Climate change and crop yields in Zambia: correlative historical impacts and future projections

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ABSTRACT

Farming systems prevalent in sub-Saharan Africa are exposed and vulnerable to climate change due to their high dependence on rainfall. However, most studies have only estimated the impacts of climate change on agricultural productivity at a regional or national level. We add to this literature by focussing on the sub-national impacts. This study uses 30 years (1981–2011) of yield and weather data in Zambia and applies the Just and Pope model to determine how rainfall and temperature affect yield and yield variability of maize and beans at the national and subnational levels. Results show a negative impact of temperature rise on yield and a positive impact of rainfall rise on yield, above the current mean levels. These results differ by agro-ecological region. Worst-case-scenario predicted impacts using HadGEM-ES2 global circulation model show that major yield decreases (25% for maize and 34% for beans) by 2050 will be in region II and will be driven mainly by temperature increase offsetting the positive gains from rainfall increase. The model mainly under-predicts yield for maize and overpredicts yield for beans. These findings call for agro-ecological region-specific adaptation strategies and well-planned policy interventions to make agriculture more resilient to climate change.

Keywords: Climate change; crop production; maize; beans; Just and Pope model; Zambia

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1 Introduction

The negative impacts of climate change on agriculture are generally recognised (Intergovernmental Panel on Climate Change, 1993; Lobell *et al.*, 2008; Deressa & Hassan, 2009; Schlenker and Lobell, 2010; Thurlow *et al.*, 2012; IPCC, 2014; Hallegatte *et al.*, 2016). Although varying spatially, these effects are more pronounced in the developing world where the majority of the rural households depend on rain-fed agriculture for livelihoods and yet, these households have low capacity to adapt to climate change. This make developing world households more vulnerable to climate change shocks. The close linkages between climate change and livelihoods is of increasing concern in developing countries (Bernstein et al., 2008). Hallegatte *et al.* (2016) estimates that climate change is likely to push 14% of the smallholder farmers who depend on ecosystem services below the poverty line by 2050 in sub-Saharan Africa alone.

Several studies measure the economic impacts on climate change in Africa. Examples include Jain (2007) in Zambia, Deressa (2007) in Ethiopia, Kabubo-Mariara and Karanja (2007) in Kenya, and Thurlow *et al.* (2012) in Zambia. In a review of the literature on the impacts of climate change in developing countries, Mendelsohn and Dinar (2009) found variations across countries and that most tropical and subtropical countries will be affected more than countries in the temperate climates.

Many of the prior studies investigating the impacts of current and future climate change on crop production have used aggregated national-level data and a combination of literature reviews and crop simulation models (Mearns *et al.*, 1997; Adams *et al.*, 1999; Kurukulasuriya and Rosenthal, 2003; Chen et al., 2004; Isik & Devadoss, 2007; Jain, 2007; Boko et al., 2007; McCarl et al., 2008; Tingem et al., 2008; Schlenker & Lobell, 2010; Knox et al. 2012; Edeh *et al.*, 2012; Hachigonta et al., 2013; Challinor et al., 2015; Bindi et al., 2015;). With a regional or national focus, these studies overlook localized subnational variations that are important in designing local and regional specific adaptation strategies (Thornton et al., 2006). Their reliance on simulations limits the external validity of results because predictions for regional precipitation may vary significantly, owing to factors such as the chaotic nature of climate change and the different approaches used by various models to resolve regional climate dynamics and uncertainty (Soussana et al., 2010). Further, these models have a low resolution, which reduces the reliability of the projections for countries with high weather variations like Zambia. This study was designed to contribute towards filling this gap.

This study extends an econometric analysis to not only understand the historical correlative impact, but also to predict the future impacts of climate change on crop yield at subnational scale. Having detailed localized information could help smallholder farmers better plan farm interventions to adapt to and mitigate the regional specific effects of climate change (Seo et al., 2009). The analysis uses observational data to assess the impacts of climate change on maize- and bean-production, both at national and agro-ecological region (AER) level. While our study contributes to this literature, it uses only climate data as data for inpur use (such as seeds and fertilizer) is not available. Hence, the results should be taken more as correlative than causal. This approach of using climate data only is similar to Barnwall and Kotani (2010), and Deressa and Hassan (2009).

Using historical observational data is preferable to conducting field trials because these data permit assessing how farmers react to weather shocks in the context of various other constraints such as credit, inputs, and labour (Schlenker & Lobell, 2010). Unlike Seo et al., (2009) and other studies that used the Ricardian model, we use an econometric production function framework partly because we did not have access to land prices and because a production framework better captures the data generating process. Although the Ricardian model is often applied, the non-existence of efficient and competitive land markets limit its application in most developing country contexts (Barnwall and Kotani, 2010).

In particular, this study uses historical weather and yield data to estimate the effects of climate change on the production of common bean (*Phaseolus Vulgaris.)* and maize (*Zea Mays)* in Zambia at national level, as well as by agro-ecological region. Maize is the most commonly grown crop among the smallholder farmers and a staple food in Zambia, supplying 60% of the nation's caloric needs (Barratt et al, 2006). Maize-centric government policies including price and input support have partially driven this domination. Among the pulses, beans are a major crop, followed by cowpeas. According to Ministry of Agriculture and Cooperatives (2004), beans rank second in economic importance after groundnuts as a leguminous crop based on the area under cultivation and the number of households producing them. Beans are consumed countrywide among most households, especially low-income ones, with about 4 kg consumed by each household every month on average.

