Climate volatility and poverty vulnerability in Tanzania

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Abstract

Climate models generally indicate that climate volatility may rise in the future, severely affecting agricultural productivity through greater frequency of yield-diminishing climate extremes, such as droughts. For Tanzania, where agricultural production is sensitive to climate, changes in climate volatility could have significant implications for poverty. This study assesses the vulnerability of Tanzania's population to poverty to changes in climate variability between the late 20th Century and early this century. Future climate scenarios with the largest increases in climate volatility are projected to make Tanzanians increasingly vulnerable to poverty through its impacts on staple grains production, with as many as 90 thousand additional people, representing 0.26 percent of the population, entering poverty in the median case. Extreme poverty- increasing outcomes are also found to be greater in the future under certain climate scenarios. In the 20th Century, the greatest predicted increase in poverty was equal to 880 thousand people, while in the 21st Century, the highest possible poverty increase was equal to 1.17 million people (approximately 3.4 percent of the population). The results suggest that the potential impacts of changes in climate volatility and climate extremes can be significant for poverty in Sub-Saharan African countries like Tanzania.

KEYWORDS: climate, volatility, poverty, vulnerability, Tanzania, GCM

1. INTRODUCTION

There is substantial evidence that the mean and extremes of climate variables have been changing in recent decades, and that rising atmospheric greenhouse gas concentrations could cause those trends to intensify in the coming decades (Diffenbaugh et al, 2005; Easterling et al, 2000; IPCC, 2007). These changes are particularly important for agriculture (Lobell et al, 2008; White et al, 2006; Mendelsohn et al, 2007) and therefore also have critical implications for developing countries, both because the majority of the poor reside in rural areas where farming is the dominant economic activity and also because the poor may spend as much as two-thirds of their income on food (Cranfield et al, 2003).

The importance of agriculture to the poor is particularly true for Tanzania, where agriculture accounts for about half of gross production, and employs about 80 percent of the labor force (Thurlow and Wobst, 2003). Agriculture in Tanzania is also primarily rain-fed, with only two percent of arable land having irrigation facilities – far below the potentially irrigable share (FAO, 2009). Tanzanian yields, especially of staple foods like maize, are particularly susceptible to adverse weather events. This threat has been recognized by policy makers, with Tanzania's National Strategy for Growth and Reduction of Poverty identifying droughts and floods as among the primary threats to agricultural productivity and poverty vulnerability.

There is a substantial literature examining the effects of climate change on food security in developing countries (see review by Dinar et al, 2008). For example, Lobell et al (2008) used statistical models to assess the potential impacts of future changes in the mean climate state on crop production. In addition, Battisti and Naylor (2009) used historical examples to highlight the significant impact that changes in the frequency of heat stress may have on agricultural output. In both cases, analyses of food insecurity are driven by inferred declines in food supply. However, food insecurity and famines are influenced by forces that constrain people's access to food, and not just its availability (Sen, 1981; Schmidhuber and Tubiello, 2007).

One such force is food prices, which have seen considerable volatility in recent years, and which is estimated to have increased poverty by 105 million people during the recent food price crisis of 2005-2008 (Ivanic and Martin, 2008). Recently, Ahmed et al (2009) provide evidence through a cross-country analysis that extreme climate events which reduce agricultural productivity can severely increase poverty in Sub-Saharan African countries. Climate induced changes in agricultural productivity thus may have severe implications for poverty through price and income effects. However, the link between climate variables and agricultural yields in this earlier work was based on simple extrapolation and lacked a tight connection between the two sets of variables.

Understanding the effects of climate volatility on crop production and food prices is thus critical to understanding the potential impacts of future climate change on poverty. However, few studies have focused on the economic effects of changes in the volatility of climate variables and the impacts on the poor. Thus, despite its expected significance for developing countries like Tanzania, the effects of changes in climate volatility on agriculture and development are not well-understood.

This paper thus fills an important gap in the literature by developing a quantitative framework that permits us to examine the vulnerability of Tanzania's population to impoverishment due to interannual climate variability that affects agricultural productivity, both in recent history as well as in the near future[1]. The next section describes the poverty profile of Tanzania, while section 3 provides details of climate volatility and agricultural variability between 1971 and 2031. Section 4 subsequently analyzes Tanzania's poverty vulnerability, while section 5 concludes.

2. POVERTY PROFILE OF TANZANIA

Following the approach of Hertel et al (2004), the population as a whole can be divided into seven distinct strata, reflecting the pattern of household earnings specialization: Agricultural self-employed (more than 95 percent of income from farming), Non-Agricultural (more than 95 percent of income from non-agricultural self-employment), Urban Labor (more than 95 percent of income from wage labor), Rural Labor (more than 95 percent of income from wage labor), Transfer dependent (more than 95 percent of income from transfer payments), Urban Diverse, and Rural Diverse. As determined by the Household Budget Survey 2000/01, there were 12.3 million Tanzanians living below the national poverty line in 2001 (NBS, 2002)[2].

Table 1 reports some key estimates of the structure of poverty in Tanzania, based on Tanzania's national poverty line and the 2001 household survey (NBS, 2002). The rows in this table correspond to the seven strata and are therefore exhaustive of the Tanzanian population. The first column reports the poverty headcount rate in each stratum. This shows that the overall poverty headcount in Tanzania was about 36 percent. The estimated headcount rate was highest in the agriculture-specialized stratum (68 percent), followed by the transfer-dependent households (56 percent), the rural diversified stratum (51 percent) and then rural labor, urban diversified, non-agriculture self-employed and urban labor. Based on these figures, it is not surprising that the agriculture, transfer and rural diversified households all account for a larger share of the total poor in Tanzania (column II) than in the total population (column III). Taken together, the agricultural specialized and rural diversified households account for about 60 percent of total poverty in Tanzania.

Table 1: Socioeconomic Distribution of Tanzania by Earnings Based Stratum (in percent)

Stratum	Stratum Poverty Rate	Share in Total Poverty	Share in Total Population
	I	II	III
Agriculture	68.79	29.95	15.54
Rural Labor	24.15	0.74	1.09
Rural Diversified	51.43	30.34	21.05
Non-Agriculture	23.71	10.02	15.08
Urban Labor	12.24	3.40	9.91
Urban Diversified	23.24	23.44	35.99
Transfers	56.01	2.11	1.35
National	35.68	100.00	100.00

Source: Authors' estimates based on data from NBS (2002)

[1] Henceforth referred to as poverty vulnerability.
[2] The national poverty line is the basic needs poverty line defined in the Household Budget Survey 2000/01 (NBS, 2002), and is TShs 7253 (2001) without correcting for Purchasing Power Parity.

From Thurlow and Wobst (2003), we know that grains are among the most important crops for impoverished Tanzanian households, both from an earnings and a consumption perspective. Volatility in the productivity of the grains sector will thus have different poverty implications for each of the seven strata of Tanzania's poor. For example, a drought will reduce agricultural productivity, and push up food prices. To a first-order approximation, whether a particular household gains or loses real income from this change depends on whether it is a net buyer or seller of the commodity. Higher prices will clearly push up the cost of living at the poverty line for non-agricultural households. However, the degree to which this will occur depends on what happens to the wages earned by these households. Given the labor intensity of agriculture in Tanzania, any shock to agriculture is likely to have an impact on unskilled wages in the economy.

It is thus difficult to ascertain, in the absence of more specific knowledge of the situation, how climate volatility affects poverty, and empirical methods are necessary. For a comprehensive analysis of the poverty implications of prospective climate volatility changes over the course of the 21st Century, we have developed an analytical framework that incorporates climate variables, analyses of crop production, and economy-wide, market equilibria, as described in the following section.

3. CLIMATE VOLATILITY AND AGRICULTURAL PRODUCTIVITY

The analytical framework used in this paper relies on several empirical methods implemented in sequence in order to shed light on the sensitivity of poverty in Tanzania to changing climate volatility. The first step in this process involves understanding how the distributions of key climate variables – temperature and precipitation – are likely to change in the future, and what those changes imply for the distribution of interannual agricultural productivity changes. In this study, we are particularly interested in climate volatility as reflected in the magnitude of year-on-year changes in productivity.

