Climate Volatility and Poverty Vulnerability in Tanzania

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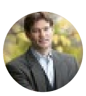

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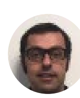

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ABSTRACT

Climate volatility could change in the future, with important implications for agricultural productivity. For Tanzania, where food production and prices are sensitive to climate, changes in climate volatility could have severe implications for poverty. This study uses climate model projections, statistical crop models, and general equilibrium economic simulations to determine how the vulnerability of Tanzania's population to impoverishment by climate variability could change between the late 20th Century and the early 21st Century. Under current climate volatility, there is potential for a range of possible poverty outcomes, although in the most extreme of circumstances, poverty could increase by as many as 650,000 people due to an extreme interannual decline in grain yield. However, scenarios of future climate from multiple climate models indicate no consensus on future changes in temperature or rainfall volatility, so that either an increase or decrease is plausible. Scenarios with the largest increases in climate volatility are projected to render Tanzanians increasingly vulnerable to poverty through impacts on staple grains production in agriculture, with as many as 90,000 additional people entering poverty on average. Under the scenario where precipitation volatility decreases, poverty vulnerability decreases, highlighting the possibility of climate changes that oppose the ensemble mean, leading to poverty impacts of opposite sign. The results suggest that evaluating potential changes in volatility and not just the mean climate state may be important for analyzing the poverty implications of climate change.

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 thus 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 (United Republic of Tanzania, 2005) identifying droughts and floods as among the primary threats to agricultural productivity and poverty vulnerability. Tanzania's National Adaptation Program of Action (NAPA) reiterates the government's recognition of the threat of climate change posed to agricultural production (United Republic of Tanzania, 2007). The NAPA identifies several vulner-

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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 National Bureau of Statistics (2002).

abilities, including unpredictable rainfall and prolonged dry spells (which are indicative of climate volatility), and lists agriculture projects as high priority for adaptation. An example of these high-priority agriculture projects is one that focuses on improving food security in drought-prone areas through the adoption of drought-tolerant crops.

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 that of 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. In the approach of Ahmed et al., future agricultural variability was determined by scaling late 20th Century ("current") variability by a scaling factor based on projected future climate volatility changes relative to current volatility. The link between climate variables and agricultural yields in this earlier work was thus based on 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 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] Section 2 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 2000/2001, there were 12.3 million Tanzanians living below the national poverty line in 2001 (National Bureau of Statistics, 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 (National Bureau of Statistics, 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.

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

[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 (National Bureau of Statistics, 2002), and is TShs 7253 (2001) without correcting for Purchasing Power Parity.

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.

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 General Circulation Model (GCM) experiments (Meehl et al., 2005, 2007) to obtain Tanzania's nationally averaged precipitation (in mm/day) and temperature (in °C) 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 late 20th Century should greenhouse gas concentrations continue to rise (column III of Table 2), with the growing season average temperature increasing by 0.2–1.11 °C across the 22 GCMs (°C differences in parentheses). In a similar vein, most models agree that the average growing season 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. GCM 02 is

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

Table 3
Estimation results for Tanzanian grains yield functions; dependent variable is yield (tonnes per hectare).

Coefficients	Maize	Rice	Sorghum
Intercept	4.5705 (9.245)	−87.5692 (−4.111)	2.2699 (6.345)
Year		0.0476 (4.402)	
Precipitation (mm/month average for January–June growing season)	0.0048 (5.597)	0.0049 (4.166)	0.0021 (3.909)
Temperature (°C average for January–June growing season)	−0.1656 (−7.364)	−0.2817 (−7.318)	−0.0673 (−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.

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.

Climate data from these series alone, however, are insufficient to tell us how variability in agricultural productivity will change. We therefore 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 or net returns. It presumes equilibrium in the land markets such that the "Ricardian" returns to land fully reflect differences in the impact of climate on agricultural productivity in all relevant uses across locations. We believe these are overly strong assumptions in the context of Tanzania—particularly given our emphasis on inter-annual changes in temperature and precipitation.

