The Role of Risk in the Context of Climate Change, Land Use Choices and Crop Production: Evidence from Zambia.

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Abstract:

This study examines the empirical importance of the effects of the risk environment on the impacts of climate change on farm land allocations and consequent effect on agricultural output in Zambia. We use a discrete-choice model consistent with a mean-variance utility function to model farm-level land allocations among alternative crops. Results indicate that risk-reducing decisions reinforce the trend to shift away from maize production in response to climate change impacts on mean temperatures and precipitation. The opportunity cost of these decisions is explored through a simulation scenario in which yield variability is reduced to zero. Important conclusions can be derived from this analysis. First, when the economic effects of climate change are considered, decision-making under uncertainty and risk should be at the forefront of the problems that issues that need to be addressed. Second, concentrating on farm-level effects of responses to climate change is not sufficient. To understand the economy wide consequences of climate change, the aggregate effects of individual decisions should be assessed. Third, results indicate that increased efforts in risk management and in policies aiming at reducing risk can lead to significant positive outcomes.

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Introduction

Climate disruptions to agricultural production have increased over the past 40 years and are projected to become more frequent over the next 25 years (Hartfield et al. 2015). Farmers in many agricultural regions already appear to have experienced declines in crop and livestock production because of climate change-induced stress (Lobell and Field 2007). Up to now, the effects of changes in mean temperatures and precipitations have been the main focus of discussions about climate change impacts on agriculture and of the quantitative modelling analyses of those impact. The effects of climate change on the volatility of agricultural production, crop and livestock prices, and longer term producer responses to the associated increased risk have received much less attention. This study therefore examines the importance of the risk environment on the impacts of climate change on farm land allocations and consequent agricultural output at the country level. The empirical question that motivates this paper is whether or not modeling farmers' responses to climate change requires accounting for risk attitudes. Is risk only a second-order effect of negligible importance or, alternatively, does accounting for risk in empirical models result in quantitatively and statistically significant different results about the effects of climate change on agricultural production and food systems?

Economists have long been aware of the potential importance and role of risk in farmers' decisions-making. In empirical climate change studies, however, in practice risk-aversion is generally assumed away even though the economic literature has emphasized the potential effects of price and yield volatility on farmers' production decisions. The results of this study indicate that omitting effects associated with risk attitudes can hide farmers' actions that are consistent with short-term adaptation, can lead to the formulation of poorly targeted polices and insidiously affect a country's production of food. Farmers are likely to make production decisions that reduce their households' vulnerability to climate change and a portion of the land reallocation strategy they choose is driven by risk considerations. We find that even if a relatively small fraction of the change is attributable to risk avoidance, the aggregate effects of small changes in land allocations at the farm level compounded with changes in crop-growing conditions caused by climate change may adversely affect overall production at the country level. These findings also indicate the potential importance of innovations that mitigate the risk effects of climate change (e.g., investments in developing drought tolerant crop varieties, irrigation systems, etc.) and providing farmers with access to efficient risk management tools.

A Model of Land Use Choices

Economists often estimate multi-crop econometric models derived under the assumption of profit maximization with land as an allocable fixed input to explain land use decisions by farmers (Chambers and Just 1989, Moore and Negri 1992; Oude Lansink and Peerlings 1996; Fezzi and Bateman 2011). An alternative approach is to model land allocation decisions using a discrete choice setting because it leads to conveniently tractable empirically relevant model specifications (Wu and Segerson, 1995; Miller and Plantinga, 1999; Livingston et al., 2008). More recently, Carpentier and Letort (2013) have shown that, under reasonable assumptions, discrete choice models (and specifically multinomial logit models) can be interpreted as solutions to a farm's land use optimization problem. However, as originally pointed out by Just, Zilberman, and Hochman (1983), three assumptions generally guide the representation of multioutput production: 1) inputs are allocated to specific crop production activities; 2) production is technically non-joint so that the allocation of inputs uniquely determines crop-specific output levels; and 3) a series of fixed inputs (e.g. land, machineries,) that can be allocated across production activities. Assumptions 1 and 2 allow for the existence of separate restricted profit functions for each crop, taking land allocations as given. Assumption 3 is responsible for jointness in farmer's multicrop profit maximizing decisions. As Carpentier and Letort state: "the multinomial logit framework imposes non-jointness restrictions of the multicrop technology in variable inputs, in outputs and in acreages." A direct consequence of these restrictions is that the non-jointness of the quasi-fixed input requirements with respect to variable input uses can only hold in the neighborhood of the current level of input usage. Therefore, the multinomial logit model framework, including Carpentier and Letort's extension, cannot be used to make long-term projections regarding crop allocation shares.

In this paper, we use this model not to make precise predictions about future land use patterns in Zambia but to gain an insight into how existing farmers would respond when exposed to climate change.

While our underlying behavioral model follows Chavas and Holt (1990), the model estimation is based on a small modification of the approach used by Wu and Segerson (1995) to allow for risk-aversion.

We consider an agricultural production system in which crops are non-joint in production and compete for shares of a fixed area of land. A household is assumed to face a one period consumption budget G in which:

$$G = W + \sum_{j=1}^{J} p_j y_j a_j - \sum_{j=1}^{J} c_j a_j \qquad \text{eq. 1}$$

where W indicates household wealth, and a_j is the area allocated to the jth crop. Thus $\sum_{j=1}^{J} a_j = A$ is the size of the farm controlled by the household. In addition, y_j indicates the output (i.e., yield per unit area) of the j^{th}crop, p_j its market price and c_j the cost of producing that crop per unit area.

The household maximizes expected utility derived from farming available land holdings by allocating a_j to each available crop J:

$$\max_{a_j}\{EU[\mathrm{G}(\Pi)|W, A]\} \quad \text{eq. 2}$$

where U is a utility function describing the attractiveness of net revenues Π conditioned on monetary (W) and land (A) endowments. Π is a function of p, y, and c which are respectively vectors of output prices, yields and crop production costs, the latter two are functions of a vector of biophysical characteristics at location l (B_l) and of a vector of characteristics for the n^{th} household (H_n). Revenues, $\sum_j p_j y_j a_j$, are stochastic because output prices and yields have some distribution with finite means and variances $\left(\bar{p}_j, \Omega_{p_j}\right)$ and $\left(\bar{y}_{jl}, \Omega_{y_{jl}}\right)$, respectively, and their realized values are not known by farmers when land allocation decisions are made. Conversely, input prices and production costs, C_j, are assumed to be known with certainty by households at that time.

For each crop j the household's optimal area allocation choice a_j^* depends on its wealth, expected net revenues, Π, second and, potentially, higher moments of the distribution of the expected net crop revenues, Ω, and farm size A. Thus, the direct area allocation by crop $a_j^* = F\left[\Pi_j, W, A, \Omega_j\right]$ is the area allocation choice that solves the utility maximization problem. We assume that $a_j^* = F\left[\Pi_j, W, A, \Omega_j\right]$

can be expressed as $a_j^* = A * f[\pi_j, W, A, \Omega_j]$ where π is now the per-hectare net revenue. Thus for each crop j there is an optimal share allocation function[1]:

$$s_j^* = \frac{a_j^*}{A} = f[\pi_j, W, A, \Omega_j] \qquad \text{eq. 3}$$

Farm-level area allocations are observed in the household survey described in the next section. These allocations depend on a crop's risk/returns profile relative to all other crops. The probability that a farmer chooses to grow a particular crop j is given by $P_j = Pr(U_j > U_i \forall\, j \neq i)$ and the expected area allocated to that crop is given by $A * P_j$. Therefore, the expected share s of farmland allocated to crop j is $s_j = \frac{1}{A}[A * Pr(U_j > U_i \forall\, j \neq i)]$. This means that the share allocated to a crop j is equal to its probability P_j to be chosen by a farmer. Acknowledging that $U = V + \xi$ where V represents a knowable-by-all component of the utility function while ξ is known to the farmer but unobserved by the researcher and assuming that ξ has an *iid* Type 1 EV distribution, then:

$$s_j = \frac{exp\{E[V_j]\}}{\sum_{i=1}^{J} exp\{E[V_i]\}} \qquad \text{eq. 4}$$

We then can rewrite the optimal share allocation function for a crop as:

$$s_j^* = \frac{exp[s(\pi_j(), W, A, \Omega_j)]}{\sum_{i=1}^{J} exp[s(\pi_j(), W, A, \Omega_j)]} \qquad \text{eq. 5}$$