1.1 A brief background on Zambian weather patterns

Intra-annual and inter-annual variations in rainfall determine the country's weather and agro-climatic characteristics. With temperatures in the summer (rainy season) not exceeding 37 ℃, Zambia is considered to have a moderate climate (Jain, 2007). Historically, the rainy season began around late October, but more recently it has tended to start in early November and to end around March to early April, with variability across the three agro-ecological regions. Agro-climatologically, Zambia is divided into four agro-ecological regions (AERs) that are summarized in Table 1.[5]

Table 1: Agro-ecological regions of Zambia

AER	Rainfall (mm/year)	Elevation (meters above sea level)	Growing Season (days)	Soil productivity	Temperature range (° C)
I	<800	300-1,200	80- 129	Highly erodible	10.3-36.5

[5] Primarily, there are three agro-ecological regions but AER II is divided into two, (a) and (b), to further capture the different soil types.

IIa	800-1000	900-1,300	100-140	More fertile	6.3- 33.6
IIb	800-1000	900-1,200	100-140	Infertile coarse sands	6.3-33.6
III	>1000	1,100-1,700	120- 150	Highly leachable, acidic	5.7- 32.1

Source: Adapted from Thurlow et al, 2008; Saasa, 2003.

Because of the high dependence on rain-fed agriculture, Zambia is projected to be one of the countries that will be most affected by climate change and weather variability (WB, 2009). Variation in rainfall from one year to the next is an important factor affecting agricultural production in Zambia. This variation is perhaps the biggest environmental factor affecting yields spatially from year to year and the observed variance in them. For example, Burke et al. (2010) found that the major driver of the bumper harvest of the 2009/2010 agricultural season was weather, which explained about 61% of the increase. Figure 1 shows the rainfall and temperature in the three AER regions.

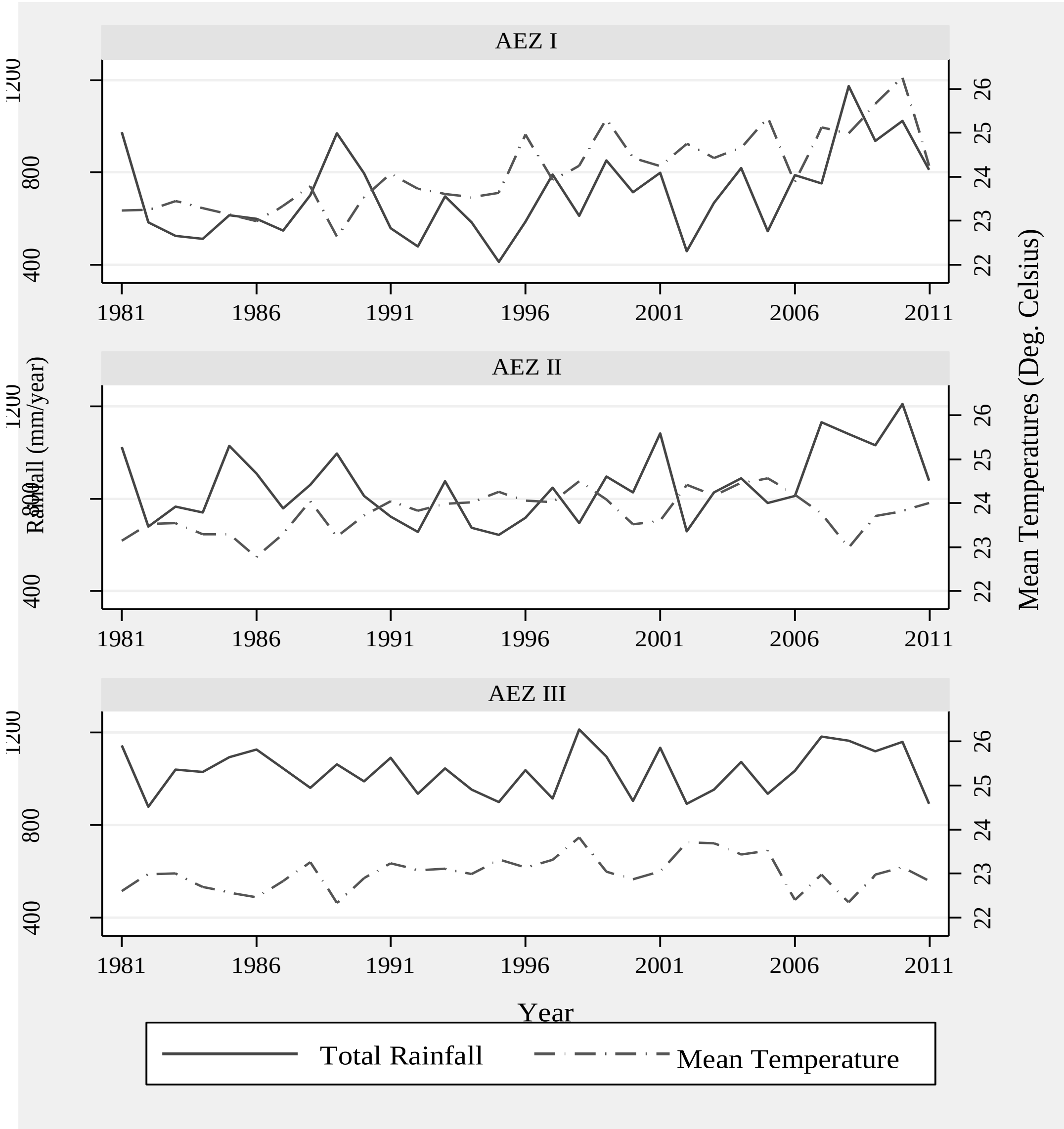

Figure 1: Rainfall and temperature trends in each agroecological region (AER), 1981-2011