We draw on Phase 3 of the Coupled Model Intercomparison Project (CMIP3) archive of Global Circulation Model (GCM) experiments (Meehl et al, 2005) to obtain Tanzania's nationally averaged precipitation (in mm/day) and temperature (in °C) data by month, for the years between 1971 and 2031. These data are drawn from an ensemble of 22 different GCMs. The period 1971-2001 characterizes the late 20th Century, while the period 2001-2031 characterizes the early 21st Century (under the SRES A2 emissions scenario). These data are aggregated to provide monthly average precipitation and temperature data series over the January-June growing season for grains, which are then recalibrated so that their mean and standard deviations in the historical period match those of the observed data[3].

Several important insights may be obtained by analyzing the bias-corrected growing season temperature and precipitation data for Tanzania between the two time periods and across the 22 GCMs. All the models agree that the average January-June growing season temperatures in the early 21st Century are going to be higher than in the 20th Century should greenhouse gas concentrations continue to rise (column III of Table 2), with the growing season average temperature increasing by 0.2 to 1.11 °C across the 22 GCMs (°C differences in parentheses). In a similar vein, most models agree that the average growing season

[3] Please see Appendix A for details on bias-correction.

precipitation will also be higher (column IV of Table 2). When it comes to the question of changes in their volatility – measured as the standard deviation across the period's time series – the models are found to agree less on temperature and not at all on precipitation (columns VI and VII of Table 2).

In order to capture the bounds of the GCM-based climate projections in the subsequent analyses of agricultural productivity and poverty vulnerability, we identify the GCMs that exhibit the greatest and smallest changes in climate volatility. GCM02 is found to display both the greatest increase in precipitation volatility and the largest decrease in temperature volatility. GCM 06 and GCM 08 exhibit the greatest increase in temperature volatility and the largest decrease in precipitation volatility, respectively.

Table 2: Difference between Climate in Tanzania in the Late 20th and Early 21st Centuries as Determined by the Period Average and Standard Deviation Values of Bias-Corrected Temperature and Precipitation by GCM.

GCM Name	GCM Code	Percent Difference in the Average Value in the 21st Century from the Average Value in the 20th Century (%)			Percent Difference in the Standard Deviation in the 21st Century from the Standard Deviation in the 20th Century (%)		
		Bias-Corrected Average Monthly Growing Season Temp.	Bias-Corrected Average Monthly Growing Season Precip.	Annual Average Grains Yield	Average Monthly Growing Season Temp.	Average Monthly Growing Season Precip.	Annual Average Grains Yield
I	II	III	IV	V	VI	VII	VIII
bccr_bcm2_0	01	1.20 (0.27)	7.21	11.72	-21.46	-4.54	-11.90
cccma_cgcm3_1	02	1.68 (0.38)	20.86	15.81	-29.40	28.09	3.28
cccma_cgcm3_1_t63	03	3.52 (0.80)	11.11	6.78	4.72	1.97	5.05
cnrm_cm3	04	3.52 (0.80)	1.99	3.17	43.29	24.37	34.21
csiro_mk3_0	05	1.17 (0.26)	3.38	10.28	37.60	14.45	18.72
gfdl_cm2_0	06	2.67 (0.60)	11.02	9.12	45.14	12.28	19.04
gfdl_cm2_1	07	1.72 (0.39)	0.12	7.46	-14.89	-19.68	-17.91
giss_aom	08	3.82 (0.86)	3.14	2.78	-8.07	-28.34	-22.84
giss_model_e_h	09	3.69 (0.83)	6.06	4.31	31.72	16.43	21.61
iap_fgoals1_0_g	10	1.70 (0.38)	0.32	7.59	-6.40	-7.60	-2.74
ingv_echam4	11	2.13 (0.48)	1.89	7.00	-8.90	7.47	5.07
inmcm3_0	12	3.53 (0.80)	11.12	6.76	9.87	6.87	-23.27
ipsl_cm4	13	3.34 (0.76)	5.13	4.91	10.33	0.93	9.69
miroc3_2_hires	14	4.90 (1.11)	8.12	1.75	19.35	7.07	5.06
miroc3_2_medres	15	2.33 (0.53)	3.74	7.18	26.51	1.31	-14.85
miub_echo_g	16	1.71 (0.39)	1.81	8.15	-3.58	-15.23	-7.32
mpi_echam5	17	0.88 (0.20)	-1.74	9.06	25.84	-6.18	1.50
mri_cgcm2_3_2a	18	1.99 (0.45)	-1.26	6.15	32.97	-8.10	-0.11
ncar_ccsm3_0	19	4.07 (0.92)	17.18	7.67	4.21	-10.38	-25.56
ncar_pcm1	20	2.80 (0.63)	-0.64	4.14	-5.64	-18.57	-13.84
ukmo_hadcm3	21	2.01 (0.45)	-10.42	2.46	-2.98	-10.95	-16.56
ukmo_hadgem1	22	3.20 (0.72)	-4.54	1.47	29.98	-14.63	-4.58
Average		2.62 (0.59)	4.35	6.62	10.01	-1.04	-1.74
Average Absolute		2.62 (0.59)	6.04	6.62	19.22	12.06	12.94
Sign Consistency		1.00	0.72	1.00	0.52	-0.09	-0.13

Source: Authors' estimates and processing of Meehl et al (2005)

Note: Sign consistency is the ratio of the average to the average of absolute values and is bounded by -1 and +1. A value of 1.0 indicates that the models all agree that the variable in question will rise, and conversely for a sign consistency measure of -1.0. The numbers in parentheses in column III indicate the difference in growing season average temperature between the 20th Century and 21st Century in °C.

Climate data from these series alone, however, are insufficient to tell us how variability in agricultural productivity will change, and we must empirically determine the crop productivity response to temperature and precipitation. A widely used statistical approach is the Ricardian technique pioneered by Mendelsohn et al (1994). This approach has been applied to examine the impact of climate change on African agriculture – albeit not for Tanzania – as reviewed in Dinar et al (2008), and in various other studies (see Kurukulasuriya et al 2006; Kurukulasuriya and Mendelsohn, 2007). The Ricardian approach takes advantage of climate variation across space to estimate the impact of decadal-scale climate outcomes on land rents, crop value or production in a given year. It presumes that the "Ricardian" returns to land have adjusted to reflect differences in climate across locations.

However, in order to quantify poverty vulnerability to volatility, our study focuses on changes in temperature and precipitation that occur on interannual time-scales – a period over which farmers do not have the ability to anticipate or significantly adapt to climate variations. As such, if we used Ricardian estimates of crop responses to analyze interannual volatility, we would be inappropriately applying estimates of farm responses to gradual climate changes in our analysis of short run variation in temperature and precipitation. Hence, a time series estimation of crop yields with annual temperature and precipitation among the explanatory variables (e.g. Lobell et al, 2006, 2008) is deemed more appropriate.

To that end, monthly climate data from the CRU TS 3.0 dataset (CRU, 2008) were used in linear regression models to analyze the relationship between mean temperature (°C) and precipitation (mm/month), and crop yields for several grains. This analysis was done at the sub-national level, more specifically at the administrative region level from 1992 to 2005. The climate data were also adapted to the growing season calendar as provided by the Famine Early Warning Systems NETwork (FEWS NET, 2008). Based on this calendar, we used a single growing season for maize, sorghum, and rice[4], extending from January to June. Thus, for each year, the 0.5° gridded climate data were averaged temporally over this 6-month period and spatially for each administrative region.

For each crop, data on harvested area and production from the Tanzanian Ministry of Agriculture as well as from Agro-MAPS (Monfreda et al, 2009) were compiled for each of the 17 regions and converted to yields (tonnes/ha). These data were available from 1992 to 2005. Forward stepwise multiple linear regression models were developed for each of the three crops linking yields to mean temperature and precipitation while accounting for temporal trends. Inclusion of higher order terms (e.g., temperature squared) would be appealing but is not supported by the limited availability of the time series data. A few observations were removed from analysis as they presented highly unlikely yield values. Moreover, harvested areas were used as weights in the fitting process.

