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Interdependence between research and development, climate variability and agricultural production: evidence from sub-Saharan Africa

Frank Bannor¹, Johane Dikgang and Dambala Kutela Gelo²

Abstract

The performance of the agricultural sector in sub-Saharan Africa (SSA) remains low compared to other regions. This is often attributed to the fact that agriculture in SSA is rain-fed, as well as to inadequate investment in research and development (R&D). It is well documented in the literature that climate variability is a possible reason for the low productivity observed in agriculture. It is similarly well documented that R&D investment affects the growth of agricultural productivity. This paper investigates whether public spending on R&D mitigates the negative effects of climate variability (measured by variability in rainfall) on agricultural productivity in SSA. We do so by employing a dynamic production model, and the Generalised Methods of Moments (GMM) technique. Based on cross-country panel data from the period 1995 to 2016, our empirical findings reveal that both climate variability and the interaction of R&D with climate variability are strongly correlated with agricultural productivity. As expected, climate variability reduces agriculture productivity by 0.433% to 0.296%. The interaction of R&D and climate variability enhances agricultural productivity by 0.124% to 0.065%. We also show that R&D is an absorption channel for the inimical effects of climate variability, and that the way in which climate variability impacts agricultural productivity depends on the magnitude of spending on R&D; in order to move from a negative to a positive impact of climate variability on agricultural productivity, public spending on R&D must increase by 3.492% to 4.554%. We conclude that to address the negative effects of climate variability, there is a need for governments to prioritise and increase spending on R&D.

KEYWORDS: Agriculture; Climate variability; R&D; Productivity; Sub-Saharan Africa (SSA).

JEL CODES: O3, Q2, Q5

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1. Introduction

Agricultural productivity is vital for most African economies, given that the agricultural sector accounts for more than 70% of the total labour force on the continent (World Bank, 2000). However, the performance of the agricultural sector in sub-Saharan Africa (SSA) remains low compared with developing countries elsewhere. Given that agriculture in SSA is rain-fed, Hansen et al. (2011) argue that low productivity in the agricultural sector of most SSA countries could be attributed to variability in climate. Amare et al. (2018) observe that there are three possible ways in which climate variability could impact agricultural productivity. Using rainfall as a proxy for climate variability, they note that rainfall variability expressed in terms of historical rainfall might be a direct input for food-crop cultivation. Second, variability in rainfall could negatively impact the behaviour of farmers, and thus influence their decision-making regarding the use of inputs such as labour and fertiliser (see Sesmero et al., 2017). Therefore, as a result of these behavioural decisions, rainfall variability could result in the loss of crop yield in the agricultural sector.

In addition, the role of research and development (R&D) in accelerating and sustaining the growth of agricultural productivity has attracted much interest and is well recognised in the literature (Pardey et al., 2013). Andersen (2015) argues that public spending on agricultural R&D is essential for future food security. Considering the deterioration in climatic conditions, therefore, one of the most important instruments SSA economies have for achieving sustained agricultural production and food security is increased public spending on R&D in the agricultural sector. There is a growing volume of empirical literature investigating the relationships between public investment in agricultural R&D, climate change, and agricultural productivity in general (see Bathla et al., 2019; Khan et al., 2018; Amare et al., 2018; Andersen, 2015; Bervejillo et al., 2012; Alene, 2010; Salim & Islam, 2010). While Bathla et al. (2019) found that public investment in agricultural R&D and subsidies have the highest marginal returns on agricultural productivity in low-income states in India, Andersen (2015) showed the real rate of return on public investment in agricultural R&D in the United States to be 10.5% per annum. Amare et al. (2018) demonstrated that rainfall variability decreases agricultural productivity (and hence household consumption) by 37%. Salim and Islam also showed that both R&D and climate change matter for long-run productivity growth in agriculture, with the long-run elasticity of total factor productivity with respect to R&D expenditure and climate change in Western Australia being 0.497 and 0.506 respectively.

Though our study is an extension of Bathla et al. (2019), Khan et al. (2018), Amare et al. (2018) and Salim and Islam (2010), we use a different approach to explicitly explain the exact relationship between R&D and climate variability on agricultural productivity using cross-country panel econometrics on selected SSA countries. Even though there is a vast amount of literature on the impacts of R&D and climate change on agriculture, economic studies on whether R&D mitigates the effects of climate variability are scarce, especially in Africa. O'Donnell et al. (2006) have shown that existing studies on this area are still qualitative – given that measurement of agricultural productivity under climate variability is an arduous task, due to a lack of data and suitable methodologies. Given the deteriorating climatic conditions and the need to ensure food security, many governments in Africa have committed to the African Union's recommendation (in Malabo in 2003) to increase their annual spending on agriculture to 10% of total national expenditure. However, to effect the course of this strategic initiative, more analysis is called for, using high-quality data and a rigorous approach.

Though there is a large body of literature on the impacts of climate change on agricultural production, individual studies generally focus on the impact of climate change on agriculture at only country and cross-country level. The range of literature on the relationship between climate variability and agricultural productivity is relatively small. By evaluating the impact of climate variability on agricultural productivity, this paper contributes to this scant literature. Moreover, although there is a growing number of studies on the impact of R&D on agricultural productivity, our study evaluation of the impact of R&D and climate variability and their interaction on agricultural productivity is a first. We investigate the role of R&D in mitigating the impact of climate change on agricultural productivity. Our study supplements the findings of past studies in several ways. First, we capture the linear effect of climate variability (proxied by rainfall variability) on agricultural productivity, in the period 1995 to 2016. We use climate variability rather than climate change, as climate variability captures changes that occur within a shorter timeframe.

Second, given that rainfall is heterogeneous and that low agricultural productivity in many SSA countries that depend on rain-fed agriculture production is often attributed to climate variability, we correlate climate variability with R&D to determine whether R&D serves as an absorption channel through which the inimical effects of climate variability could be mitigated, which has not traditionally been carried out in the literature. This is crucial, since risk-averse farmers cannot

adapt to climate variability unless they can access credit, crop insurance and market information – all non-existent in many SSA countries. Given that climate variability induces risk, the farmers' anticipation of such climatic shocks might influence their behavioural and production decisions – such as those regarding hire of labour, use of fertiliser, and capital – with the aim of avoiding losses, which results in low agricultural productivity. Therefore, these behavioural decisions might result in noticeable and time-varying changes in market conditions such as prices of food and profitability. Against this backdrop, it becomes desirable to have evidence regarding the absorption channel through which the negative effects of climate variability on agricultural production could be mitigated. This gains significance when one considers that increased agricultural productivity can lead to a reduction in food prices, which in turn increases the real income and purchasing power of households.

Third, we document that R&D is a source of non-linearity between climate variability and agricultural productivity, and that the way in which climate variability affects agricultural productivity depends on the magnitude of spending on R&D. Thus, we compute the threshold at which governments should increase spending on R&D in order to move from a negative to a positive impact on climate variability.

The rest of the paper proceeds as follows. Section 2 provides an overview of agriculture in SSA, followed by a critical review of the recent literature in Section 3. Data sources are documented in Section 4. Section 5 presents the analytical framework, followed by an analysis of empirical results in Section 6. A summary of findings and policy implications is provided in the final section.

