# CLIMATE VOLATILITY AND POVERTY VULNERABILITY IN TANZANIA

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**Selected Paper prepared for presentation at the**
**Agricultural & Applied Economics Association 2009 AAEA & ACCI Joint Annual Meeting,**
**Milwaukee, Wisconsin, July 26-29, 2009**



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**Abstract**[7]

Climate volatility will increase in the future, with agricultural productivity expected to become increasingly volatile as well. For Tanzania, where food production and prices are sensitive to the climate, rising climate volatility can have severe implications for poverty. We develop and use an integrated framework to estimate the poverty vulnerabilities of different socio-economic strata in Tanzania under current and future climate. We find that households across various strata are similarly vulnerable to being impoverished when considered in terms of their stratum's populations, with poverty vulnerability of all groups higher in the 21st Century than in the late 20th Century. When the contributions of the different strata to the national poverty changes are taken into account, the rural and urban households with diversified income sources are found to account for the largest poverty changes due to their large shares in initial total poverty.

KEYWORDS: climate, volatility, poverty vulnerability, Tanzania

[7] This research was funded by the World Bank's Trust Fund for Environmentally and Socially Sustainable Development. The views and opinions expressed in this paper are solely those of the authors. The authors are grateful to Tasneem Mirza for research assistance and to Oliver Morrissey and Vincent Leyaro for price data.

## 1. INTRODUCTION

There is substantial evidence that rising atmospheric GHG concentrations are likely to increase temperature and precipitation extremes in the future (IPCC, 2007), with Easterling et al (2000) making the case that greater climate volatility is already occurring. These changes to the distribution of climate outcomes in a given year are particularly important for agriculture (White et al, 2006; Mendelsohn et al, 2007). They also have implications for developing countries where agriculture is important for the poor as both a source of income as well as for consumption – since the majority of the poor reside in rural areas where farming is the dominant economic activity and because the poor may spend as much as two-thirds of their income on food.

This 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 2 percent of arable land having irrigation facilities – far below the potential 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.

Despite its significance for developing countries, like Tanzania, the effects of changes in climate volatility on agriculture and development are not well-understood. While there is a substantial literature examining the effects of shifts in mean climate variables, fewer studies focus on the economic effects of increased volatility of those climate variables, and their impacts on the populations most vulnerable to climate volatility, namely the poor.

This paper fills an important gap in the literature by developing a quantitative framework for examining the impact of greater volatility of key climate variables on agricultural productivity, and the subsequent effect on poverty. After outlining the methodology, this framework is used to determine how greater climate volatility affects the vulnerability of the poor in Tanzania. This is achieved by first characterizing the poverty vulnerability of different socio-economic groups under the climate volatility of the late 20$^{th}$ Century as it affects grains productivity, and then showing how these vulnerabilities will evolve in the first few decades of the 21$^{st}$ Century.

The next section describes the poverty profile of Tanzania, while section 3 provides details of the integrated assessment strategy that is developed and used. Section 4 analyzes the vulnerability of the poor under the current and future climate volatility. Section 5 outlines some ideas for future work with this framework, and section 6 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 poverty line in 2001 (NBS, 2002).

Table 1 reports some key estimates of the structure of poverty in Tanzania, based on Tanzania's national poverty line[8] . 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 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 two-thirds of total poverty in Tanzania.

Table 1: Earnings-Based Socio-Economic of Tanzania by (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)

From Thurlow and Wobst (2003), we know that grains are among the most important crops for Tanzanian households, as shares of both household income and consumption, and especially so for the rural poor. So, changes in the volatility in the productivity of the Grains sector will have different poverty implications for each of the seven strata of Tanzania's poor.

For example, a drought-like climate event would reduce agricultural productivity, and push up food prices. To a first-order approximation, whether a particular household gains or loses income from this change depends on whether it is a net buyer or seller of the commodity. Higher prices will simply push up the cost of living for net consumers, like urban populations.

It is thus difficult to ascertain, in the absence of more specific knowledge of the situation, how climate volatility would affect 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 need to use an integrated analytical framework that

[8] 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 PPP.

incorporates analyses of crop production, climate science, and general equilibriums of economic systems. Such a method is described in the following section.

## 3. METHODOLOGY

The analytical framework used in this paper relies on several empirical methods implemented in sequence. The first is to characterize interannual agricultural productivity volatility under current climate (section 3.1), followed by the volatility under future climate (section 3.2). A global computable general equilibrium model is then developed (section 3.3) to implement stochastic simulations productivity volatility in the Grains sector under current and future climates.

### 3.1 AGRICULTURAL PRODUCTIVITY VOLATILITY UNDER CURRENT CLIMATE

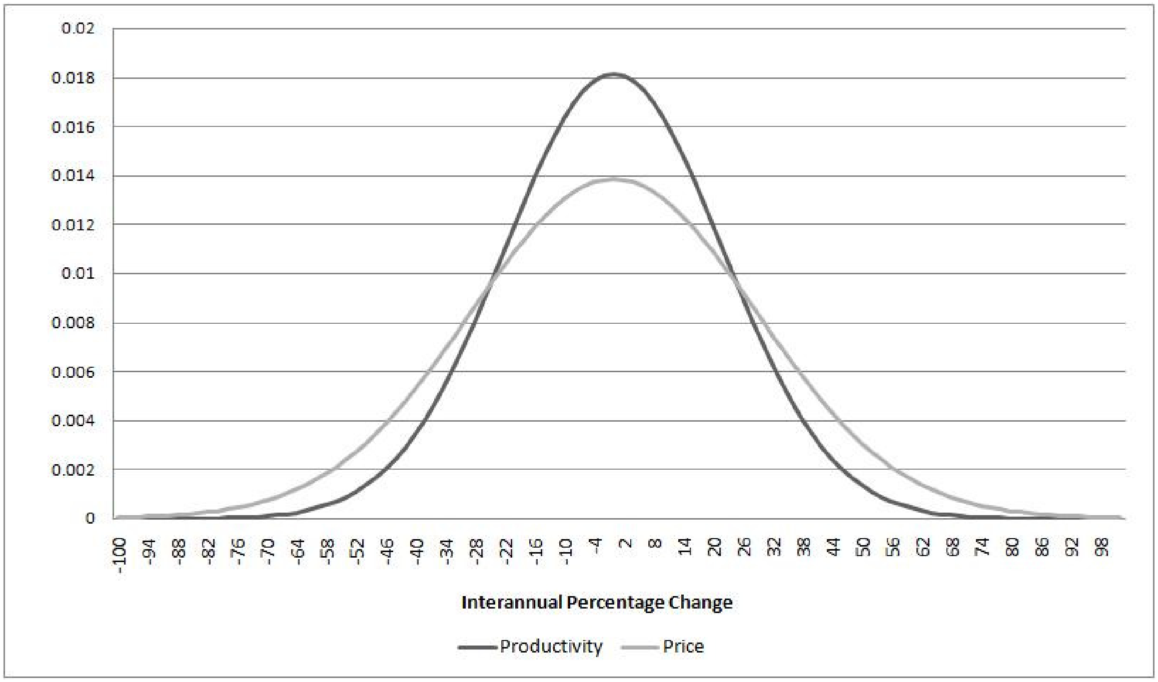
There are many potential ways to capture climate volatility and the resulting impacts on agriculture. In this work we focus on the distribution of interannual changes in agricultural productivity. For our purposes, under any given climate regime, this will be characterized via a mean-zero normal distribution, with an empirically estimated variance. Of course as climate change occurs, both the variance of this distribution and its mean, are subject to change.