Empirical work in Sub-Saharan Africa and elsewhere suggests that climate risks are an important determinant of household behavior. Dercon (2006) reports that drought was the predominant source of source of income and asset loss for rural households in Ethiopia. Households which experienced a drought in the last two years showed an average consumption reduction of 16 percent. The production strategy pursued by rural households to minimize the impact of climate risk depends importantly on household wealth. In a case study of South African farmers, Ziervogel et al. (2006) found that wealthier households tended to specialize more, thereby raising their expected returns from a given amount of land. In their path-breaking work on Indian poverty, Rosenzweig and Binswanger (1993) found that increasing the coefficient of variation of rainfall by one standard deviation reduced farm profits for the poorest households by 35 percent, while leaving the richest households expected profits unchanged. Clearly inter-annual variation climate shocks are disproportionately important for the poor and this fact is not reflected in simple Ricardian analysis. Therefore, we combine our economic model of poverty with time series estimation of crop yields, with annual temperature and precipitation among the explanatory variables (e.g. Lobell et al., 2006, 2008).

To that end, monthly climate data from the CRU TS 3.0 dataset (Climate Research Unit, 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 and the 0.5° gridded climate data were averaged temporally over this 6-month period and as well as 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 per hectare). 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 time series data available for Tanzania. A few observations were removed from the analysis as they presented unusual yield values which were likely the result of reporting errors. Harvested areas were used as weights in the fitting process.

The analysis finds that when considering yields as functions of climate, 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 grain yields, while rising precipitation will enhance yields. An increase in average growing season precipitation by 1 mm/month is enough to increase maize and rice yields by 0.005 tonnes per hectare, and 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 17 percent loss per 1 °C is consistent with earlier estimates of roughly 10 percent in the literature for Sub-Saharan Africa (e.g. Jones and Thornton, 2003). Time trends are significant only in the rice yield function, where they are significant and positive, suggesting the presence of ongoing technological progress.

The estimated statistical model, by being based on ex-post data, has the added advantage of endogenizing some adaptive farmer behavior. In any given year, it can be assumed that farmers make production decisions such as planting, harvesting, and input use, based on the best knowledge available to them. Among other things, this best knowledge includes the priors they have about the climate (e.g. knowledge of when rains are likely to arrive) as well as information based on observation (e.g. rainy season onset has occurred and there is optimal post-onset moisture). The historical yields thus reflect some adaptability, as do the estimated parameters in the statistical model.

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

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

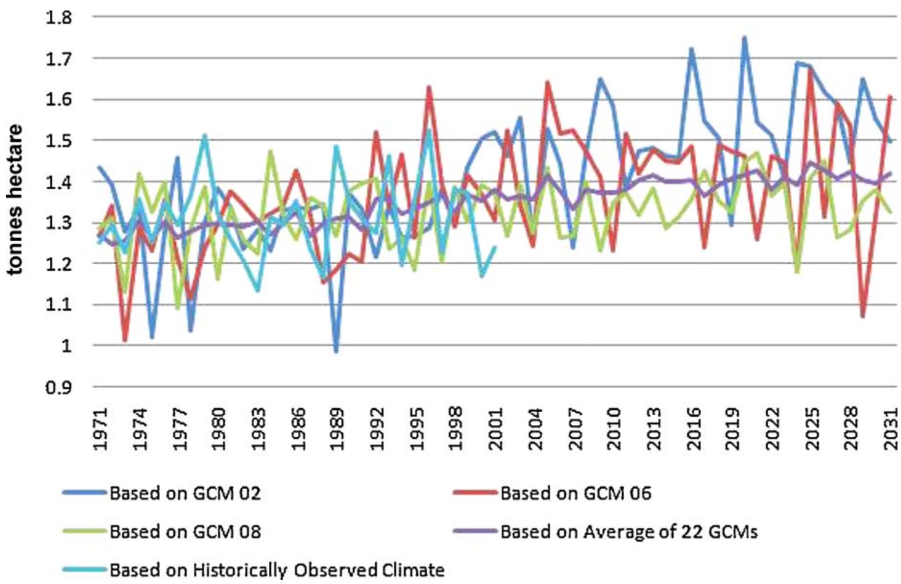

Fig. 1. Predicted grains yields in Tanzania for the period 1971–2031 explained solely by bias-corrected climate data and historically observed climate.Source: Authors' processing of Meehl et al. (2005) and CRU TS 3.0.