Equation 3 explicitly accounts for the influence of net revenue variability on land allocation decisions by farmers who account for both expected returns and the volatility of those returns in their land use

[1] Wu and Segerson (1995) assume that their land use function is linear homogenous of degree one in area and therefore the function can be written removing area itself as a potential determinant of land allocation decisions and impose constant returns to acreages. However, removing area from the function arguments is not necessary except as a convenience. In fact, the homogeneity of degree one assumption could be dropped altogether. Retaining total farm size among the arguments of the optimal share function can account for differences in fixed costs of multiple activities or risk-spreading decisions available to farmers that manage farms of different sizes.

decisions. The variable Ω_j is constructed to provide a crop specific measure of net revenue variability based on the product of the two stochastic variables yield and price:

$$\Omega_j = E(y_i^2) * E(p_j^2) - [E(y_j p_j)]^2 + Cov(y_i^2 p_j^2) \qquad \text{eq. 6}$$

Wu and Segerson (1995) and Holt and Kaminsky et al (2013) assume that the optimal share function is linear in parameters while Chavas and Holt (1990) use a first order expansion to linearize the optimal acreage function. Following this literature, we assume that the optimal share function for each crop can be approximated by a linear in parameters combination of explanatory variables (X) such that $\ln\left(\frac{s_{jn}}{s_{on}}\right) = \boldsymbol{\beta}_j \boldsymbol{X}_{jn} + \xi_{jn}$, where $\boldsymbol{\beta}_j$ and $\boldsymbol{X}_j$ are vectors and the subscript 0 in s_0 indicates a reference crop and $\boldsymbol{n}$ identifies the n^{th} household.

The parameters $\boldsymbol{\beta}_j$ are estimated using two models. The first is a standard multinomial logit model; the second is a two-level nested multinomial logit model (see Figure 1). In both models, the probability of a crop being chosen is interpreted as the share of the available land to be allocated to the crop (Theil 1969, Berry 1994, Greene 2003). Nested multinomial logit models are estimated under assumptions analogous to the multinomial logit model with respect to $\boldsymbol{\xi}$, but with the error terms for crop shares correlated within each nest but uncorrelated among nests. The explanatory variables are partitioned with some used to choose among the nests and the others to choose among the options within each nest.

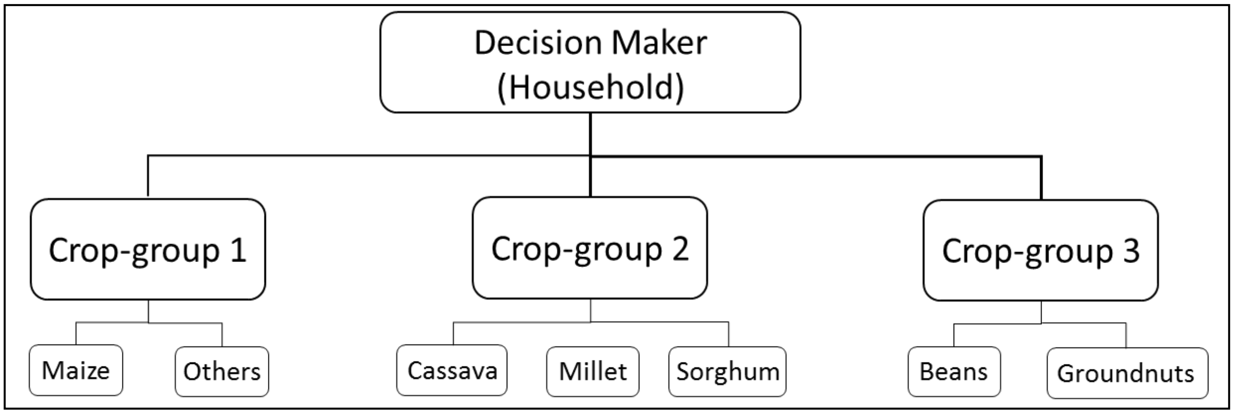

Figure 1: Structure of the Nested Multinomial Logit Model

Under these assumptions, the probability that household *n* chooses alternative *j* ($j \in k$) can be derived from the product of two multinomial logit probabilities (McFadden 1977, Train 2003); that is,

$P_{nj} = P_{nk} * P_{nkj|k}$, where

$$P_{nk} = \frac{\exp(\boldsymbol{\beta}_k \boldsymbol{X}_n + \lambda_k I_{nk})}{\sum_{k'=1}^{K} \exp(\boldsymbol{\beta}_k \boldsymbol{X}_n + \lambda_k I_{nk})} \qquad \text{eq. 7}$$

and $\boldsymbol{X}_n$ is a vector of household-specific characteristics such as off farm wages and household size, $\boldsymbol{\beta}_k$ is vector of coefficients for $\boldsymbol{X}_n$, and where

$$P_{nkj|k} = \frac{\exp(\boldsymbol{\beta}_{kj} \boldsymbol{X}_{nj}/\lambda_k)}{\sum_{j' \in k} \exp(\boldsymbol{\beta}_{kj} \boldsymbol{X}_{nj}/\lambda_k)} \qquad \text{eq. 8}$$

and $\boldsymbol{X}_{nj}$ is a vector of location-specific variables influencing crop suitability like weather conditions and soil characteristics and $\boldsymbol{\beta}_{kj}$ is a vector of coefficient parameters specific to crop *j*. I_{nk}, often referred to the inclusive value of nest k, is defined as $I_{nk} = \ln\left(\sum_{j \in k} \exp(\boldsymbol{\beta}_{kj} \boldsymbol{X}_{nj}/\lambda_k)\right)$. [2] Equation 7 defines the marginal probability of choosing any alternative in nest *k* and equation 8 the conditional probability of

[2] I_{nk} is called the inclusive value or inclusive utility for alternative *k* in the first level. The inclusive value links the two levels of the nested logit model by bringing information from the bottom level into the upper level. In essence, $\lambda_k I_{nk}$ measures the expected value or utility to individual *n* of the alternatives available in particular nest.

choosing alternative *j* given that any alternative in nest *k* is chosen. We refer to the marginal probability as the upper-level model and to the conditional probability as the lower-level model, reflecting their relative positions in the hierarchy structure in Figure 1.

The Data

The data used to estimate the land use models are obtained from several sources and include nation-wide survey information on individual farm households, province level information on crop prices, simulation-based information on crop yields, biophysical information, and weather data.

Household Data

Cross section data on farm practices and household characteristics of a country-wide stratified sample of 5319 smallholder farmers were obtained from the 2004 Zambia Rural Income and Livelihoods Survey. This is a country-scale smallholder farmer survey designed and administered by the Central Statistical Office (CSO) of the government of Zambia (Central Statistical Office, 2012). The 2004 CSO survey sampled households from 72 districts. The survey provides information for the 2003-2004 crop year on land allocations among crops, information on households' crop-specific revenues but limited information about costs of production. Six crops were selected to be modeled (Table 1) while all land allocated to other crops, including land in fallow, were grouped in a category called "others". Land reported as fallow accounts for approximately 58 percent of the "others" category.

