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Sensitivity of field crops to climate shocks in Zambia

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Abstract

This paper examines the sensitivity of common field crops in Zambia to climate shocks, including inter-annual changes in precipitation and temperature and intra-seasonal variability. We use data on district-level crop yields and local climate conditions over eleven years to construct statistical yield models. We find that crops exhibit varying levels of sensitivity to different climate shocks, and intra-seasonal variability consistently impacts yield. Exposure to high temperatures also has a large influence on crop yield. This is noteworthy, as future climate predictions for Zambia diverge with regard to rainfall but agree that temperatures will rise by over 2°C. The models are used to predict yield responses to climate change under several future climate scenarios. A stochastic simulation of crop yield drawn from historical climate observations is used to quantify crop sensitivity to climate shocks under the current regime.

1. Introduction

Annual crop outcomes are a critical determinant of household welfare in rural Zambia, where off-farm income opportunities are rare (Siegel and Alwang 2005) and even the non-farm rural economy is tightly tied to agricultural outcomes. Given the nature of agriculture and the fact that most production in the country is rain-fed, Zambia is highly vulnerable to climate shocks. Furthermore climate change is expected to bring higher temperatures, an altered precipitation pattern, and more frequent weather extremes to southern Africa (Christensen et al 2007).

A first step towards reducing Zambia's climate vulnerability is to identify its sources. For example, crops exhibit varying levels of sensitivity to different climate variables. Some crops have higher water requirements or a lower ability to survive periods of drought, and higher temperatures may be especially important for crops whose phenology is mainly regulated by temperature. To understand the possible effects of a changing climate on rural households, it is important to quantify climate sensitivity across a range of crops (Schlenker and Lobell 2010). While extensive research has focused on a limited number of crops in specific regions of Africa, others have been largely overlooked (Knox et al. 2012). Further work is therefore needed to discern the generality of findings across different crops and growing conditions (Lobell and Burke 2010).

Statistical models are a common tool for quantifying the influence of climate on crop yield. Despite their limitations, they have been found useful for estimating the future effects of climate change on crop productivity (Lobell and Burke 2010; Holzkamer et al. 2012). While many studies have explored the impact of climatic means (e.g. seasonal temperature and rainfall) on yield, few have focused on the impact of intra-seasonal variability (Rowhani et al. 2011) and the possible effect of changing variability in the future (Thornton et al. 2009). Yet it is possible that intra-seasonal variability has as impact on crop yield that is as great, or even greater, than seasonal means (Morton 2007). Such variability can take the form of droughts, floods, or heat spells that exceed a critical temperature threshold.

In this paper, we aim to understand the relationship between historical climate and crop yield in Zambia over the 2000/01-2010/11 period. We use meteorological station weather data and field-level data on crop yield to explore the impact of both climatic means (inter-seasonal variability) and intra-seasonal variability across three common field crops: groundnuts, sorghum, and millet. We discuss the relative sensitivity of each crop to climate shocks. We then estimate the possible effects of a change in different climate variables on crop yield.

This exercise will expand the evidence base on crop response to climate in southern Africa. Because resources for agricultural development and climate change adaptation are limited, it is necessary to prioritize investments and policies appropriate for each country (Lobell et al. 2008). While the Zambian Ministry of Agriculture has prioritized maize production with its national Farmer Input Support Program (FISP), this decision has yet to be explored through a climate sensitivity lens. We hope this study will inform agricultural policy and extension services that aim to mitigate climatically-induced uncertainty for farmers, both in the short- and long-run.

2. Statistical yield models

Both statistical and process-based models are commonly used to understand the impact of climate on crop yield. Statistical yield models are often relatively simple regression models trained on historical data of crop yields and weather. Among their advantages, they require minimal information and are able to capture poorly understood processes related to climate, such as erosion, pest behavior, and pollination dynamics (Lobell et al. 2007). They are also able to account for non-climatic determinants of yield, such as management choices or farmers' adaptive capacity (Cabas et al. 2010). Finally, it is easy to understand how well a model captures crop yield response to climate through both the coefficient of determination (R^2) and the size of confidence interval for a particular coefficient or model prediction (Hertel and Rosch 2010, Lobell and Burke 2010a).

Statistical models do exhibit several drawbacks: They often can only capture an extremely simple relationship between yield and climate, and it is difficult to account for interactive effects of multiple climate variables. Results may be confounded when there is a low signal-to-noise ratio in yield and weather records (Lobell and Burke 2010). Climatic predictors may be collinear which results in biased coefficients, although the model still produces unbiased yield predictions (Holzkämper et al. 2012). When using statistical models to project the yield impacts of climate change, there is an assumption of stationarity in which the historical relationships are understood to remain constant in the future. Statistical models also display an uncertain ability to project beyond the historical range of observed climate conditions (e.g. higher temperatures than those currently observed) or account for increased CO_2 concentration in the atmosphere (Lobell and Burke 2010; Lobell et al. 2007).

Process-based models are a common alternative to statistical models that exhibit substantially greater complexity and the ability to capture interactions between climate variables. However they also exhibit several drawbacks: They require greater informational inputs (e.g. site-specific parameterization of the soil conditions, crop management options, and cultivars), which makes them difficult to calibrate and validate in data-poor environments. There remains considerable uncertainty about the physiological process of crop growth and the parameters included in these models. They cannot represent all processes relevant to crop production, such as pest behavior or interspecies competition triggered by climate, and this results in an underestimate of the negative impacts of climate change (Lobell and Burke 2010).