1. An overview of agriculture in sub-Saharan Africa (SSA)

Alene (2010) argues that productivity growth in agriculture has been identified as vital to the general economic growth of SSA countries. Therefore, much agricultural and development economics research has focused on measuring and explaining productivity growth in agriculture. Despite the great strides made in improving agriculture productivity, agricultural production has been unable to meet the higher and more diversified food requirements of SSA populations. NEPAD (2003) noted that in many SSA countries, population growth has exceeded growth in agricultural production, exposing large numbers of people to hunger, food insecurity and malnutrition. In terms of exports, SSA's world share of agricultural exports declined from 8% in 1971-80 to 3.4% in 1991-2000, whereas agricultural imports accounted for about 15% of total

imports. Additionally, FAO (2016) documented that grains and cereals continue to be the main energy source for about 962 million people in the SSA sub-region. FAOSTAT (2010) noted that total consumption of cereals is projected to increase by more than 52 metric tonnes by 2025.

However, cereal productivity in Africa is lower than half the world average. Badu-Apraku and Fakorede (2017) observed that maize – which is the biggest food crop cultivated in SSA – accounts for more than 40% of overall cereal consumption and occupies 25 million hectares in SSA. It is cultivated primarily on smallholder farms and provides around 20% of the population's calorie intake. AfDB (2015) argued that although a significant number of countries in SSA have achieved increases in productivity, average maize productivity in SSA (estimated at about 1.8 million tonnes per hectare) is still well below the global mean production of 5 million tonnes per hectare. At the same time, Bhagavatula (2013) observed that sorghum is the second-biggest crop (after maize) cultivated in SSA, covering 22% of total cereal area. The African continent accounts for about 61% of total sorghum area globally, and production of about 41%. However, FAO (2011) showed that in SSA, mean yields of sorghum have remained static at or below 700 thousand tonnes per hectare, compared with the world average of 1.37 million tonnes per hectare.

In addition, the World Bank (2000) observed that agriculture in SSA differs from agriculture in the rest of the world. FAOSTAT (2005) showed that in SSA, agriculture accounts for 35% of gross domestic product (GDP) and employs 70% of the population. At the same time, more than 95% of the farmed land is rain-fed. The IPCC (2014) projected that a 1.5°C to 2°C increase in global temperatures would mean greater risks for Africa in the form of more severe droughts, more heat waves and more potential crop failures. Therefore, the brunt of the adverse impacts of climate change is expected to be borne by countries with large agricultural sectors in the tropics and subtropics where agricultural production is weather sensitive and adaptive capacity is low. Sensitivity to climate influences the strategies adopted by farmers, who are mostly reluctant to invest in intensive agriculture, and therefore affects agricultural production. Morton (2007) observed that the effects of climate change are most extreme for small-scale farmers, compared to large-scale farmers. Abid et al. (2016) and Ncube and Lagardien (2014) have shown that in the face of climate change, small-scale farmers resort to several coping strategies including the use of traditional adaptation techniques such as crop switching.

However, Burke and Lobell (2010) postulated that in most parts of SSA, the magnitude and speed of the predicted changes due to climate change are likely to outstrip local efforts to manage those

changes. This will require enormous public as well as private investment in R&D to meet the needs of farmers in SSA, small-scale farmers especially. Alene and Coulibaly (2009) provided evidence that investment in agricultural R&D can generate adequate growth in agricultural productivity, and thus increase per capita income and minimise poverty in developing economies.

Gert-Jan and Beintema (2015) showed that investment in public agricultural R&D for SSA was estimated at \$1.7 billion in 2011. This was more than a third higher than the \$1.2 billion reported in 2000. However, a country-by-country analysis revealed that spending growth in 2000-2011 was primarily driven by only a handful of countries (Nigeria and Uganda in particular). At the same time, Ghana, Kenya, and Tanzania also reported relatively high increases in total spending in 2000-2011. Although increases and decreases in absolute rates of agricultural R&D spending by the larger economies in SSA outweigh those of the smaller economies, a closer look at the relative changes in investment levels over time shows substantial cross-country disparities and challenges. Furthermore, the World Bank (2017) showed that SSA had recorded a negative agricultural R&D investment growth rate, but that this had increased with time, from an overall annual growth rate of -2.7% in 1980-1989 to -2.3 in 1990-1999 and -0.6 in 2000-2011. Investment in R&D accounted for approximately 1.1% of the agricultural value added per year between 1980 and 2011 in SSA. About 40% of SSA countries spend at least 1% of the agricultural value added on R&D, as part of the goal set by the New Partnership for Africa's Development (NEPAD) of the African Union. Botswana, Mauritius, Namibia and South Africa had at least 2% of the largest investment shares each year. Additionally, countries including Nigeria, Ethiopia, Tanzania and Ghana spent on average less than 0.7% of the amount of their agricultural value added per year on R&D. In all, the total amount of spending on R&D in SSA either stagnated or declined in the period 1980-2011.

2. Review of literature

2.1 Climate change and agricultural productivity

In recent years, a large number of studies (Amare et al., 2018; Chang et al., 2016; Salim and Islam, 2010; Schlenker and Roberts, 2009) have shown that climate change plays an important role in agricultural productivity. This means there is a wide range of empirical studies analysing the effects of climate change on agricultural productivity in the literature. Our study reviews some of the past and the most recent studies on the relationship between climate change and agricultural productivity.

Barrios et al. (2008) examined the impact of climate change on the level of total agricultural production in SSA and non-SSA (NSSA) countries. In doing so, they used a new cross-country panel climatic dataset in an agricultural production framework. Their results showed that climate, measured as changes in countrywide rainfall and temperature, has been a major determinant of agricultural production in SSA. In contrast, NSSA countries appear not to be affected by climate in the same manner.

Schlenker and Roberts (2009), pairing a panel of county-level yields for corn, soybeans and cotton with a new fine-scale weather dataset that incorporates the whole distribution of temperatures within each day and across all days in the growing season, found that yields increase with temperature up to 29°C for corn, 30°C for soybeans, and 32°C for cotton. However, temperatures above these thresholds are very harmful to crop productivity. The study showed that if current growing regions remain fixed, area-weighted average yields are expected to decrease by 30-46% before the end of the century.

Knox et al. (2012) analysed the impacts of climate change on the yield of eight major crops in Africa and South Asia, using a systematic review and meta-analysis of data from 52 original publications. They showed that average change in yield of all crops in Africa and Asia will hit -8% by the year 2050. The results were particularly serious for Africa, where average yield variations were estimated to be around -17% for wheat production and -5% for maize.

Chen et al. (2015) estimated the relationship between weather elements and crop yields in China, using an empirical framework. Their study discovered that there is a non-linear relationship between crop yields and climate variables; and further that climate variability has caused an economic loss of about US\$820 million in China's corn and soybean sectors in the last decade.

Ma and Maystadt (2017) examined the impact of weather variations on maize yields and household income in China. They observed that temperature, drought, and precipitation have detrimental effects on maize yields. Their study revealed that the impact is stronger in the Northern spring; one standard deviation in temperature and drought conditions decreases maize yields by 1.4% and 2.5% respectively.

In another study, Kuwayama et al. (2018) estimated the impacts of drought on crop yields in the US between 2001 and 2013. They found that drought has negative and statistically significant effects on crop yields – reductions in the range of 0.1% to 1.2% for corn and soybean yields.

