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Current Climate Variability and Future Climate Change

Estimated Growth and Poverty Impacts for Zambia

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Abstract

Economy-wide and hydrological-crop models are combined to estimate and compare the economic impacts of current climate variability and future anthropogenic climate change in Zambia. Accounting for uncertainty, simulation results indicate that, on average, current variability reduces gross domestic product by four percent over a ten-year period and pulls over two percent of the population below the poverty line. Socio-economic impacts are much larger during major drought years, thus underscoring the importance of extreme weather events in determining climate damages. Three climate change scenarios are simulated based on projections for 2025. Results indicate that, in the worst case scenario, damages caused by climate change are half the size of those from current variability. We conclude that current climate variability, rather than climate change, will remain the more binding constraint on economic development in Zambia, at least over the next few decades.

Keywords: climate change, weather variability, economic growth, poverty, Zambia

JEL classification: D58, O13, Q54

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Figures and tables appear at the end of the paper.

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1 Introduction

Uncertainty over future climate and weather patterns complicates the design of robust development strategies, especially in Sub-Saharan Africa, where most countries rely on rain-fed agriculture—a sector highly exposed to climate risk. Climate variability continues to threaten rural households' livelihoods and undermines economic development. Extreme weather events, such as droughts and floods, also cause substantial socio-economic damages. Despite our experiences with historical climate variability, most attention today is afforded to *anthropogenic* climate change (i.e., long-run changes in global and local climate caused by human activity). The possibility that future climate change may exacerbate the damages already being caused by current climate variability has heightened uncertainty and captured the attention of policy makers at national and international levels.

What is lacking in the literature, however, is a comparison of the incremental damages from future climate change with those already being caused by current climate variability. To address this gap, we develop an analytical framework linking hydrological-crop (HC) models to a recursive dynamic computable general equilibrium (CGE) model. We use this framework to estimate and compare the impacts of climate variability and climate change on economic growth and household income poverty.

Ours is not the first study to combine biophysical and economic models to evaluate climate impacts. However, previous studies have focused on extreme weather events, climate variability, or climate change, without jointly evaluating these phenomena. For instance, Pauw et al. (2010) combined hydro-meteorological and CGE models to assess droughts and floods in Malawi, and Block et al. (2008) used a multi-market model of Ethiopia that linked rainfall and crop yields to compare economic outcomes under static and variable climate patterns. While adopting comparable frameworks to address current climate variability, neither study considered anthropogenic climate change. Conversely, Arndt et al. (2010) combined various sector models with a CGE model to estimate climate change impacts in Mozambique, but did not compare these to current climate variability. Our study extends these previous studies by jointly estimating and comparing relative impacts of current and future changes and extreme weather events.

We apply our modeling framework to Zambia—a low-income, landlocked country with a history of erratic economic growth, at least part of which is attributable to climate variability. Climate shocks may contribute to widespread poverty in Zambia, especially since small-scale subsistence farmers comprise most of the country's poor population. Zambia therefore represents a typical low-income, agriculture-based African country and is an ideal case in which to examine climate's growth and poverty impacts. We first review Zambia's climate characteristics in Section 2 drawing on historical data. Section 3 then describes the modeling framework and our treatment of uncertainty and climate change projections. The framework is used in Section 4 to estimate the economic impacts of current climate variability and extreme weather events, and in Section 5 to estimate the incremental impacts from future climate change. We conclude by summarizing our findings and identifying areas for further research.

2 Zambia’s climate characteristics

2.1 Precipitation and evapotranspiration

A country’s climate characteristics are primarily determined by intra-annual distributions and inter-annual variations in precipitation and temperature. Zambia has a moderate climate with temperatures rarely exceeding 35°C. Rainfall is unevenly distributed throughout the year, with most occurring during the six-month summer season when the important smallholder staple maize is grown. Only large-scale commercial farms have the irrigation needed to grow wheat or sugarcane during the dry-season.

Five agro-climatic zones were identified using monthly observations from 30 weather stations for the period 1976–2007 (see Figure 1). Climate data were aggregated to these zones, taking into consideration the influencing domain of each weather station, namely the Thiessen polygon whose boundary defines the area that is closest to the station relative to all other stations. Average annual rainfall exhibits a downward gradient from north to south (see Table 1). Zone 5 in the north has the highest annual rainfall (1228mm) while zone 1 in the south has the lowest (786mm). We calculated ‘reference evapotranspiration’ (ETo) at each weather station using the Penman-Monteith equation (Allen et al. 1998), a standard method recommended by the Food and Agricultural Organization of the United Nations (FAO) for determining evapotranspiration, which is the water being transported to the atmosphere from soil surface and vegetation, in this case, a reference crop. This provides the basis for measuring crop water requirements that, in turn, determine the effect of water availability on crop yields. In contrast to rainfall’s declining northtosouth trend, ETo increases from north to south. This suggests that rainfall is lowest where crop water requirements are highest, thus exposing rain-fed agriculture in the south to greater risk of yield losses (or crop failure during droughts).