The analysis finds that when considering a yields as functions of climate and time trends (where significant), the temperature coefficients are negative, while the coefficients for precipitation are positive (Table 3). Coefficients on both climate variables are highly significant in all models. That is, rising temperatures will put downward pressure on grains yields, while rising precipitation will enhance yields. An increase in average growing season precipitation by one mm/month is enough to increase maize and rice yields by 0.005 tonnes per hectare, and

[4] Selected due to reliable production data availability, representing 93 percent of cereals production (FAO, 2009)

sorghum yields by 0.002 tonnes per hectare. Temperature has the smallest effect on sorghum yields (coefficient of -0.07 tonnes per hectare) and the greatest on rice yields (coefficient of -0.28 tonnes per hectare). The effect on maize yield of roughly 12 percent loss per °C is consistent with estimates of 10 percent in the literature for Sub-Saharan Africa (e.g. Jones and Thornton, 2003). The rice and sorghum sensitivities represent roughly 17 percent and 7 percent loss per °C, respectively. Time trends are significant only in the rice yield function, where they are significant and positive suggesting the presence of ongoing technological progress.

Table 3: Estimation Results for Tanzanian Grains Yield Functions; Dependent Variable is Yield (tonnes/hectare)

Coefficients	Maize	Rice	Sorghum
Intercept	4.5705	-87.5692	2.2699
	(9.245)	(-4.111)	(6.345)
Year		0.0476	
		(4.402)	
Precipitation (mm/month average for Jan-June growing season)	0.0048	0.0049	0.0021
	(5.597)	(4.166)	(3.909)
Temperature (°C average for Jan-June growing season)	-0.1656	-0.2817	-0.0673
	(-7.364)	(-7.318)	(-4.062)
Adjusted R-Squared	0.209	0.181	0.074

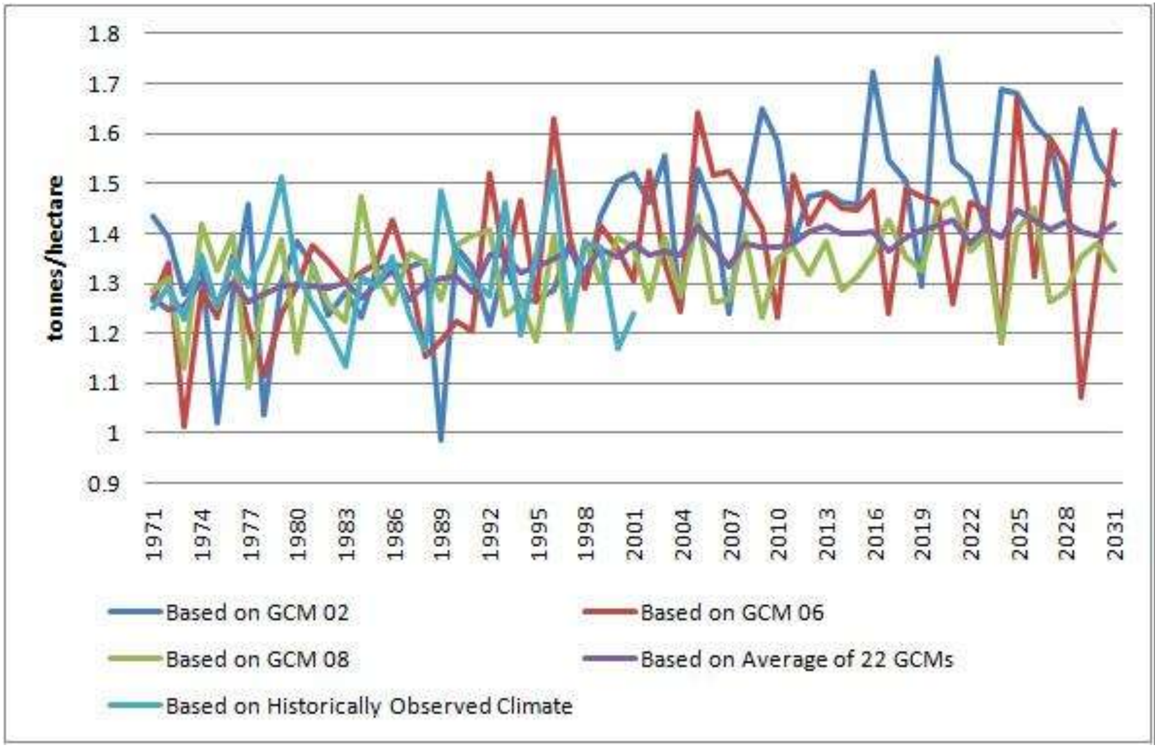
Source: Authors' estimates

Note: The t-statistics are in parentheses and all estimates are significant at least at the 0.01 level of confidence.

We can now apply climate data to the coefficients estimated to determine climate-instrumented interannual variation in yields for each of the three grains under consideration. In addition to climate data based on the average of the values across the 22 sets of GCM results, we also quantify the envelope of yield predictions using output from GCM 02 (greatest increase in precipitation volatility and largest decrease in temperature volatility), GCM 06 (greatest increase in temperature volatility), and GCM 08 (largest decrease in precipitation volatility). The aggregate grains[5] yield series associated with each climate series is then obtained by taking the weighted average of the yields across the three crops, with the weights being the 2001 harvested area shares obtained from FAOSTAT (FAO, 2009).

In contrast to the exception of the grain yield series based on GCM 08, the predicted yield series from GCM 02 and GCM 06 exhibit higher volatility in the 21st Century compared to the volatility in the 20th Century (columns VIII, Table 2). Figure 1 illustrates these series, whose interannual differences we will now implement in our economic simulation analysis to determine poverty sensitivity to climate in Tanzania.

[5] These three crops collectively proxy for the grains sector that we use in our CGE analysis, aggregated from the Paddy Rice, Wheat, and Other Grains GTAP sectors. Details on how the maize, rice, and sorghum yields are aggregated to grains can be found in Appendix A.



Source: Authors' processing of Meehl et al (2005) and CRU TS 3.0

Figure 1: Predicted Grains Yields in Tanzania for the period 1971-2031 Explained Solely by Bias-Corrected Climate Data and Historically Observed Climate[6]

4. POVERTY ANALYSIS

4.1 SIMULATION FRAMEWORK

We are now in a position to analyze the poverty impacts of the interannual productivity change distributions of the late 20th Century and the early 21st Century. In order to estimate the changes in consumer prices and earnings stemming from changes to agricultural productivity due to climate effects, we employ a widely used computable general equilibrium economic simulation model.

We begin with the GTAP Database Version 6 (Dimaranan, 2006) and use this with a modified version of the standard GTAP model (Hertel, 1997). We retain the empirically robust assumptions of constant returns to scale and perfect competition, and introduce factor market segmentation which is important in countries where the rural sector remains a dominant source of poverty following the methodology of Keeney and Hertel (2005). Farm and non-farm mobility of factors are restricted by specifying a constant elasticity of transformation function which "transforms" farm employed versions of labor and capital into non-farm uses and vice-versa. This allows for persistent wage differences between the farm and non-farm sectors, and is the foundation of the intersectoral distributional analysis. In order to parameterize these factor mobility functions we draw on the OECD's (2001) survey of agricultural factor markets. We assume a constant aggregate level of land, labor, and capital employment reflecting the belief that the aggregate supply of factors is unaffected by climate change.

[6] Please see electronic version for color image

The model is also adjusted to distinguish between lands with different biophysical characteristics, following the approach of Hertel et al (2009a), distinguishing land by Agro-Ecological Zone (AEZ), based on the data of Lee et al (2009) and Monfreda et al (2009). The model is then calibrated such that simulations of estimated historical productivity volatility of Grains for the 1971-2001 period replicate observed historical price volatility[7].