Amare et al. (2018) noted that negative rainfall shocks have heterogeneous effects on crop-specific

agricultural productivity, also dependent on geographical zones. Using an instrumental variables regression approach, where agricultural land productivity is instrumented with negative rainfall shocks, they found that a negative rainfall shock decreases agricultural productivity (and hence household consumption) by 37%.

In a very recent study, Bocchiola et al. (2019) examined the impact of climate change on agricultural productivity and food security in the Himalayas. They observed that on average, climate variability will decrease wheat (25%), rice (42%) and maize (46%) production by 2100. However, under a modified land-use scenario, wheat yield would decrease further (38%), while rice and maize yield would improve very slightly (22% and 45% respectively) in response to occupation of higher altitudes. In light of these studies, the general conclusion that arises from the literature is that climate change could affect agricultural production significantly.

2.2 Public spending on R&D and agricultural productivity

Following the work of Griliches (1958), several studies have included R&D expenditure as an explanatory variable in productivity or production outcomes. Hall and Scobie (2006) observed that higher productivity may result from many sources, but an increase in the stock of knowledge is widely seen to be the primary source of productivity. Hence, investing in R&D can lead to a change in productivity, by changing the quality of conventional inputs and outputs (Fan, 2000). In the article by Griliches (1979) on assessing the contribution of R&D to productivity growth, he opines that since it is not possible to quantify the amount of knowledge stock, it is appropriate to take spending on R&D as a proxy for knowledge stock. In turn, the literature supposes that climate variability significantly affects agricultural productivity, given that agricultural activity is one of the major contributors to climate change in recent times (Antle and Mullen, 2008).

Fan et al. (2008) observed that the main determinant of government allocation of resources to the agricultural sector is its public good nature. Therefore, government expenditure on agriculture is a means by which the government pursues developmental as well as welfare policies by increasing capital stock (Armas et al., 2012). Fan (2000) measured economic returns on R&D investment in Chinese agriculture using the production function approach. The study showed that rates of return on investment in R&D in Chinese agriculture are high, ranging from 36% to 90% within the study period, and that the rates increase over time.

Alene (2010) measured and compared total factor productivity growth in African agriculture under contemporaneous and sequential technology frontiers in the period 1970-2004. Using a fixed-effects regression model and a polynomial distributed lag structure, the study further examined sources of agricultural productivity growth. While their conventional estimates showed an average productivity growth rate of 0.3% per annum, their improved measure under sequential technology showed that African agricultural productivity grew at a higher rate, of 1.8% per annum. At the same time, agricultural R&D, weather, and trade reforms turned out to have significant effects on productivity in African agriculture. R&D was a socially profitable investment in African agriculture, having a rate of return of 33%t per annum. The study showed further that a strong R&D expenditure growth of about 2% per annum in the 1970s yielded strong productivity growth after the mid-1980s. However, a stagnation in R&D expenditure in the 1980s and early 1990s led to slower productivity growth in the 2000s.

Salim and Islam (2010) explored the impact of R&D and climate change on agricultural productivity growth in Western Australia during the period 1977-2005. They adopted the augmented Cobb-Douglas production function to estimate the equilibrium relationship to output, as well as to productivity growth in the long run. They concluded that both R&D and climate change matter for long-run productivity growth. The long-run elasticity of total factor productivity with respect to R&D expenditure is 0.497. Further, they showed that an increase in R&D investment in deteriorating climatic conditions in the agricultural sector improves the long-run prospects of productivity growth.

Using newly constructed data, Bervejillo et al. (2012) modelled and measured agricultural productivity growth and return on public agricultural R&D in Uruguay in the period 1961-2010. They showed that public funding for agricultural R&D spurred sustained growth in agricultural productivity when productivity growth was stagnating in many other countries. Their study revealed further that the benefit-cost ratio varied significantly across models with different lag structures, and that internal rate of return on R&D was very stable, ranging from 23% to 27% per annum in the study period. Andersen and Song (2013) examined the relationship between public investment in agricultural R&D in the US and the productivity-enhancing benefits it generates. In particular, they found that the real rate of return (RRR) on public investment in agricultural R&D in the US ranged between 8% and 10% per annum.

To better understand the relationship between public investment in agricultural R&D and productivity, Andersen (2015) – using R&D expenditure data from 1949-2002, in the US – showed that the real rate of return on public spending on agricultural R&D was 10.5% per annum, indicating that government spending in agricultural R&D earns healthy economic returns, which justifies these expenditures to the general public and to policymakers.

Recently, using a unique state-level dataset covering the period 1995-2007, Khan et al. (2018) examined the role of R&D in Australia's broadacre farming. They found that R&D investments significantly increase output. Their results also showed that there are substantial variations in the impact of R&D on output across the average farm at state level, because of technology parameters and technical inefficiencies. Jaijit et al. (2019) explored the economic, social and environmental impact of Thai rice research expenditure, using the simultaneous equation modelling technique. Their results show that production-research expenditure was the most obvious means of reducing the amount of nitrogen fertiliser used, while breeding-research expenditure had the same effect in terms of improving farmers' economic status through planting rice.

And in a recent study on agriculture in India, using data on public investment from 1981/82 to 2013/14, it was found that public investment in agricultural R&D has the highest marginal returns in low-income states in India (Bathla et al., 2019). Therefore, there is consensus in the literature that there are significant returns from R&D spending, particularly in the agricultural sector.

3. Data sources

Panel data on agricultural production and conventional agricultural inputs (land, capital, labour and fertiliser) for 14 SSA countries for the period 1995-2016 have been obtained from the FAO database (FAO, 2020) and the ILOSTAT database. They are Benin, Botswana, Burkina Faso, Ivory Coast, Ethiopia, Ghana, Kenya, Malawi, Mali, Niger, Nigeria, South Africa, Togo and Zambia, chosen for the availability of their data. Data on agricultural R&D (measured in millions of US dollars) were taken from the IFPRI (International Food Policy Research Institute) Agricultural Science and Technology Indicators database. A summary and description of the data sources is presented in Table 1 below.

Table 1: Data description and sources

Variable	Description	Data Source
Maize	Crop yield in 1000 per hectare	FAO
Agricultural land area	Land under permanent crops in 1000 per hectare	FAO
Labour	Measured as the total number of ILO employments in agriculture	
Capital	Gross fixed capital formation in agriculture (millions of US\$)	FAO
Fertiliser	Fertiliser applied to crops in tonnes	FAO
Rainfall	Monthly average rainfall in millimetres	World Bank climate change knowledge portal
Literacy	The proportion of the adult population that is literate	World Bank, World Development Indicators database
R&D	Data on agricultural research and investments (millions of US\$)	International Food Policy Research Institute

Based on Table 1, one of our main variables of interest is climate variability. This is proxied by annual rainfall (in millimetres) to capture the effect of climate variability on agricultural productivity. Despite the crucial role of rainfall in the largely rain fed SSA agriculture, the actual impact of climate variability on agricultural production is still nascent. We follow the literature (Trong-Anh, 2019; Amare et al., 2018) to capture climate variability (proxied by rainfall variability) as follows:

$$\text{Rainfall Variability (RV}_{it}) = \log\left(\frac{\bar{x}_{it} - x_{it-1}}{x^{SD}}\right) \quad (1)$$

where \bar{x}_{it} represents the average historical rainfall calculated for the sample period in country i at a time (t) , x_{it-1} indicates past rainfall, and x^{SD} represents the standard deviation from the mean rainfall within the sample period (1995-2016).