Unsurprisingly, economic growth in Zambia is heavily linked to the country's climatic conditions. Some of the worst weather disasters such as droughts have coincided with the slowest economic growth (Thurlow et al., 2009). Normal weather (i.e., between −0.5 and 0.5 on the Palmer drought index) has never simultaneously occurred in all the three agro-ecological regions during 1976–2007, indicating that Zambia is prone to extreme rainfall events (Thurlow et al., 2007). According to Jain (2007) and Mulenga *et al.* (2017), rainfall patterns in Zambia have changed since the late 1980s, with rainy seasons tending to start later and end earlier than the historical average. In the past decade, Zambia endured droughts in 2000/2001, 2001/2002, and 2004/2005 agricultural seasons and relatively below normal rainfall in the 2011/2012 agricultural season, while floods occurred in 2005/2006 and 2006/2007 agricultural seasons.

Because temperature and precipitation are direct inputs into crop production, some of the largest effects of a changing climate, as observed through weather variability, are likely to be in the agricultural sector (Deressa & Hassan, 2009). Crop yield is a defining characteristic of crop production, and studies have shown that year-to-year variability in crop yields are normally associated with weather changes; for example, good weather is highly correlated with bumper maize harvests in Zambia (Jain, 2007; Deressa & Hassan, 2009). How weather variations influence the production of crops needs to be understood given that yields have been decreasing for some crops like beans over the past few decades (Govereh et al., 2006). In addition, other crops like maize have had greater yield variability in recent decades, with yields varying by more than 40 percent of the long-term average (Jain, 2007).

2 Methods

2.1 Empirical specification and estimation

Traditional positive approaches to yield response analysis use econometric methods that involve estimating the production technology parameters from observed input and output values or figures (Fufa & Hassan, 2003). A deterministic production function relates mean input levels to output levels while alternative specification will include an error term to capture the strict exogenous and uncontrollable factors such as weather and differences in efficiency (for example, Chiona, 2012). Traditional production functions assume that an input has the same type of effect on the mean and variability of the output (Just & Pope, 1979). For example, if an input such as fertilizer has a positive effect on yield, then it will also cause a positive effect on the variability of yield. However, linking the two is empirically and conceptually incorrect if done *a priori* because one input may have a different effect on yield than on yield variability.

The Just and Pope (1978) model has been widely used to estimate the effects of weather on yield and yield variability (Cabas et al., 2009; Chen et al., 2004; Deschenes & Greenstone, 2006). In the Just and Pope stochastic production function, crop yield for district *i* in year *t* (y_{it}) is represented as

$$y_{it} = f\left(X_{it};\beta\right) + \mu \qquad (1)$$

where y_{it} is output per hectare or crop yield, X_{it} is a vector of explanatory variables, $f(.)$ is the mean function or the deterministic part that relates X to average yield, β is an associated vector of parameters to be estimated, and μ is the heteroscedastic disturbance term with mean zero. Equation (1) can be re-written to decompose μ as

$$y_{it} = f\left(X_{it};\beta\right) + h\left(X_{it};\alpha\right)^{0.5}\varepsilon_{it} \qquad (2)$$

where $h(X_{it},\alpha)$ is the variance of the stochastic component of output that relates X to yield variability, α is the corresponding vector of parameters to be estimated for yield variability, and ε_{it} is the random error term with zero mean and constant variance σ^2. With this formulation, ‘inputs’ such as climate can independently influence mean crop yield $E(y_{it})$ through $f(X_{it};\beta)$ and variance of crop yields $V(y_{it})$ through $h(X_{it},\alpha)^{0.5}\varepsilon_{it}$. Estimation of the former helps in understanding the effects of rainfall and temperature on mean yields, while estimation of the latter helps in understanding yield variability arising from changes in rainfall and temperature.

With regard to estimation, in their seminal paper, Just and Pope (1978) proposed using the feasible generalised least squares (FGLS) or maximum likelihood estimation (MLE) to estimate the mean and variance functions. FGLS is a three-step procedure under heteroscedastic conditions. Saha et al. (1997) showed that the estimators under MLE are more efficient than those of FGLS if the sample size is small. Given that we estimate the impact at sub-national level, our sample size reduces and we use MLE for this reason. The log-likelihood function below is maximized,

$$\ln L = -\frac{1}{2}\left[n\ln(2\pi) + \sum_{i=1}^{n}\ln h^2(\boldsymbol{x}|\boldsymbol{\alpha}) + \sum_{i=1}^{n}\frac{\left(y_i - f(\boldsymbol{x}|\boldsymbol{\beta})\right)^2}{h^2(\boldsymbol{x}|\boldsymbol{\alpha})}\right] \tag{3}$$

The log-likelihood can be estimated in one step procedure resulting in a weighted regression. This procedure leads to a consistent and asymptotically efficient estimator of β under the usual conditions of stochastic production function (i.e., monotonicity, concavity, and smoothness). Following Isik and Devadoss (2006), we estimate the model using two alternative functional form specifications, the quadratic and the Cobb-Douglas (CD).