Despite their simplicity, statistical yield models can be important tools for understanding the historical relationship between climatic variation and crop yield (Lobell et al. 2007). Lobell and Burke (2010) use a "perfect model" approach to test the prediction capacity of statistical models. A process-based maize model is used to simulate "historical" yields at sites across sub-Saharan Africa, as well as yields under future climate change scenarios. A statistical model is trained on the simulated historical data and then used to predict the yield response under each scenario. The capacity of the statistical model is measured by its ability to reproduce future yields of the process-based model. The authors conclude that relatively simple statistical models are able to predict yield responses to a changing climate, though their accuracy and usefulness is higher at coarser spatial scales. Holzkämper et al. (2012) similarly use a "perfect model" approach with maize to test the ability of statistical models to predict yield response to both mean and intra-season variability of climate predictors. The authors find that statistical models are able to measure climate effects with reasonable accuracy, although temporal disaggregation is often unhelpful.

Many papers have explored the relationship between climate and crop yield using statistical yield models, although most focus on the impact of seasonal climate means. Lobell et al. (2007) study the relationship between three monthly climate variables (rainfall and minimum and maximum temperature) and crop yield for a set of horticultural crops in California. Using 23 years of meteorological and crop data, the authors identify the most relevant climate variables for each crop in order to produce fairly simple models with just two or three explanatory variables. Kucharik and Serbin (2008) study the impact of monthly and seasonal climate on maize and soybean yields in Wisconsin. Simple models with one temperature- and one precipitation-related regressor are used to estimate the climate-yield relationship. Tao et al. (2008) study this relationship for wheat, maize, and soybean yields in China.

Some studies do measure the impact of intra-seasonal variability on crop yield. Cabas et al. (2010) explore the effects of climatic and management factors on maize, soybean, and winter wheat yields in Ontario, Canada over 26 years. Stochastic production function models are used to account for both inter- and intra-seasonal variability of climate variables on yield. However this study has been criticized for its inclusion of many predictor variables, which may lead to model over-fitting (Holzkämper et al. 2013). Rowhani et al. (2011) study the impact of both season averages and intra-season variability of climate on maize, sorghum, and rice yields in Tanzania. This study uses district-level crop yields and monthly climate data over 13 years. Climate predictors include seasonal precipitation and average temperature, as well as the coefficient of variation of these climate variables for each season. From among this set of candidate climate predictors, the relevant variables for each crop model are identified using statistical procedures.

Given the multitude of empirical studies of climate and crop yield, a number of meta-analyses seek to synthesize results and identify gaps in our knowledge base. Zinyengere et al. (2013) review 19 studies of the projected climate change impact on crops in southern Africa. They observe that all studies conclude that adaptation of crop production systems to a changing climate is necessary. Knox et al. (2012) conduct a systematic review of publications focused on eight crops in Africa and South Asia. Across studies the authors find robust negative impacts in Africa for wheat, maize, sorghum, and millet for the 2050s and beyond. However the projected impacts are crop- and region-specific, which indicates that results are not generalizable. Furthermore most evidence relates to maize, while other crops such as rice or sweet potatoes are almost entirely overlooked. The authors note that "major gaps in climate impact knowledge still exist for particular crops and regions, despite the apparent large evidence base within the scientific literature."

3. Data sources

Information on crop yields comes from the Crop Forecast Survey (CFS), which is conducted by the Government of Zambia Central Statistical Office (CSO) each year. This nationally representative household survey focuses on expected crop production, and it takes place before or during harvest, once farmers are able to estimate their crop yields. This paper refers to CFS data from the 2000/01 through 2010/11 agricultural seasons, and the number of households surveyed ranges from 6,924 in 2001 to 13,453 in 2012. Field-level observations are converted into yields (tons/ha planted), and observations with zero harvest are omitted from analysis, as these may represent other events (e.g. fire or theft) unrelated to climate. Obvious outliers, such impossibly high yields, are also omitted. The calorie content of field crops are taken from the Food Consumption Table for Use in Africa (We Leung et al. 1968). Sampling weights are used in all analyses using the field level observations.

Historical rainfall and temperature data are obtained from records maintained at 35 meteorological stations run by the Zambian Meteorological Department (ZMD). These dekad-level records include total precipitation, average minimum nightly temperature, and average maximum daily temperature. Missing values are imputed using an average of nearby meteorological stations of similar altitude, and Table 1 provides the rate of missing dekad-level observations. For the growing season, these range from 24.19% for precipitation to 48.01% for average temperature. Although the rate for temperature is higher than we would prefer, it was determined that imputed observations should be reliable as temperature is less localized than rainfall, with weak gradients over much of Zambia.