In order to link price changes in the CGE model to poverty, we use the household model of Hertel et al (2004) to examine households in the neighborhood of the poverty line. That study used the AIDADS (An Implicitly Directly Additive Demand System) consumer demand system of Rimmer and Powell (1996) to determine household consumption and the household's maximum possible utility for a given set of prices and income. For poverty analysis, the utility of the household at the poverty line is then defined as the poverty level of utility. If an adverse climate shock pushes households' utility below this level, they enter poverty. Conversely, if they are lifted above this level of utility, they are no longer in poverty.

The framework of Hertel et al (2004, 2009b), and that which this paper adopts, uses the AIDADS system to represent consumer preferences. This choice is based on AIDADS' strength in capturing food expenditure patterns across the income spectrum (Verma et al, 2009), and for its ability to perform well out of sample when compared to other demand systems (see Cranfield et al, 2002, 2003)[8]. Reflecting its suitability for poverty analysis is that AIDADS devotes two-thirds of its parameters to characterizing consumer behavior at very low levels of income. Estimation of this demand system is undertaken using the 80 country, per capita consumption data set offered by Version 6.1 of the GTAP database, also following Hertel et al (2004). For each commodity, we have estimates of subsistence quantities of consumption, from which we may infer (for average prices), budget shares at the subsistence level of income.

The poverty line in Tanzania is set to match the observed national poverty headcount ratio reported by the World Bank (2006) and this in turn dictates the poverty level of utility in the initial equilibrium. So, in the wake of a change in climate, commodity prices and wages will adjust, household incomes will change, as will the consumption profile of households at the poverty line, thereby resulting in new utility level. If household utility rises above the poverty level of utility, then it is lifted out of poverty. Conversely, if the household utility level falls below the poverty utility threshold, then it has become impoverished.

Equations (1) to (3) describe how the model can then be used to predict the change in the national poverty rate – the percentage of the population living below the poverty line in 2001 – in percentage points of poverty. Equation (1) details how we compute the percentage change in the poverty headcount ratio in Tanzania, $\hat{H}_r$, in the wake of a shock to the prices and wages in the economy (Hertel et al, 2009b):

$$\hat{H}_r = -\sum_s \Theta_{rs}\varepsilon_{rs}\sum_j \Omega^p_{rsj}\left(\hat{W}^p_{rj} - \hat{C}^p_r\right) \qquad \text{EQ (1)}$$

The term in parentheses on the right hand side of the equation reports the change in the real after tax wage rate for endowment *j* in region *r* (Tanzania in this case), by deducting the

[7] Please see Appendix B for details of model calibration
[8] Please see Appendix C for details of AIDADS formulation and parameterization.

percentage change in the cost of living at the poverty line, $\hat{C}_r^p$, from the percentage change in the after-tax $\hat{W}_{rj}^p$. This real earnings term is pre-multiplied by three important poverty-parameters which deserve additional discussion[9].

The first, Ω_{rsj}^p, is the share of earnings type *j* in total income of households in the neighborhood of the poverty line in stratum *s* of Tanzania. By definition, the earnings shares in a given stratum sum to one and serve to determine the impact of a change in wages on household income. For example, if there is a 10 percent increase in the wages of unskilled agricultural labor, and imputed unskilled wages represents 70 percent of the agricultural stratum's household income in the neighborhood of the poverty line, then this wage rise will contribute 7 percent (0.70 * 10 percent) to the stratum's income change at the poverty line.

As seen in this simple example, implementation of equation (1) requires mapping factor earnings in the general equilibrium model (e.g., agricultural unskilled wages) to income sources obtained from the household survey (imputed returns to self-employed unskilled labor in agriculture). In the micro-simulation analysis, self-employed agricultural labor and capital receive the corresponding farm factor returns from the general equilibrium model, as do non-agricultural labor and capital. Wage labor for diversified households reported in the surveys presents a problem because information is lacking to assign it to a specific industry. Accordingly, we apply the composite wage for skilled or unskilled labor determined by the general equilibrium model in these respective labor markets. Finally, transfer payments are indexed by the growth rate in net national income.

Summing over the share-weighted change in factor returns yields the total real income change for households in the neighborhood of the poverty line for a given stratum-region combination. The real cost of living at the poverty line is obtained by solving the demand system for the level of income required to attain the poverty level of utility, given a vector of prices. By solving this for the initial consumer prices and then for the post-exogenous shock prices, we can obtain the change in the cost of living at the poverty line, taking into account price-induced changes in the mix of goods and services consumed.

The ensuing change in real income is, in turn, multiplied by the second class of parameters in (1): ε_{rs}. This is the estimated elasticity of the stratum-specific poverty headcount (H_{rs}) with respect to income which is obtained by evaluating the density of the stratum population in the neighborhood of the poverty line. In order to turn these stratum changes into the estimated percentage change in national poverty headcount, they must be weighted by each stratum's share in national poverty, the third class of parameters:

$$\Theta_{rs} = \left[\left(POP_{rs} * H_{rs} \right) / POP_r \right] / H_r = \left(POP_{rs} * H_{rs} \right) / \sum_k \left(POP_{rk} * H_{rk} \right) \qquad \text{EQ (2)}$$

Summing across strata, we thus obtain the percent change in national poverty headcount, $\hat{H}_r$. By multiplying $\hat{H}_r$ with the national poverty rate we ultimately obtain the

[9] Please see Appendix D for more details on the poverty parameters.

percentage point change in the national poverty rate due to changes in factor earnings as well as the cost of living at the poverty line, dh_r:

$$dh_r = \hat{H}_r * \left(100 * \frac{H_r}{POP_r}\right) \qquad \text{EQ (3)}$$

If this rises by one percentage point, then poverty has risen by one percent of the national population, equivalent to more than 344 thousand people. Such a change would indicate a very large poverty impact in Tanzania.

4.2 POVERTY IMPACTS

The assessment of poverty vulnerabilities to interannual climate variation over different time periods is complicated by the dynamics of the global and Tanzanian economies as we go forward from the late 20th Century to the early 21st. By 2031, the composition of Tanzanian poverty, as well as the household earnings sources and expenditure patterns will change in ways that cannot be fully anticipated. We resolve this complication by treating all economic changes as comparative static deviations from the 2001 economy, allowing us to attribute poverty changes solely to climate-based agricultural productivity changes, and not any other event that may cause vulnerability to change between climates in two different periods. Since we are interested in the poverty impacts of interannual variability, we adopt a short run factor market closure in which land, capital, and natural resources are immobile across sectors. Thus we assume that a farmer has already made planting decisions before the climate outcome for that year is realized, and therefore cannot respond to a (e.g.) favorable climate outcome by expanding area under cultivation.

Tanzanian poverty vulnerability to interannual climate volatility between 1971 and 2031 is determined by simulating the interannual productivity change for each year of the four (GCM-based) predicted yield series, generating a change in the poverty rate for each of those years by series. Bear in mind that all simulations are perturbations from our 2001 base year, and the resulting poverty rate changes are solely those due to climate realizations. This has the essential property of rendering our results comparable across years. For each climate-yield series that we consider, we thus have a time series of poverty impacts that are the result of simulating climate-instrumented productivity changes from 1971 to 2031.

We now analyze the distributions of these series of poverty changes. Based on the climate data that are the average across the 22 GCMs, we find that the median poverty change – measured as the percentage point difference from the national poverty rate in 2001 – is higher in the early 21st Century than in the late 20th Century (panel A, Figure 2). In the 20th Century, this median poverty change was -0.06 percent of the population – a poverty decrease. However, in the 21st Century, the median poverty change was -0.01 percent – a smaller decrease in the poverty rate. The 0.05 percentage point difference is equivalent to approximately 17.23 thousand people. There are fewer years in the future when climate outcomes would have been poverty decreasing than under current climate, as evidenced by a rightward (i.e. poverty increasing) shift of the mass of the interannual poverty change distribution.