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 the overall impact of climate on grains productivity. To determine the standard deviation of the interannual output changes, production data is obtained for Tanzanian Grains (maize, paddy rice, and sorghum)[9] from FAOSTAT for the years 1971 to 2001 (FAO, 2009). These are treated as an aggregate to simplify our task and in order to better match up with the poverty analysis framework to be used below. The interannual percentage changes are then calculated for the Grains aggregate and tested for time trends[10], before the standard deviations of the percentage change time series is determined.

While climate-induced productivity volatilities are fundamentally unobservable, they result in price volatility which can be observed. Since price effects are important mechanisms by which supply side climate shocks to agriculture affect poverty, it is necessary to understand the price volatilities to put the poverty vulnerability in perspective. We also utilize these observed price volatilities to validate our economic model. The price volatility for the aggregated Grains crop is determined through a more complex approach, involving data from a variety of sources for the period 1990 to 2003, and is the value share weighted average of the real price of the disaggregate grains crops[11].

[9] 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.
[10] None were found.
[11] 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. Details on the aggregate price determination can be found in Appendix A.

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. Figure 1 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, with the price volatility being somewhat greater – suggesting an inelastic farm level demand for grains.




Source: Authors' estimation

Figure 1: Grains Productivity and Price Volatilities in Tanzania Characterized as Mean-Zero Normal Distributions of Interannual Percentage Changes, 1971-2001 ( $\sigma_{\text{Productivity}}$ =21.97, $\sigma_{\text{Prices}}$ =28.77))

## 3.2 AGRICULTURAL PRODUCTIVITY VOLATILITY UNDER FUTURE CLIMATE

We determine future agricultural productivity by recalibrating the standard deviations characterizing current productivity distributions for Grains. If FAOSTAT data were available for a period of future climate, we could simply re-estimate the variance of the productivity distribution and use these two empirical distributions as the basis for our poverty vulnerability analysis. However, all we have at hand are historical production levels, and we need to determine future productivity volatility in some other fashion. Our approach is to adjust the empirically estimated productivity distribution (from section 2.1) by two scaling factors: $\delta$ and $\xi$.

$\delta$ is the ratio between simulated productivity volatility under current climate and simulated volatility under future climate. In this way we can avoid confusing the differences between empirical and simulated distributions with the impact of climate change itself. $\xi$ is the percentage change in the mean simulated productivity between the current period and the future, and will be the mean values in the normal distribution characterizing future interannual grains productivity volatility. Since we are maintaining internal consistency by using only simulated volatilities, the $\delta$ and $\xi$ scaling factors are pure measures climate change. By adjusting the empirical distribution in this way, we obtain our best possible estimate of what the productivity distribution will look like under future climate.

Productivity volatility, however, is a function of the volatility in both yields and harvested area. While it is possible to determine statistical projections of yields explained by climate, harvesting decisions are much more difficult to predict. So, we estimate δ and ξ based on current and future yields, as opposed to current and future production levels. Since we are ignoring the variation due to harvesting decisions, the estimate of future production volatility will thus be more conservative than one which accounts for variations in harvested areas.

To determine yields, we use the results of Rowhani et al (2009), from where we adopt the best yield functions for maize, rice, and sorghum in Tanzania:

$$\text{Yield}^{\text{Maize}}_{\text{historic}}(\text{year})=\beta_0+\beta_T^{\text{Maize}}T_{\text{historic}}(\text{year})+\beta_P^{\text{Maize}}P_{\text{historic}}(\text{year}) \qquad \text{EQ (1)}$$

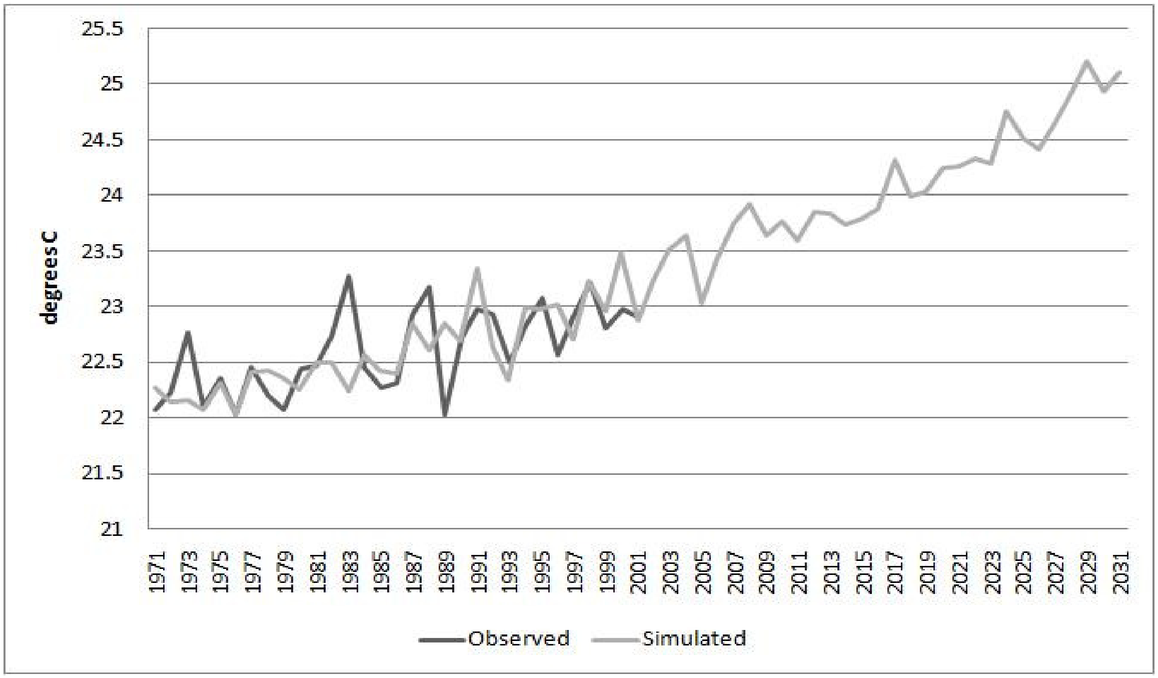
$$\text{Yield}^{\text{Rice}}_{\text{historic}}(\text{year})=\beta_0+\beta_Y^{\text{Rice}}\text{YEAR}+\beta_T^{\text{Rice}}T_{\text{historic}}(\text{year})+\beta_P^{\text{Rice}}P_{\text{historic}}(\text{year}) \qquad \text{EQ (2)}$$

$$\text{Yield}^{\text{Sorghum}}_{\text{historic}}(\text{year})=\beta_0+\beta_T^{\text{Sorghum}}T_{\text{historic}}(\text{year})+\beta_P^{\text{Sorghum}}P_{\text{historic}}(\text{year}) \qquad \text{EQ (3)}$$

$T_{historic}$ and $P_{historic}$ are grid-level historically observed mean temperature (°C) and mean monthly precipitation (mm/month) for the January-June growing season, and are taken from the CRU TS 2.1 database (Mitchell, 2004). Yields are for 20 regions in Tanzania from Monfreda et al (2009). Trends are not significant for maize yields in Tanzania and were thus ignored, while both temperature and precipitation are both revealed to be strongly significant. The temperature coefficients are found to be negative, while the coefficients for precipitation are positive[12]. That is, rising temperatures will put downward pressures on grains yields, while rising precipitation will help increase yields. Since Tanzanian agriculture is almost exclusively rain-fed, these coefficients make sense, and with these estimates in hand, we can determine two yield series, using different sets of climate data.