Also, another variable of interest is agricultural R&D investment, acknowledged in the literature to increase agricultural productivity (Khan et al., 2018; Andersen, 2015; Alene, 2010; Salim and Islam, 2010; Alston et al., 1995). Khan et al. (2018) found that R&D investment significantly increases output in Australia's broadacre farming. In the US, Andersen (2015) showed that the real rate of return (RRR) on public spending on agricultural R&D was 10.5% per annum. Alene (2010) and Salim and Islam (2010) indicated that R&D investment in Africa and Australia improves agricultural productivity. Alston et al. (1995) outlined a structural model that ties expenditure on agricultural research to growth in agricultural productivity.

According to the literature, literacy – our third variable of interest from Table 1 – also affects agricultural productivity. Hayami and Ruttan (1985) have noted that the percentage of the adult population that is literate (the adult literacy rate) is used as an educational metric to compensate for differentials in labour efficiency. We can expect that literacy to improve farmers' ability to make use of the information provided by extension officials. Alene (2010) observed that in general, a more educated population is able to provide better agricultural services and thus increase agricultural production, even without increasing the quality of agricultural labour.

4. Model specification

Over the years, agricultural productivity measurement has become a vital area of development economics and agricultural research (see for example Amare et al., 2018; Alene, 2010; Craig et al., 1997; Evenson and Pray, 1991; Hayami and Ruttan, 1985). To address the research problem, this paper employs a production function approach, following on from Griliches (1995) and Andersen (2015). We adopt a neo-classical production function to show the relationship between climate variability and agricultural productivity growth over time. We assume a farmer's objective is to maximise farm output, and thus we define the function of production as:

$$Y_{it} = f(A_{it}, L_{it}, K_{it}, l_{it}, f_{it}, Z_{it}) \quad (2)$$

where Y represents agricultural output for crop (i) at time (t) proxied by yield of maize and sorghum; t is a time index – that is, $t = 1995, 1992, \dots, 2016$; A_{it} represents land used for farming crop (i) at time (t) . L_{it} represents labour, K_{it} represents capital, l_{it} indicates literacy rate, f_{it} indicates

fertiliser and Z_{it} is climate variability (proxied by variability in rainfall). Our model also assumes that soil quality remained constant over the study period across countries (see Schlenker and Roberts, 2009; Welch et al., 2010). It is important to note that our function does not necessarily represent the true relationships between the inputs and the output; rather, its purpose is simply to serve as a vehicle for exploration and interpretation of the outcomes. Equation 3 below thus depicts our linear dynamic model, which captures the linear effects of climate variability on agricultural output. We specify a dynamic model because the literature suggests that changes in climatic patterns influence farmers' expectations and are more likely to prompt behavioural changes (especially the adoption of conventional inputs), and thus affect agricultural production (see Sesmero et al., 2017; Barrios et al., 2010).

$$Y_{it} = \beta Y_{t-1} + \gamma \text{Climate_Var}_{it} + \alpha \text{Labor}_{it} + \phi \text{Capital}_{it} + \theta \text{Land}_{it} + \phi \text{Literacy}_{it} + \eta \text{Fertilizer}_{it} + \varepsilon_{it} \quad (3)$$

where Y_{t-1} is the lag of agricultural output; ε_{it} is the error term, supposedly uncorrelated with all of the explanatory variables, and β , γ , α , θ , ϕ and η are parameters to be estimated. Though several studies (see Bathla et al., 2019; Khan et al., 2018; Andersen, 2015; Bervejillo et al., 2012; Alene, 2010) have specified a similar function to Equation 3, few have tried to understand whether the impact of climate variability may be mitigated by public spending on R&D. To account for this, we augment Equation 3 with an interaction term, to capture the absorption channel through which the inimical effects of climate variability could be mitigated. This is important because the literature has shown that rainfall (proxy for climate) is heterogenous, and that the yield of a specific crop may depend not only on the amount of rainfall, but also on the adoption of new technology (e.g., improved seeds) pioneered by spending on R&D (see Amare et al., 2018; Huffman et al., 2018; Salim and Islam, 2010). We expand the production function of equation 3 as follows:

$$Y_{it} = \beta Y_{t-1} + \gamma \text{Climate_Var}_{it} + \delta \text{Climate_Var} * \text{R\&D}_{it} + \alpha \text{Labor}_{it} + \phi \text{Capital}_{it} + \theta \text{Land}_{it} + \phi \text{Literacy}_{it} + \eta \text{Fertilizer}_{it} + \omega_{it} + \varepsilon_{it} \quad (4)$$

where $\text{Climate_Var} * \text{R\&D}_{it}$ denotes the interaction of climate variability and R&D, and δ is a parameter to be estimated. This is key to our research, given that climate variability poses crop production risks, raising the risk of adoption of farm technology – especially in rain-fed, liquidity-constrained and imperfect market settings – and thus reducing agricultural production (see Barrios et al., 2010; Brown et al., 2010; Dercon and Christiaensen, 2011; Di Falco and Chavas, 2009). By

introducing the interaction term, we envisage that spending on R&D will absorb the negative effects of climate variability on agricultural production, and thus increase productivity. A time variant effect ω_{it} is used to control for country heterogeneity in agricultural production. However, agricultural production, which is supposed to be concurrently determined by farmers' application of inputs, may be an autonomous decision on the part of the farmers. It is also predicted that agricultural production will be associated with the non-observable characteristics of farmers that influence their decision to adopt inputs. Therefore, our pooled ordinary least square (OLS) specification in Equation 4 will yield biased predictions (Bellemare, 2013; Hausman and Taylor, 1981).

The literature further documents that OLS specifications are biased if independent variables are correlated with the dependent variables – coupled with the issue that OLS does not capture country-specific heterogeneity (Bathla, 2017). There is the possibility of simultaneity bias between agricultural production and the explanatory variables – labour, fertiliser, capital, etc. – as the use of these inputs is dependent on farmers' income, which is also dependent on agricultural productivity. However, these biases can be addressed by estimating a system of moment equation using a system GMM technique (Arellano and Bond 1991; Blundell and Bond 1998). According to Arellano and Bond (1991), such an estimation can be achieved by transforming all the regressors through differencing. Therefore, our final estimation is based on Equation 5 below.

$$\Delta Y_{it} = \Delta \beta Y_{t-1} + \gamma \Delta \text{Climate_Var}_{it} + \delta \Delta \text{Climate_Var} * \text{R\&D}_{it} + \alpha \Delta \text{Labor}_{it} + \phi \Delta \text{Capital}_{it} + \theta \Delta \text{Land}_{it} + \phi \Delta \text{Literacy}_{it} + \eta \Delta \text{Fertilizer}_{it} + \epsilon_{it} \quad (5)$$

From Equation (5) above we take the partial derivative with respect to climate variability, and thus arrive at Equation 6 below.

$$\frac{dY}{d\text{Climate_Var}} = \gamma + \delta \text{R\&D} \quad (6)$$

Equation 6 shows that R&D is a source of non-linearity between climate variability and agricultural productivity, and that the way climate variability impacts agricultural productivity depends on the magnitude of spending on R&D.