Inter-annual variation in rainfall is highest in the drier southern zones and lowest in the wetter northern zones. Table 1 reports rainfall’s coefficient of variation (CV). The dry zones 1 and 2 have the highest variability with coefficients of 0.18 and 0.20, respectively. Assuming annual rainfall follows a normal distribution, according to the quantile function of normal distribution the CV value implies that in zone 2, for example, there is about a 30 percent probability that rainfall in any given year is 20 percent (i.e., 164mm) above or below the mean (i.e., 818mm). This indicates potential droughts or floods depending on the spatial and intra-annual distribution of rainfall, particularly within the rainy season. Finally, zone 2 has a higher CV than zone 1, despite having slightly higher average annual rainfall. This confirms these two zones’ exposure to weather risk and extreme weather events.

2.2 Extreme weather events

Droughts are complex phenomena and so an index is often used to measure their severity. For agriculture, drought indices typically reflect the amount of soil water available to the crop rather than focusing on rainfall deficits. We use a ‘Palmer Z Index’ as a drought severity metric (Palmer 1965; Alley 1984). This index is based on the supply-demand concept of soil water balance and provides a standardized measure of moisture conditions, thus permitting comparisons across locations and time. Monthly indices were calculated for each zone and were averaged over the wet season to create annual drought indices for the 1976–2007 harvest years. A negative value for the index indicates dry conditions within a zone, while a positive value indicates wet conditions. As shown in Table 2, threshold values were chosen to categorize growing seasons into severe dry years (-1.5), moderate dry years (-0.5), normal years, moderate wet years (0.5), and very wet years (1.5).

A drought's spatial extent is important for agriculture since simultaneous drought conditions over large areas complicates mitigation efforts, including supplementing drought-afflicted markets with supply from unaffected regions. Table 2 reports frequencies of simultaneous weather events across zones. The worst drought during 1976–2007 occurred in the 1991/92 season when zones 1–3 simultaneously experienced severe droughts. Other severe droughts occurred in zones 1–2 during 1994/95 and 2004/05 and in zone 2 during 1986/87. These four seasons represent the major drought years in historical data. By contrast, moderate droughts occurred more often and affected larger areas. 'Normal' weather (i.e., an index between -0.5 and 0.5) never occurred simultaneously in more than three zones during 1976–2007, reflecting Zambia's proneness to extreme weather events. Finally, wet events occur less frequently than droughts in Zambia. Only in 1977/78 were four zones simultaneously affected by 'very wet' conditions.

Two conclusions can be drawn. First, Zambia is prone to droughts and floods, with a high probability of at least one zone experiencing abnormal weather events in any given year. Second, the central and southern regions of the country (i.e., zones 1–3) are especially prone to extreme events, whereas zone 5 has relatively stable weather conditions with no severe droughts and only one wet season over the last three decades. In the following sections we will develop and use spatially-disaggregated models to translate zonal climate variability and extreme events into economic outcomes.

3 Integrated modeling framework

Two types of models were used to evaluate climate's economic impacts. HC models predict crop yield responses, which are then passed top-down to a dynamic CGE model to measure changes in sectoral/national production and household incomes/poverty.

3.1 Hydro-crop model

We used a two-stage semi-empirical HC model. First, actual evapotranspiration (ET) is simulated based on a calibrated soil water balance module for the crop's root zone (see Allen et al. 1998). Second, crop yield responses to water deficits are estimated using an empirical crop water production module (see Jensen 1968). Separate models were developed for 12 crops in each agro-climatic zone.

The soil water balance module estimates crops' water requirements expressed as the rate of potential ET according to the procedure developed by Allen et al. (1998). Since accurate field measurements were unavailable, crop-specific water requirements were derived by estimating potential ET based on a reference crop (i.e., alfalfa) adjusted by a calibrated crop coefficient combining crop transpiration and soil evaporation. This gives crop-specific potential ET under a given set of climate conditions. Based on rainfall and potential ET, the soil water balance module then measures the water flowing into the crop's root zone via precipitation (without irrigation) and the water leaving via ET, surface runoff, and deep percolation. The module balances these flows using the crop's root zone available water capacity (AWC) as storage. If the soil water content is above a threshold AWC then actual ET takes place at the potential rate. Otherwise, actual ET is stressed by soil moisture. Surface runoff and deep percolation occur when end-of-period soil water content exceeds AWC. Drawing on historical climate data, this module provides crop/zone-specific estimates of soil water deficits for each season during 1976–2007.