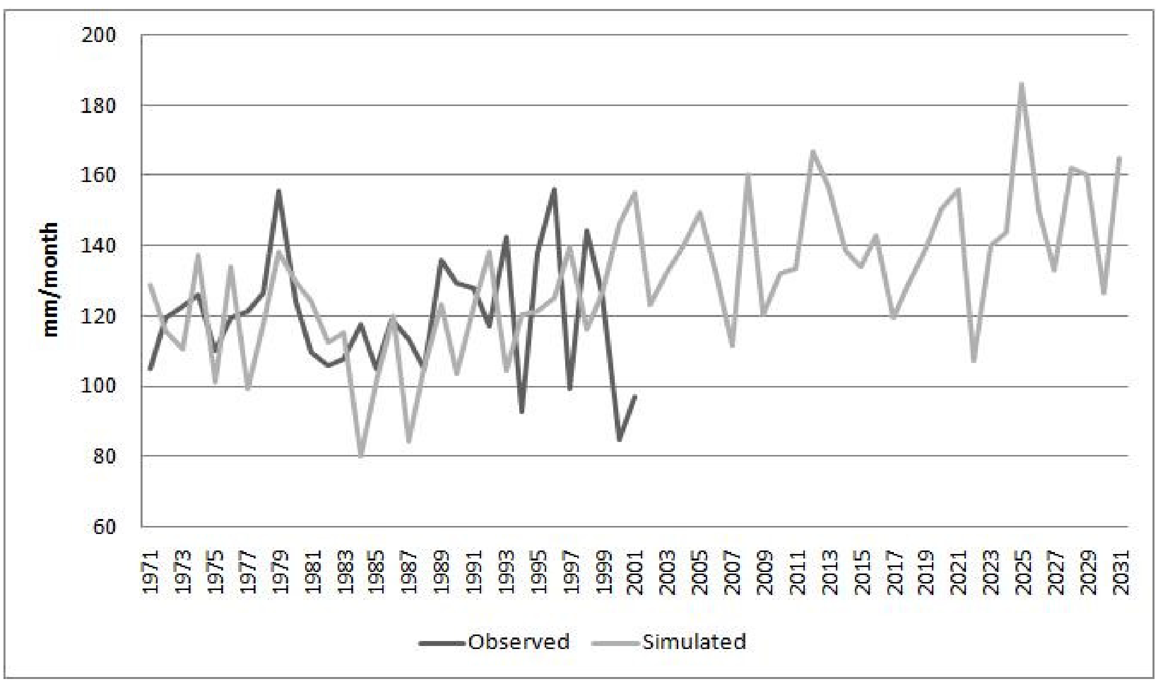
The first set is the historically observed temperature and precipitation, from the CRU TS 2.1 dataset. The second set of climate data are from the CMIP3 archive of GCM results used by the IPCC Fourth Assessment Report (2007) , for the two periods 1971-2001 (late 20$^{th}$ Century) and 2001-2031 (early 21$^{st}$ Century), after they have been recalibrated such that their mean and interannual standard deviations in the historical period match with those from the observed data[13]. Figure 2 shows the temperature data from the two sets, while Figure 3 shows the precipitation. As can be seen, the means and volatilities of both climate variables rise in the 2001-2031 period compared to the end of the 20$^{th}$ Century. However, the exact impact of climate on yields is not clear from visual examination of just the climate data, and we must estimate the yields themselves[14].

[12] Please see Appendix B for yield function estimation results.
[13] Please see Appendix C for details on bias-correction.
[14] Please see Appendix C for details on the yield series estimation.




Source: CRU TS 2.1 and authors' analysis of CMIP3

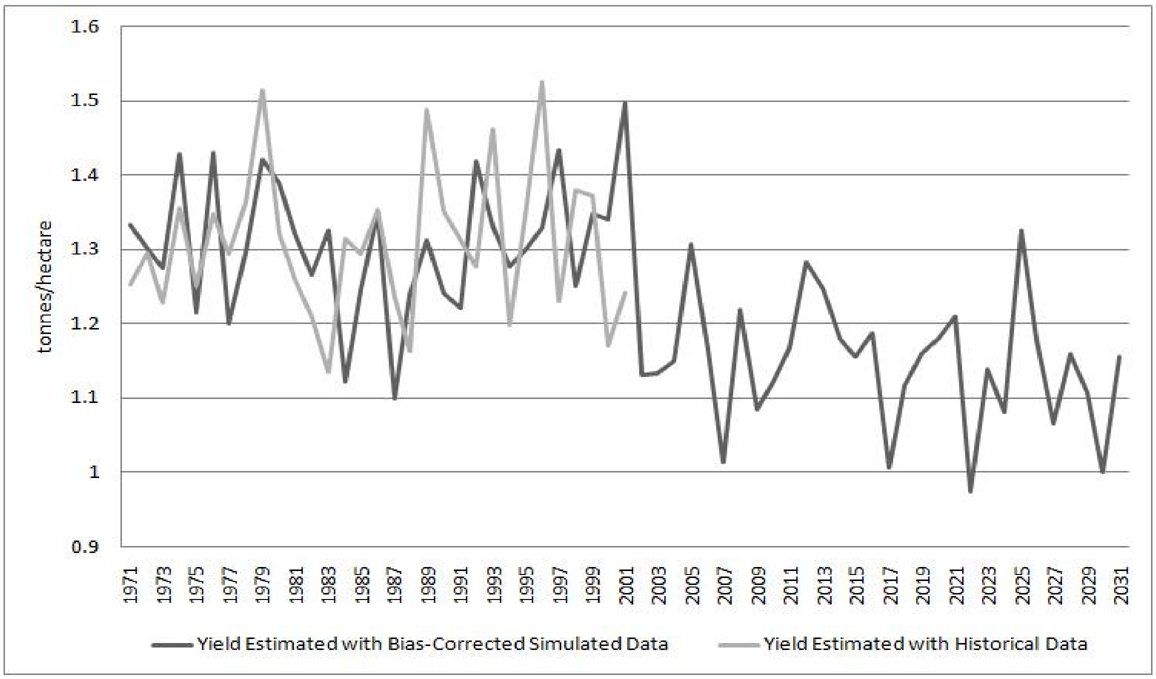
Figure 2: Observed and Simulated Annual Average Temperature over the January-June Growing Season in Tanzania (1971-2031)




Source: CRU TS 2.1 and authors' analysis of CMIP3

Figure 3: Observed and Simulated Annual Average Precipitation over the January-June Growing Season in Tanzania (1971-2031)

Figure 4 illustrates two aggregate grains yield series. The first series is based on the actual observed temperature and precipitation between 1971 and 2001. A second series is based on the climate model simulated temperature and precipitation for the 1971-2031 timeframe, after the latter have been bias-corrected such that their historical mean and interannual standard deviation match those of the observed climate data. This is then recalibrated such that its mean and interannual volatility are consistent with the yield based on observed climate in the historical period. Mirroring the rising climate volatility illustrated in Figures 3 and 4, we see that interannual yield volatility increases in the future, with the volatility in interannual changes in yields found to be 34 percent greater in the early 21st Century, than in the late 20th Century. The production volatility is then found to become 17.45 percent more volatile (δ), while the mean change in yields over the two periods (ξ) is determined to be -11.47 percent.




Source: Authors' estimation
Figure 4: Grains Yields in Tanzania (1971-2031)

### 3.3 COMPUTABLE GENERAL EQUILIBRIUM FRAMEWORK

In order to predict the changes in real earnings stemming from changes to agricultural productivity due to climate effects, we use a general equilibrium model. We begin with the GTAP Version 6 Database (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 a wage differences between the farm and non-farm sectors, and is the foundation of the distributional analysis. In order to parameterize these CET 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 trade facilitation. The model is also adjusted, following Hertel et al (2009) to distinguish between lands with different biophysical characteristics, following the approach of Hertel et al (2009) that distinguishes land into different Agro-Ecological Zones (AEZ), and using the data of Lee et al (2009) and Monfreda et al (2009). This model is then calibrated such that simulations of estimated historical productivity volatility of Grains will replicate the estimated historical price volatility.