5. Empirical results and discussion

5.1 Descriptive statistics

Table 2 below presents descriptive statistics from the raw data used in our study. The number of observations for each variable was 308. This comes from the fact that our panel data covered 14

countries in SSA over a 22-year period (1995-2016). The mean yields for Maize and Sorghum were 16575 and 10087 respectively. Our main variables of interest, climate variability and its interaction with R&D, had a mean of approximately 68mm and 1.4, respectively.

Table 2: Descriptive statistics of selected variables

VARIABLES	Observation	Mean	Std. Dev	Minimum	Maximum
Maize	308	16575.510	8292.679	849	53009
Sorghum	308	10087.580	5991.669	1281	34286
Climate	308	68.386	30.446	11.357	144.889
R&D	308	48.115	66.318	0.000	276.900
Capital	308	453.369	791.063	2.325	4875.112
Land	308	8904.922	9849.266	184	43400
Labour	308	6057702	7728374	76914.74	33500000
Literacy	308	54.446	21.522	12.800	94.368
Fertiliser	308	77874.24	110329.4	11	570800
LnMaize	308	9.552	0.675	6.744	10.878
LnSorghum	308	9.069	0.554	7.155	10.442
LnClimat	138	1.366	1.490	-3.807	3.279
LnR&D	300	3.158	1.192	0.956	5.624

LnR&D*Climate	135	4.114	4.141	-10.626	9.713
LnCapital	308	4.984	1.545	0.844	8.492
LnLand	308	8.582	1.126	5.215	10.678
LnLabour	308	14.972	1.219	11.250	17.326
LnLiteracy	308	3.903	0.462	2.549	4.547
LnFertiliser	308	10.282	1.642	2.398	13.255

The results for our conventional inputs are as follows. Land had a mean of 8904 hectares (the average land use for the 14 countries). Labour had a mean of 6057702, signifying the average number of people employed in agriculture in the 14 countries. The mean literacy for the 14 countries used in the study was 54%. This supports the assumption that more than half of the population above the age of 15 have had some form of formal education. The mean use of fertiliser in the 14 countries was 77874 tonnes. From Table 1 above, we plot a graph for climate variability and maize output to establish a correlation. This is particularly important because several studies (see Shaw, 1988; Mugo et al., 1998) have been undertaken to identify the stage of growth most susceptible to climate variability in maize. These have shown that climate variability from two weeks before cultivation until two weeks after germination lowers maize yield most significantly. NeSmith and Ritchie (1992) observed that climate variability can limit grain productivity by as much as 90% before maize tassel. As SSA agriculture mainly depends on rainfall, the trend of movement for maize production seems mostly to follow the trend of variations in climate (see Figure 1 below).

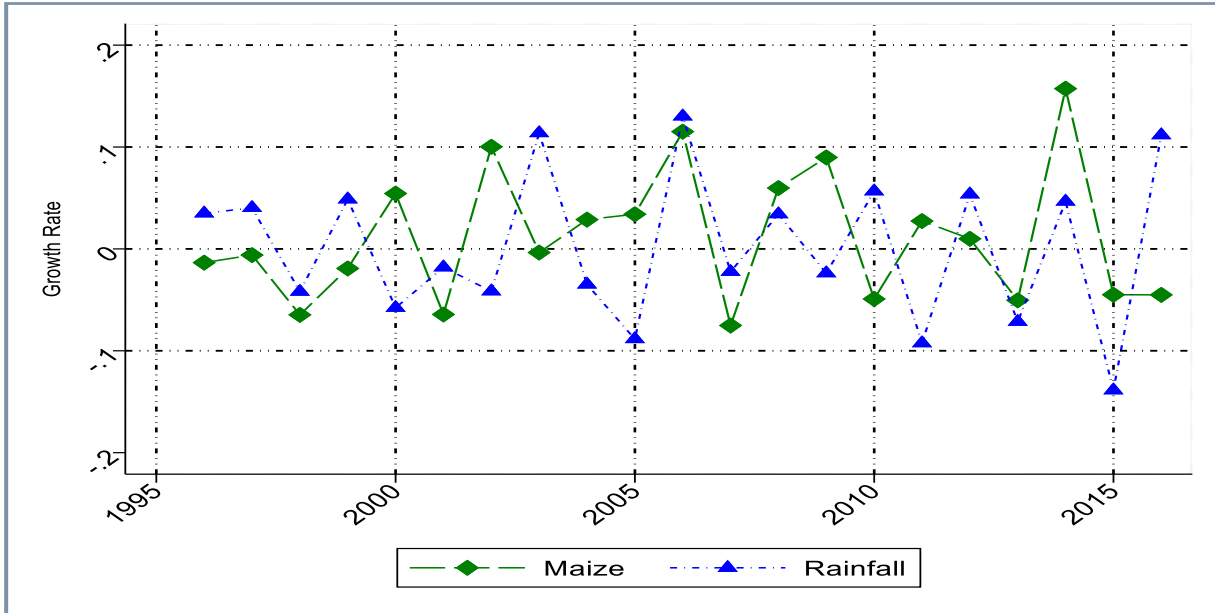


Figure 1: Trends in maize output and rainfall variation in sub-Saharan Africa, 1995-2016

As sorghum is the second-biggest crop (after maize) cultivated in SSA, we also plot a graph for sorghum output and climate variability to determine the trend of the relationship between the two variables. Fawusi and Agboola (1980) showed that sorghum requires average temperatures between 24°C and 27°C in order to attain optimum yield.

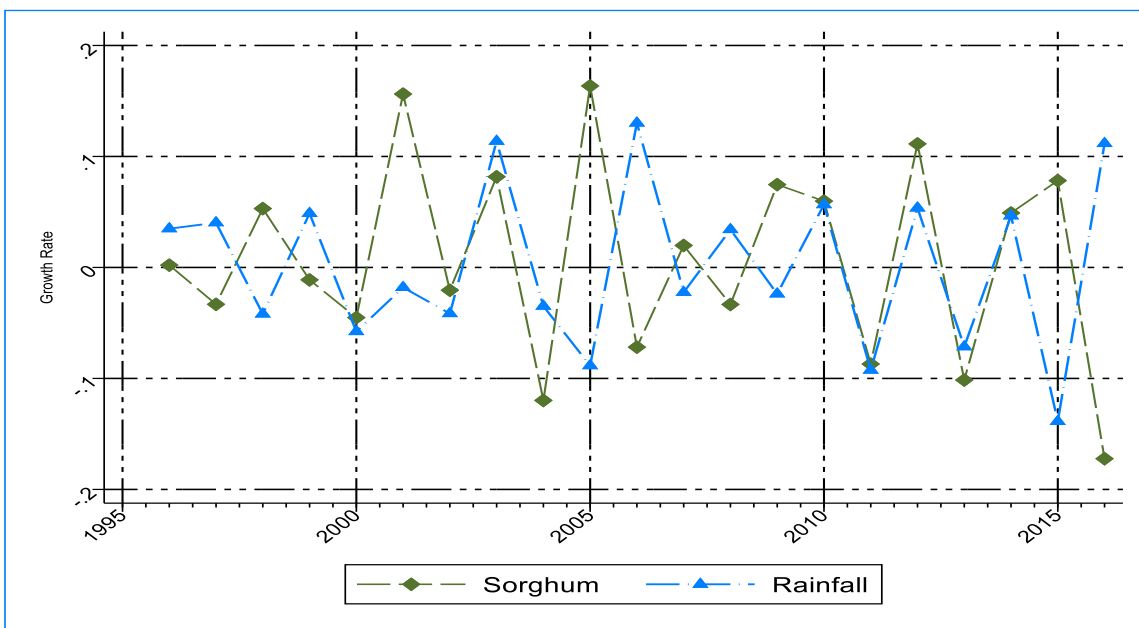


Figure 2: Trends in sorghum output and rainfall variation in sub-Saharan Africa, 1995-2016

Figure 2 below shows that sorghum productivity between 1995 and 2016 has fluctuated among the 14 SSA countries. At the same time, the rainfall pattern (proxy for climate variability) has been erratic.