There is an extensive literature measuring crop yield responses to water deficits. We used the Jensen (1968) crop water production model since it captures monthly climate variations. Crop water sensitivity indices were estimated using ordinary least squares regressions and yield response factors for each growing stage from FAO (1979). These were mapped to months in crops' growing periods using the cumulative sensitivity index method (Tsakiris 1982; Kipkorir 2002). The output of the HC models are yield deviations between zero and one, with one representing the yield during a 'normal' climate year.

3.4 Computable general equilibrium model

We used a neoclassical class of CGE models (see Dervis et al. 1982). Economic decision-making is the outcome of decentralized optimization by producers and consumers within a coherent economy-wide framework. Production occurs under constant returns to scale. Intermediate demand is determined by fixed technology coefficients (i.e., Leontief demand), while constant elasticity of substitution (CES) production functions allow factor substitution based on relative prices. Profit maximization implies that factors receive income where marginal revenue equals marginal cost. The model identifies 34 sectors, half of which are in agriculture.[1] Based on the 2004 living conditions monitoring survey (LCMS), labor markets are segmented into self-employed farm workers; unskilled workers (working both on and off the farm) and skilled workers (off-farm only). Agricultural land is divided into small-scale, large-scale, and urban farms based on crop forecasting surveys. Small-scale agricultural sectors are further disaggregated across the five agro-climatic zones. Labor is fully employed and mobile, whereas, once invested, capital is fixed by sector. Farmers can therefore change their cropping and livestock patterns and engage more/less intensively in non-farm activities, thus allowing for some autonomous adaptation to climate changes. However, we limit the extent to which farmers can adjust their cropping patterns in response to short-term climate variability, by assuming crop choices are determined at the start of each season, and, once planted, land cannot be reallocated to different crops during the growing season. They can, however, reallocate their labor time and thereby influence production levels.

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[1] See Thurlow et al. (2008) for an earlier application of the Zambia Model. The structure of the model's underlying database (i.e., social accounting matrix) is provided in the Appendix.

Substitution possibilities exist between production for national and foreign markets. This decision of producers is governed by a constant elasticity of transformation function, which distinguishes between exported and domestic goods. Profit maximization drives producers to sell in markets where they achieve the highest returns based on relative prices. Substitution possibilities also exist between imported and domestic goods under a CES Armington specification (for both final and intermediates usage). Under the small-country assumption, world demand/supply is perfectly elastic at fixed world prices, with the final ratio of traded to domestic goods determined by endogenous relative prices. Production and trade elasticities are from Dimaranan (2006).

The model identifies 15 representative household groups disaggregated by rural/urban areas, the size of farms (small-scale rural, large-scale rural, and urban farmers), and by zone (for small-scale farmers). Households receive income from producers for use of their factors of production, and then pay direct taxes, save, and make foreign transfers (all at fixed rates). Households use remaining income to consume commodities under a linear expenditure system of demand. The model includes a micro-simulation module with each respondent in LCMS linked to their corresponding household group in the model. Changes in commodity prices and households' consumption spending are passed top-down from the CGE model to the survey, where per capita consumption levels and poverty measures are recalculated.

Government revenues from direct and indirect taxes are used for domestic/foreign transfers and recurrent consumption spending. Remaining revenues are saved (with deficits being negative savings). All private, public, and foreign savings are collected in a savings pool from which investment is financed. To ensure macro-economic balance it is necessary to specify a set of 'closure' rules. A savings-driven closure balances the savings-investment account, implying that households' marginal savings rates are fixed and investment adjusts to income changes to equate investment and savings. For the current account, we assume that a flexible exchange rate adjusts to maintain a fixed level of foreign savings (i.e., the external balance is held fixed in foreign currency terms). Finally, in the government account, direct tax rate rates are fixed and the fiscal deficit adjusts to equate total revenues and expenditures.

The model is 'recursive dynamic', implying that it is solved as a series of static equilibria, with key parameters updated between periods (see Thurlow 2004). Unlike full inter-temporal models, which include forward-looking expectations, a recursive dynamic model adopts a simpler set of adaptive rules in which investors expect prevailing price ratios to persist indefinitely. Sectoral capital stocks are adjusted each year based on previous investment levels, net of depreciation. The model adopts a 'putty-clay' formulation, whereby new investment can be directed to any sector in response to differential rates of return, but installed equipment must remain in the sector (see Dervis et al. 1982). Unlike capital, growth in the total supply of each labor and land category is determined exogenously. Sectoral productivity growth is also specified exogenously. Using these simple relationships to update key variables, we can generate a series of growth paths based on different climate outcomes and results from the HC models.

