (0.0033)
Time trend squared	0.0001*** (0.0000)	0.0001*** (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* (0.0014)	−0.0020 (0.0008)
$TEMP_{t-2}$	0.0052 (0.0036)	0.0015 (0.0040)
WDF_{t-1}	−0.0026** (0.0010)	−0.0026** (0.0011)
WDF_{t-2}	0.0073 (0.0061)	0.0007 (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.

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

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

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

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

	NS	SDM
Direct Effect[a]		
TEMP	−0.2034*** (0.0904)	−0.2187*** (0.0533)
WDF	0.0227*** (0.0023)	0.0210*** (0.0058)
VPD	−0.2704*** (0.1082)	−0.2106*** (0.0336)
TEMPsq	0.0107*** (0.0036)	0.0031** (0.0016)
WDFsq	−0.0031*** (0.0009)	−0.0007*** (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*** (0.1096)	−0.2228*** (0.0436)
WDF	0.0227*** (0.0023)	0.0279*** (0.0011)
VPD	−0.2704*** (0.1082)	−0.2064*** (0.0412)
TEMPsq	0.0107*** (0.0036)	0.0013** (0.0006)
WDFsq	−0.0031*** (0.0009)	−0.0002*** (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.

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, Jäger, & Fehér, 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, Feng, Oppenheimer, & Pytlikova, 2016; Bohra-Mishra, Oppenheimer, & Hsiang, 2014; Gray & 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 indirect 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.

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

Dependent Variable log (yield)	NS	SDM
$TEMP_{t-1}$	−0.0028* (0.0014)	−0.0035 (0.0024)
$TEMP_{t-2}$	0.0052 (0.0036)	0.0032 (0.0041)
WDF_{t-1}	−0.0026** (0.0010)	−0.0029** (0.0014)
WDF_{t-2}	0.0073 (0.0061)	0.0019 (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.

4.1.2. Temporal lag effects

The results in Table 4 indicate that the impacts of time lags are dissimilar in the NS model and the SDM. 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 the supplementary section (Appendix C).

The above results reflect the *delayed* effect or the *temporal* persistence of weather shocks cited in several studies (Hsiang, 2016; Burke et al., 2015; 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 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*-

[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.*

[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*** (0.0533)	−0.1923*** (0.0512)	−0.2170*** (0.0531)	−0.2258*** (0.0651)	−0.1224* (0.0930)	0.2281*** (0.0555)
WDF	0.0210*** (0.0058)	0.0205*** (0.0078)	0.0227*** (0.0057)	0.0244*** (0.0077)	0.0108*** (0.0066)	0.0270*** (0.0061)
VPD	−0.2106*** (0.0336)	−0.226*** (0.0466)	−0.2380*** (0.0316)	−0.2032*** (0.0433)	−0.2451*** (0.0270)	0.2079*** (0.0321)
Indirect effects						
TEMP	−0.0041 (0.0055)	−0.0031 (0.0073)	−0.0036 (0.0072)	−0.0014 (0.0083)	−0.0020 (0.0114)	−0.0026* (0.0012)
WDF	0.0069** (0.0028)	0.0063** (0.0030)	0.0063** (0.0032)	0.0059** (0.0027)	0.0030* (0.0014)	0.0046** (0.0020)
VPD	0.0042 (0.0096)	0.0047 (0.0055)	0.0051 (0.0050)	0.0032 (0.0027)	0.0054 (0.0061)	0.0061 (0.0063)
Temporal Effects						
$TEMP_{t-1}$	−0.0035 (0.0024)	−0.0024 (0.0047)	−0.0026 (0.0047)	−0.0030 (0.0035)	−0.0011 (0.0053)	−0.0032 (0.0046)
WDF_{t-1}	−0.0029** (0.0014)	−0.0025* (0.0013)	−0.0025* (0.0013)	−0.0031 ** (0.0014)	−0.0019 (0.0015)	−0.0047** (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°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.

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. (2015) argue that poor and rich countries respond 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. (2015), 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

Table 6
Effects by Income Classification of SSA Countries.

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

[32] Auffhammer and Schlenker (2014) attenuate this claim by suggesting that the introduction of nonlinear 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, Cui, Ghanem, & Mérel (2018) for more intuition).

Table 7
Alternative Estimation Procedures.

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

*Notes:*Column (1) is the results of the non-spatial version of Eq. (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°C and VPD in kPa. ***p < 0.01, **p < 0.05, *p < 0.1.

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 the supplementary section (Appendix D). 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 Eq. (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. (2015), 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, Di Falco, Doku, and Mahajan (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.

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

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

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.

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 & 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 & 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. (2015), 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. (2015), 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. Our results in subsection 4.4 also corroborate their findings. 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 (GCMs) for current climate in some locations.[38] We recognize 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)

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

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 & 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 Fig. 3 show 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, 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 Eq. (1) while controlling for statistical (or regression) uncertainty as noted by Burke et al. (2015). To sidestep statistical (or regression) uncertainty, we re-estimate Eq. (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 × 3 GCMs) predicted impacts. The construction of the bootstrapped prediction interval is detailed in the supplementary section (Appendix E).