5.2 Results and discussion

In this section, results are presented from the production functions specified in Equation 6 in the analytical framework. We discuss these results, beginning with the pooled OLS and followed by the GMM specification. Our output variable of interest is agricultural productivity, measured by the natural log of maize yield per hectare. Since our output and input variables in the model are expressed in natural logarithms, their coefficients with respect to each value are interpreted as elasticities. We start with Table 3 below, which shows findings from the pooled OLS including conventional and major inputs. From Model 1, we show that our main variable of interest (climate variability) is negative, as expected without controlling for other inputs. In Model 2, we introduce our second variable of interest (the interaction term) in addition to climate variability. Though it is not significant, the sign of the coefficient is positive, signalling that investment in R&D mitigates the effects of climate variability. In Models 3-6 we introduce our conventional inputs one after the other; the signs of our key variables (climate variability and the interaction term) remain as expected and are also significant. In Model 7, a complete specification with all input variables, climate variability is seen to reduce agricultural productivity by an elasticity of 0.403. As shown in previous studies (see Sesmero et al., 2017; Dercon and Christiansen, 2011), this negative effect might be as a result of climate variability inducing risk, which affects farmers' behavioural decisions regarding the adoption of farm technology and inputs, and thus increases the risk of loss in yield which tends to affect productivity in agriculture.

Our estimated coefficient of climate variability (-0.401) from Model 7 is statistically significant at 1%. This indicates that with all other things being equal, a 10% variation in climate decreases agricultural production by about 4.01%. However, according to Model 7, when we correlate climate variability with R&D, the resultant coefficient is positive (0.121) and significant at 1%. This is consistent with the literature (see Amare et al., 2018; Salim & Islam, 2010) that rainfall is heterogenous and that its effect on crop yield also depends on other inputs – especially the use of improved seeds, which is derived from R&D investment. Besides climate variability and the

interaction term, agricultural productivity is also influenced significantly by land, with an elasticity of 0.261, which is highly significant at 1%. This implies that with all other things being equal, a 10% increase in agricultural land will result in an increase in agricultural productivity of about 2.61%.

Given that we use a dynamic model, the lag of maize (output variable) is significant in Models 1-7, showing that the past maize yield affects the current production of maize. Of the other factors of agricultural production, none of labour, capital, literacy or fertiliser was significant for the pooled OLS model. These factors together explain 92.4% of the variations in agricultural productivity, as indicated by the R^2 . However, these are only reported as a benchmark, given that our pooled OLS technique does not account for either endogeneity or heterogeneity within our estimates. Therefore, our pooled OLS estimates are biased: there is a possibility of simultaneity bias between our explanatory independent variables (i.e., capital, fertiliser and labour) and the output variable. This is alluded to by Wooldridge (2010), who observed that the difficulty with predicting agricultural productivity drivers is that non-observed characteristics (i.e., inputs) are likely to be correlated with output.

Table 3: OLS estimates for agricultural productivity (proxied by maize)

	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)
VARIABLES	LnMaize	LnMaize	LnMaize	LnMaize	LnMaize	LnMaize	LnMaize
Lnlag1Maize	0.942*** (0.035)	0.918*** (0.042)	0.429*** (0.074)	0.434*** (0.075)	0.434*** (0.075)	0.403*** (0.077)	0.403*** (0.077)
LnClimate	-0.021 (0.022)	-0.091* (0.049)	-0.358*** (0.054)	-0.402*** (0.072)	-0.402*** (0.072)	-0.405*** (0.072)	-0.401*** (0.079)
LnR&D*Climate		0.025 (0.017)	0.111*** (0.020)	0.122*** (0.024)	0.122*** (0.024)	0.123*** (0.023)	0.121*** (0.026)
LnLand			0.270*** (0.055)	0.298*** (0.063)	0.298*** (0.063)	0.259*** (0.068)	0.261*** (0.070)
LnLabor				0.055 (0.048)	0.055 (0.048)	0.036 (0.050)	0.035 (0.051)
LnCapital					-0.040 (0.044)	0.024 (0.061)	0.020 (0.069)

LnLiteracy						-0.142 (0.097)	-0.142 (0.098)
LnFertilizer							0.005 (0.041)
Constant	0.577* (0.336)	0.916** (0.434)	2.543*** (0.542)	2.271*** (0.538)	2.271*** (0.538)	3.669*** (0.936)	3.362*** (0.973)
Observations	130	127	127	127	127	127	127
R-squared	0.862	0.880	0.922	0.923	0.923	0.924	0.924

Note: Standard errors in parentheses (), *** p<0.01, ** p<0.05, * p<0.1

Therefore, such an association could bias the estimators of pooled OLS. To mitigate such prospective bias, we follow the literature (see Rocha and Soares, 2015; Björkman-Nyqvist, 2013; Macinni et al., 2009) and employ two- to five-period lagged levels of the interaction variable as an instrument in Equation 6 above using the Generalised Methods of Moments (GMM) technique. Our estimated results from the GMM specification in Table 4 below show that agricultural production is determined by all the explanatory variables except literacy and fertiliser. However, the estimated coefficients for climate variability, the interaction variable, land, labour and capital all differ from those obtained in the pooled OLS model. Furthermore, we undertook diagnostic tests to ascertain the robustness of our estimates and instruments. The AR test for no second-order serial correlation was passed at 1% significance level. The Sargan test for over-identifying restrictions was also passed at 1% significance level. Therefore, we fail to reject the null hypothesis and conclude that our instruments are legitimate and valid.

Table 4: GMM estimates for agricultural productivity (proxied by maize)

VARIABLES	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)
	LnMaize	LnMaize	LnMaize	LnMaize	LnMaize	LnMaize	LnMaize
Lnlag1Maize	0.400* (0.224)	0.234** (0.094)	0.220** (0.090)	0.252*** (0.092)	0.079 (0.098)	0.104 (0.099)	0.109 (0.100)
LnClimate	0.101 (0.244)	-0.430*** (0.140)	-0.393*** (0.134)	-0.379*** (0.135)	-0.438*** (0.126)	-0.426*** (0.126)	-0.433*** (0.128)
LnRandD*Climate		0.114***	0.109***	0.103***	0.121***	0.122***	0.124***