The ensemble mean of the 22 GCMs (which is bias-corrected to the historical mean and interannual standard deviation) thus suggests that changes in temperature and precipitation volatility could have the net effect of increasing poverty vulnerability, with the distribution shifting in the positive direction (panel A, Figure 2). However, near-term, decadal-scale climate prediction remains one of the most challenging problems in climate science (e.g. Keenlyside et al, 2008), and it is thus unclear exactly how Tanzanian climate volatility will actually change in the next two decades. Nonetheless, the CMIP3 GCM ensemble does provide some quantification of the envelope of potential change based on different representations of climate system processes and "initial conditions" (for a discussion of sources of uncertainty in regional climate change, see Giorgi et al, 2008). We therefore also analyze the pooled and individual GCM realizations that represent the bounds of changes in temperature and precipitation volatility.

Panel B of Figure 2 demonstrates the robustness of the ensemble mean results to the variation in the climate data across the GCMs that define the bounds of potential changes in temperature and precipitation volatility. For each period, the poverty results from GCM 02, 06, and 08 were pooled to give a poverty distribution that considered climate data from GCMs where climate volatility increased and decreased the most. We continue to find that the mass of the poverty change distribution shifts rightward in the future relative to the 20th Century – although the shift is more marked than in panel A – implying that climate outcomes in the future will be more frequently poverty increasing.

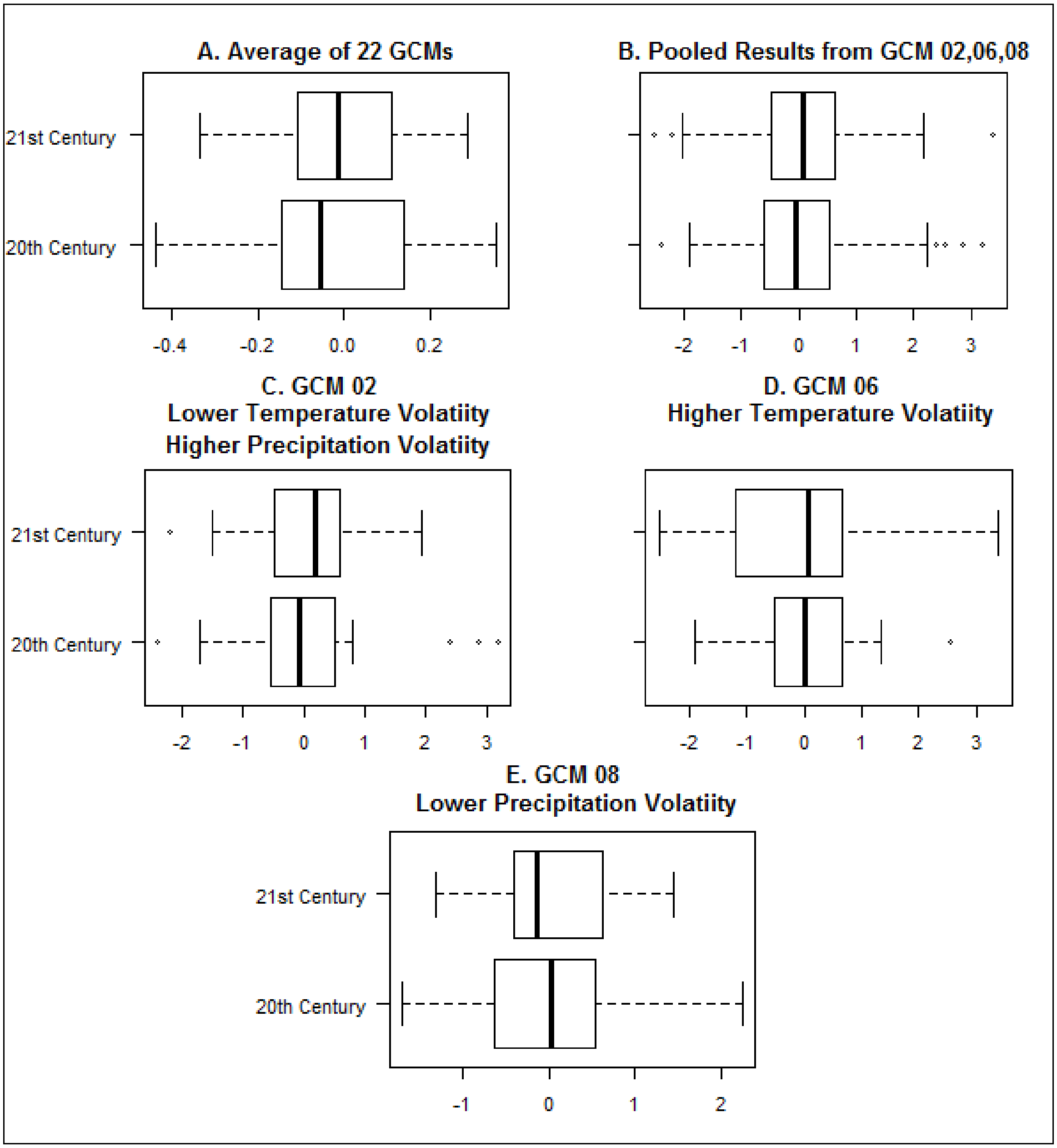
The poverty distributions for the 20th and 21st Centuries that are based on the individual GCMs that characterize the upper and lower bounds of the climate volatility changes (panels C, D and E of Figure 2), demonstrate that we observe the shift in the probability mass in the more aggregated climate-poverty results due to shifting median values, the interquartile range, or both. The use of individual GCMs also reveals the possibility of even larger poverty headcount changes. Poverty results based on GCM 02, 06, and 08 indicate that the years with the greatest poverty increases may see more than 2 percent of Tanzania's total population – equivalent to nearly 700 thousand people – become impoverished.

In analyzing GCM 02, which shows the greatest increase in precipitation volatility as well as the largest decrease in temperature volatility (Table 2), we see that the median poverty value and the left tail of the distribution shift in the positive (poverty increasing) direction, and that the right tail of the distribution becomes substantially more positive (panel C, Figure 2). Analyzing GCM 06, which shows the greatest increase in temperature volatility (Table 2), we see that the right "whisker" of the poverty change distribution is higher for the 21st Century than in the 20th Century, , although the left tail and lower quartile both become more negative (panel D, Figure 2). This change in the distribution suggests that, in response to the greatest increase in temperature volatility, there are many more years with very large poverty increases. This highlights the potential importance of changes in climate volatility for poverty vulnerability, even when there is essentially no change in the median poverty value. For GCM 02 and GCM 06, the median poverty change increases by 0.26 and 0.07 percentage points of the national poverty rate, respectively. Based on Tanzania's 2001 population, these 0.26 and 0.07 percentage point increases in the poverty rate would translate into 89.7 and 24.3 thousand additional poor.

The magnitudes of the extreme poverty increasing outcomes are also found to be greater in the future under GCM 06. In the 20th Century, the greatest predicted increase in poverty was of 880 thousand people (2.6 percent of the population), while in the 21st Century, the highest possible poverty increase was of 1.17 million people, equivalent to 3.4 percent of the Tanzanian population.

Alternatively, when analyzing GCM 08, which shows the largest decrease in precipitation volatility (Table 2), we see that the poverty distribution is contracted, with the median and right whisker being lower in the future than in the 20th Century (panel E, Figure 2). However, even though the median poverty change decreased for GCM 08, the mass of the poverty change distribution shifted rightward, with the first quartile value poverty change increasing by 0.21 percentage points of the poverty rate, and the third quartile value increasing by 0.04 percentage points. Nonetheless, the results of this GCM realization lie in contrast to those from the whole GCM ensemble and from the other boundaries of the ensemble-envelope, highlighting the uncertainty in the impacts of climate volatility on poverty.

While the exact realization of the climate system over the next two decades is unknown, the poverty results from the overall the CMIP3 GCM ensemble suggest slightly increasing poverty vulnerability in Tanzania. However, if the real climate system displays behavior similar to GCM 08 over the next two decades, then poverty vulnerability could instead decrease by some measures. Further development of decadal-scale climate prediction techniques could help to resolve the climate-based uncertainty, although it is possible that the temporal (and spatial) scales being considered exceed the limits of predictability.