The distributions of predicted impacts from the GCMs' scenarios spanning 2040–2069 are displayed in Fig. 4. Assuming that present socio-economic conditions persist, Fig. 4 reveals that the median

[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, Stouffer, and Meehl (2012), whereas the dataset can be retrieved from the CMIP5 websitehttps://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).

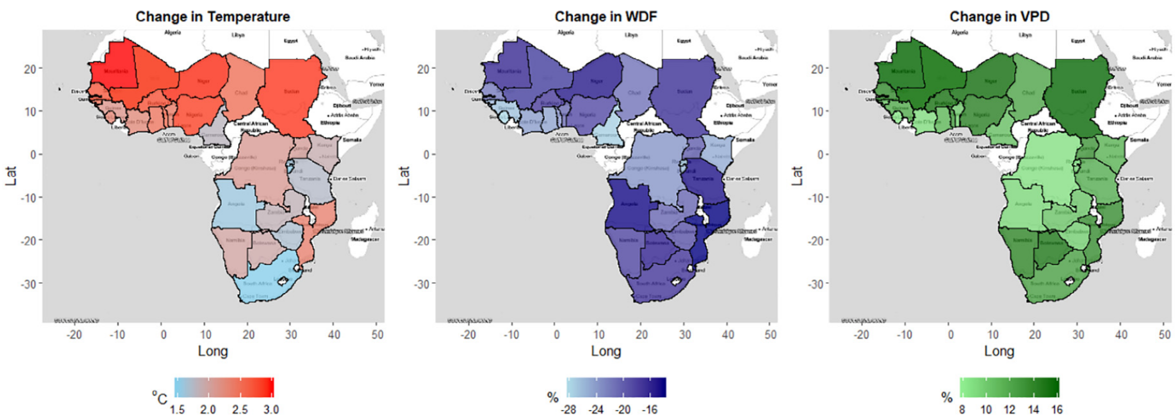
[37] In principle, climate uncertainty cannot be totally eliminated, no matter the number of GCMs used, because the influence of climate on aerosols is complex (Hawkins & Sutton, 2009). At best, uncertainty can be reduced by using forecasts from several GCMs.

[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. (2015), Auffhammer et al. (2013).

Table 9
Summary Statistics of Projected Climate Change.

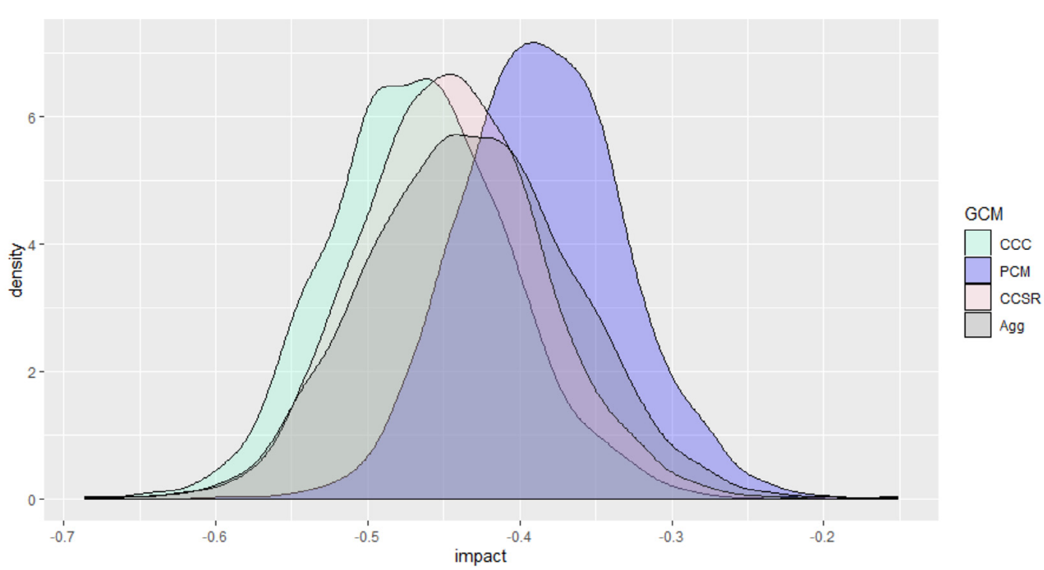
Variables	Baseline (1981–2010)	(1) PCM	(2) CCSR	(3) CCC
Average Temperature (°C)	25.7	26.2	27.5	28.3
Average WDF	15.6	17.43	14.9	12.14
Average VPD (kPa)	1.431	1.451	1.521	1.586

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.



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.

Fig. 3. Spatial Variation in Projected Climate Change.



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.

Fig. 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.

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.

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 effects 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 several alternative empirical specifications such as use of more lags, different weight matrix, *etc.* Further, we do not find any evidence of adaptation to gradual changes 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 the 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 intercontinental 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 the African Union (AU) leaders. Collaborative programs of this sort will help maximize the impact of the AU's support for 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 & 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.

CRediT authorship contribution statement

Lotanna Emediegwu: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Visualization, Writing - original draft. **Ada Wossink:** Conceptualization, Resources, Supervision, Writing - review & editing. **Alastair Hall:** Methodology, Resources, Supervision, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2022.105967.

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