The Cobb-Douglas is empirically specified as;

$$Y = \alpha T^{\beta_o} Rain^{\beta_1} Temp^{\beta_2} \tag{4}$$

Where T is the time trend, *Rain* is total rainfall, *Temp* is temperature and α, and β are parameters to be estimated.

A monotonic transformation of equation (4) is then taken to make it linear in parameters by applying the natural logarithm (ln). The estimated linear model is of the form;

$$\ln Y = \ln\alpha + \beta_o \ln T + \beta_1 \ln Rain + \beta_2 \ln Temp + \varepsilon \tag{5}$$

The quadratic form is specified without the natural logarithm but with rainfall and temperature square terms as;

$$Y = \beta_0 Trend + \beta_1 Rain + \beta_2 Temp + \delta_1 Rain^2 + \delta_2 Temp^2 + \varepsilon \tag{6}$$

We further compute model prediction error to help interpret the future predictions within the context of our model accuracy. To do this, the cross-validation approach by splitting the dataset for each regression is used (i.e. national level, and AER-specific regression) into two and use both halves of the data set for training and prediction. Because we lack data on fertilizer use at district level for all the years, and some management and adaptation variables, we include only rainfall and temperature in the predictions. Our prediction must be taken as a worst-case scenario in this case, i.e. that farmers do not adapt and keep growing the same crops, that they do not use fertilizer, and that they maintain the current management practices.

There is no agreement in literature as to which statistics are more accurate at presenting the model prediction error between mean absolute error (MAE) and root mean square error (RMSE). However, some recent studies and those in the environmental sciences have suggested using MAE as opposed to RMSE (see for example, Willmott &Matsuura, 2005; Chai & Draxler, 2014). Willmott & Matsuura (2005) argue for MAE because with RMSE, it is impossible to discern to what extent it reflects central tendency (average error) and to what extent it represents the variability within the distribution of squared errors or $n^{1/2}$. In the cases when the concern is average error such as in this study, MAE is the plausible choice as it is an unambiguous measure of error magnitude. To also understand if the regressions over- or under-predict yield, minimum bias error (MBE) is also reported. MAE is calculated as; $MAE = n^{-1}\sum(|e_i|)$ and MBE as $MBE = n^{-1}\sum(e_i)$ where e_i is the error for the i^{th} observation.

In the AER regressions, we used only the Cobb-Douglas approach because it is a preferred functional form for estimating the Just and Pope production model (Isik & Devadoss, 2006; Sarker et al., 2012). In the quadratic specification, the models include squared terms for rainfall and temperature. These squared terms help to determine if the effect on yield and yield variability diminish or increase at higher levels—they capture the curvature of the function.

Temperature was expected to have a negative effect and rainfall a positive effect on yield and yield variability.

Given that we did not observe the same districts during the study period, the result is an unbalanced panel. Our choice of regressors—temperature, rainfall, and trend— are strongly exogenous, meaning we are not worried of omitting any variables that can be correlated them, hence it would not be plausible to use fixed effects. Further, because data is aggregated at district level, random effects does not conceptually make sense. Pooled OLS remains as the only natural choice.

2.2 Data

This study used district-level crop forecast survey data collected by the Zambia Central Statistical Office and the Ministry of Agriculture and Livestock between 1981 and 2011. Zambia is divided into the following administrative units: province, district, constituency and ward, with the ward being the lowest administrative unit in the country. All 72 districts were represented in the crop forecast survey data, with each ward being further divided into census supervisory areas and standard enumeration areas, the smallest of the areas which is used as a sampling unit. The yield data from the survey were aggregated to district level. The data on average, minimum, and maximum rainfall and temperature during the same period were obtained from the Meteorological Department (MD). The MD collected weather data using more than 30 synoptic weather stations and about 45 part-time weather stations distributed across the country, supplemented by voluntary weather stations and support from the Department of Water Affairs, the Zambia National Service, and donor-funded initiatives such as the Emergency Drought Rehabilitation Programme. The MD used data collected from these stations to derive district-level aggregate data. For some districts without weather stations, weather data were generated through interpolation procedures such as satellite rainfall estimates by the MD. Altogether, 29 districts are used in the analysis because some districts do not have weather stations while others did not report consistently during the period under consideration. In Table 2 below, we describe the variables used in the regressions.

Table 2: Description of the variables used in the regressions

Variable name	Variable description	Measurement of the variable
yield	Yield of a given crop in each year	Kilogram/hectare (kg/ha)
Trend	Trend (capturing any advances in technology)	Numeric
Temperature	Average long-term temperature (1981-2011)	℃
Rainfall	Average long-term rainfall (1981-2011)	millimetres/growing season*
$Temperature^2$	Square of average long-term temperature	℃
$Rainfall^2$	Square of average long-term rainfall	millimetres/growing season

*Growing season, which as earlier defined is from October to April the following year, is later used interchangeably with year and/or annum

Crop production data sets were merged with the metrological data at district level only for the 29 districts with weather data. In cases in which more than two weather stations were present at the district level, data were averaged between stations to generate a single district-level value for the period. Beans are not a popular crop in the southern parts of the country, hence some districts had no area planted with the crop for some years. For such districts reporting zero crop production for beans or maize, they were dropped from the analysis, reducing the total number of observations for beans to 513, and for maize to 679. A summary of the variables is presented in Table 3.