Table 1. Missing observations in meteorological station data (2000/01 - 2010/11)

Climate variable	Time interval	% missing
Average temperature	July-June	45.38%
	Nov-April	48.01%
Maximum temperature	July-June	40.02%
	Nov-April	41.87%
Minimum temperature	July-June	37.14%
	Nov-April	39.62%
Rainfall	July-June	22.16%
	Nov-April	24.19%

To link the climate data to local agricultural production, each district is matched with a single meteorological station. This is either the station found within the district, or where no station is found, a nearby station of similar altitude as the district. Using this simple method, all field-level observations within a district are considered to experience the same climate outcomes.

For future climate scenarios, we first reference the Intergovernmental Panel for Climate Change (IPCC) website for predictions of climate around the year 2050. These are based on four global circulation models (GCMs) and the A1B emission scenario of future human activities. Future energy source are balanced under this scenario, and this is neither the most, nor the least, fossil-fuel intensive climate change scenario (IPCC 2013). For each district, spatial averages of monthly total rainfall and both minimum and maximum temperature are calculated. Based on this set of predictions, we then roughly estimate changes in climate variables for all of Zambia (e.g. +2°C, +20% increase in intra-season variability) to evaluate the impact of each change on crop yield.

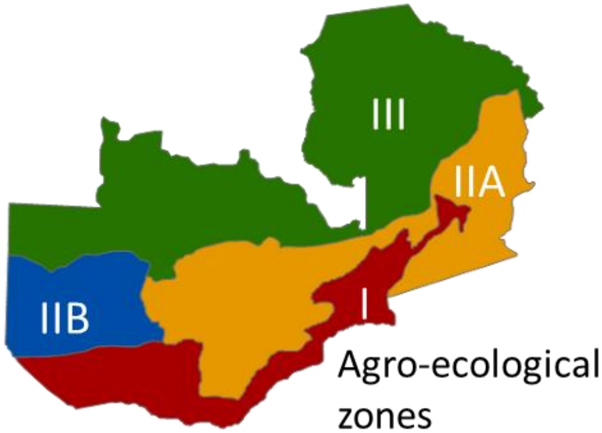
4. Zambia

Zambia is a landlocked country in southern Africa that is characterized by low population density, where roughly 45% of the population live in rural areas and depend on agriculture for their livelihoods (Jain 2006). Among smallholder and emergent farmers, almost all production is rain-fed and very few farmers use mechanized irrigation. Zambia has a single growing season that extends from approximately November through May, when crops are harvested. Just 55% of farmers applied fertilizer in 2010, with the majority used for maize production. However fertilizer adoption rates have been consistently increasing since 2000 (Tembo and Sitko 2013), and this is likely due to the national Farmer Input Support Program (FISP). This program offers subsidized fertilizer and hybrid maize seed to farmers with the capacity to grow between one and five hectares of maize (Mason et al. 2013).

4.1 Climate

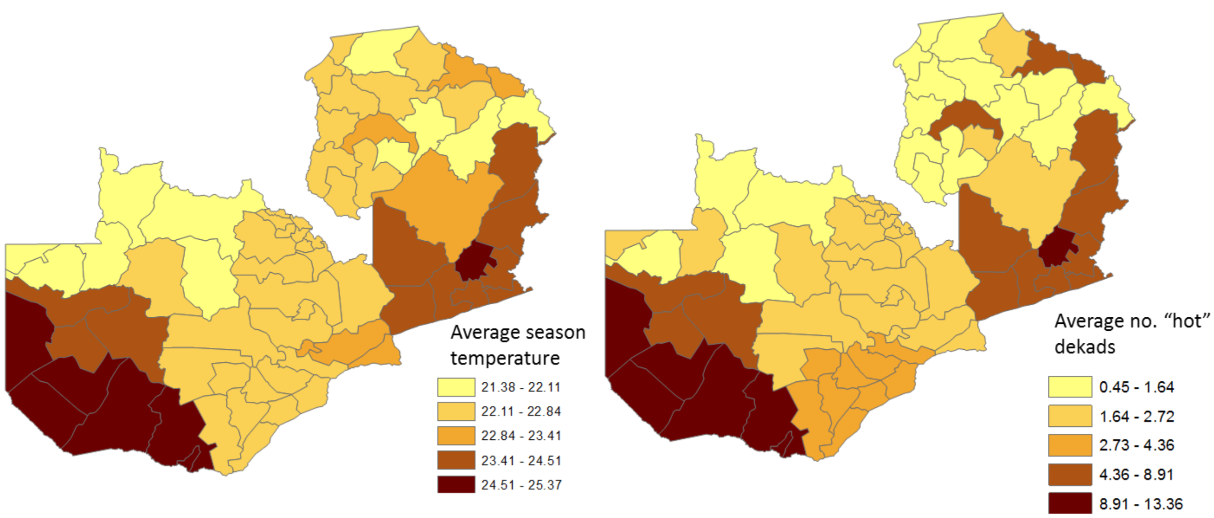
Zambia is divided into four agro-ecological zones distinguished by divergent rainfall patterns (Figure 1). Zone I, located in the south, is relatively dry with unpredictable and poorly distributed rainfall and limited potential for crop production. Zone IIa covers the central-eastern part of the country and has the highest agricultural potential, with fertile soil and rain that is evenly distributed throughout the growing season. Zone IIb is characterized by lower rainfall, sandier soils, and a high risk of drought. Zone III in the north experiences high rainfall, although this pattern has produced leached and acidic soils (Jain 2006).