Table 1: Land allocation by crop in Zambia as reported by household survey

Crop	Maize	Millet	Sorghum	Cassava	Groundnuts	Beans	Others
Share	0.36	0.03	0.02	0.12	0.07	0.03	0.38

Crop prices

The 2004 Zambia Rural Income and Livelihoods Survey reports crop yields and crop specific revenues from which it is possible to derive crop market prices. However, this information is insufficient to derive a measure of price variability, which is required to compute Ω_j as defined in equation 6 above.

Therefore, time series data on crop prices for maize, millet, cassava, beans, sorghum, and groundnuts at the province level were obtained from the CSO (Central Statistical Office, 2014) for the period 1994 to 2012. Within each province, prices were reported for major market towns and/or districts. Province wide crop prices in a given year are computed as the simple arithmetic average of the crop prices from the three major towns or districts in each of the Zambian nine provinces that existed prior to 2011[3]. These data are used to compute alternative estimates of price volatility for each crop, including simple "raw" estimates of crop price standard deviations computed using nominal prices and standard deviations estimates based on de-trended prices. The assumption is that, even though some prices included in the estimates of standard deviations are observed after the cross-sectional household sample was collected in 2004, the volatility reflected in those prices reflects the crop price data generating process extant in 2004[4].

Crop Yields

The 2004 national smallholder survey reports household yields for each crop only for the 2003-2004 crop year. Estimates of the volatility of crop yields for farms in any given location therefore have to be based on other information. The approach we follow is to combine information on weather variables, and soil type at the district level to generate yield distributions for each crop using the Decision Support

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[3] In 2011, provincial boundaries were redefined and ten provinces were established.

[4] We estimated alternative land use models using several different measures of price volatility, including estimates based on deviations from in sample price predictions obtained from linear and semi-log models in which prices are a function of time. However, results are reported only for models that use estimates of the simple standard deviations of crop prices. The signs of the parameter estimates did not vary across alternative measure of price volatility, but models utilizing simple standard deviations as measures of price volatility were consistently preferred when log-likelihood values were compared across models.

System for Agrotechnology Transfer (DSSAT). Specifically, we directly modeled the following crops under rainfed conditions: beans, cassava, groundnuts, maize, millet, and sorghum.

Crop yields are obtained using historical daily weather in DSSAT. A representation of future weather under the climate of the mid-twenty-first century was constructed by applying climate change patterns extracted from MIROC-ESM-CHEM under RCP 8.5 (Wantanabe, et al., 2011) to the historical daily weather.

Weather and climate

The baseline weather data used to represent the situation in 2004 consist of historical climate information reconstructed by the NCEP model covering the years 1950-2010 (Kalnay et al., 1996). The daily precipitation values were refined to match the data gathered by the GPCC project at the monthly level, since they are believed to be more reliable (Schneider, et al., 2011; Schneider, et al., 2013; Rudolf, et al., 2005; Rudolf and Schneider, 2005; Rudolf, et al. 1994; Rudolf, et al. 2003; Back, Grieser, and Rudolf, 2005). Future climate (in the middle of the century) is obtained using an adjusted version of the historical weather. First, raw climate change data were obtained from the Potsdam Climate Institute (PIK). In those data, the daily raw GCM outputs were spatially resampled to a half-arc-degree grid and then debiased to match appropriate historical benchmarks (Hempel, Frieler, Warszawski, Schewe, and Piontek, F., 2013; Piani, Haerter, and Coppola, 2010.; Müller and Robertson, 2014; Weedon, et al, 2011).

Production Cost data

As discussed above, the household survey provides limited information about crop-specific production costs. The survey reports district-level wages and unit cost of fertilizer but other factors that influence production costs are nor reported in the household survey (for example, field operations like sowing, harvesting, processing, transportation and the use of other chemical inputs like pesticides). Therefore, we include elevation in our data set (using the GLOBE 1km dataset, National Geophysical Data Center, 1999) and a cost-of-access measure based on time to the nearest city of 20,000 people (Nelson, 2008).

A complete list of variables and variable definitions together with data on sample means, ranges, and (where relevant) standard deviations for each variable is presented in Table 2.

Table 2: Variable Sample Means, Ranges and Other Descriptive Statistics

	Mean	Std.Deviation	Notes
Precipitation	1,042.83	274.52	Millimeters
Precipitation inner quartile range	14.93	17.48	Millimeters
Temperature	178.80	21.71	Degree Celsius
Temperature innerquartile range	16.66	12.71	Degree Celsius
Cost of access	5.90	0.51	ln(Travel time in minutes)
Cost of access innerquartile range	1.03	0.27	ln(Travel time in minutes)
Elevation	1,066.98	258.52	Meters
Elevation innerquartile range	206.27	161.32	Meters
Revenue maize	318,624.0	15,509.20	Kwacha ha^{-1}
Revenue millet	279,297.5	27,552.66	Kwacha ha^{-1}
Revenue sorghum	180,277.2	11,029.49	Kwacha ha^{-1}
Revenue cassava	139,837.9	77,470.27	Kwacha ha^{-1}
Revenue groundnuts	736,941.5	26,579.24	Kwacha ha^{-1}
Revenue beans	509,114.6	11,868.22	Kwacha ha^{-1}
Maize net-revenue variability	77.81	10.29	
Millet net-revenue variability	29.84	14.27	
Sorghum net-revenue variability	24.38	13.88	
Cassava net-revenue variability	17.79	9.44	
Groundnuts net-revenue variability	97.86	67.37	
Beans net-revenue variability	82.72	55.84	
Off-farm cost of labor	40.59	8.14	Off-farm payments for one day's work in Kwacha day^{-1}
Fertilizers price	1,859.52	214.24	Kwacha $kilogram^{-1}$
Farm size	2.37	2.80	Hectares
Education level of head of household	5.27	3.91	Years

Gender head of household	0.22	0.42	Dummy variable (1 = female)
Value of assets	43.46	277.19	Kwacha
Number of head of livestock	2.52	13.88	

Estimation Models and Estimation Results

We estimate several alternative discrete choice land use models. Parameter estimates are reported in Table 4 andTable 3 for four models that are representative of the results we obtain[5]. The first is a multinomial logit model that imposes the IIA (independence of irrelevant alternatives) assumption which implies that error terms for the equations explaining all choices are uncorrelated with one another. The multinomial logit includes all the variables used in the nested logit model that performs best according to a likelihood ratio test, including the variables that account for the variability of crop revenues. The second is a nested logit model (as described in figure 1) that relaxes the IIA assumption and includes the same set of explanatory variables as the multinomial logit. Likelihood ratio tests indicated that a nested logit model is preferred to a multinomial model.

The third and fourth empirical models are estimated to examine whether the inclusion of a range of explanatory variables is warranted. Model three is a nested logit model that excludes explanatory variables that account for risk but otherwise has an identical set of explanatory variables. Finally, model four is also a nested logit but omits temperature and rainfall, two of the explanatory variables that attempt to control for production costs.[6]

Log-likelihood ratio tests indicate that that a nested logit model that includes the risk related variables and the variables to control for costs of production is to be preferred to the others. In all nested logit

[6] Yields capture the productivity effects of temperature and rainfall but our insights into production costs are very limited and the use of temperature and precipitation in the set of explanatory variables can potentially help in controlling for the field operation costs that are affected by weather conditions.

models, other variables generally have the same signs. One difference is that in the model that includes the risk related variables, more of the parameter estimates for crop price variables are statistically significant, while retaining the same signs which accord with prior expectations.