Table 3: Summary of variables used in the regression

Agro-ecological region	Rainfall (mm/year)		Temperature (℃)		Maize (kg/ha)		Beans (kg/ha)	
	Total	Std Dev	Mean	Std Dev	Yield	Std Dev	Yield	Std Dev
AER I	689.50	222.76	24.19	1.50	1210.19	1039.93	354.55	254.55
AER II	837.87	234.42	23.78	0.81	1568.01	954.17	440.90	303.16
AER III	1028.87	239.70	22.99	0.81	1889.16	735.13	602.58	381.71
Overall	909.69	267.88	23.45	1.06	1673.32	899.84	524.43	358.27

Note: Std Dev is standard deviation. Authors computation using data from the Meteorological Department

Yields for both maize and beans were lower in AER I and higher in AER III compared with AER II. This same pattern was observed for rainfall, but the temperature seemed to be the same among all three regions, with only region II having a slightly higher temperature of close to 24 ℃.

3 Results and Discussion

3.1 Impacts of climatic variables on mean yields for beans and maize at national level

Table 4 presents the MLE results for the mean model based on the national sample. The results are presented for both the quadratic and CD functional forms. The CD elasticities are interpreted while the signs and significance of the squared terms in the quadratic functional form specification are used to determine non-linear effects.

Temperature, as in most studies conducted in the tropics and warmer regions (Blanc, 2012; Exenberger & Pondorfer, 2011; Traore et al., 2013), was found to have a negative and statistically significant effect on beans yield under the CD approach, and a negative and significant effect on maize yield under both specifications. CD results suggest that a 1% increase in temperature is associated with a 3% reduction in beans yield, but without any statistically significant non-linear effects. For maize, a 1% increase in temperature reduces yield by about 3.3% (CD) and this effect is at a decreasing rate (using the sign of the coefficient on the squared variable in the quadratic specification).

Total rainfall during the growing season (October–March) had a statistically significant effect on the yields for beans and maize under both functional forms, indicating the importance of rainfall in crop production. A 10% increase in rainfall under the CD specification is associated with 5% and 4.4% increases in yields for beans and maize, respectively. The positive signs on the square terms in the quadratic specification indicates that the increase in yield resulting from increased rainfall is at an increasing rate for both beans and maize.

Beans is typically grown twice in a single season (October–March), which means the longer the rain season, the better for the two plantings. A rainfall increase arising from the duration of the rain season rather than rainfall intensity is more important. Moreover, since this estimate is pooled at national level, the average annual rainfall at ca. 900mm masks the differences in rainfall across the AERs. At these levels, both beans and maize productivity could benefit from increased rainfall. (We return to the regional specific results in subsection 3.2).

The beans yield trend was negative for both crops under the two approaches. The negative trend could have arisen from factors other than technological advances. For example, other production problems (such as low input use, poor management, low adoption of improved varieties) could have overshadowed the effect of technological advances. Other studies, such as Boubacar (2012) and Exenberger and Pondorfer (2011), also found a negative trend for maize yield in sub-Saharan Africa.

Table 4: Regression results for the national beans and maize yield mean models

VARIABLES	**Beans**		**Maize**	
	CB	Quadratic	CB	Quadratic
Trend	-0.008**	-5.549***	-0.002	-6.734
	(0.004)	(1.811)	(0.002)	(4.107)
Temperature	-3.046***	-38.904	-3.303***	-730.138**
	(0.891)	(58.123)	(0.618)	(344.15)
Rainfall	0.490***	0.450**	0.442***	2.507***
	(0.405)	(0.208)	(0.095)	(0.493)
Temprature^2		-0.284		11.372*
		(1.166)		(6.612)
Rainfall^2		-0.00014		-0.001***
		(0.0000)		(0.000)
Observations	357	318	573	573

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Observations are fewer than stated in the data section because of missing data for some models.

3.2 Impacts of climatic variables on mean yields for beans and maize by agro-ecological region in Zambia

Because the effects of climatic variables are expected to differ by AER, AER-specific models are also estimated (Table 5). For the sub-national level (AER-specific) regressions, only the CD specification was used as it is theoretically more plausible and able to handle the small sample sizes under MLE. Estimating by AER reduces the effects to a short range for rainfall and temperature that is observed in each region and a wide enough range was not expected to be able to observe non-linear relationships. The difference in the economic significance of climatic variables in each AER becomes apparent. This detail would be missed in estimates made at regional and national levels.

Table 5: Impact of climatic variables on maize and beans yield by agro-ecological regions

	AER I		**AER II**		**AER III**	
VARIABLES	Beans	Maize	Beans	Maize	Beans	Maize
Trend	-0.045***	-0.013	-0.015**	-0.008	0.001	0.001
	(0.016)	(0.014)	(0.007)	(0.005)	(0.004)	(0.003)
Temperature	16.444**	-2.688	-0.203	-5.554***	-3.123***	-1.716**
	(7.302)	(2.092)	(2.043)	(1.263)	(1.167)	(0.793)
Rainfall	1.100***	1.485***	0.299	0.476***	0.271	-0.186*
	(0.405)	(0.329)	(0.218)	(0.160)	(0.189)	(0.112)
Observations	26	66	123	233	208	274

Notes: Standard errors in parentheses; ***, ** and * signify statistical significance at 1%, 5% and 10% levels; AER I, II and III signify agro-ecological regions one, two and three, respectively.