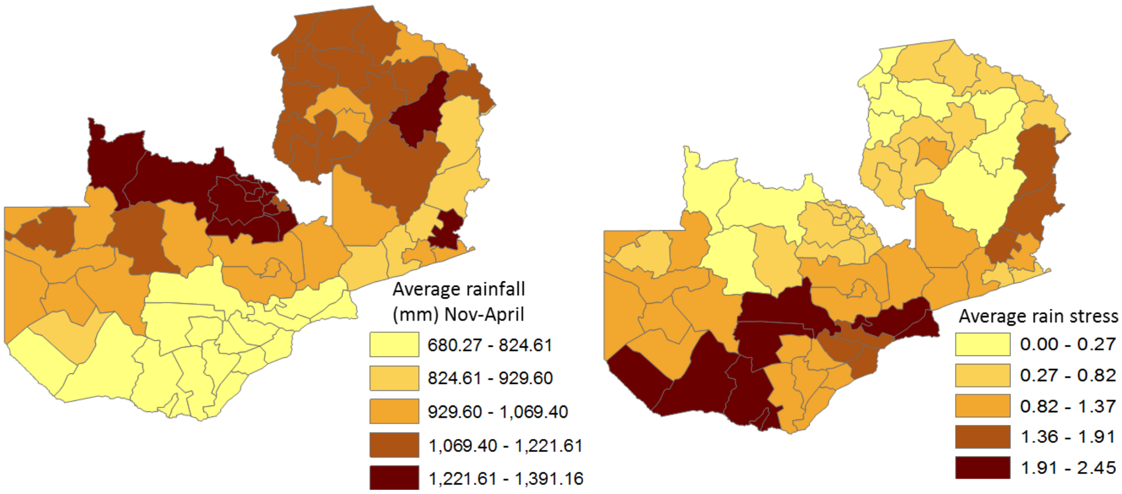
Figure 1. Agro-ecological zones in Zambia



An examination of average climate variables over the study period further reveals a more nuanced picture: Districts in the east and south west experience the hottest growing seasons (Figure 2) and the highest number of dekads with an average daytime temperature above 30°C. Most crops suffer when exposed to temperatures beyond this threshold (Porter and Semenov 2005). Patterns of total seasonal rainfall closely track the agro-ecological zone descriptions, and accordingly districts in the south and east tend to experience more periods of drought during the growing season.

Figure 2. Geographic patterns of seasonal climate during the study period





Drought has been the biggest shock to food security during the last two decades (Muchinda 2001, cited in Jain 2006), with large shortfalls in maize yield consistently occurring in seasons with below normal rainfall. At the same time, Zambia sometimes experiences heavy localized floods that also threaten agricultural production. The climate outlook for southern Africa is characterized by a rise in temperatures and a higher frequency and severity of extreme rainfall events (Kotir 2011). Thus, the general consensus among climatologists is that climate change will act as a multiplier of existing threats to food security in the region.

4.2 Crop production

Over the study period maize has been the most widely cultivated crop, followed by cassava. Figure 3 illustrates the crop distribution over just a subset of years (2007/08-2009/10) because estimated cassava yields over the previous 12 months were only collected in these years. These proportions are based on total area planted to field crops and total estimated calorie production from field crops in Zambia each year. The yearly values are then averaged. Evidently, maize provides more calories per hectare planted than other crops. It is noteworthy that crop distribution varies across the country (Figure 4). Maize is much less prominent in agro-ecological zones IIB and III, where cassava is also grown, while sorghum is almost entirely concentrated in zone I. Although maize is produced in zone IIB, lower yields mean that this does translate into higher calories per hectare than other crops in the region. Cotton is a sizable element of the agricultural landscape in zones I and IIA, while is it nearly absent elsewhere.