An increase in the volatility of net revenues for a crop is expected to reduce the amount of land allocated to that crop, other things being equal. The signs of the estimated parameters corresponding to the risk related variables included in both the nested logit and the multinomial logit model are as expected (that is, negative, which indicates that an increase in risk decreases the attractiveness of that crop or nest being chosen) with one exception (the risk related variable for maize in the multinomial logit model and in the nested logit without controls for costs). In the nested logit model, the estimated risk related variable parameters are also statistically significant for all crops except maize and cassava.

The results also indicate that including farm size as a determinant of land allocation in crop share models may be important. The parameter estimates for farm size in the nested logit model suggest that as farm size increases, a greater share of available farm-land is allocated to group-one crops. That group includes maize and the “others” category. The nested logit model, however, cannot indicate whether within that group, a larger share of land is being allocated to both maize and the “others” category or only one of the two land uses. The parameter estimates for farm size in the multinomial logit suggest the increased share of land allocated to group one crops will be concentrated on the “others” crops. All farm size parameter estimates are negative, indicating that all crops become less attractive than reference category crops (“others”) as farm area increases. It is useful to remember that the “others” category includes two cash crops, sugarcane and cotton, along with fallow which suggests that at the farm householder level larger land holdings may lead to crop diversification and risk management.

Among the household demographic variables included in the nested logit model, gender and education levels appear to affect land allocation decisions. Households headed by women tend to allocate less land to group 2 crops, which include cassava, millet and sorghum, and more land to group 1 crops (maize and "others") and group 3 crops (beans and groundnuts) which are protein crops[7]. Farms with more well educated heads of household also allocate less land to group 2 crops. The off farm wage variable (wage) also has a similar effect; higher off farm wages reduce the amount of land allocated to group 2 crops. Households with more assets also are likely to allocate less land to group 2 crops and more land to group 1 and 3 crops. Parameter estimates also suggest that higher fertilizer prices reduce the amount of land allocated to group 1 crops (which include maize) and increase the amount of land allocated to crops in the other two groups.

The results also indicate that as average rainfall increases and the interquartile range for rainfall increases, land is reallocated from the "others" category to maize, millet, cassava, sorghum, groundnuts and beans. As average temperatures and the interquartile of temperatures increase, land is reallocated to the "others" category from maize, millet, cassava, sorghum, groundnuts and beans. Similar results are obtained with respect to average elevation within a district and its interquartile range. These results are as expected.

Table 3: Parameter estimates for the Multinomial Logit model specification

Labor Costs	**Multinomial Logit (reference category "Others")**
Maize	0.008621
Millet	0.007941
Cassava	-0.022497***
Sorghum	0.006618
Groundnuts	0.026739***

[7] This result is consistent with anecdotal evidence, also observed in the field by the authors, that traditionally and culturally men favor the production of maize while women allocate the land they control to vegetables and legumes.

Beans	-0.004750
Fertilizer Price	
Maize	-0.00063
Millet	0.002347*
Cassava	0.003558***
Sorghum	0.000571
Groundnuts	-4.12E-05
Beans	-0.00014
Farm Size	
Maize	-0.148493***
Millet	-0.181044***
Cassava	-0.301199***
Sorghum	-0.282901***
Groundnuts	-0.132275***
Beans	-0.096306**
Education	
Maize	0.031215***
Millet	-0.035080
Cassava	-0.020642
Sorghum	-0.005389
Groundnuts	0.021020
Beans	0.021693
Female Head HH	
Maize	-0.042397
Millet	-0.359645
Cassava	-0.275900
Sorghum	0.166792**
Groundnuts	0.180988
Beans	0.058495
Assets	
Maize	0.000345**
Millet	-0.005625
Cassava	-0.001648
Sorghum	0.000140
Groundnuts	0.000270
Beans	0.000228
Livestock	
Maize	0.004754
Millet	0.009663

Cassava	-0.005019
Sorghum	-0.003508
Groundnuts	0.006654
Beans	0.005100
Rain Median	
Maize	0.000666***
Millet	-0.00074
Cassava	-0.00104***
Sorghum	-0.00112
Groundnuts	0.000202
Beans	-0.00018
Rain Inner Quartile Spread	
Maize	-0.00111*
Millet	-0.00256*
Cassava	0.003104***
Sorghum	-0.00313
Groundnuts	0.001205
Beans	0.004935***
Temp. Median	
Maize	-0.02534***
Millet	0.008999***
Cassava	-0.00175
Sorghum	-0.02326
Groundnuts	0.009665
Beans	-0.01737
Temp. Inner Quartile Spread	
Maize	-0.00164
Millet	0.036019**
Cassava	-0.0475***
Sorghum	0.032948**
Groundnuts	-0.01572
Beans	-0.00379
Elevation median	
Maize	-0.00273***
Millet	-0.00164
Cassava	-0.000609
Sorghum	-0.00069
Groundnuts	0.000869
Beans	-0.00394**
Elevation Inner Quartile	
Maize	-0.00266***
Millet	0.00378

Cassava	-0.00385***
Sorghum	-0.00073
Groundnuts	-0.0006
Beans	-0.000966
Distance median	
Maize	-0.168221*
Millet	-0.906247***
Cassava	-0.900635***
Sorghum	-1.3278
Groundnuts	-0.07486
Beans	-0.121728
Distance Inner Quartile	
Maize	0.217916
Millet	1.14634**
Cassava	-0.98228***
Sorghum	2.17095***
Groundnuts	1.1487
Beans	0.421764
Revenue	
Maize	0.000344*
Millet	0.000046**
Cassava	-0.000437
Sorghum	0.000202
Groundnuts	0.000049*
Beans	0.000124
Revenue Volatility	
Maize	0.000620
Millet	-0.001041*
Cassava	-0.003579**
Sorghum	-0.000391
Groundnuts	-0.000051*
Beans	-0.000134
Log-Likelihood	- 5594.625

Table 4: Parameter estimates for three Nested Logit model specifications

	Nested Logit with risk and controls for costs	**Nested Logit with controls for costs but without risk variables**	**Nested Logit without controls for costs but with risk**
Upper Nest (reference category: Group 1, maize and "others")			
Labor Costs			

Group 2	-0.024275***	-0.024275**	-0.036283***
Group 3	0.009777 *	0.009777 **	0.0123783
Fertilizer Price			
Group 2	0.000269	0.000269	0.000880***
Group 3	-0.001204 ***	-0.001204 ***	9.23E-05
Farm Size			
Group 2	-0.153443 ***	-0.153443 ***	-0.193421***
Group 3	-0.053611 **	-0.053611 **	-0.042722*
Education			
Group 2	-0.030827 ***	-0.030827 **	-0.030349**
Group 3	0.003266	0.003266	0.008858
Female Head HH			
Group 2	-0.213764 **	-0.213764 **	-0.160669
Group 3	0.135199	0.135199	0.201159
Assets			
Group 2	-0.005579 ***	-0.005579 ***	-0.002226***
Group 3	-9.66E-05	-9.66E-05	3.12E-05
Livestock			
Group 2	-0.019909***	-0.019909**	-0.003442
Group 3	-0.002386	-0.002384	0.001011
Lower Nest (reference category: "others")			
Rain median			
Maize	0.000655***	0.000582***	-
Millet	0.049750**	0.041326	-
Cassava	0.052387***	0.044157	-
Sorghum	0.047599**	0.039569	-
Groundnuts	0.008927**	0.001237***	-
Beans	0.007999***	0.000244*	-
Rain Inner Quartile Spread			
Maize	0.000593*	0.000733**	-
Millet	0.070298***	0.069502	-
Cassava	0.076341	0.075912	-
Sorghum	0.068161*	0.068089*	-
Groundnuts	0.008032	0.001062	-
Beans	0.014539**	0.002112*	-
Temp. median			
Maize	-0.021756***	-0.021994***	-
Millet	-0.873497	-0.799480	-
Cassava	-0.882187	-0.803358	-
Sorghum	-0.922685*	-0.840691	-