Beans yield trend was negative and significant in AER I and AER II just like at the national level but with a small marginal effect. Beans is not normally cultivated on large areas in AER I and AER II and in some districts, there are no farmers growing the crop. Overtime, trend shows that yields have been decreasing. Temperature had a negative and significant effect on beans yields in AER III as it did for maize in AER II and III. Each 1% increase in temperature is associated with a reduction of approximately 3% in beans yield in AER III, while maize yield in AER II and III reduce by 5.6% and 1.7%, respectively. The negative effects of temperature will be highest in the medium rainfall region (AER II). In AER I, temperature had a positive effect on yield of beans. This result, however, should be taken with caution for two reasons. First, beans are not a common crop in AER I, resulting in a small sample size. Second, because beans are not a priority crop in this region, inefficiencies may characterize its production such that estimates from other regions may be more informative.

The influence of rainfall on beans yield was positive and significant in low to medium rainfall AERs I and II. The increase in rainfall favours beans and allows the double planting that takes place in northern parts (AER III) where the rain season is longer than in the southern parts (AER I and II).

For maize, the effects of rainfall were positive and significant in AER I and AER II but negative in AER III. An increase in rainfall in AER III may harm maize yields because the region already receives more than the national average amount of rainfall. However, an increase in rainfall would benefit maize yield in AER I and II, which have low and moderate rainfall, respectively. The AER results are different from the the national-level estimates, which indicated a generally positive influence on maize yields. As expected, the effect of rainfall on crop yield was higher in the low rainfall regions compared to the high rainfall regions. On average, a 1% increase in rainfall in the low rainfall regions was associated with more than 1% yield gain.

Taken together, the AER and national level results in this paper are illuminating. Both AER and national level models show that changes in temperature will have larger negative effects on beans and maize productivity in Zambia and across the agro-ecological regions. These findings are in agreement with extant literature. For example, Schlenker & Lobell (2010) similarly found that changes in current and projected temperature were associated with larger negative effects on maize yield than did changes in rainfall in sub-Saharan Africa. This result is expected. Average annual temperatures ranging between 22^0 and 24^0, with large standard deviations of up to 1.5^0 in Zambia (Table 3) are close to the optimal crop productivity temperature of 28^0 – 30^0 (Schlenker & Lobell, 2010). Thus, marginal changes in temperature are expected to have large effects on crop productivity.

Results on the effects of rainfall are also as expected and show the added value of disaggregating analysis to the local level. While national models show positive yield gains from rainfall increases, the AER models show that this is only the case in low rainfall regions. Decreasing returns dictate that while rainfall is an important input for rainfed farming systems, it may reduce productivity at high levels. Overall, region I will benefit more from rainfall increase for both beans and maize while region III will benefit the least. These results have implications on the distribution of crops across regions and call for region-specific drought and heat tolerate crop varieties as climate continues to change. Without a doubt, the shifts in cropping patterns will affect other crops and supply chains.

3.3 Impact of climatic variables on yield variability

In the second stage of the Just and Pope procedure, the influence of climatic variables on yield variability, was determined. The quadratic and the linear Cobb-Douglas functional forms were also used here, and the results are summarized in Table 6. Yield variability for maize and beans increased as temperature increased. The increase in yield variability for beans is at an increasing rate while for maize it is at a decreasing rate. For rainfall, an increase by 1% reduces the variability of beans yield by 1.1% and reduces the variability of maize yield by about the same percent.

Table 6: Impact of climatic variables on yield variability of beans and maize

VARIABLES	**Beans**		**Maize**	
	CB	Quadratic	CB	Quadratic
Trend	-0.010	-0.054***	-0.0299***	-0.016**
	(0.009)	(0.010)	(0.006)	(0.007)
Temperature	3.719*	-1.455**	3.710**	3.028**
	(1.919)	(0.575)	(1.469)	(1.336)
Rainfall	-1.137***	0.003**	-1.097***	0.001
	(0.2607)	(0.001)	(0.169)	(0.001)
Temoerature^2		0.024**		-0.065**
		(0.012)		(0.028)
Rainfall^2		-0.000**		-0.000
		(0.000)		(0.000)
Observations	357	357	573	573

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 77 presents results of AER-specific models. AER I data may be noisier due to the small sample size. Rainfall increase reduces the variability of maize yield in regions I and II while increasing the variability of maize yields in region III. This seems to follow the yield pattern where increase in rainfall has a negative effect in region III but positive effect in regions I and II. This means that, with climate models predicting more rainfall, growing maize would become a less risky venture in these regions and would be able to compete favourably with other enterprises. Rainfall has no effect on beans yield variability except in region II where it reduces it. Temperature changes did not have any major effect on yield variability of maize in all regions. However, increase in temperature increased beans yield variability in region I and III.