Figure 3. Distribution of crops

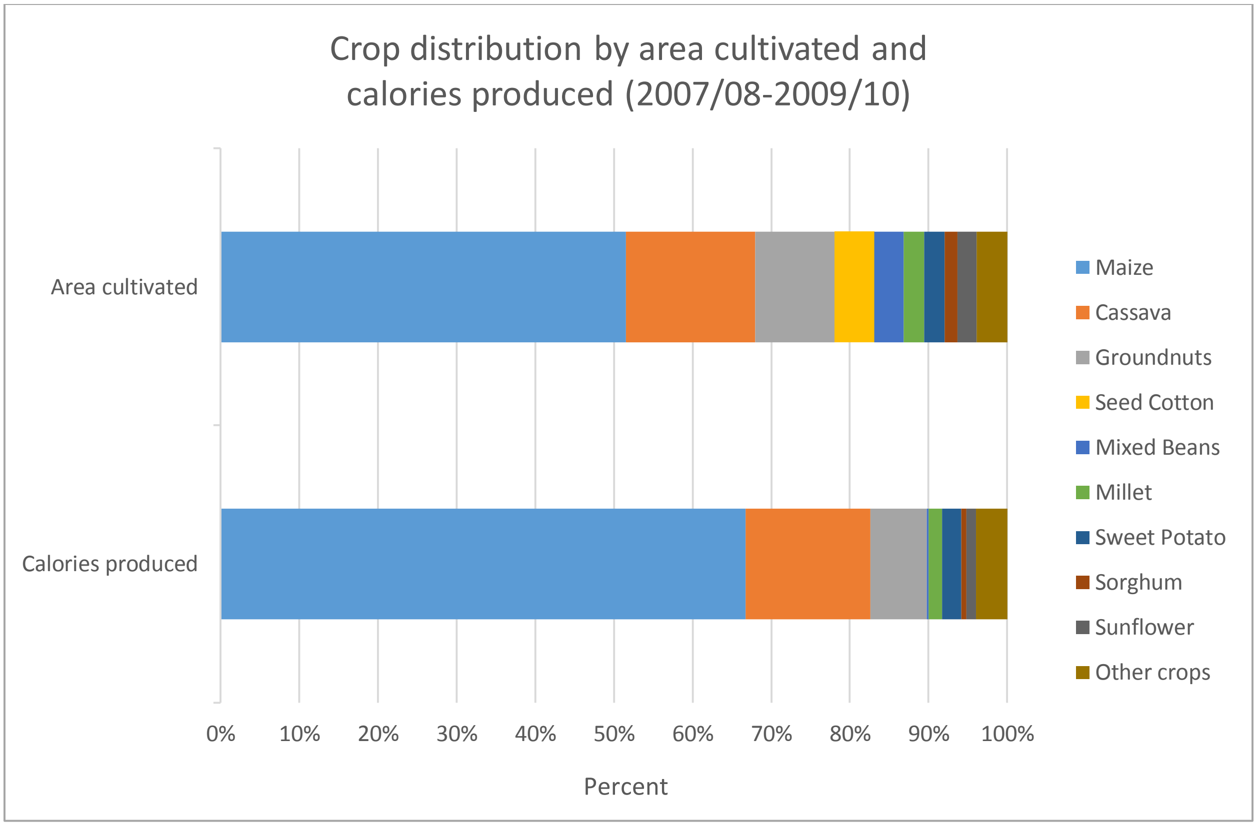
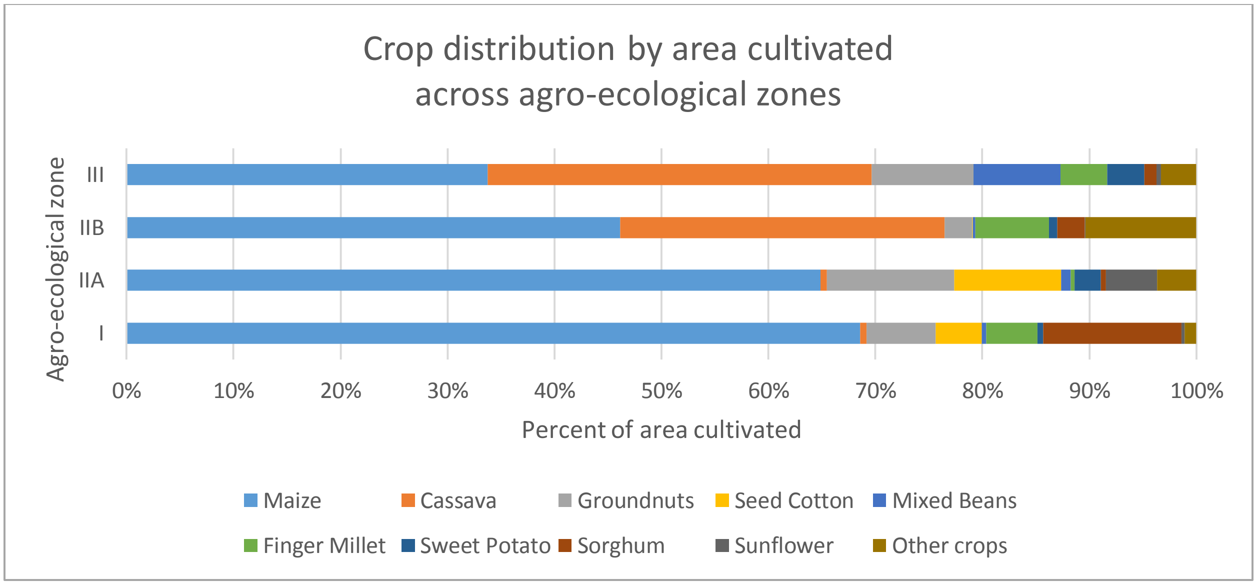
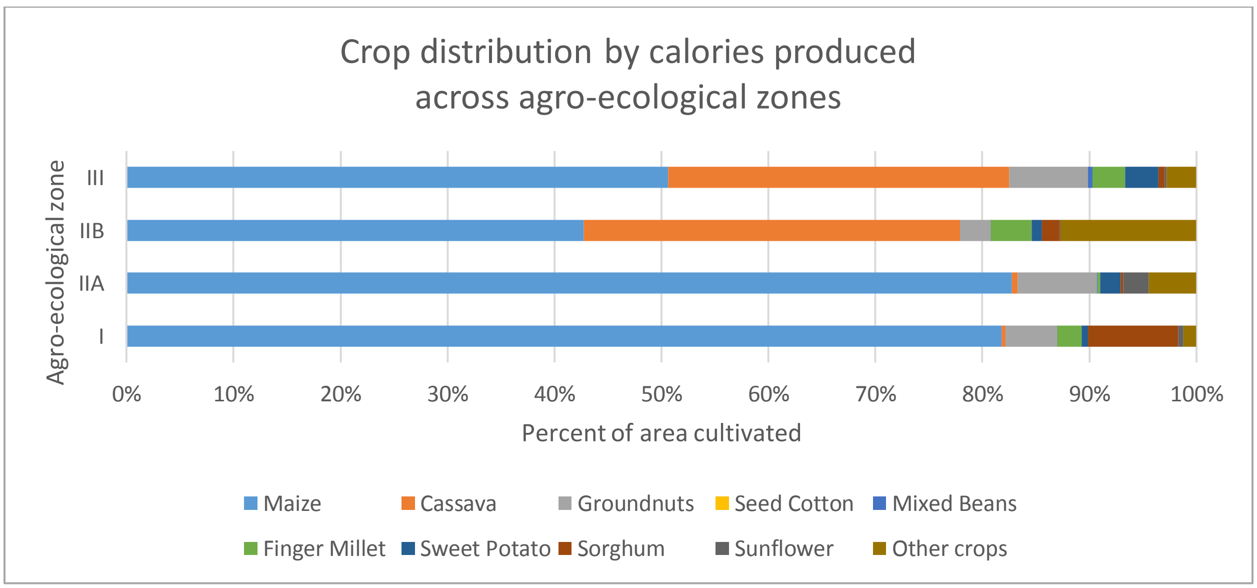