Sources: Authors' estimates

Figure 2: Panels A-E indicate the distributions of percentage point changes in the national poverty rate in Tanzania attributable to of distribution of interannual grains productivity changes in the 20th Century and 21st Century, based on the source of the climate data used to estimate the grains productivity changes. The middle dark lines indicate median values, while the edges of the boxes describe the first (Q1) and third (Q3) quartiles. The left whiskers indicate the greater of the lowest values and Q1-1.5*(interquartile range). The right whiskers indicate the lesser of the greatest value and Q3+1.5*(interquartile range).

5. CONCLUSION

Climate volatility in Tanzania could increase in the future as greenhouse gas concentrations increase (Figure 1, Table 2), with agricultural productivity expected to become increasingly volatile as well. For agriculture-dependant developing countries, where poverty is sensitive to food production and food production is sensitive to climate (as is the case in Tanzania), rising climate volatility could have important implications for poverty vulnerability.

We develop an analytical framework which allows us to estimate the interannual changes in grains sector productivity that can be attributed solely to temperature and precipitation. We then simulate these interannual changes in a comparative static general equilibrium simulation model, to derive the poverty responses of the 2001 Tanzanian economy to each of these changes. This enables us to determine how the distribution of poverty changes attributable to climate volatility in a given 30-year period could change in the future. We apply this framework to Tanzania's climate in the 20th Century and 21st Century, and find that changes in climate volatility are likely to render Tanzanians increasingly vulnerable to poverty episodes through its impacts on staple grains production in agriculture.

Under scenarios with the greatest increase in precipitation volatility and the largest changes in temperature volatility the median climate outcome in the future may lead to 24.3 to 89.7 thousand additional poor than the median poverty outcome under current climate. Individual GCM results show climate-induced interannual poverty increases as high as 700,000 in some cases. Further, since there is the possibility that climate volatility could increase further as greenhouse gas concentrations rise beyond those prescribed here, there is a danger that the poverty vulnerability identified could intensify beyond the horizon of our analysis.

Several factors not considered in the current study may also be important for refining adaptation strategies to adapt to climate impacts in Tanzania. One is that crops may be more or less sensitive than the values inferred by our yield estimation, as these statistical estimates are subject to some uncertainty. Although most studies, including this one, focus on uncertainties in climate scenarios, uncertainties in crop responses can be equally important for projecting near-term impacts (Lobell and Burke, 2008).

In addition, food prices in Tanzania will be affected to a large degree by changes in crop productivity throughout the world, as these will influence local prices. The current analysis implicitly assumed negligible impacts in other regions, as a way of focusing on the question of how much poverty volatility could be driven by changes in local production. However, international linkages are clearly important for projecting poverty changes (Hertel et al, 2009c), and will be incorporated into future work.

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APPENDIX A: CLIMATE AND YIELD PROJECTION

We use climate data from two different sources: the CRU TS 3.0 database (CRU, 2008) of historically observed climate data and from 22 models of the CMIP3 archive of GCM-generated climate predictions for the SRES A2 scenario. From these sources we retrieve hat lets us calculate monthly average temperature and rainfall under current and future climate for the January to June growing season. We specify these as:

- T_{obs} (year)= observed temperature between 1971 and 2001
- P_{obs} (year) = observed rainfall between 1971 and 2001
- $T_{current,\ model}$ (year)= Model simulated temperature between 1971 and 2001 by GCM
- $P_{current,\ model}$ (year) = Model simulated rainfall between 1971 and 2001 by GCM
- $T_{future,\ model}$ (year) = Model simulated temperature between 2001 and 2031 by GCM
- $P_{future,\ model}$ (year) = Model simulated rainfall between 2001 and 2031 by GCM
- T_{model} (year)= Model simulated temperature between 1971 and 2031 by GCM
- P_{model} (year) = Model simulated rainfall between 1971 and 2031 by GCM

Now, the GCM generated- climate data is systematically biased, and so we adjust the climate data so that the moments of the simulated climate for the present day match those of the historic observations from the CRU dataset. We bias correct the means, following equations A1 and A2. This will adjust the GCM based climate data such that the mean values in the period 1971-2001 will match the historically observed mean from the CRU series. Equations A3 and A4 then adjust the mean bias-corrected climate data such that their late 20th Century interannual volatility matches the historically observed volatility, following Ramankutty et al (2006).

$$T_{model}^{mean\ corrected}(year)=T_{model}(year)+\frac{\left(\sum_{year}T_{obs}(year)-\sum_{year}T_{current,model}(year)\right)}{\text{Number of Years Observed}} \qquad \text{EQ (A1)}$$

$$P_{model}^{mean\ corrected}(year)=P_{model}(year)\frac{\sum_{year}P_{obs}(year)}{\sum_{year}P_{current,model}(year)} \qquad \text{EQ (A2)}$$

$$T_{model}^{bias\text{-}corrected}(year)=\left(\frac{T_{model}^{mean\ corrected}-\mu^{1971\text{-}2001}_{T_{model}^{mean\ corrected}}}{\sigma^{1971\text{-}2001}_{T_{model}^{mean\ corrected}}}\right)*\sigma_{T_{obs}}+\mu_{T_{obs}} \qquad \text{EQ (A3)}$$

$$P_{model}^{bias\text{-}corrected}(year)=\left(\frac{P_{model}^{mean\ corrected}-\mu^{1971\text{-}2001}_{P_{model}^{mean\ corrected}}}{\sigma^{1971\text{-}2001}_{P_{model}^{mean\ corrected}}}\right)*\sigma_{P_{obs}}+\mu_{P_{obs}} \qquad \text{EQ (A4)}$$

23 different series of yields for each crop can now be calculated using the yield estimates described in Table 3 and the climate data from equations A3 and A4. The first series uses the historically climate data from CRU to generate a series from 1971 to 2001, while the remaining 22 series uses the bias-corrected GCM climate data to give us 22 series from 1971 to 2031. The GCM-data based yield series are then bias-corrected following the same strategy used

in equations A3 and A4, to generate predicted yields of maize, rice, and sorghum. For each GCM-based series, an aggregate grains yield series is then obtained by taking the weighted average of the yields across the three crops, with the weights being the 2001 harvested area shares obtained from FAOSTAT (FAO, 2009).

APPENDIX B: MODEL CALIBRATION

We calibrate the GTAP economic simulation model parameters for Tanzania to be able to replicate historical grain price volatility when historical grains productivity is simulated, following the approach of Valenzuela et al (2009). The approach used can be summarized as broadly following the steps below:

- Volatility Estimates: Estimate output and price volatility for a given commodity, with volatility referring to the standard deviation of interannual percentage changes in the variables. The estimated standard deviations are then used to determine the endpoints of a symmetric triangular distribution.

- Simulation: Conduct systematic sensitivity analysis (SSA) using the Gaussian Quadrature based approach of Pearson and Arndt (2000), specifically to determine the sensitivity of grains prices with respect to output changes. The extreme value for the grains output SSA is the estimated endpoints of the symmetric triangular distribution described above.

- Comparison and recalibration: If the variations in the simulated grains prices for a region are inconsistent with the estimated variations, then the model requires recalibration. In the case of grains prices, the substitution parameters of the model's demand equation are recalibrated

Agricultural productivity is difficult to observe, and so we use interannual output changes as a proxy. An alternative would be to use yields. However, in the available data sets, yields are defined as production divided by harvested area. Since harvested area is also subject to climate volatility (some planted area may not be harvested in a bad year), we view the interannual random change in production as a better measure of climate induced productivity. To determine the standard deviation of the interannual output changes, production data is obtained for three Tanzanian grains – maize, paddy rice, and sorghum – from FAOSTAT for the years 1971 to 2001 (FAO, 2009). These three crops collectively proxy for the grains sector that we use in our CGE model analysis. The interannual percentage changes are then calculated for the aggregate and tested for time trends, with none being found. The standard deviation of the interannual percentage changes over the time-series is determined to be 21.97.