Groundnuts	-0.146151*	-0.022175**	-
Beans	-0.169935***	-0.031379***	-
Temp. Inner Quartile Spread			
Maize	-0.016554***	-0.018140***	-
Millet	-0.388266	-0.297328	-
Cassava	-0.406741	-0.331363	-
Sorghum	-0.412721	-0.330990	-
Groundnuts	-0.100938	-0.016730	-
Beans	-0.110131*	-0.005679	-
Elevation median			
Maize	-0.003076 ***	-0.002881 ***	-0.000819***
Millet	0.005670***	0.005601	0.005123**
Cassava	0.003817**	0.003860	0.002545
Sorghum	0.000768**	0.000783	0.003268
Groundnuts	0.000327 *	0.000269	-0.000841
Beans	0.005765 ***	0.006693	0.005183
Elevation Inner Quartile			
Maize	-0.000241 ***	-0.000203 **	-0.001250**
Millet	0.002633	0.000271	0.004660
Cassava	-0.000646 *	-0.001435 *	0.000606
Sorghum	-0.001234	-0.001373	0.001099
Groundnuts	0.001106	0.001151	-7.80E-05
Beans	0.001096 **	0.001340	0.002577*
Distance median			
Maize	0.167631	0.117253 *	-0.067982
Millet	0.908551 *	0.498201	0.824505
Cassava	0.700175	0.749880	0.407358**
Sorghum	1.375820 *	1.377460	1.383040
Groundnuts	-0.272172 *	-0.287786	-0.391187
Beans	-0.085024	0.047049	-0.253748
Distance Inner Quartile			
Maize	0.491206 ***	0.428927 **	0.478249*
Millet	0.872536	0.425615	-0.542959
Cassava	0.525384	0.579727	-0.317602
Sorghum	0.891878	0.921008	1.402770
Groundnuts	-1.242590 **	-1.211640 **	-1.156690*
Beans	-0.364122 **	-0.491562 **	-0.659957
Revenue			
Maize	0.000159	0.000009***	-0.000364

Millet	0.000352 **	0.000052	0.000035**
Cassava	0.000209	-0.000074	0.001106**
Sorghum	0.000518 ***	0.000499	0.000100
Groundnuts	0.000240 ***	0.000240**	0.000002
Beans	0.000338 *	0.000468*	0.000120
Revenue Volatility			
Maize	-0.000579	-	0.001097
Millet	-0.001397 ***	-	-0.001641**
Cassava	-0.002660	-	-0.002614***
Sorghum	-0.000075 **	-	-0.000061
Groundnuts	-0.000013 ***	-	-0.000089*
Beans	-0.000165 *	-	-0.000274**
Inclusive Value Parameters			
Group 1	3.6996***	1.1381***	0.868592
Group 2	0.0946	0.8456	0.883843
Group 3	0.6812**	1.1457**	0.990369
Log-Likelihood	- 5591.242	- 5602.246	-5690.143

Simulation Results

Overall effects of climate change on farm-land allocations and country production

The same comparative statics approach can be used to simulate the cumulative, country-level effects of climate change on land allocations by aggregating the decisions made at the farm-level in response to changes in temperatures, precipitation, yield and yield variability projected for 2050. Prices and price volatility are kept constant at the 2004 level, implicitly assuming that climate change will not have an appreciable effect on relative crop prices and that future price variability remains the same as the one historically recorded. Furthermore, because of the limitation of the nested logit modeling approach, we simulate farm household responses in terms of farmland shares as represented in the 2004 household survey. Thus, the simulation results reported in this study should not be interpreted as a forecast of what farms in Zambia will look like in 2050. These findings, however, are directly relevant to our understanding of the effects of climate-induced changes in yield volatility and the role of risk in relation to those impacts.

Table 5 reports average temperatures and precipitations in Zambia for the two time periods. As discussed above, changes in growing conditions also affect yields and the variability of net crop revenues through changes in yield variability. Changes in yields and the variability of net revenues for each crop are also reported in Table 5. Growing conditions deteriorate for all crops but lower rainfall and higher temperatures have different plant growth impacts for each crop. Thus different climate change impacts on crop specific yield distributions result in different relative effects for crop specific net revenue variability. Net revenues become more variable for maize, millet, groundnuts, and beans but less variable for cassava and sorghum. Yields of all crops are negatively affected except for sorghum which is projected to experience an increase in yields by 10%.

Table 5: Changes in average rainfall, temperature and net revenue variability induced by climate change

	Climate		Average Net Revenue Variability						Average Yields					
Year	**Average Rainfall (mm)**	**Average Temperature (°C)**	**Maize**	**Millet**	**Sorghum**	**Cassava**	**Groundnuts**	**Beans**	**Maize (Kg Ha^{-1})**	**Millet (Kg Ha^{-1})**	**Sorghum (Kg Ha^{-1})**	**Cassava (Kg Ha^{-1})**	**Groundnuts (Kg Ha^{-1})**	**Beans (Kg Ha^{-1})**
2005	1042.8	14.9	77.8	29.8	24.4	17.8	97.9	82.7	1,558.8	3,289.1	753.3	5,195.8	5,952.7	1,674.0
2050	961.8	17.7	89.8	31.0	19.7	13.7	110.3	101.0	1,452.7	3,101.6	842.1	4,936.8	5,732.8	1,549.3
Change	**-74.6**	**+2.8**	**+13%**	**+4%**	**-16%**	**-18%**	**+11%**	**+19%**	**-7.3%**	**-6.0%**	**+10.6%**	**-5.2%**	**-3.8%**	**-8.1%**

Table 6 provides information on the average change in land allocations among crops at the farm household level for the sample of 5319 farms included in the 2004 CSO household survey caused by the shift to 2050 climate conditions. In the sample, average farm size is approximately one and a half hectares and at the farm level the projected average changes in land use are relatively small. The most important change appears to be a transition away from maize in favor of all other crops, particularly cassava. For maize the median change is a reduction of 0.33 hectares and for cassava an increase of 0.15 hectares.

Table 6: Projected farm-area changes caused by changing climatic conditions

Crop	Maize	Millet	Sorghum	Cassava	Beans	Groundnuts	Other
Median (Ha)	-0.33	0.06	0.00	0.15	0.02	0.00	-0.01
Upper and lower quartiles of predicted changes in planted area	1.29 / - 0.67	1.01 / 0.02	1.10 / - 0.02	6.71 / 0.05	1.34 / - 0.02	12.67 / - 0.01	7.64 / - 0.15

To understand the regional and country wide impacts of the relatively small land reallocations that occur at the farm level, those household level effects are combined with the biophysical characteristics of the locations where the land use changes are taking place. The cultivation of a given crop seems likely to shift toward areas where growing conditions become more favorable as climate conditions change. These locational shifts in the production of a crop may be important for total country wide production and are driven by the relative changes in growing conditions vis a vis local biophysical characteristics.

To evaluate climate change impacts on crop production at the country level, we aggregate projected household level decisions and, for each province,[8] calculate the changes in shares allocated to each

[8] It is worth recalling that the household survey is statistically significant at the provincial level.

crop. Total output effects are computed using the projected provincial shares and DSSAT-derived changes in yields given 2050 climate conditions.