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 (column VIII, Table 2). Fig. 1 illustrates these series, whose interannual differences we will now implement in our economic simulation analysis to determine poverty sensitivity to climate in Tanzania.

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). Given the primary focus in this paper on the agricultural sector, economic behavior in that sector is of central importance to our results. Absent strong evidence to the contrary, we assume that farmers minimize production costs, and, given the large number of agricultural producers in Tanzania, we assume that they each take market prices as given. Coupled with the assumption of ready entry and exit of farms, this results in behavior which mimics constant returns to scale and perfect competition at the sector level. Sexton and Lavoi (2001) and Sexton and Zhang (2001) have shown that the existence of imperfect competition in food processing markets can substantially distort prices—as well as price transmission—compared to perfect competition, by depressing producer prices and increasing retail prices. Furthermore, the extent of these distortions depends heavily on the nature of imperfect competition and the number of firms involved in any oligopoly market. Since a review of the literature does not offer strong evidence on the nature of competition in the Tanzanian food sector, we opt for the empirically robust assumptions of constant returns to scale and perfect competition here as well. Clearly, this assumption could be altered as more evidence becomes available on the nature of market structures in the food sector.

Following the methodology of Keeney and Hertel (2005), we also model factor market segmentation, which is important in countries where the rural sector remains a dominant source of poverty. 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 inter-sectoral distributional analysis. In order to parameterize these factor mobility functions, we draw on the Organization for Economic Cooperation and Development (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.

The model is also adjusted to distinguish between agricultural land 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.[6]

In order to link price changes in the CGE model to poverty, we use the household model of Hertel et al. (2004) to examine

[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.

[6] Please see Appendix B for details of model calibration.

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 household's 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)[7]. 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.

Eqs. (1)–(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. Eq. (1) details how we compute the percentage change in the poverty headcount ratio in Tanzania, $\hat{H}$, in the wake of a shock to the prices and wages in the economy (Hertel et al., 2009b):

$$\hat{H} = -\sum_{s} \Theta_s \varepsilon_s \sum_{j} \Omega^{p}_{sj} (\hat{W}^{p}_{j} - \hat{C}^{p}) \tag{1}$$

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, by deducting the percentage change in the cost of living at the poverty line, $\hat{C}^{p}$, from the percentage change in the after-tax $\hat{W}^{p}_{j}$. This real earnings term is pre-multiplied by three important poverty-parameters which deserve additional discussion.[8]

The first, Ω^{p}_{sj}, 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 Eq. (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_s: this is the estimated elasticity of the stratum-specific poverty headcount (H_s) 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:

$$\Theta_s = \frac{[(\mathrm{POP}_s \times H_s)/\mathrm{POP}]}{H} = \frac{(\mathrm{POP}_s \times H_s)}{\sum_k (\mathrm{POP}_k \times H_k)} \tag{2}$$

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

$$dh = \hat{H} \times \left(100 \times \frac{H}{\mathrm{POP}}\right) \tag{3}$$

If this rises by one percentage point, then poverty has risen by one percent of the national population, equivalent to more than 344,000 people. Such a change would indicate a very large poverty impact in Tanzania.

4.2. Estimated 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 all production decisions under best available adaptive behavior in that timeframe. Adaptive responses to

[7] Please see Appendix C for details of AIDADS formulation and parameterization.
[8] Please see Appendix D for more details on the poverty parameters.