The price volatility for each aggregated crop is then determined through a more complex approach, involving data from a variety of sources for the period 1990 to 2003. The time series for the price volatility estimation is smaller than the series for the productivity volatility estimation due to the unavailability of reliable data necessary for the estimation. The three different types of data used are:

Q_{tir} – Production data in tonnes from FAOSTAT for disaggregated crop i.
P_{tir} – Price data from before 1991 in LCU/tonne from price data of Morrissey and Leyaro (2007).
D_{tr} – GDP deflator from the IMF's International Financial Statistics (IMF, 2009).

A composite real price for grains in US dollars can then be calculated following equations B1-B4:

$$\text{RealP}_{\text{tir}} = \frac{\text{P}_{\text{tir}}}{\text{D}_{\text{tr}}} \quad \text{EQ (B1)}$$

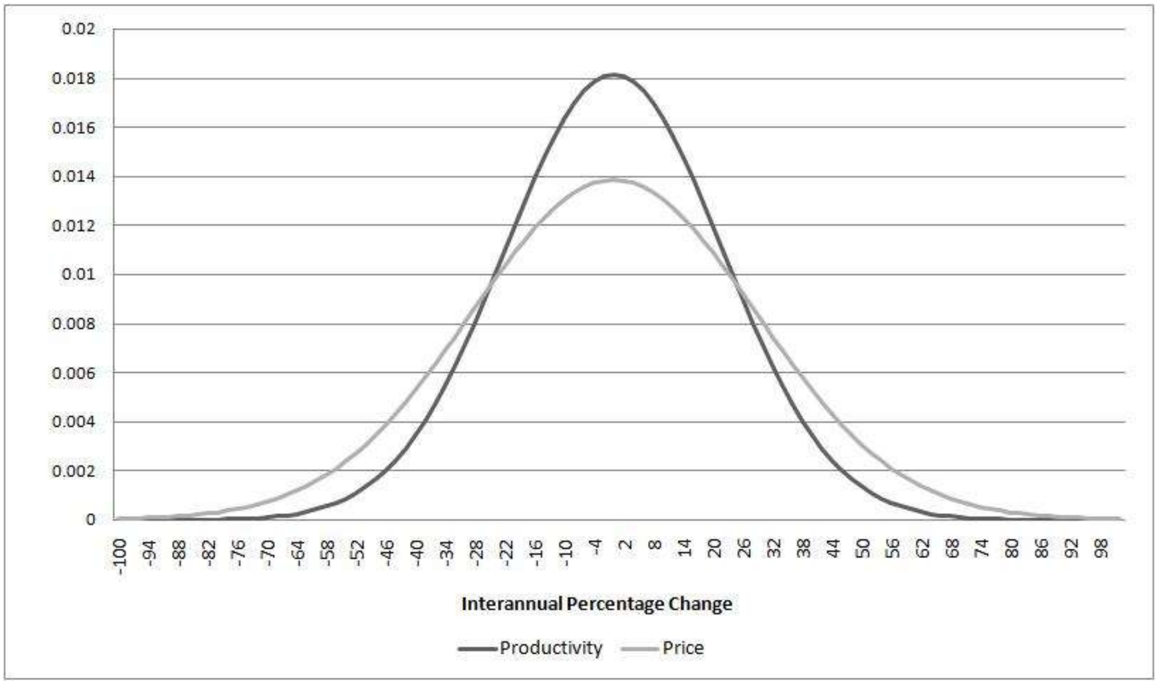
$$\text{TotalValue}_{\text{tr}} = \sum_{\text{r}} \left(\text{RealP}_{\text{tir}} * \text{Q}_{\text{tir}} \right) \quad \text{EQ (B2)}$$

$$\text{ValueShare}_{\text{tir}} = \frac{\text{RealP}_{\text{tir}} * \text{Q}_{\text{tir}}}{\text{TotalValue}_{\text{tr}}} \quad \text{EQ (B3)}$$

$$\text{PAggCrop}_{\text{tr}} = \sum_{\text{i}} (\text{ValueShare}_{\text{tir}} * \text{RealP}_{\text{tir}}) \quad \text{EQ (B4)}$$

As before, no trends were found in the price series and the price volatility is estimated as the standard deviation of the interannual percentage changes in price. This is found to be 28.77. However, when stochastic simulations of the estimated productivity volatility are implemented, the price volatility is found to be excessively high. In order to reduce the domestic grain price volatility in Tanzania, it is necessary to increase their own price elasticities of domestic demand for grains. This is achieved by reducing the substitution parameter for grains in the model's utility function, which in turn increases the magnitude of the compensated own-price demand elasticity of grain. Once the simulated price volatility matches the estimated volatility we can be confident that the model is able to accurately delineate grains price sensitivity to productivity changes.

Figure B1 illustrates the volatilities of grains productivity and prices. It can be seen that in the last 30 years of the 20th Century, Tanzanian grains price and productivity had similar volatilities.



Source: Authors' estimates

Figure B1: Grains Productivity and Price Volatilities in Tanzania Characterized as Mean-Zero Normal Distributions of Interannual Percentage Changes, 1971-2001 ($\sigma_{\text{Productivity}}$ =21.97, σ_{Prices} =28.77)

APPENDIX C: AIDADS FORMULATION AND PARAMETERS

The AIDADS utility function is assumed to be common across all individuals within a country – Tanzania in the case of this paper – with consumption patterns varying solely as a function of income level. A household micro-simulation model can then be specified by maximizing per capita utility, subject to a per capita budget constraint, and based on household endowments.

The household model can then be characterized as a constrained maximization problem, choosing $\left(x_{1s},...,x_{is},...,x_{ns}\right)$, where *i* indexes the commodities and *s* households, to maximize u_s subject to constraints C1 to C4:

$$\sum_{i=1}^{n} U_i\left(x_{is},u_s\right) = 1, \tag{C1}$$

$$U_i\left(x_{ik},u_k\right) = \phi_{ik}\left(u_k\right)\ln\left(\frac{x_{ik} - \gamma_i}{A\exp(u_k)}\right) \quad \forall\ i \tag{C2}$$

$$\phi_{is}\left(u_s\right) = \frac{\left[\alpha_i + \beta_i \exp\left(u_s\right)\right]}{\left[1+\exp\left(u_s\right)\right]} \tag{C3}$$

$$\sum_{i=1}^{n}\left(p_i x_{is}\right) = Y^k = \sum_f W_f \bar{E}_f^k + T^k Y \tag{C4}$$

In this formulation, equations (C1) to (C2) define the AIDADS utility function with parameters $\alpha_i, \beta_i, \gamma_i$ and A. α_i and β_i are the AIDADS marginal budget shares of commodity *i* at the subsistence and high incomes, respectively. γ_i characterizes AIDADS subsistence consumption of *i*, and A is a scaling parameter in the utility function. The marginal budget share is thus defined by (B3). Equation (B4) is the per capita budget constraint, with income inclusive of any transfers. W_f is the wage paid to endowment $\bar{E}_f^k$, and T^k is the transfer rate for household k, which is assumed to be a constant share of net national income, Y.

The poverty line in Tanzania is set to match the observed national poverty headcount ratio reported by the World Bank (2006). This is used to calibrate the poverty level of utility in the initial equilibrium. So, in the wake of a change in climate, commodity prices and wages will adjust, household incomes will change, as will the consumption profile of the household and consequently its new utility level. If household utility rises above the poverty level of utility, then it is lifted out of poverty. Conversely, if the household utility level falls below the poverty utility threshold, then it has become impoverished.

Hertel et al (2004), in their analysis of the poverty impacts of trade liberalization, solve this micro-simulation model for representative households in 20 income vingtiles in each of the seven population strata. They then report growth incidence curves showing the impact across the entire population spectrum. The advantage of this approach is that it allows assessment of impacts across the entire population. However, in the context of the present analysis, wherein the focus is on poverty impacts, and the simulation methodology involves repeated solution of the model to produce an entire distribution of outcomes, this is overly burdensome.