Results are reported in Figure 2 where baseline production (Baseline – 2004 Yields), production under the 2050 climate but no changes in land allocations (Baseline – 2050 Yields) and production under the 2050 climate compounded with shifting land allocations (2050 Yields and Full Volatility) are displayed. At the national level, deteriorating growing conditions lead to a significant reduction in output of most crops even without changes in land allocations. These reductions are exacerbated by farmers' responses in the case of maize (output is reduced by approximately 380 million tons dry matter per year[9]) and beans (output decreases by 36 million tons per year). These losses are compensated by increases in the output of sorghum (16 million tons per year), millet (37 million tons per year), cassava (125 million tons per year), and groundnuts (104 million tons per year) when land use reallocations are simulated. Interestingly, since changing climate conditions induce a reduction in yields for groundnuts and millet but the average effect on land allocations are effectively zero (Table 6), the increase in total output is due to increases in productivity for these crops at the locations to which production has shifted. The net effect of land reallocation is a reduction in total dry-matter yearly output of 137 million tons compared to the 2004 baseline but an increase of some 190 million tons compared to production if land allocations had not changed.

We can obtain insights about the effects of farmers' responses to increased risk by comparing the simulated land allocation using the model that accounts for the volatility in net revenues with the simulated land allocation impacts using the same model when yield volatility is reduced to zero leaving

[9] We report dry matter values to be consistent with the crop models output and reduce the possibility of errors in properly accounting for moisture content.

price volatility unchanged (displayed in Figure 2 as 2050 Yields; Yield Volatility Reduced). While this is an admittedly unrealistic scenario, it provides an upper-bound for the effect of reducing yield volatility[10].

Land still transitions away from maize but the transition is mitigated when risk is reduced. In addition, instead of a significant increase in cassava production, cassava production actually declines. Under 2050 climate conditions, reducing net crop revenue volatility as a result of setting yield variance to zero leads to an increase in production of millet, sorghum, and groundnuts. However, cassava and bean production decrease. In this simulation, land reallocations lead to an increase in annual total dry-matter production, aggregated across all crops, of 40 million tons. These results indicate the potentially important benefits of mitigating the effects of climate change on crop yield distributions. It is important to note that the projections with reduced volatility (2050 Yields; Yield Volatility Reduced) are qualitatively similar to those obtained using a model specification that does not account for net revenue volatility and does not include the risk variables like the one reported in Table 4[11]. This provides an indication of the potentially significant errors that could occur if the risk effects of climate change on land allocation decisions were not taken into account.

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[10] Many possible alternative scenarios can be constructed in which volatility (in net-revenues, or in prices) can be reduced in total or by a fraction. Some of these were explored but not reported because they do not change qualitatively the results and do not provide additional general insights.

[11] The nested logit model that does not include the net revenue variability explanatory variables returns different parameter estimates and differs from the others in its estimation of the effects of temperatures and precipitations on land allocations (

Table 4). We explored the crop production outcomes using this model. While there are some differences in the magnitude of the projected changes, they are qualitatively similar to the model that reduces yield volatility to 0.

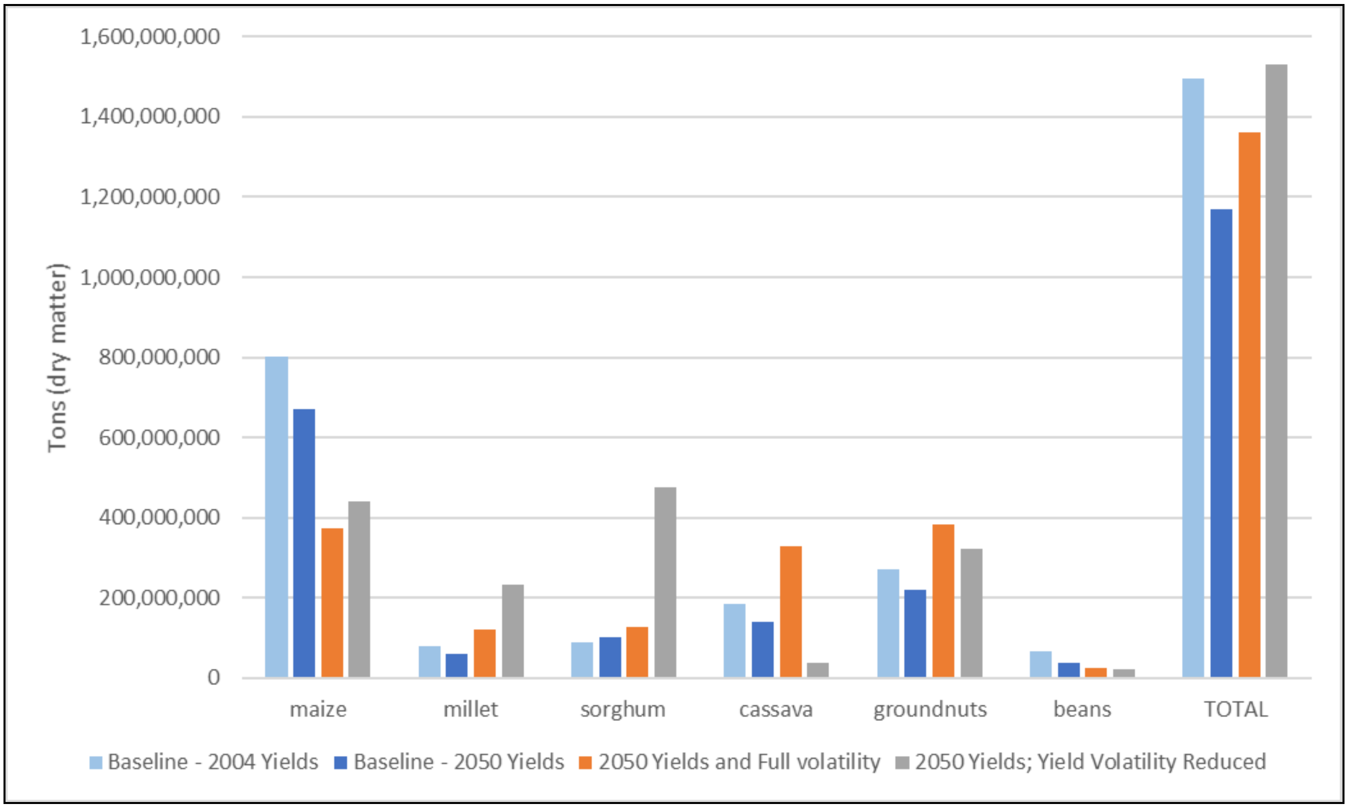

Figure 2: Comparison of projected future production with no land use change and with land use change and full and reduced yield volatility (ignoring moisture)

Conclusions

It is well known that price and yield volatility and more generally risk matter in farmers' decisions and many studies have evaluated the effects of risk on decision processes at the farm level. Here we have examined some of the potential effects that climate change may have on farm-land allocations by taking into account farmers' risk and risk-avoidance preferences. Further, this study examines the aggregate country wide effects of individual farmers' decisions and the potential implication for total production and nutrient availability under the 2050 climate regime.

While the results of this study should not be interpreted as explicit forecasts of what production and land use will look like in Zambia in 2050, they demonstrate that climate change impacts on the risk environment in which farmers operate have substantial and quantitatively important effects on their production decisions.

The empirical results confirm our expectations about the likely strategies to be followed by farmers to mitigate the additional risks caused by climate change. Farmers shift land from higher-risk crops toward lower-risk crops. In Zambia, this shift is away from maize production towards cassava, millet, sorghum and groundnuts whose "riskiness" appears to decrease relative to maize in the 2050 climate regime.

The findings also indicate that farm size could play a potentially important role in climate change related risk management. Larger farms seem to be able to allocate more land to cash crops like sugar cane, cotton, and vegetables and therefore take advantage of multiple markets (e.g. cash crops like sugar cane and cotton). Also, they can devote more land to fallow, a practice that restore soil fertility and improve soil water retention.