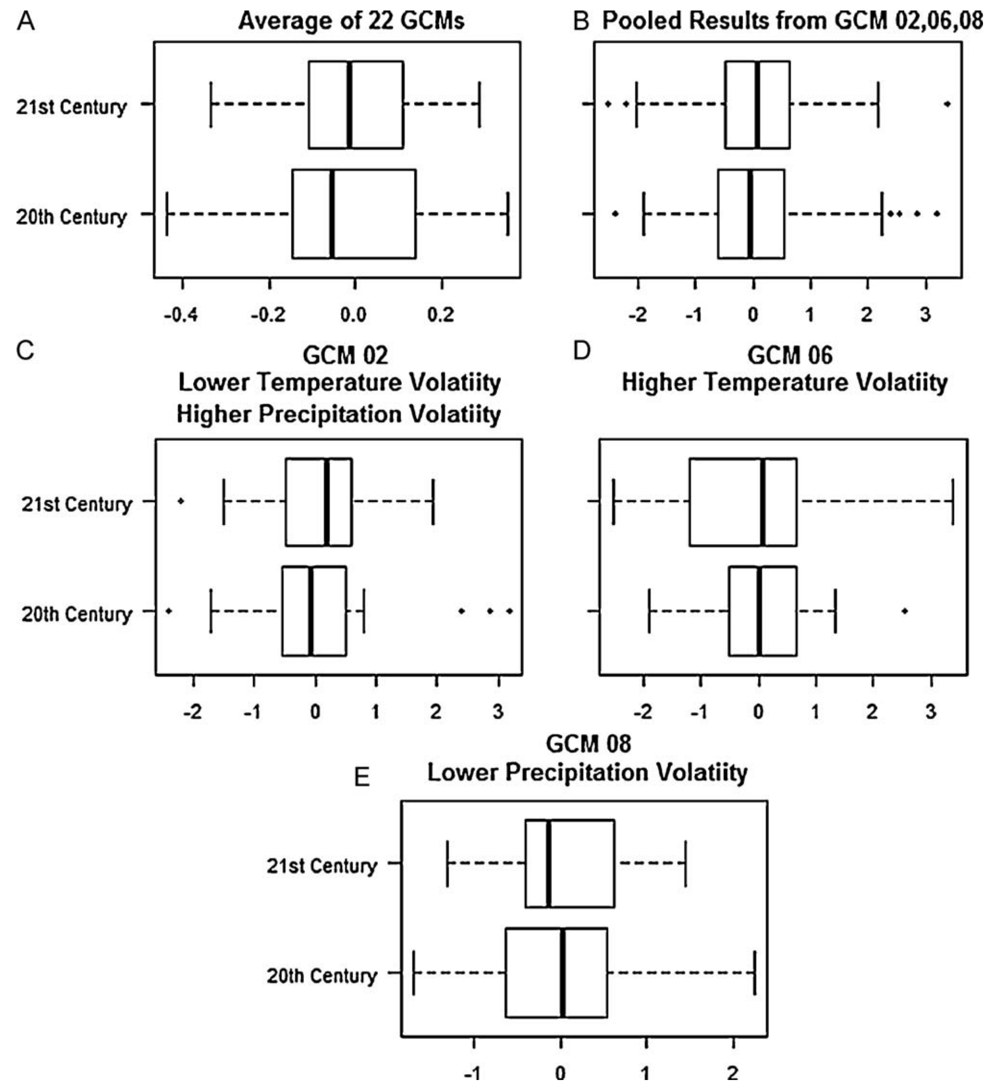

Fig. 2. Panels (A)–(E) indicate the distributions of percentage point changes in the national poverty rate in Tanzania attributable to of distribution of interannual grains productivity changes in the 20th Century and 21st Century, based on the source of the climate data used to estimate the grains productivity 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).Sources: Authors' estimates.

unexpected circumstances that take extended periods of time to implement—such as digging canals for irrigation after the rainy season has commenced—is not possible within the context of the inter-annual changes analyzed here.