Table 7: Impact of climate on yield variability by agro-ecological regions (AER)

	AER I		AER II		AER III	
VARIABLES	Beans	Maize	Beans	Maize	Beans	Maize
Trend	-0.055	-0.005	0.006	0.006	-0.039***	-0.044***
	(0.041)	(0.028)	(0.014)	(0.012)	(0.013)	(0.009)
Temperature	26.620***	2.838	-5.796	1.189	7.680**	0.339
	(9.710)	(4.138)	(5.261)	(2.691)	(3.170)	(3.028)
Rainfall	0.078	-1.345***	-1.419***	-1.049***	-0.512	0.995***
	(1.317)	(0.504)	(0.545)	(0.371)	(0.478)	(0.376)
Observations	26	66	123	233	208	274

4 Model prediction and future impact

Using the coefficients from the regressions, we simulated the yield of maize and beans using one general circulation model (GCM) generated using the RCP 4.5 scenario[6]. HadGEM2-

[6] "Representative Concentration Pathway (RCP) 4.5 is a scenario of long-term, global emissions of greenhouse gases, short-lived species, and land-use-land cover which stabilizes radiative forcing at 4.5 Watts per meter squared (approximately 650 ppm CO2-equivalent) in the year 2100 without ever exceeding that value." Thomson et al, 2011 pg 1.

ES[7] GCM which, as shown in figures 2 and 3, projects an increase in rainfall in all regions with highest increase being in the low rainfall region I of about 359 mm/annum and the lowest being in the high rainfall region III is used for projected weather. The model also indicates that temperature will increase in all regions by 2050 as shown in table 8. Temperature in region I will increase by about 0.7 ℃ while region II will see temperature decrease by about 0.4 ℃. The differences in the projections of the model across regions also warrant a region-specific analysis.

Table 8: Current and HadGEM2-ES projected weather

	Region I		Region II		Region III	
	Temp (℃)	Rainfall (mm/year)	Temp (℃)	Rainfall (mm/year)	Temp (℃)	Rainfall (mm/year)
Actual Average	24.076	695.220	23.670	836.666	23.088	1076.705
	(1.200)	(220.956)	(0.459)	(169.271)	(0.4622)	(104.481)
Predicted	24.292	1054.465	23.702	1182.358	22.303	1250.492
	(0.5610)	(156.930)	(0.5542)	(172.756)	(0.521)	(128.894)
Increase/Decrease	**0.216**	**359.245**	**0.043**	**345.692**	**-0.785**	**173.787**

The national-level model is used to predict the future impact on yield at national level and the AER-specific regressions to predict impact on yield in each AER. However, to interpret these predictions correctly, the model prediction error is presented first. Model prediction error is measured using two statistics; the mean absolute error (MAE) and the minimum bias error (MBE).

Table 9: Model prediction error

Crop	Level	Mean Absolute Error	Mean Bias Error
Maize	National	0.464	-0.014
	AER I	1.265	-0.989
	AER II	0.490	0.032
	AER III	0.324	-0.027

[7] HadGEM2-ES GCM is the Hadley Centre Global Environmental Model 2-Earth System (HadGEM2-ES) developed by the UK Met Office. It is one of the models used for the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) and the associated cycle of the fifth phase of the CMIP5. For a detailed description, see Bellouin et al, 2011.

	National	0.465	0.002
Beans	AER II	0.524	-0.011
	AER III	0.410	-0.009

Notes: Predictions are in natural logarithm of yield in kgs/ha. Prediction error for AER 1 for beans could not be calculated due to small sample size when split

From Table 9, it can be seen that all models mean absolute error is not so big with the exception of maize for AER I, even though this could be due to smaller sample size. The national-level maize yield model under-predicts yield with MBE which is less than zero. (MBE is not related to actual error magnitude and its interpretation here is to just show under- or over-prediction). The MAE is about 0.464 for maize national-level (which is about 1.6 kg/ha when exponentiated) model. For maize, in region I and III, the models under-predict yield while over-predicting for AER II. Regressions for region I have the biggest MAE, followed by region II with region III having the best fit for maize. For beans, the national-level regression over-predicts yield and has a bigger absolute error compared to region III. In both region II and III, the model under-predicts yield. Because of the foregoing, we consider our projections below for say an increase in yield as lower bound estimates for maize at national, region I, and region III levels and for beans in both regions (I and II), and as upper bound estimates for beans at national level and for maize in region II.

With the information of how the models perform in terms of prediction, yields by 2050 are predicted given the projected climate data. Results are presented in Table 10. At the national level, the model shows that maize yields will decrease by about 6% by 2050 at worst while beans yields will decrease by about 14% at minimum. AER II will experience major maize yield losses if the HadGEM2 weather predictions will be realised, or generally an increase in temperature combined with minimal increase in rainfall while for beans, region I will experience the worst yield losses of about 67%, at worst. Maize and beans yields will decrease by about 25% and by 34% by 2050 from the 1981-2011 average in region II. Region

III will experience an increase in beans yields of about 19%. The region will likely benefit from a mild increase in rainfall and a decrease in temperature while maize yields will marginally increase by 3%.

While the national models project climate change to reduce maize yield by 6%, AER models show these impacts will vary spatially. AER II will be worst affected with projected maize yield reductions of up 25%, while AER III will gain, albeit marginally. Overall, these results on the impacts of climate change are in line with Schlenker & Lobell (2010) who suggest that climate change will reduce maize yield in sub-Saharan Africa by 22% by the end of the century. The results help to shade light on the contrasting predictions between regions and crops. A drop in temperature coupled with mild increase in rainfall is good for improved crop yields while a rise in temperature, regardless of the increase in rainfall, has harmful effects on yield because crops are more sensitive to heat stress. Moreover, high temperatures increase evapotranspiration and can compound water scarcity even in seasons with high rainfall.