Figure 4. Distribution of crops by agro-ecological region





5. Exploratory analysis of climate data

This study is based on dekadal records of precipitation and minimum and maximum temperature collected at 35 meteorological stations across Zambia. These are used to construct a set of possible climate predictors (Table 2) to be included in the statistical yield models. As noted earlier, each district and all field-level observations therein are matched to a single meteorological station. For both rainfall and temperature variables, the growing season is considered to be November-April.

Table 2. *Climate variable definitions*

Climate variable	**Variable construction**
Average maximum temperature (°C) for 3 intervals (Oct-Apr, Nov-Mar, mid-Dec-Feb)	Average of dekadal daytime high temperatures
Average minimum temperature for 3 intervals	Average of dekadal nighttime low temperatures
Average season temperature for 3 intervals	Average of dekadal maximum and minimum temperatures
Monthly average temperature	Average of dekadal maximum and minimum temperatures

	for each month
No. hot dekads (Nov-Mar)	No. dekads in growing season with average daytime high temperature >= 30°C
CV Temperature (Oct-April)	Coefficient of variation = $\sqrt{\sum(Avg\ temp_i} - Avg\ season\ temp)^2$, where i indexes each dekad
Season rainfall (mm) for 3 intervals	Total precipitation
Monthly rainfall	Total precipitation for each month
Rain stress (Nov-Mar)	No. 20-days periods with <= 40 mm rainfall
CV Rainfall (Oct-April)	Coefficient of variation = $\sqrt{\sum(Rain_i} - Avg\ dekadal\ rain)^2$, where i indexes each dekad
Rain start	No. dekads from the beginning of November until >= 20 mm rainfall
Length of rainy season	No. days between rain start and rain end (the last dekad with >= 20 mm rainfall)
Rain-temp interaction (Nov-Mar)	Season rainfall * average season temperature

The interaction between rainfall and temperature is intended as an indicator of soil moisture (Rowhani et al. 2011). The criteria for a "hot dekad", with an average maximum temperature above 30°C, is based on studies of the nonlinear and asymmetric relationship between temperature and crop yield, whereby yields increase up to a certain temperature threshold and then sharply decrease. This threshold has been identified for maize and soybeans (29°C) and cotton (33°C) in the U.S. (Schlenker and Roberts 2006) and for maize (30°C) in sub-Saharan African (Lobell et al. 2011). Threshold temperatures are found not to differ greatly for different crops (Porter and Semenov 2005).

Because collinearity among explanatory variables in a regression leads to biased coefficients, we explore the correlations between climate observations at meteorological stations (Tables 3 and 4). There is a high level of correlation among the various climate variables, including between temperature and rainfall. For example the correlation between average season temperature and total rainfall is negative and significant (-0.32). When constructing a statistical yield model, this underscores the need to maintain a simple model with a minimum number of climate predictors.

Table 3. *Correlations among seasonal climate variables*

	Avg season temp	Avg max temp	Avg min temp	CV temp	No. hot dekads	Total rainfall	CV rain	Start of rainy season	Length of rainy season	Rain stress
Nov-Mar avg season temp	1.00									
Nov-Mar avg max temp	0.88***	1.00								
Nov-Mar avg min temp	0.84***	0.72***	1.00							
CV temp	0.02	-0.08	-0.05	1.00						
No. hot dekads	0.80***	0.91***	0.63***	-0.07	1.00					
Nov-Mar total rainfall	-0.32***	-0.36***	-0.21***	-0.10*	-0.40***	1.00				
CV rain	0.29***	0.31***	0.25***	0.10*	0.33***	-0.52***	1.00			
Start of rainy season	0.26***	0.24***	0.25***	0.09	0.24***	-0.27***	0.29***	1.00		
Length of rainy season	-0.26***	-0.21***	-0.24***	-0.10*	-0.23***	0.32***	-0.45***	-0.81***	1.00	
Rain stress	0.31***	0.33***	0.23***	0.11*	0.35***	-0.69***	0.75***	0.33***	-0.44***	1.00