		(0.033)	(0.032)	(0.032)	(0.030)	(0.030)	(0.030)
LnLand			0.774***	1.066***	0.658**	0.721**	0.727**
			(0.237)	(0.304)	(0.303)	(0.306)	(0.308)
LnLabor				-0.229	-0.328**	-0.418***	-0.457***
				(0.148)	(0.139)	(0.151)	(0.161)
LnCapital					0.229***	0.169**	0.142*
					(0.064)	(0.075)	(0.084)
LnLiteracy						0.535	0.550
						(0.347)	(0.351)
LnFertilizer							0.041
							(0.055)
Observations	106	105	105	105	105	105	105
AR(1)	-3.15	-5.63	-5.48	-5.52	-5.41	-5.42	-5.42
AR(2)	0.79	0.44	1.04	1.44	0.60	0.63	0.63
Wald χ^2	3.21	22.58	35.53	37.53	56.97	59.34	59.34
Sargan Test	13.74	99.13	98.57	95.06	98.95	96.57	96.57
	(0.201)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: Standard errors in parentheses (),*** p<0.01, ** p<0.05, * p<0.1

We follow the same specification as in the pooled OLS by showing that our main variable (climate variability) is negative and its interaction with R&D is positive, as expected in Model 2 without controlling for other inputs. In Models 3-6 we introduce our conventional inputs one after the other, and the signs of our key variables of interest, climate variability and the interaction term remain as expected and are significant. In Model 7, where we have a complete specification with all input variables, climate variability is seen to reduce agricultural productivity by an elasticity of 0.433 and is significant at 1%. Controlling for country heterogeneity and endogeneity within our GMM specification, this indicates that the coefficient of our main variable of interest is higher than that of the pooled OLS, further underlining that the pooled OLS underestimated the effect of this variable.

The negative coefficient of climate variability (-0.433) shows that with all other things being equal, a 10% increase in climate variability will result in a decrease in agricultural productivity of 4.33%. However, in Model 7 the interaction of climate variability with R&D is 0.124 and is significant at

1%. This shows that investment in R&D mitigates the negative effects of climate variability on agricultural productivity and thus serves as an absorption channel. The positive coefficient of the interaction variable also shows that not only does R&D mitigate the inimical effects of climate variability, it also improves agricultural productivity. This is of major significance to this study, given that the literature indicates that there are several mechanisms through which enhancing agricultural productivity can reduce poverty. These include creation of jobs, increases in income, and reduction in food prices (see Benin, 2016; Fan, 2008; Irz and Tiffin, 2006; Gollin et al., 2002). Gollin et al. (2014) and Christiaensen et al. (2011) describe the effect of growth in agricultural productivity on poverty alleviation as a dual effect. They conclude that agricultural productivity growth creates jobs, which in turn generate income, especially for farmers. At the same time, improving productivity in agriculture also creates jobs along the value chain process, thereby generating income for those involved.

The GMM specification also revealed higher coefficients for the conventional input variables, compared to the pooled OLS specification. Again, unlike in the pooled OLS, all conventional inputs for agricultural productivity are significant except fertiliser. Land shows a higher positive-magnitude effect on agricultural productivity with an elasticity of 0.727 and is significant at 5%. This shows that all other things being equal, a 10% increase in agricultural land will result in an increase in agricultural productivity of 7.27%. However, labour was significant at 1% but had an elasticity of -0.457. Capital was found to exert a positive effect on agricultural productivity with an elasticity of 0.142 and is significant at 10%. This shows that all other things being equal, a 10% increase in capital will result in a 1.42% increase in agricultural productivity. While fertiliser is a major determinant of crop yields, the findings show that the use of fertiliser does not affect agricultural productivity; this variable was found not to be significant. Ochieng et al. (2016) argue that this could be attributed to low application levels of fertiliser in agriculture, especially in SSA. However, the literature (see Sarker et al., 2012) shows that while chemical fertiliser may improve crop production, it also has the tendency to emit greenhouse gases into the atmosphere, which further contributes to the warming of the climate.

Though literacy rate has a positive coefficient, it was also found not to significantly affect agricultural output. Also, given that we used a dynamic model, the lag of maize (output variable) is significant in Models 1-4 but not significant in Models 5-7 when we control for all inputs of agriculture production. From the final model, we conclude that past production of maize does not

significantly affect current production of maize. Our results are consistent with previous studies (Dhehibi et al., 2017; Chebil et al., 2014), which investigated the impact of research, development, and extension (RD&E) and climate change on agriculture productivity growth and total factor productivity in Tunisia. Dhehibi et al. (2017) found that while climate change reduces agriculture productivity by an elasticity of -0.109, RD&E increases agriculture productivity by an elasticity of 0.05. Chebil et al. (2014) observed that drought reduces total factor productivity of cereals, while RD&E positively affects the cereal sector in Tunisia.

In addition, the Model 7 results for the interaction variable show that climate variability and agricultural productivity are linked, with a slope that could be expressed as:

$$\frac{dYield}{dRain} = -0.433 + 0.124R\&D \quad (7)$$

From Equation (7) it is obvious that the threshold from a negative to a positive impact of climate variability on agricultural productivity is determined by spending on R&D. According to the function, in order to move from a negative impact of climate variability on agricultural productivity to a positive impact, investments in R&D in SSA should be increased by a threshold of 3.492%.

5.3 Extended approach

To corroborate our estimates using maize yield, we also use sorghum yield as a proxy for agricultural productivity. This is because sorghum is the second-biggest crop (after maize) cultivated in SSA, covering 22% of total cereal area. In general, the African continent accounts for about 61% of total global sorghum area, with production of about 41%. Our output variable of interest is agricultural productivity, measured by the natural log of sorghum yield per hectare. Since our output and input variables in the model are expressed in natural logarithms, their coefficients with respect to each value are interpreted as elasticities.

We start with Table 5 below, which shows findings from the pooled OLS which includes conventional and major inputs. Model 1 shows that our main variable of interest, climate variability, is negative as expected without controlling for other inputs. In Model 2, we introduce our second variable of interest, the interaction term in addition to climate variability, which is positive and significant as expected. The pooled OLS results from Model 7 show that both climate variability and the interaction variable are strongly correlated with agricultural productivity, and thus corroborate our estimates when using maize yield.

Table 5: OLS Estimates for Agricultural Productivity (proxied by Sorghum)

	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)
VARIABLES	LnSorghum	LnSorghum	LnSorghum	LnSorghum	LnSorghum	LnSorghum	LnSorghum
Lnlag1Sorghum	0.803*** (0.052)	0.546*** (0.088)	0.500*** (0.093)	0.500*** (0.094)	0.450*** (0.095)	0.429*** (0.095)	0.403*** (0.098)
LnClimate	-0.023 (0.026)	-0.323*** (0.081)	-0.353*** (0.083)	-0.352*** (0.084)	-0.245** (0.097)	-0.236** (0.096)	-0.206** (0.101)
LnR&D*Climate		0.106*** (0.027)	0.115*** (0.028)	0.114*** (0.030)	0.086*** (0.032)	0.083** (0.032)	0.071** (0.034)
LnLand			0.042 (0.028)	0.050 (0.061)	-0.042 (0.074)	-0.127 (0.086)	-0.108 (0.088)
LnLabor				-0.009 (0.064)	0.002 (0.063)	-0.036 (0.065)	-0.048 (0.066)
LnCapital					0.125** (0.060)	0.231*** (0.081)	0.194** (0.089)
LnLiteracy						-0.237* (0.124)	-0.246* (0.125)
LnFertilizer							0.056 (0.056)
Constant	1.820*** (0.485)	3.944*** (0.804)	4.103*** (0.860)	4.172*** (1.008)	4.616*** (1.015)	6.454*** (1.392)	6.290*** (1.358)
Observations	130	127	127	127	127	127	127
R-squared	0.675	0.762	0.767	0.767	0.777	0.785	0.787

Note: Standard errors in parentheses (), *** p<0.01, ** p<0.05, * p<0.1

Climate variability is seen to reduce agricultural productivity by an elasticity of 0.206 and is significant at 5%. This indicates that with all things being equal, a 10% variation in climatic conditions will reduce agricultural productivity by 2.06%. At the same time, the interaction between R&D and climate variability increases agricultural productivity by an elasticity of 0.071 and is significant at 5%. This also confirms our findings from the maize estimate that spending on R&D serves as an absorption channel for the inimical effect of climate variability on agricultural productivity. Capital is found to be positive, with an elasticity of 0.194, and is significant at 5%.