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. The demand system in that study was the AIDADS consumer demand system, and was used to determine household consumption and the household's the maximum possible utility for a given set of prices and income. This utility specification is taken to be common across all households in a given country. 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, 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.

In the context of a poverty analysis, the poverty level of utility is then defined as the utility of a representative household at the poverty line. In the wake of a change in climate the realized utilities of households will rise or fall. 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.

In their analysis of the poverty impacts of trade liberalization, Hertel et al (2004) solve this micro-simulation model for representative households in 20 vingtiles in each of the seven population strata. They then report growth incidence curves showing the impact across the entire population spectrum. While comprehensive, this strategy requires exiting from the parent general equilibrium model and solving separate micro-simulation models for each household. This is problematic when undertaking stochastic simulations as is the case here. In addition, since our primary focus is on the vulnerability of the poor, we would prefer to focus our attention on those at and below the poverty line.

Accordingly, this paper follows the integrated poverty analysis approach of Hertel et al (forthcoming) 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. In particular, the former study derives the following equation for predicting the percentage change in poverty headcount, $\hat{H}_r$ . This is the share of the population below the poverty level of utility, in the wake of a shock to the prices and wages in the economy:

$$\hat{H}_r = -\sum_s \Theta_{rs} \varepsilon_{rs} \sum_j \Omega^p_{rsj} \left( \hat{W}^p_{rj} - \hat{C}^p_r \right) \qquad \text{EQ (4)}$$

The term in parentheses on the right hand side of the equation reports the change in the after tax wage rate for endowment *j* in region *r* (Tanzania in this case), $\hat{W}_{rj}^{p}$, relative to the change in the cost of living at the poverty line, $\hat{C}_{r}^{p}$. This real earnings term is pre-multiplied by three important parameters which deserve additional discussion.

The first is $\Omega_{rsj}^{p}$, which is the share of earnings type *j* in total income of households in the neighborhood of the poverty line in stratum *s* of region *r*. By definition, the earnings shares in a given region sum to one. So, if there is a change in a specific earnings source, there will be a change in total household income for a given stratum in the neighborhood of the poverty line. For example, if there is a 10 percent increase in the wages of unskilled labor, and that type of earnings represents 95 percent of household income for household around the poverty line in the rural wage earner stratum, then that stratum's representative household's income will rise by 9.5 percent (0.95 * 10 percent).

Implementation of equation 4 requires the mapping factor earnings in the general equilibrium model to household income sources. 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 allocate it between agricultural vs. non-agricultural activities. We simply assign to it the composite wage for labor determined by the CET endowment function. 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 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 then obtained by solving the demand system for the level of income (i.e., expenditure) 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. This will account for any change in the mix of goods and services consumed owing to changing relative prices, thereby producing an accurate estimate of the change in real income in a given stratum.

This change in real income is, in turn, multiplied by the second important parameter of equation 4, $\varepsilon_{rs}$. This is the estimated elasticity of stratum-specific poverty headcount ($H_{rs}$) with respect to income. 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 parameter:

$$\Theta_{rs}=\left[\left(POP_{rs}*H_{rs}\right)/POP_{r}\right]/H_{r}=\left(POP_{rs}*H_{rs}\right)/\sum_{k}\left(POP_{rk}*H_{rk}\right) \qquad \text{EQ (5)}$$

Summing across strata, we thus obtain the deflated (by net national income) change in national poverty headcount due to earnings changes. Since we also have estimates of the poverty headcount by stratum, we are able to adapt equations 4 and 5 to determine poverty changes by stratum as well[15].

4. ANALYSIS

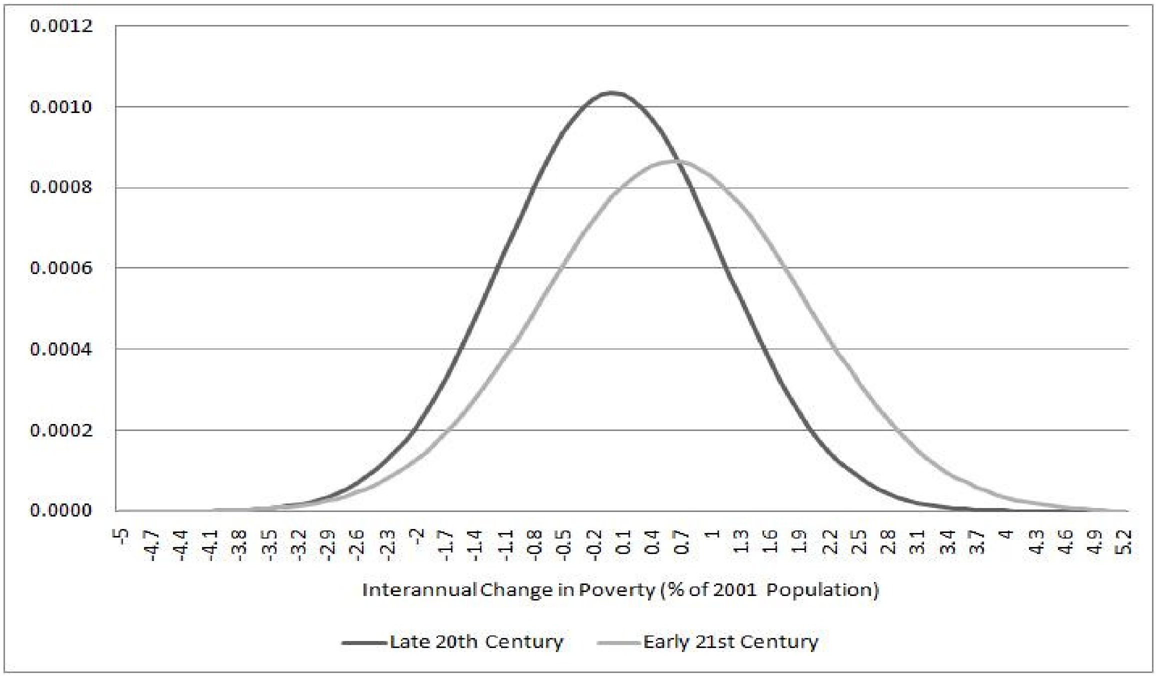
We now simulate the interannual productivity change distributions of the late 20th Century and the early 21st Century using the integrated analytical framework. The assessment of poverty vulnerabilities over different time periods is complicated by the fact that in the real world, the global and Tanzanian economies are changing between the late 20th Century and the early 21st. The comparative static framework that we use resolves this complication since all economic changes – and subsequent poverty effects – are deviations from the situation in 2001, allowing us to attribute poverty changes solely to the climate-based agricultural productivity changes, and not any other event that may cause vulnerability to change between climates in two different periods.

Since the model is comparative static, the two experiments are implemented as stochastic simulations, following the strategy of Hertel et al (forthcoming). The stochastic simulations thus generate a distribution of possible interannual changes to the poverty headcount by stratum. The relative magnitudes of the standard deviations of these normal distributions can then be interpreted as a measure of the vulnerability of a specific income-based socio-economic stratum to climate volatility in a given period, providing a sense of how many households are either entering or exiting poverty within a time period due to the productivity volatility. Changes in the means of these distributions simply characterize the changing level of Tanzanian poverty.

Figure 5 compares the Tanzanian poverty vulnerability in the late 20th Century and the early 21st Century. The two graphs depict the normal distributions of the interannual poverty changes in each time period, and provide two immediate insights. The first is that the volatility of interannual poverty changes attributable to Grains productivity volatility will be higher in the early 21st Century, relative to what it was in the end of the last century. That means that in a given year, the number of households that may potentially enter poverty for a random draw from the distribution of possible climate outcomes is much greater in the future. That is, Tanzanian households are more vulnerable to becoming impoverished.