We thus adopt the simpler approach utilized in Hertel et al (2009b), which summarizes the household behavior modeled from Hertel et al (2004) in the neighborhood of the poverty line via a highly disaggregated poverty elasticity based analysis.

The results generated by the household micro-simulation module depend on the parameter values for $\alpha_i, \beta_i, \gamma_i$, and A in the AIDADS utility maximization problem. The values for α_i, β_i, and γ_i are reported in Table C1, while the value of A is 0.3139.

Table C1: AIDADS parameter values

	α	β	γ
Crops	0.2757	0.0000	0.1624
Meat and Dairy	0.1187	0.0605	0.0000
Other Food and Beverages	0.3587	0.1924	0.0291
Textiles and Apparel	0.0600	0.0691	0.0000
Household Utilities	0.0126	0.0246	0.0000
Wholesale and Retail Trade	0.0795	0.3579	0.0135
Manufacturing	0.0427	0.1443	0.0514
Transport and Communications	0.0262	0.0454	0.0188
Financial Services	0.0014	0.0120	0.0049
Other Household Services	0.0245	0.0939	0.0152

Source: Golub (2006) and Dimaranan et al (2006)

APPENDIX D: POVERTY PARAMETERS

While conceptually simple, this approach to poverty analysis is actually quite data intensive and requires careful processing of the Tanzanian household survey data. Table D1 illustrates the estimated earnings shares in the neighborhood of the national poverty line (Ω^{p}_{rsj}) in Tanzania, with earnings sources disaggregated into ten categories. These categories are agricultural land, self-employed agricultural labor (both unskilled and skilled), self-employed non-agricultural labor (both unskilled and skilled), wage labor (both unskilled and skilled), agricultural capital, non-agricultural capital, and transfer payments.

The most difficult part of estimating these earnings shares derives from the need to impute returns to factors of production when the source of income is self-employment. This is achieved matching self-employed household members with similar wage-earning individuals in the survey and assigning the average earned wage for this class of workers (ideally, same sex and age, same skill level, same sector, same region). The residual earnings are assigned to capital in the case of non-agricultural income and shared between capital and land in the case of farming. To split non-wage income between capital and land, we use the factor payment shares from the GTAP database, which are based on econometric studies of cost shares in agriculture.

As can be seen, the wages of unskilled labor are important for households at the poverty line nationally, with this reflected in across the various strata. In the case of the agricultural stratum, in which households earn more than 95 percent of their income from agricultural self-employment, the bulk of their income (77 percent) is imputed labor income. Non-agricultural, self-employed households in the neighborhood of the poverty line, appear to control relatively more capital, as the imputed earnings share is lower than for farming. However, the imputed wage share is an underestimate, and capital and land shares are overestimates due to the lack of data on purchased inputs in the household survey. This means that we overstate net income from self-employment, thereby leaving a larger residual once imputed wages have been deducted.

Turning to the wage labor households, we see that the share of income coming from skilled labor is higher in urban areas. This is perhaps not surprising, as increased education and training is often required in order to access the formal urban labor market. On the other hand, the rural and urban diversified households are just that – highly diversified. This diversification is further accentuated by the fact that we have created this earnings profile by taking all households within +/-5 percent (i.e. 10 percent of the total stratum) of the poverty line in each stratum. This diversified group earns income from agricultural activities, as well as non-farm activities, it receives transfer payments and also receives income from capital.

As we have seen from equation (1), the earnings shares translate wage changes into income changes, but it is the poverty elasticities, ε_{rs} , that translate the latter into poverty changes, by stratum. Table D2 reports these stratum-specific poverty elasticities for Tanzania. These are so-called “arc elasticities”, obtained by examining the change in income as we move across the stratum decile surrounding the poverty line. As these are expressed in elasticity form, we expect these elasticities to diminish as the total poverty headcount in the stratum rises (i.e., it is harder to reduce poverty by one percent when it represents nearly half of the population, as in the agricultural stratum, as opposed to less than 10 percent in the urban labor and diversified households. Accordingly, in the urban diversified stratum, the poverty elasticity reaches 1.75. By applying the earnings source shares from Table D1 to these elasticities, Table D3 reveals the income elasticities of poverty by earnings source and stratum.

The final piece of data required to implement equation (1) is the stratum share of national poverty, Θ_{rs}, which was previously reported in Table 1, where we saw that the bulk of poverty in Tanzania resides in the rural areas. With these pieces of data and parameters in hand, we are now ready to evaluate the impact of climate volatility on poverty in Tanzania.

Table D1: Earnings Shares at the National Poverty Line in Tanzania, by Stratum

	Stratum						
Earnings Source	Agriculture	Rural Labor	Rural Diversified	Non-Agriculture	Urban Labor	Urban Diversified	Transfers
Agricultural Land	5.45	0.12	3.14	0.02	0.01	1.99	0.00
Self-Employed Agricultural Labor - Unskilled	65.04	0.13	32.87	0.13	0.12	19.38	0.07
Self-Employed Agricultural Labor - Skilled	0.21	0.00	0.17	0.00	0.00	0.32	0.00
Self-Employed Non-Agricultural Labor - Unskilled	0.04	0.00	11.29	63.50	0.06	19.81	0.14
Self-Employed Non-Agricultural Labor - Skilled	0.00	0.00	0.04	2.03	0.00	0.34	0.00
Wage Labor - Unskilled	0.02	95.42	11.02	0.04	86.12	14.10	0.00
Wage Labor - Skilled	0.00	4.17	0.36	0.00	13.51	1.31	0.00
Agricultural Capital	29.00	0.12	15.76	0.12	0.06	10.32	0.00
Non-Agricultural Capital	0.05	0.00	18.35	34.00	0.02	18.69	0.00
Transfer Payments	0.21	0.04	7.00	0.15	0.11	13.74	99.79
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Source: Authors' estimates based on data from NBS (2002)

Table D2: Arc Income Elasticities of Poverty by Stratum in Tanzania

Stratum	Elasticity
Agricultural	0.41
Rural Labor	0.74
Rural Diverse	0.59
Non-Agricultural	0.79
Urban Labor	0.78
Urban Diverse	1.02
Transfer	0.48

Source: Authors' estimates from NBS (2002)

Table D3: Income Elasticities of Poverty by Stratum and Earnings Source

	Stratum						
Earnings Source	Agriculture	Rural Labor	Rural Diversified	Non-Agriculture	Urban Labor	Urban Diversified	Transfers
Agricultural Land	0.0225	0.0009	0.0184	0.0002	0.0001	0.0203	0.0000
Self-Employed Agricultural Labor - Unskilled	0.2688	0.0010	0.1928	0.0010	0.0009	0.1977	0.0003
Self-Employed Agricultural Labor - Skilled	0.0009	0.0000	0.0010	0.0000	0.0000	0.0032	0.0000
Self-Employed Non-Agricultural Labor - Unskilled	0.0002	0.0000	0.0663	0.5025	0.0005	0.2021	0.0007
Self-Employed Non-Agricultural Labor - Skilled	0.0000	0.0000	0.0002	0.0161	0.0000	0.0035	0.0000
Wage Labor - Unskilled	0.0001	0.7016	0.0646	0.0003	0.6719	0.1438	0.0000
Wage Labor - Skilled	0.0000	0.0306	0.0021	0.0000	0.1054	0.0133	0.0000
Agricultural Capital	0.1198	0.0009	0.0924	0.0010	0.0004	0.1053	0.0000
Non-Agricultural Capital	0.0002	0.0000	0.1077	0.2691	0.0001	0.1907	0.0000
Transfer Payments	0.0009	0.0003	0.0410	0.0012	0.0009	0.1402	0.4758
All Endowments	0.4132	0.7353	0.5867	0.7914	0.7802	1.0200	0.4768

Source: Authors' estimates based on data from NBS (2002)

APPENDIX E: ADDITIONAL REFERENCES USED IN APPENDICES A-D

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