At the same time, literacy is found to reduce agricultural productivity, with an elasticity of -0.246, and is significant at 10%.

Also, given that we use a dynamic model, the lag of sorghum (an output variable) is significant in Models 1-7, thus showing that past sorghum yields affect current production of sorghum. However, given the limitations of pooled OLS estimates, these results are considered benchmark. We therefore perform the GMM technique to overcome these limitations.

In Table 6 below, Model 7 shows that persistent variability in climate reduces agricultural productivity by an elasticity of 0.296. This indicates that all things being equal, a 10% variation in the climate will reduce agricultural productivity by 2.96%. However, the interaction of R&D and climate variability significantly enhances agricultural productivity, by an elasticity of 0.065, thus confirming our findings from the maize estimates that investment in R&D mitigates the inimical effect of climate variability on agricultural productivity

Table 6: GMM estimates for agricultural productivity (proxied by sorghum)

VARIABLES	(Model 1) LnSorghum	(Model 2) LnSorghum	(Model 3) LnSorghum	(Model 4) LnSorghum	(Model 5) LnSorghum	(Model 6) LnSorghum	(Model 7) LnSorghum
Lnlag1Sorghum	-0.311 (0.216)	0.015 (0.098)	0.024 (0.094)	-0.200** (0.099)	-0.249*** (0.095)	-0.249*** (0.095)	-0.256*** (0.098)
LnClimate	-0.166 (0.217)	-0.244 (0.171)	-0.262 (0.164)	-0.259* (0.137)	-0.272** (0.129)	-0.273** (0.129)	-0.296** (0.133)
LnR&D*Climate		0.057 (0.040)	0.058 (0.038)	0.057* (0.032)	0.061** (0.030)	0.060** (0.030)	0.065** (0.031)
LnLand			-0.487* (0.283)	-1.170*** (0.312)	-1.429*** (0.308)	-1.432*** (0.310)	-1.431*** (0.317)
LnLabor				0.634*** (0.155)	0.544*** (0.150)	0.550*** (0.160)	0.442** (0.173)
LnCapital					0.162*** (0.060)	0.166** (0.069)	0.094 (0.079)
LnLiteracy						-0.039 (0.360)	-0.002 (0.369)
LnFertilizer							0.119** (0.059)

Observations	106	105	105	105	105	105	105
AR(1)	-2.01	-8.14	-8.06	-5.55	-4.85	-4.85	-4.60
AR(2)	1.17	3.92	3.82	1.95	1.01	1.01	0.438
Wald χ^2	2.52	2.27	5.43	22.89	33.24	33.25	35.71
Sargan Test	25.03	100.95	107.11	114.54	121.90	121.87	111.83
	(0.283)	(0.518)	(0.246)	(0.000)	(0.000)	(0.000)	(0.000)

Note: Standard errors in parentheses (), *** p<0.01, ** p<0.05, * p<0.1

Additionally, our conventional inputs are significant, with the exception of literacy. Land is significant but tends to exert a negative effect on agricultural production, with an elasticity of -1.43. Labour is found to increase agricultural productivity by an elasticity of 0.442 and is significant at 5%. Capital is found to enhance agricultural productivity by an elasticity of 0.166. This implies that all things being equal, a 10% increase in capital will raise agricultural productivity by 1.66%. Fertiliser is found to enhance agricultural productivity by an elasticity of 0.119. This indicates that in the case of sorghum, with all other things being equal, a 10% increase in fertiliser application will raise agricultural productivity by 1.19%. We also performed diagnostic tests to ascertain the robustness of our estimates and instruments. The AR test for no second-order serial correlation was passed at 1% significance level. The Sargan test for over-identifying restrictions was passed at 1% significance level, and therefore we fail to refute the null hypothesis that our instruments are legitimate and valid.

From our dynamic specification, the lag of sorghum (output variable) is not significant in Models 1-3. However, it tends to be significant from Models 4-7 with negative coefficients, revealing that past sorghum yield significantly reduces current production of sorghum. Furthermore, given that R&D mitigates the inimical effect of climate variability, we can show that the relation between climate variability and agricultural productivity is linked with a slope that could be expressed as:

$$\frac{dYield}{dClimate_Var} = -0.296 + 0.065R\&D \quad (8)$$

Equation (8) shows that spending on R&D is an absorption channel for the negative effect of climate variability on agricultural productivity. Therefore, to move from a negative to a positive effect of climate variability on agricultural productivity, there is a need to increase spending on R&D in SSA by a threshold of 4.554%.

6. Conclusions and policy implications

This paper aims to investigate whether public spending on research and development (R&D) mitigates the negative impacts of climate variability on agricultural productivity. The analysis is based on panel data for 14 countries in sub-Saharan Africa (SSA) from 1995 to 2016 using the Generalised Method of Moments (GMM) estimation technique. The empirical results show that climate variability significantly reduces agricultural productivity. However, the interaction of R&D with climate variability enhances agricultural productivity. Estimates from both OLS and GMM techniques show consistent outcomes. The estimated GMM results show that climate variability will have a greater impact on maize productivity than on sorghum productivity.

In addition, climate variability is expected to reduce agricultural productivity by an elasticity of 0.433 and 0.296, respectively for maize and sorghum. However, the interaction of R&D with climate variability mitigates the negative effect of climate variability and thus enhances agricultural productivity by an elasticity of 0.124 (maize) and 0.065 (sorghum) using maize and sorghum as proxies of agricultural production. Additionally, to move from a negative to a positive impact of climate variability on agricultural productivity, our analysis shows that public spending on R&D should increase between 3.492% and 4.554% for maize and sorghum respectively. The estimates further show that R&D is an absorption channel for the inimical effect of climate variability, and that the way climate variability impacts agricultural productivity depends on the magnitude of spending on R&D.

Therefore, our study demonstrates the importance of increasing public investment in R&D in the agricultural sector. Furthermore, given that there are no insurance markets in most developing countries – and that in places where they do exist, they often suffer from information asymmetry, lack of data infrastructure, and limited access of insurers to reinsurance – it is difficult for farmers to mitigate risks posed by climate variability, which leads to loss of yield. Our study makes the point that increasing investment in R&D in the agricultural sector could serve as an adaptation mechanism by farmers regarding climate change. Therefore, governments must give priority to and increase spending on R&D, as opposed to providing disaster relief programmes and insurance premium subsidies to farmers. Finally, it should be noted that the model used in this paper is not designed to estimate the long-term effect of the interaction term on agriculture production; future research could explore such long-run relationships.

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