The second insight is that in addition to a higher standard deviation, there is a shift in the mean of the interannual poverty change distribution. The simulation results indicate that 0.62 percent of the Tanzanian population is expected to enter poverty in the course of a "normal year" due to Grains productivity declining by 11.5 percent.

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




Source: Authors' simulations

Figure 5: Poverty Vulnerabilities in the Late 20th Century and Early 21st Century Depicted as Normal Distributions of Internnual Changes in Poverty Arising from Interannual Productivity Volatilities ($\mu_{20th\ Century}=0$, $\sigma_{20th\ Century}=1.12$; $\mu_{21st\ Century}=0.62$, $\sigma_{21st\ Century}=1.34$)

To begin understanding how the vulnerabilities of individual strata are affected, we must examine the volatility in household income, and identify the sources of the variation. As equation 4 described, changes to the poverty headcount and rate are determined by the changes in the income of a household around the poverty line and the income elasticity of poverty in that stratum. So, we must first examine the volatilities in the real factor returns at the poverty line deflated by the cost of living, i.e. $\left(\hat{W}_{rj}^{p}-\hat{C}_{r}^{p}\right)$ from equation 4.

Table 2 shows the standard deviations of the interannual percent changes in this income by earnings source attributable to Grains productivity volatility in the late 20th Century. The low volatility of earnings from agriculture-specific land and capital is due to their sluggishness across sectors in the one-year (i.e. short run) timeframe of the simulation framework and the fact that they are aggregates over a cluster of sectors (agricultural and non-agricultural). Specifically, when the price of Grains changes due to the a change in productivity, it changes not only the returns to the factors that the Grains sectors uses as inputs, but also changes the prices of other agricultural and non-agricultural products, and the factors that those industries employ. Whether the Grains price change increases or decreases the prices of the other commodities is determined in general equilibrium by that commodity's relationship – as a substitute or intermediate input – to the other commodity. Since Grains are substitutes for all agricultural commodities, except for the raw materials for textiles, the prices of the other agricultural commodities always change in a manner opposite to how the price of Grains are changing.

Table 2: Standard Deviation of Interannual Percent Changes in Real Factor Returns Deflated by the Cost of Living

| Earnings Source | Percent Change |
|---|---|
| Agricultural Land | 0.05 |
| Self-Employed Agricultural Labor - Unskilled | 5.67 |
| Self-Employed Agricultural Labor - Skilled | 5.62 |
| Self-Employed Non-Agricultural Labor - Unskilled | 6.48 |
| Self-Employed Non-Agricultural Labor - Skilled | 6.05 |
| Wage Labor - Unskilled | 6.09 |
| Wage Labor – Skilled | 6.03 |
| Agricultural Capital | 2.26 |
| Non-Agricultural Capital | 6.02 |
| Transfer Payments | 5.03 |
| Average | 4.93 |

Source: Authors' simulations

For example, if the price of Grains rises, due to a year with a bad draw from the productivity change distribution, then the prices of other agricultural commodities will rise. The rising Grains price will push up the earnings from land and capital that Grains producers use. However, the returns to land and capital used by other agricultural sectors will decline. Due to these opposite effects, when considered over all agricultural sectors, the change in agricultural land and capital will be smaller than the changes in individual agricultural sectors. This explains why the volatility of incomes from agriculture-specific endowments is lower than average.

Following equation 4, we must now determine the volatilities in real income by stratum and source, by weighing the real factor returns with the stratum earnings shares at the poverty line, i.e. $\Omega^{p}_{rsj}$ (Table D1). Table 3 shows, for each stratum, standard deviations of the interannual percent changes in this income by earnings source attributable to Grains productivity volatility in the late 20$^{th}$ Century. As the last row reveals, the incomes of households across strata are similarly volatile, although the primary sources of these volatilities vary. For example, the income volatility of households in the Urban Diversified strata is mostly due to self-employed unskilled workers and non-agricultural capital, whereas a Transfer-dependent household's income volatility is accounted for almost exclusively by transfer payments.

Table 3: Standard Deviation of Interannual Percent Changes in Real Income of Marginal Households by Earnings Source and Stratum Deflated by the Cost of Living

| | Stratum | | | | | | |
|---|---|---|---|---|---|---|---|
| Earnings Source | Agriculture | Rural Labor | Rural Diversified | Non-Agriculture | Urban Labor | Urban Diversified | Transfers |
| Agricultural Land | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Self-Employed Agricultural Labor - Unskilled | 3.69 | 0.01 | 1.86 | 0.01 | 0.01 | 1.10 | 0.00 |
| Self-Employed Agricultural Labor - Skilled | 0.00 | 0.00 | 0.00 | 0.11 | 0.00 | 0.02 | 0.00 |
| Self-Employed Non-Agricultural Labor - Unskilled | 0.00 | 0.00 | 0.73 | 4.12 | 0.00 | 1.28 | 0.01 |
| Self-Employed Non-Agricultural Labor - Skilled | 0.00 | 0.25 | 0.02 | 0.00 | 0.82 | 0.08 | 0.00 |
| Wage Labor - Unskilled | 0.00 | 5.81 | 0.67 | 0.00 | 5.25 | 0.86 | 0.00 |
| Wage Labor - Skilled | 1.75 | 0.01 | 0.95 | 0.01 | 0.00 | 0.62 | 0.00 |
| Agricultural Capital | 0.12 | 0.00 | 0.07 | 0.00 | 0.00 | 0.05 | 0.00 |
| Non-Agricultural Capital | 0.00 | 0.00 | 1.11 | 2.05 | 0.00 | 1.13 | 0.00 |
| Transfer Payments | 0.01 | 0.00 | 0.35 | 0.01 | 0.01 | 0.69 | 5.02 |
| All Sources | 5.58 | 6.08 | 5.77 | 6.30 | 6.08 | 5.82 | 5.03 |