The yearly cumulative country wide output of the crops included in the analysis, measured in dry matter, is estimated to decrease by 137 million tons, mainly because of the projected decrease in maize production.

This result highlights the importance of accounting for the cumulative effects of individual decisions vis a vis the spatial characteristics of the location where production takes place. The simulations based on reducing crop yield volatility also provide insights about the opportunity costs of farmers' choices driven by their risk-averse behavior. The results indicate that there may be substantial overall benefits from innovations in crop varieties that reduce yield volatility and increase crop resilience to adverse, climate change induced growing conditions. Policies directed to those objectives, such as improved varieties, new agronomic practices and technologies, effective public investments in irrigation and flood control systems, may also generate substantial social returns.

Farmers’ actual responses to climate change are likely to evolve over time as crop growing conditions change incrementally from one year to the next and deteriorate at certain locations and for certain crops. Therefore, policy-makers at both the global and country level have the opportunity to develop responses the enable agricultural producers to mitigate these impacts. These responses include facilitating the development and introduction of new production technologies and varieties, and the use of information and communication technologies that provide timely and accurate weather forecasts and input/output price information. All these options require that policy-makers be aware and understand the importance of managing the new and exacerbated risks brought about by climate change.

References

Aloafe, H, I. Kohler, D.Taren, M.J. Mofu, J. Chileshe, and N. Kalungwana. 2014. Zambia Food Consumption and Micronutrient Status Survey Report. National Food and Nutrition Commission, Lusaka, Zambia.

Aregheore, E.M. 2009. Zambia country pasture/forage resource profiles. Food and Agriculture Organization.

Baron, D. P. (1970). Price uncertainty, utility, and industry equilibrium in pure competition, International Economic Review 11(3): 463–480.

Beck, C., J. Grieser and B. Rudolf (2005): A New Monthly Precipitation Climatology for the Global Land Areas for the Period 1951 to 2000. DWD, Klimastatusbericht KSB 2004, ISSN 1437-7691, ISSN 1616-5063 (Internet), ISBN 3-88148-402-7, 181-190.

Berry, S. (1994): “Estimating Discrete Choice Models of Product Differentiation,” RAND Journal of Economics, 25, 242–262

Carpentier, A., Letort, E., 2013 Multicrop Production Models with Multinomial Logit Acreage Shares. Environ Resource Econ 59:537–559

Chambers R, Just R., 1989. Estimating multiouput technologies. Am J Agr Econ 71(4):980–995

Chapoto, A., Haggblade, S., Hichaambwa, M., Kabwe, S., Longabaugh, S., Sitko, N. and D. Tschirley. 2012. Agricultural Transformation in Zambia: Alternative Institutional Models for Accelerating Agricultural

Productivity Growth and Commercialization. Working Paper, 64. Indaba Agricultural Policy Research Institute (IAPRI), Lusaka.

Chavas J-P, Holt T (1990) Acreage decisions under risk: the case of corn and soybeans. Amer J Agr Econ 72(2):529–538

Chavas, J-P, and M. T. Holt (1996). " Economic Behavior under Uncertainty: A Joint Analysis of Risk Preferences and Technology." The Review of Economics and Statistics, 78: 329-335.

Dorosh, P.A., S. Dradri and S. Haggblade. 2009. Regional trade, government policy and food security. Food Policy 34, 350-366.

FAO. 2016. Zambia Economic Indicators. FAOSTAT. Available at: http://faostat.fao.org/CountryProfiles/Country_Profile/Direct.aspx?lang=en&area=251

FAO. 2016. The state of food and agriculture. Climate change, Agriculture and Food Security. Rome. Accessed January 10 2018. Available at: http://www.fao.org/publications/sofa/2016/en/

Fanzo, J., McLaren, R., Davis, C., Choufani, J.. 2017. Climate change and variability: What are the risks for nutrition, diets, and food systems? IFPRI Discussion Paper Series. Accessed January 10 2018. Available at: http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/131228

Fezzi C, Bateman IJ (2011) Structural agricultural land use modelling for spatial agro-environmental policy analysis. Am J Agr Econ 93(4):1168–1188

Finkelshtain, I. and J. A. Chalfant. (1991). "Marketed surplus under risk: Do peasants agree with Sandmo?" American Journal of Agricultural Economics 73: 557-67

Govereh, J., Jayne, T., Mason, N. and A. Chapoto. 2006. Trends in agricultural and poverty indicators in Zambia. Strategic analysis and knowledge support system for Southern Africa (SAKSS-SA) Policy Brief, 1.

Govereh, J., Jayne, T.S. and A. Chapoto. 2008. Assessment of Alternative Maize Trade and Marketing Policy Interventions in Zambia. Working Paper No. 33, Food Security Research Project, Lusaka.

Greene, W. H. 2003. Econometric analysis. 5th ed. Upper Saddle River, NJ: Prentice Hall

Hansen, J., Sato, M., Kharecha, P., Beerling, D., Masson-Delmotte, V., Pagani, M., Raymo, M., Royer, D.L., Zachos, J.C., 2008 Target Atmospheric CO2: Where Should Humanity Aim?. Open Atmos. Sci. J. 2, 217-231.

Harrison, G. W., S. J. Humphrey, and A. Verschoor (2010). "Choice under Uncertainty: Evidence from Ethiopia, India and Uganda." Economic Journal, 120 (March): 80-104.

Hatfield, J.L. and Prueger, J.H. 2015. Temperature extremes: effect on plant growth and development. Weather and Climate Extremes, 10(Part A), 4-10.

Hempel, S., Frieler, K., Warszawski, L., Schewe, J., Piontek, F., 2013. A trend preserving bias correction: The ISI-MIP approach. Earth Syst.Dyn. Discuss. 4, 49-92. (newer version: http://www.earth-syst-dynam.net/4/219/2013/esd-4-219-2013.html)

Henson, R. 2011. Warming World: Impact by Degree. National Research Council, Washington DC.

Hurkman, W.J.; Vensel, W.H.; Tanaka, C.K.; Whitehand, L.; Altenbach, S.B. Effect of high temperature on albumin and globulin accumulation in the endosperm proteome of the developing wheat grain. J. Cereal Sci. 2009, 49, 12–23.

IPCC, 2012: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 582 pp.

IPCC, 2014: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1132 pp.

Jain, Suman. 2007. An empirical economic assessment of impacts of climate change on agriculture in Zambia. Policy Research working paper ; no. WPS 4291. Washington, DC: World Bank.

Jayne, T.S., Govereh, J., Chilonda, P., Mason, N., Chapoto, A. and H. Haantuba. 2007. Trends in agricultural and rural development indicators in Zambia. ReSAKSS Working Paper No. 2, Food Security Research Project, Lusaka.

Jones PG, Thornton PK. 2008. Croppers to livestock keepers: livelihood transitions to 2050 in Africa due to climate change. Environmental Science & Policy 12(4):427–437

Jones, J. W., Hoogenboom, G. Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., Ritchie, J. T., 2003. “The DSSAT Cropping System Model.” Eur. J. Agron. 18, 235–265.

Kaminski J, Kan I, Fleischer A (2013) A structural land-use analysis of agricultural adaptation to climate change: a proactive approach. Am J Agr Econ 95(1):70–93.

Kalnay et al. (1996). The NCEP/NCAR 40-year reanalysis project, Bull. Amer. Meteor. Soc., 77, 437-470, 1996.

Kumar, N., Harris, J., Rawatet, R., 2015. If they grow it, will they eat and grow? Evidence from Zambia on agricultural diversity and child undernutrition Journal of Development Studies, 51: 1060-1077

Lobell D. B., Field C. B. 2007 Global scale climate–crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2, 1–7.