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, Fig. 2). In the 20th Century, this median poverty change was −0.06 percent of the population which represents a small 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, Fig. 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 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 Fig. 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 Fig. 2) demonstrate a shift in the probability mass in the more aggregated climate–poverty results due to shifting median values, the inter-quartile range, or both. The use of individual GCMs also reveals the possibility of even larger poverty headcount changes under plausible climate outcomes. 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 700,000 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, Fig. 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, Fig. 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 little 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.

Alternatively, when analyzing GCM 08, which shows the largest decrease in precipitation volatility (Table 2), we see that the poverty distribution contracts, with the median and right whisker being lower in the future than in the 20th Century (panel E, Fig. 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.

The distributions of poverty changes based on individual GCM realizations also illustrate that the extreme poverty outcomes can be substantial. Under 20th Century climate, the poverty headcount can increase by more than 2 percent of the population (approximately 650,000 people) due to an extreme interannual decline in grain yield. Estimates based on certain GCMs—such as GCM 06—shows that extreme poverty-increasing outcomes have greater magnitude in the 21st Century than in the 20th Century. In the 20th Century, the greatest predicted increase in poverty was of 880,000 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.

While the exact realization of the climate system over the next two decades is unknown, the poverty results from the overall 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 (e.g. Meehl et al., 2009), although it is possible that the temporal and spatial scales being considered exceed the limits of predictability.

5. Conclusion

Climate volatility in Tanzania could increase in the future as greenhouse gas concentrations increase (Fig. 1 and Table 2), with agricultural productivity expected to become increasingly volatile as well. For agriculture-dependent 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.

Individual GCM results show that climate-induced interannual poverty increases could be as high as 650,000 in extreme cases even under current climate volatility. The range of possible poverty outcomes due to climate volatility is thus large, and potentially important. 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 24.3–89.7 thousand additional poor when compared with the median poverty outcome under current climate. While this represents a small proportion of Tanzania's population, it is still a large number of people. Furthermore, since future climate volatility could well increase further as greenhouse gas concentrations rise beyond those prescribed here, there is a danger that the poverty vulnerability identified in this paper could intensify beyond the horizon of our analysis, with the potential for even greater extreme poverty outcomes.

The range of poverty headcount changes is directly linked to the interannual yield variability. That is, lower average interannual changes in crop yields correspond to high interannual changes in poverty. It thus follows that policy interventions to increase agricultural productivity, and subsequently average interannual yield changes, would also translate into lower interannual changes in poverty due to climate volatility. These measures would be consistent with Tanzania's current agricultural policy objective of increasing agricultural growth as stated by the Agricultural Sector Development Strategy and its operational program (United Republic of Tanzania, 2005)—a goal present in even more recent initiatives like Kilimo Kwanza (''Agriculture First'') (Tanzania Business Council, 2009). These initiatives to increase agricultural productivity will have to account for changes in the climate more generally, such as through updates to crop calendars and improved crop varieties to account for changing rainfall patterns (Munishi, 2009).

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., submitted for publication), and will be incorporated into future work.

International trade policy presents another tool that can be used to reduce the impacts of climate volatility on agriculture and the poor. In the short run, when resources may not be easily reallocated across economies, open trade regimes have the potential to reduce domestic price volatility. For example, an open trade regime restricts the increase in food prices to the import parity price in the event of a severe productivity shock, such as a drought (Dorosh et al., 2007). However, Tanzania currently has an export ban in place on grain: a policy that has the potential to increase domestic grain price volatility by pushing grain prices below export-parity prices in years with good harvests, with severe implications for poor grain producers. Tanzanian trade policy thus requires careful analysis and reform to be able to successfully exploit beneficial climate outcomes, while mitigating the impacts of detrimental climate. This is thus the focus of ongoing research (Ahmed et al., 2010).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.gloenvcha.2010.10.003.

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