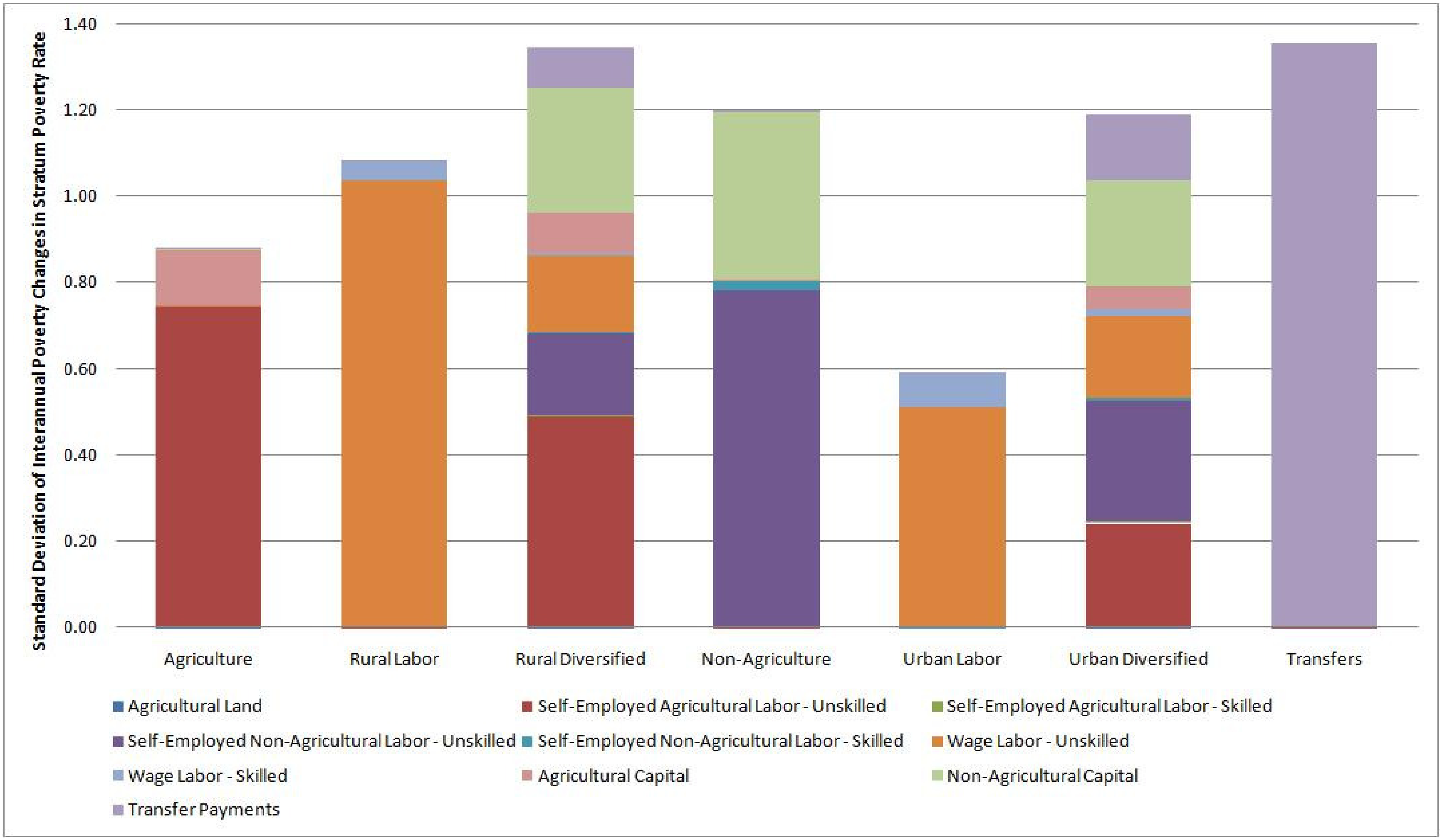
Source: Authors’ simulations

With this information in hand and knowing income elasticities of poverty by earnings source and stratum (Table D3) we can identify the most vulnerable strata, as well as decompose the contribution of each earning source to that vulnerability. Figure 6 presents this by depicting the standard deviations of the interannual changes in stratum poverty rates for the late 20$^{th}$ Century. It can be seen that the Urban Labor and Agricultural strata are the most insulated from changes in their poverty, while the Transfer and Rural Diverse strata – two strata with high initial poverty rates (Table 1) are the most vulnerable.

From the perspective of poverty vulnerability based on stratum poverty rates, it thus seems that found that various strata have similar levels of vulnerability. The average vulnerability across strata is characterized by an interannual poverty change standard deviation of 1.09 percent of stratum population. However, this does not mean that all strata are equally vulnerable to climate effects, since that would discount the share of each stratum in the total population. Strata with higher populations are more important to the national poverty vulnerability than strata with smaller populations but the same vulnerability. Rural wage laborers and Transfer-dependant households are good examples of this, with the population of these strata together less than 2.5 percent of Tanzania's total population.

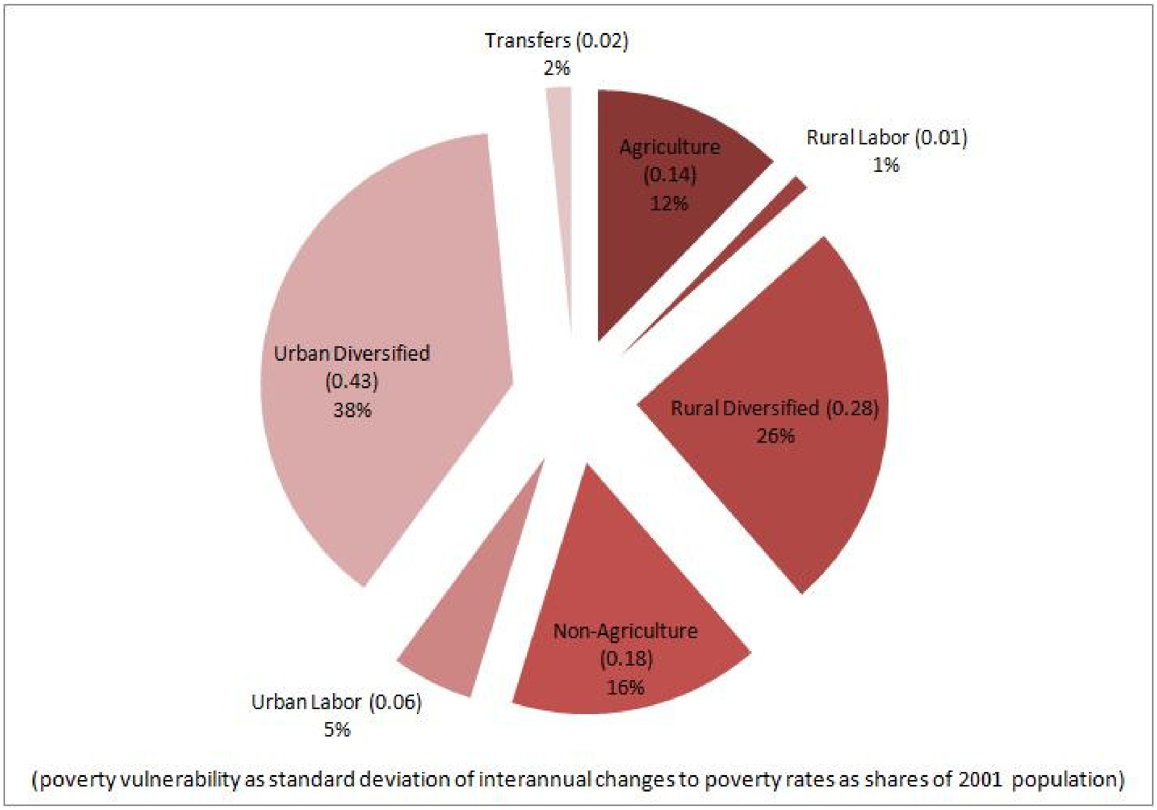
As figure 7 indicates, their poverty vulnerabilities in the national context (standard deviations of less than 0.02 percent of national population) are much less than the average vulnerability across strata. Furthermore, these strata contribute less than 2 percent to any change in the national poverty profile. In contrast, the Urban Diversified and Rural Diversified strata will account for 64 percent of the total change in national poverty that will arise from Grains productivity changes.

This is in evidence when we examine the mean Tanzanian poverty change. As mentioned earlier, there was a mean shift in climate volatility between the late 20$^{th}$ Century and the early 21$^{st}$ Century, which led to shifts in the period average yields and subsequently period average poverty. Figure 5 mentioned this mean increase in national poverty as being 0.62 percent of the 2001 population, or 0.21 million additional poor. Close examination of this rise in poverty reveals that the contributions of each stratum to the greater numbers of poor match the contributions indicated in Figure 7. For example, 38 percent of the 0.21 million additional poor are from the Urban Diversified stratum, while one percent are from the Rural Labor group.




Source: Authors' simulations

Figure 6: Poverty Vulnerability in the Late 20th Century due to Climate Volatility Decomposed by Contribution from Earnings Sources




Source: Authors' simulations
Figure 7: Contribution of Each Stratum to National Poverty Vulnerability Measured as Standard Deviation of Interannual Poverty Changes Arising from Grains Productivity Volatility in the Late $20^{th}$ Century

5. FURTHER WORK

There several possible avenues by which this work will be developed in the future. One is by using yield estimation results from Rowhani et al (2009), conducted at the administrative unit level, to obtain yield projections for the three crops at a more spatially disaggregate level. This will allow us to conduct simulations specific to the various Agro-Economic Zones.