Table 10: Projected impact of climate change on maize and beans yield by 2050

Crop		Statistic	National	AER I	AER II	AER III
Maize		Observations	605	71	245	289
	Current	Yield (kgs/ha)	1477.479	989.67	1378.328	1745.23
			(348.366)	(898.2306)	(389.7494)	(125.4027)
		Observations	2457	390	897	1170
	Predicted	Yield (kgs/ha)	1390.292	986.2504	1032.915	1794.765
			(448.2839)	(1033.129)	(412.9008)	(149.5792)
		Percent Change	**-05.901**	**-0.346**	**-25.06**	**02.8383**
Beans		Observations	389	33	137	219
	Current	Yield (kgs/ha)	453.7375	518.3798	386.6193	513.1228
			(105.7784)	(817.9884)	(56.26517)	(81.74327)
		Observations	1253	195	469	589
	Predicted	Yield (kgs/ha)	390.5168	167.7088	254.2459	612.827
			(126.8067)	(87.4381)	(50.1025)	(107.9732)
		Percent Change	**-13.933**	**-67.648**	**-34.239**	**19.4309**

Numbers in parenthesis are standard deviation. Current refers to the yield under actual weather while predicted is the predicted yield under HadGEM2-ES, RCP 4.5.

5 Conclusion

Climate change will have varied effects on agricultural productivity across regions and crops in sub-Saharan Africa. However, most studies to date are done at country level and therefore mask local level effects that are important to inform local adaption policies. In this study, we determined the influence of long term rainfall and temperature on yield and yield variability for maize and beans at national and agro-ecological region (AER) level in Zambia. The Just and Pope production function framework was estimated using quadratic and Cobb-Douglas functional forms while a general circulation model was used to predict the impacts of climate change on crop yield up to 2050.

The main results suggest that temperature will negatively affect maize and beans yield. The elasticity for the impact of temperature on crop yield is larger than the impact of rainfall on yield in absolute terms, suggesting that marginal changes in temperature will have severe consequences on crop productivity in Zambia. Future climate projections from the selected GCM suggest a general increase in temperature and moderate rise in rainfall by the end of the century, although there are regional variations. The rise in temperature is further projected to increase the variability of yields, making agriculture even more risk.

Rainfall increase has a positive effect on yield. This seems to be more pronounced in low rainfall AERs I and II. Global circulation models that show an increase in rainfall will therefore show a reduced overall impact of weather on yields. In AER III, the impact of temperature is moderated by high rainfall and even minimal increase in rainfall might be beneficial to crop production.

The worst-case-scenario predicted impacts differ across AERs and crops. For maize, nationally, given that our model under-predicts the yield, the projected reduction of about 6% percent could be on the higher end if actual yields will be higher than the predicted yield, while for beans, the predicted yield reduction of about 14% could be worse as the model over predicts. However, whether the actual effect will be higher (lower) also depends on whether the effects of climate change will reduce (increase) the crop yield gaps. For most AERs, the models under-predict, but this prediction without other inputs used in crop production, must be taken as the worst-case scenario. The interpretation is that if farmers will not use fertilizers, and not adapt to a changing weather patterns, then these impacts are possible. Understanding which regions will be impacted the most is critical for prioritizing investments that focus on climate adaptation relative to the many other potential uses of scarce resources for agricultural development (Schlenker & Lobell, 2010). We have shown that impacts will not be the same across regions and depending on the likely climate scenario, impacts will vary but generally increase in temperature will be harmful while increase in rainfall will be somewhat beneficial in other regions.

The findings in this paper should not be seen to be casting a dark shadow on the efforts to reduce poverty and ensure food security but should raise the impetus to develop and disseminate appropriate technologies to enable smallholder farmers raise productivity despite climate change. Investments in research and development to determine region-specific crop varieties tolerant to heat and droughts, and adapting ‘climate-smart’ agricultural practices to varying edaphic conditions are needed. Improving smallholder farmers’ access to credit to enable them afford appropriate agricultural technologies will be key as will be access to extension to enable farmers choose appropriate technologies.

While every care was taken to ensure that the results in this paper are consistent, some caveats are in order. First, due to data limitations, the analysis in this paper is only limited to the physical relations between climate variables and crop yield and does not explicitly control for other inputs such as fertilizer, labour and socioeconomic factors such as access to credit and market access. Second, climate data and climate models are associated with some uncertainties, which may compromise the data quality. Despite the foregoing, the methods used in this paper are fairly standard in the agricultural economics literature and although we don't explicitly control for other yield determinants, their effects are expected to be complementary rather than substitutive. The global climate model used here is also among the main climate models used in the IPCC AR5. Thus, the findings in this paper have policy relevance, but should be taken as lower bound estimates for regions where the model over-predicts yield.

Future research could incorporate other inputs and socioeconomic variables that are yield augmenting in the analysis and use the increasingly available spatial climate data products to increase sample sizes and the number of crops included in the analysis. One limitation of our study was that we did not include other inputs that influence yield. This means we lacked a causal interpretation of the results as there are potentially some omitted variables.

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