Table 4. *Correlations among monthly rainfall and average temperature*

		Temp						Rain					
		Nov	Dec	Jan	Feb	Mar	Apr	Nov	Dec	Jan	Feb	Mar	Apr
Temp	Nov	1.00											
	Dec	0.77***	1.00										
	Jan	0.49***	0.71***	1.00									
	Feb	0.35***	0.53***	0.76***	1.00								
	Mar	0.41***	0.52***	0.67***	0.78***	1.00							
	Apr	0.41***	0.44***	0.43***	0.55***	0.71***	1.00						
Rain	Nov	-0.32***	-0.33***	-0.18***	-0.10*	-0.15**	-0.16***	1.00					
	Dec	-0.13**	-0.20***	-0.25***	-0.17***	-0.19***	-0.14**	0.18***	1.00				
	Jan	-0.03	-0.11**	-0.16***	-0.17***	-0.16***	-0.10*	0.11**	0.28***	1.00			
	Feb	-0.13**	-0.13**	-0.14**	-0.05	-0.03	0.07	0.20***	0.22***	0.09	1.00		
	Mar	-0.20***	-0.28***	-0.24***	-0.11*	-0.10*	-0.05	0.24***	0.08	0.06	0.29***	1.00	
	Apr	-0.14**	-0.11*	-0.08	-0.04	0.05	0.05	0.07	-0.09	-0.11**	0.02	0.18***	1.00

6. Models

In all models we pool observations across space rather than construct a time-series model for each sites. Although this restricts all sites to the same yield-climate relationship, this approach expands the sample size and exploits the wider variation in both temperature and rainfall found across the country. We identify the relevant variables for each crop model using a range of procedures outlined below. We also use multiple model specifications with the aim of identifying a relationship between climate and yield that is consistent across models.

We first aggregate the yield observations from field- to district-level, as spatial aggregation has been found to produce more reliable results (Lobell and Burke 2010). This is because noise in the explanatory variables (a low signal-to-noise ratio) induces attenuation bias, in which we are less likely to detect a significant effect. Aggregation to broader spatial scales improves model performance because measurement errors at individual sites are independent and therefore cancel out. In our study, yield measurement errors found in farmer estimates of the CFS may cancel out through this process, and the measurement error of climate variables should also decrease as microclimatic variations become less important at broader scales.

Model 1

We use a forward stepwise model selection procedure based on the Akaike Information Criterion (AIC) (Rowhani et al. 2011; Holzkämper et al. 2012). Candidate regressors include Nov-Mar rainfall, Nov-Mar rainfall^2, CV rain, Nov-Mar average temperature, temp^2, no. hot dekads. We also include district dummy variables. The model is

$$y_{cdt} = \beta_0 + [Climate\ variables_{dt}] + \alpha_d + \varepsilon$$

where y_{cdt} is average yield of crop c in district d in year t, $Year_t$ is a time variable (year from 1999), and and α_d captures the district fixed effects. T Goodness of fit is based on a likelihood ratio test using the AIC. The AIC is used to minimize the number of climate predictors in the model, as too many variables may lead to over-fitting and a model that is difficult to interpret (Lobell et al. 2007; Lobell et al. 2011).

Model 2

[Note: Folllowing Rowhani et al. (2011), this will be a mixed-effects model with random intercepts and an autoregressive feature (one lag). I'm not sure how to incorporate the variable selection process into a mixed effects model.]

7. Results

Table 5 presents the coefficients estimated in Model 1, using the stepwise selection procedure. Coefficients on significant district dummies are not shown.

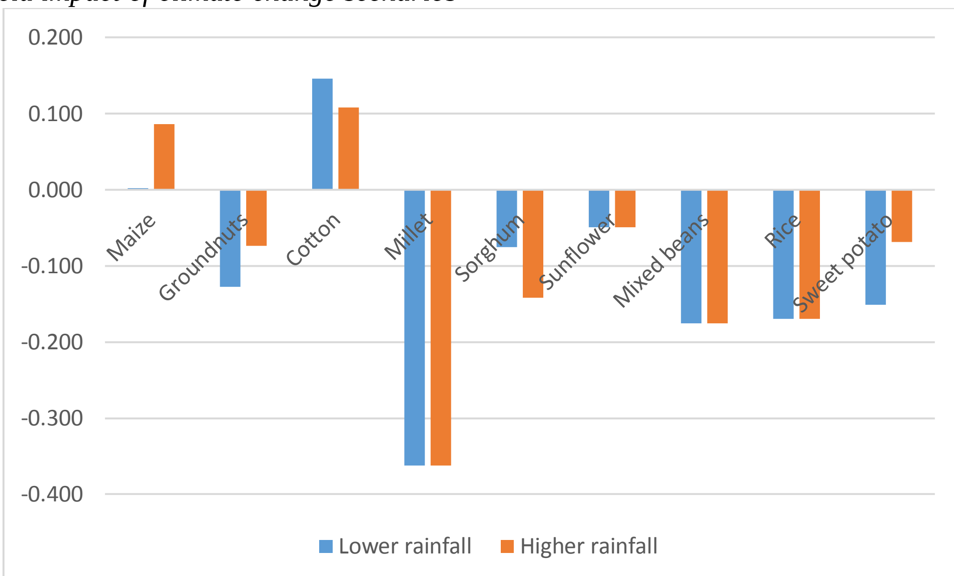
Table 5. *Coefficients of yield models, Model 1*