Another avenue for further work is the implementation of a parallel simulation strategy. The simulation strategy used in this paper involved the estimation and simulation of Grains productivity volatility under current climate, shifting this distribution by an empirically determined scaling factor, and then simulating the perturbed distribution. In contrast, the alternative strategy will use the yield estimates for every year between 1971 and 2031 to calculate for each year, the percentage difference in the yield from the 2001 yield. The differences from the 2001 yield will then be simulated, analyzing the interannual changes in poverty by stratum. This will provide another perspective from which to decompose the poverty changes by stratum, to better understand the mechanisms that drive the poverty changes, and to identify and scrutinize the poverty changes in years with the highest (or lowest) productivity changes.

Finally, the current analysis does not consider any potential adaptation policies and the poverty impacts presented here can be considered to represent a "business as usual scenario". Future iterations of this research can thus incorporate adaptation policy measures that the Tanzanian government can adopt, along with estimates of their relative cost.

## 6. CONCLUSION

Climate volatility will increase in the future, with agricultural productivity expected to become increasingly volatile as well. For agriculture-dependant developing countries where food production is very sensitive to the climate, like Tanzania, the rising climate volatility can have severe implications for poverty.

In this paper we developed an integrated framework by which to estimate future agricultural productivity climate volatility based on estimates of current agricultural volatility, current climate volatility, and future climate volatility. Using an economic simulation model that has an embedded household modeling component, we determined the vulnerabilities of seven different income-based socio-economic strata to rising poverty as a result of changes in climate.

We used this integrated analytical framework to examine the poverty vulnerability of the various income strata in Tanzania under late 20$^{th}$ Century climate volatility, and found that households across the various strata were similarly vulnerable to being impoverished when considered in terms of their stratum's populations. In the early 21$^{st}$ Century, when there have been increases in both climate means and climate volatility, households in all strata are predicted to become more vulnerable. Households that are depend on transfer payments or rural wage earnings are particularly vulnerable to becoming impoverished by adverse climate affecting Grains production.

When the contributions of the different strata to the national population are taken into account, it is found that vulnerabilities of these rural wage dependent and transfer-dependent strata have less of an impact on national scale vulnerability than those of other socio-economic groups. That is because these groups account for a small share of Tanzania's population. In contrast, it is the rural and urban households with diversified earnings sources that account for most changes in the national poverty due to their large shares in the national population. Policy responses that aim to mitigate poverty vulnerability should thus take these varying contributions into account for better targeting.

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APPENDIX A: AGGREGATED PRICE

The aggregated Grains price is developed using three different types of data and following equations (A1), (A2) and (A3)

$Q_{tir}$ – Production data in tons from FAOSTAT for disaggregated crop I (FAO, 2009).
$P_{tir}$ – Price data from before 1991 in LCU/ton from price data of Morrissey and Leyaro (2007).
$D_{tr}$ – GDP deflator from the IMF's International Financial Statistics (IMF, 2008).

$$\text{TotalValue}_{tr} = \sum_{r} \left( P_{tir} * Q_{tir} \right) \qquad \text{EQ (A1)}$$

$$\text{ValueShare}_{tir} = \frac{P_{tir} * Q_{tir}}{\text{TotalValue}_{tr}} \qquad \text{EQ (A2)}$$

$$\text{PAggCrop}_{tr} = \sum_{i} \left( \frac{\text{ValueShare}_{tir} * P_{tir}}{D_{tr}} \right) \qquad \text{EQ (A3)}$$

APPENDIX B: YIELD FUNCTION ESTIMATION

The estimation of maize, rice, and sorghum yields is detailed in Rowhani et al (2009). To summarize, however, that study used annual crop yields (tonnes/hectare) from 17 administrative regions of Tanzania from 1992 to 2005. Gridded monthly mean climate data were obtained from CRU (Mitchell, 2004) where temperature is the mean temperature (°C) and precipitation is the mean precipitation (mm/month) over the January-June growing season. Table B1 describes the results of the estimation.

Table B1: Estimation Results for Tanzanian Maize Yield function

| Coefficients | Maize | Rice | Sorghum |
|---|---|---|---|
| Intercept | 4.5705 | -87.5692 | 2.2699 |
| Year | | 0.0476 | |
| Precipitation | 0.0048 | 0.0049 | 0.0021 |
| Temperature | -0.01656 | -0.2817 | -0.0673 |
| R-Squared | 0.209 | 0.181 | 0.074 |

Source: Rowhani et al (2009)

Note: All coefficients are significant

APPENDIX C: CLIMATE AND YIELD PROJECTION

We use climate data from two different sources: the CRU database of historically observed climate data and from the CMIP3 archive of GCM-generated climate predictions. From these two sources we retrieve annual mean temperature and rainfall for current and future climate for the January to June growing season, and specify them 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
- $P_{current, model}$ (year) = Model simulated rainfall between 1971 and 2001
- $T_{future, model}$ (year) = Model simulated temperature between 2001 and 2031
- $P_{future, model}$ (year) = Model simulated rainfall between 2001 and 2031
- $T_{model}$ (year)= Model simulated temperature between 1971 and 2031
- $P_{model}$ (year) = Model simulated rainfall between 1971 and 2031

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 C1 and C2. 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 C3 and C4 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). The resulting climate data series can be seen in Figures 2 and 3.

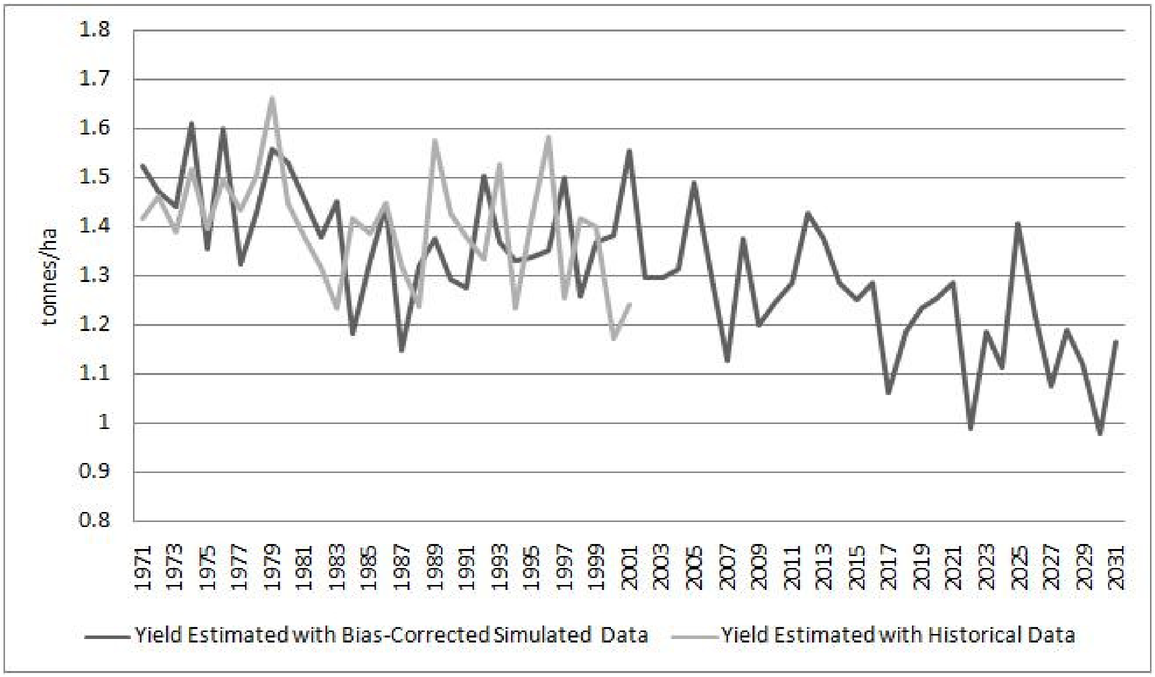
$$T_{model}^{mean\ corrected}(year)=T_{model}(year)+\frac{\left(\sum_{year}T_{obs}(year)-\sum_{year}T_{current,model}(year)\right)}{\text{Number of Years Observed}} \qquad \text{EQ (C1)}$$

$$P_{model}^{mean\ corrected}(year)=P_{model}(year)\frac{\sum_{year}P_{obs}(year)}{\sum_{year}P_{current,model}(year)} \qquad \text{EQ (C2)}$$