Livingston M, Roberts MJ, Rust J (2008) Optimal corn and soybean rotations. Paper presented at the AAEA annual meeting, Orlando, Florida, 27–29 July

Mason, M.N., T.S. Jayne & R. Mofya-Mukuka. (2013). Zambia's input subsidy program. Agricultural Economics 44, 613-628.

Marenya, P., V. H. Smith and E. Nkoyna. (2014). " Relative Preferences for Soil Conservation Incentives among Small Holder Farmers: Evidence from Malawi." American Journal of Agricultural Economics, 96(3): 690-710.

Miller, D.J. and A.J. Plantinga, (1999). Modeling Land Use Decisions with Aggregate Data, American Journal of Agricultural Economics, 81, (1), 180-194

Monteith, J.L. 1981. Evaporation and Surface Temperature. Q. J. Roy. Meteor. Soc. 107. 1-27

MooreMR, NegriDH(1992)Amulticrop productionmodel of irrigated agriculture, applied towater allocation policy of the Bureau of reclamation. J Agr Res Econ 17:29–43

Mwala, M. & D. Gisselquist. 2012. Private-Sector Agricultural Research and Innovation in Zambia Overview, Impact, and Policy Options. Agricultural Science and Technology Indicators, International Food Policy Research Institute. Available at: http://www.asti.cgiar.org/pdf/private-sector/Zambia-PS-Report.pdf

Müller, Christoph, and Richard D. Robertson, 2014. Projecting future crop productivity for global economic modeling. Agricultural Economics 45: 37-50.

Myers, SS, Zanobetti, A, Kloog, I et al. 2014. Increasing CO2 threatens human nutrition. Nature; 510: 139–142.

National Geophysical Data Center, 1999. Global Land One-kilometer Base Elevation (GLOBE) v.1. Hastings, D. and P.K. Dunbar. National Geophysical Data Center, NOAA.

National Research Council. 2011. Climate Stabilization Targets: Emissions, Concentrations, and Impacts over Decades to Millennia. Washington, DC: National Academies Press.

Nelson A (2008) Global 1 km accessibility (CostDistance) model using publicly available data. World Bank, Washington, DC.

Oude Lansink A, Peerlings J (1996) Farm-specific impacts of quantitative restrictions of N-fertiliser use in Dutch arable farming. J Agr Econ 52:38–52

Piani, C., Haerter, J.O., Coppola, E., 2010. Statistical bias correction for daily precipitation in regional climate models over Europe. Theoret. Appl. Climatol. 99, 187-192.

Power S, Casey T, Folland C, Colman A, Mehta V (1999) Interdecadal modulation of the impact of ENSO on Australia. Clim Dyn 15:219–324

Rudolf, B., C. Beck, J. Grieser, U. Schneider (2005): Global Precipitation Analysis Products. Global Precipitation Climatology Centre (GPCC), DWD, Internet publication, 1-8

Rudolf, B., U. Schneider (2005): Calculation of Gridded Precipitation Data for the Global Land-Surface using in-situ Gauge Observations, Proceedings of the 2nd Workshop of the International Precipitation Working Group IPWG, Monterey October 2004, EUMETSAT, ISBN 92-9110-070-6, ISSN 1727-432X, 231-247.

Rudolf, B., H. Hauschild, W. Truth and U. Schneider (1994): Terrestrial Precipitation Analysis: Operational Method and Required Density of Point Measurements. In: Global Precipitations and Climate Change (Ed. M. Desbois, F. Desalmond), NATO ASI Series I, Vol. 26, Springer-Verlag, p. 173-186.

Rudolf, B., T. Fuchs, U. Schneider and A. Meyer-Christoffer (2003): Introduction of the Global Precipitation Climatology Centre (GPCC), Deutscher Wetterdienst, Offenbach a.M.; pp. 16, available on request per email gpcc@dwd.de or by download from GPCC's Website

Saha, A. 1993. Expo-Power Utility: A ‘flexible’ form for absolute and relative risk aversion. Am. J. Agric. Econ. 75:905-13.

Sandmo, A. (1971). On the Theory of the Competitive Firm Under Price Uncertainty, American Economic Review 61, 65-73.

Schneider, Udo; Becker, Andreas; Finger, Peter; Meyer-Christoffer, Anja; Rudolf, Bruno; Ziese, Markus (2011): GPCC Full Data Reanalysis Version 6.0 at 1.0degree: Monthly Land-Surface Precipitation from Rain-Gauges built on GTS-based and Historic Data. DOI: 10.5676/DWD_GPCC/FD_M_V6_100

Schneider, U. et al (2013): GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. Theoretical and Applied Climatology http://dx.doi.org/10.1007/s00704-013-0860-x.

Siegel, P.B. and J. Alwang. 2005. Poverty Reducing Potential of Smallholder Agriculture in Zambia. Africa Region Working Paper Series No. 85. World Bank, Washington, D.C.

Seshamani, V. 1998. The impact of market liberalization on food security in Zambia. Food Policy, 23(6), 539-551.

Sitko, N. J., Chapoto, A., Kabwe, S., Tembo, S., Hichaambwa, M., Lubinda, R., Chiwawa, H., Mataa, M., Heck, S. and D. Nthani. 2011. Technical compendium: Descriptive agricultural statistics and analysis for Zambia in support of the USAID mission’s Feed the Future Strategic Review (No. 104016). Michigan State University, Department of Agricultural, Food, and Resource Economics.

Tanaka, T., C. F. Camerer, and Q. Nguyen (2010). "Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam." American Economic Review, 100 (1): 537-551.

Tanaka, Y., and A. Munro (2013). "Regional Variation in Risk and Time Preferences: Evidence from a Large Scale Field Experiment in Rural Uganda." Journal of African Economics, 23(1): 151-187.

Theil H (1969) A multinomial extension of the linear logit model. Int Econ Rev 10(3):251–259.

Thornton P K, van de Steeg J, Notenbaert A and Herrero M (2009). The impacts of climate change on livestock and livestock systems in developing countries: a review of what we know and what we need to know. Agricultural Systems 101, 113-127.

USDA. 2015. National Nutrient Database for Standard Reference Release 28. United States Department of Agriculture Agricultural Research Service. Available at: https://ndb.nal.usda.gov/ndb/search

Watanabe, S., T. Hajima, K. Sudo, T. Nagashima, T. Takemura, H. Okajima, T. Nozawa, H. Kawase, M. Abe, T. Yokohata, T. Ise, H. Sato, E. Kato, K. Takata, S. Emori, and M. Kawamiya. 2011. "MIROC-ESM 2010: Model Description and Basic Results of CMIP5-20c3m Experiments." Geoscientific Model Development 4 (4): 845–872.

Weedon, G.P., Gomes, S., Viterbo, P., Shuttleworth, W.J., Blyth, E., Oesterle, H., Adam, J.C., Bellouin, N., Boucher, O., Best, M., 2011. Creation of the WATCH forcing data and its use to assess global and regional reference crop evaporation over land during the twentieth century. J. Hydrometeorol. 12, 823-848.

Wik, M., T. W. Kebede, O. Bergland and S.T. Holden (2004). "On the Measurement of Risk Aversion from Experimental Data." Applied Economics, 36: 2443-2451

Wu J, Segerson K (1995) The impact of policies and land characteristics on potential groundwater pollution in Wisconsin. Am J Agr Econ 77(4):1033–1047

Zilberman, and Hochman (1983): Estimation of Multicrop Production Functions. American Journal of Agricultural Economics (65) pp. 770 – 780.

Zulu, B., Jayne, T. S., and Beaver, M. 2006. Smallholder household maize production and marketing behavior in Zambia. Working Paper 17, Food Security Research Project, Lusaka.