	NM rain	NM rain squared	CV rain	NM avg season temp	NM temp squared	Hot dekads
Maize	0.002	0.000	-0.257	0.061		-0.025
Groundnuts	0.002	0.000	-0.484			
Cotton	0.000		-0.594	2.518	-0.049	-0.036
Millet			-0.435	-0.133		
Sorghum	0.000		-0.468			-0.017
Sunflower			-0.254			
Mixed beans			-0.649			-0.048
Rice			-0.670			-0.039
Sweet potato	0.002	0.000		-0.042		-0.012

8. Crop yield projections under climate change

We now estimate the impact of two climate change scenarios on expected crop yield. Scenario 1 includes a 10% decrease in seasonal rainfall, a 20% increase in CV rain, a 9% increase in temperature, and a 25% increase in the number of hot dekads in the season. Scenario 2 is similar except that rainfall increases (rather than decreases) by 10%.

Figure 6. *Yield impact of climate change scenarios*



[Note: I don't know how to estimate standard errors here because more than one independent variable is changing. I have questions about how to decide on a climate change scenario for the whole country, as well as what should be considered the "baseline". (Here, I just averaged across all met stations.)]

9. Summary and conclusions

Our investigation of historical crop yields establishes a clear link between climate shocks and crop yield in Zambia. Crops exhibit varying degrees of sensitivity to climate, and this has implications for both the crops that are prioritized in agricultural policy in the near-term (when climate shocks can affect crop production within a season) and crops that are prioritized in agricultural development in the long-term. The differing crop sensitivities surely also play a role in the choices farmers make about which crops (or crop cultivars) to produce under a changing climate. We hope the information compiled in this paper can be used to support farmers in adapting their agricultural practices to current climate variability. As noted by Twomlow et al. (2008), this is the first step in building adaptive capacity to cope with future climate change.

For the crops considered in this paper, sensitivity to temperature is much larger than sensitivity to changes in rainfall. This may be because rainfall has not historically been a limiting factor in crop production, making it difficult to detect a relationship within a multiple regression. The relatively large effect of temperature suggests that the development of heat-tolerant seed varieties should be prioritized along with continued efforts to make short- and long-duration varieties available to farmers. We also observe that different time intervals within the season are important to different crops (Table --). Some conclusions about yield impacts are consistent across different model specifications (e.g. temperature effects for groundnuts), while other conclusions differ across models. Perhaps the main lesson to be gleaned is that the model structure needs to be thoughtfully identified when building a statistical yield model to quantify the effects of climate change.

Several caveats are in order: The use of dekad-level climate data masks daily extremes that may be important to crop production, such as very heavy rainfall or short heat spells that damage the crops. We also do not address the impact of climate on crop quality. These statistical models do not account for any adaptation responses on the part of farmers, and this is a major shortcoming of all empirical models trained on historical data. The final caveat is that our estimates are yield impact are likely to be larger than those found using other methods. In at least two meta-analyses or comparative studies of empirical and process-based crop models, the authors find that empirical models project larger yield losses or smaller gains (Estes et al. 2013; Zinyengere et al. 2013). Lobell and Burke (2010) also find that empirical models overestimate yield losses from warming in dry years, relative to a process-based model. This is because the statistical models did not capture interactions between variables, as when yields do not suffer due to warming when they are already low due to moisture stress.

Future work on this topic will include an exploration of whether different crop cultivars or management regimes exhibit structurally different yield functions. This would indicate that the yield models should be constructed separately for crops according to these key characteristics, and would produce policy-relevant conclusions about which management regimes are most robust to climate shocks. We would also like to more deeply explore the construction of yield models with varying time intervals for the climate variables. Using the meteorological station data, we would also like to identify a more nuanced way to match climate data to field-level observations, as with Thiessen polygons or thin plate smoothing splines used along with a digital elevation map. Using the latter method, climate data for individual sampling areas within each district can be estimated, and this may result in sounder estimate of the relationship between climate and yield.

With the annual Crop Forecast Survey, Zambia is able to closely monitor crop yields at field-level across the country. Echoing the sentiments expressed by Rowhani et al. (2011) for Tanzania, it is imperative that Zambia match this trove of crop data with improved climate records. There are currently 35 meteorological stations throughout the country. While this may be adequate for estimating temperature across space, it becomes problematic when estimating rainfall. This is because rainfall is more localized than temperature, and in a series of focus group discussions in Zambia (Mulenga and Wineman, forthcoming), farmers observed than rainfall has become increasingly localized in recent years. This warrants a greater number of rainfall stations to be maintained in Zambia, for example at schools and health clinics. With improved climate data at a higher temporal and spatial resolution, we will be better able to understand the impact of climate on crop yield and to inform policies that reduce farmer vulnerability to climate shocks.

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