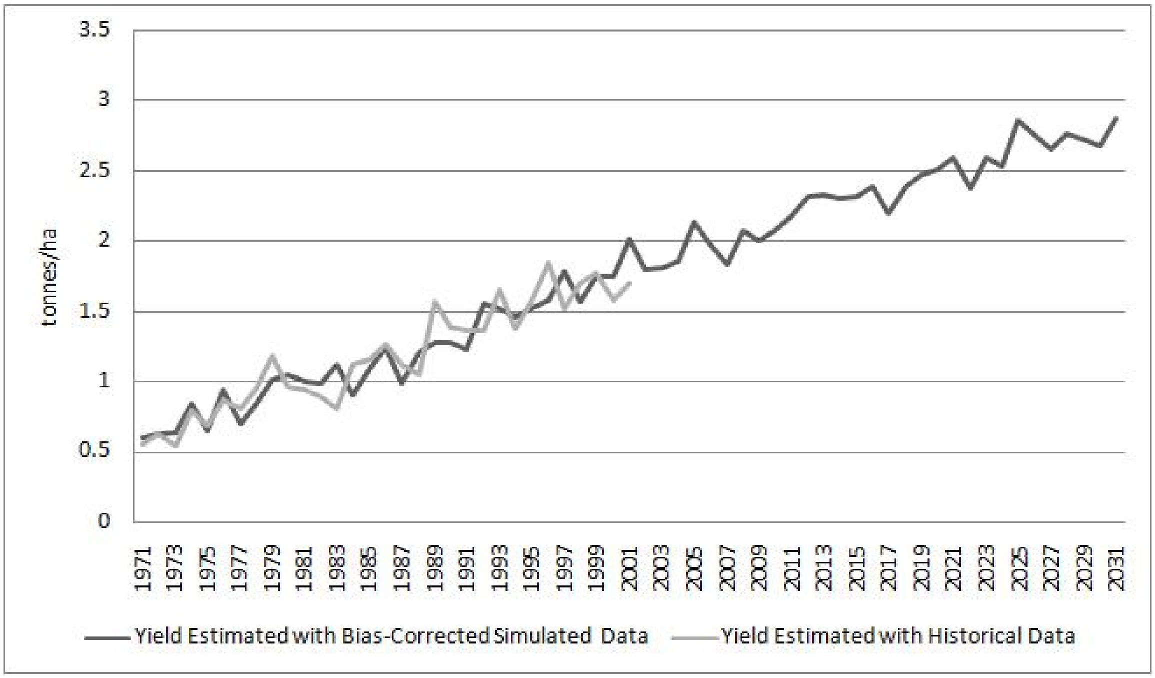
$$T_{model}^{bias\text{-}corrected}(year)=\left(\frac{T_{model}^{mean\ corrected}-\mu_{T_{model}^{mean\ corrected}}^{1971\text{-}2001}}{\sigma_{T_{model}^{mean\ corrected}}^{1971\text{-}2001}}\right)*\sigma_{T_{obs}}+\mu_{T_{obs}} \qquad \text{EQ (C3)}$$

$$P_{model}^{bias\text{-}corrected}(year)=\left(\frac{P_{model}^{mean\ corrected}-\mu_{P_{model}^{mean\ corrected}}^{1971\text{-}2001}}{\sigma_{P_{model}^{mean\ corrected}}^{1971\text{-}2001}}\right)*\sigma_{P_{obs}}+\mu_{P_{obs}} \qquad \text{EQ (C4)}$$

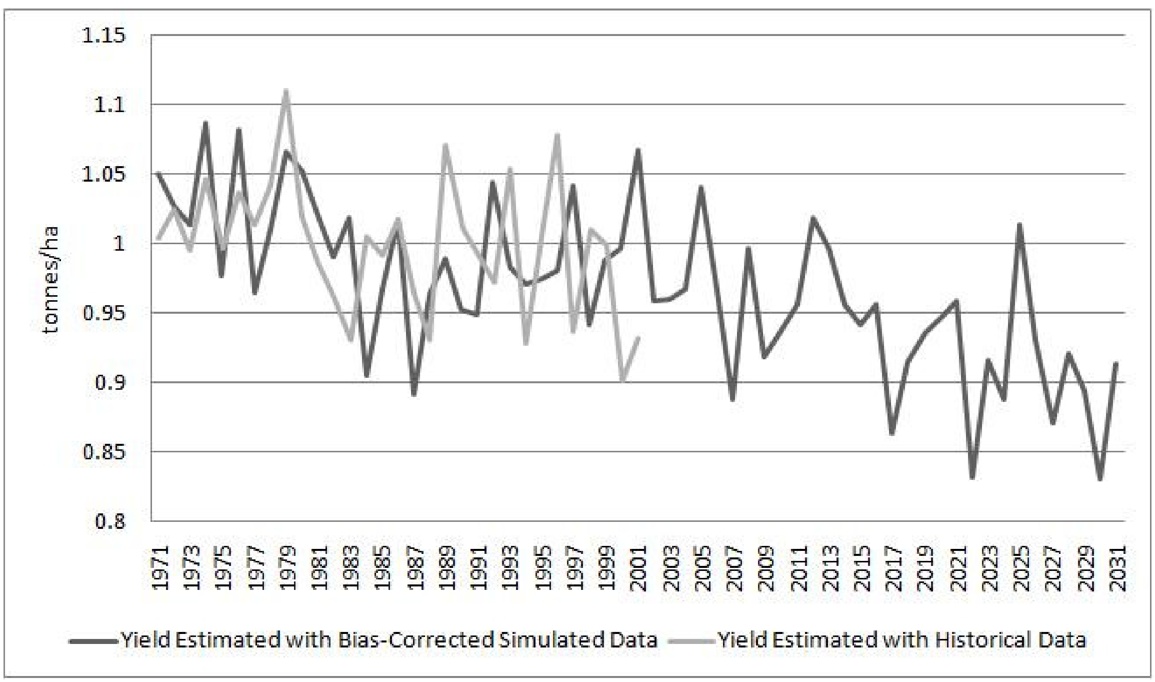
Two different series of yields for each crop can now be calculated using the coefficients from Table B1 and the climate data from equations C3 and C4. The first series uses the historically climate data from CRU to generate a series from 1971 to 2001, while the second series uses the bias-corrected climate data to give us a series from 1971 to 2031. The second yield series has a bias in the variance, in that its interannual standard deviation in the historical period is not the same as the volatility in the first (historical) series. The second yield series is then bias-corrected in the same strategy used in equations C3 and C4, to generate three sets of series (Figures C1 to C3). The aggregate Grains yield series (Figure 4) are 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).




Source: Author's projections
Figure C1: Maize Yields in Tanzania (1971-2031)




Source: Author's projections
Figure C2: Rice Yields in Tanzania (1971-2031)




Source: Author's projections
Figure C3: Sorghum Yields in Tanzania (1971-2031)

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 ($\Omega^{p}_{rsj}$) 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[16].

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[17].

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 4, the earnings shares translate wage changes into income changes, but it is the poverty elasticities, $\varepsilon_{rs}$, 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

[16] 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.

[17] 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.

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 4 is the stratum share of national poverty, $\Theta_{rs}$, 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)