3.3 Linking HC and CGE models

The models are used to estimate the economic impact of climate variability over the 10-year period 2006–16. Since we cannot accurately predict Zambia's future weather patterns, we use an 'index sequential method' to simulate a range of possible patterns using historical data (Prairie et al. 2006). Assuming a circular time series, we draw 32 ten-year weather sequences from 32 years of historical climate data for the period 1976–2007 (i.e., 32 different starting years for each 10-year consecutive sequence in which the first year, 1976, follows the final year, 2007). Individual years within each sequence are not randomly drawn. This method preserves observed inter-annual correlations and captures the full distribution of past climate variability.

The CGE model was calibrated to the base-year 2006. We first simulate a baseline scenario assuming 'normal' rainfall for each of the ten years 2006–16 (i.e., no yield losses caused by climate variability). Yield levels and land allocations expand according to yield potentials from field trials and historical land expansion trends (see Thurlow et al. 2008). We call this the 'normal rainfall' scenario. We then simulated 32 10-year scenarios reflecting possible weather sequences. The crop/zone-specific annual yields estimated by the HC models were imposed on the shift parameter of the production functions of the CGE model for each 10-year weather sequence (i.e., on total factor productivity or TFP).

When an extreme weather event year is drawn from the historical data, as defined by the Palmer drought index (see Section 2), we imposed additional shocks on the CGE model (see Table 3). First, harvested land area for drought-affected crops was reduced during severe drought years (based on historical production data) and slowly recovers over two subsequent years (i.e., the recovery period). Similarly, cultivated land area is reduced during major flood events (based on World Bank 2009). Second, livestock numbers fall during severe droughts and have a lagged recovery period. Finally, severe droughts reduce physical capital via higherthannormal depreciation rates. Thus, while crop yield losses are the primary impact channel, the CGE model also captures the additional economy-wide impacts of extreme weather events.

3.4 Climate change scenarios

Even with global mitigation measures, the current scientific consensus holds that greenhouse gas emissions and atmospheric concentrations will increase over coming decades, causing global mean temperatures to rise (IPCC 2007). Two opposing factors will, in part, determine climate change's impact on agriculture. On the one hand, rising atmospheric CO_2 concentrations may increase crop yields via 'carbon fertilization', but, on the other hand, rising temperatures should reduce yields. Given the uncertainty surrounding these opposing impacts, we do not examine the effects of temperature changes and carbon fertilization. Rather, we focus on hydrological impacts. This is appropriate since changes in water availability are expected to have the largest consequences for agriculture (Houghton 2004; Hulme 1996; Rogers 2008).

Climate change scenarios vary based on global levels of carbon emissions and future economic and demographic developments. We used the 'SRES B1a' scenario from the Hadley Centre's coupled atmosphere-ocean general circulation model (GCM) (i.e., henceforth referred to as 'HadCM3-B1a'). For this scenario we obtained mean changes in precipitation, minimum, and maximum daily average temperature, relative humidity, and wind speed for grid cells in Zambia from the IPCC Data Distribution Center reflecting climatic projections for the period around 2020.[2] The HadCM3-B1a scenario represents a future climate where rainfall declines and temperatures increase throughout Zambia. Mean monthly changes in climate variables from the HadCM3-B1a scenario were downscaled to the 30 meteorological stations by finding the grid cell center of the GCM grid nearest to a weather station, and applied to historical monthly weather observations for 1976–2007 in order to construct new climate data reflecting climate changes in 2025. The HC models used these new climate data to estimate yield responses to climate change.[3]

Given the uncertainty surrounding climate change, especially at the country level, two additional or hypothetical scenarios were developed to examine crop yield responses under larger rainfall and temperature changes. For both scenarios we assumed that temperatures are 2°C higher each month throughout the country. We then assumed that rainfall is either 15 percent above or below the observed 1976–2007 series (i.e., the ‘T2P+15’ and ‘T2P-15’ scenarios, respectively). These two hypothetical scenarios are not based on GCM projections but represent more dramatic changes for Zambia over the near-term. They imposed uniform changes in temperature and precipitation on historic data from all weather stations. Such hypothetical scenarios are often used to examine responses to wide ranges of climate change (see Zhu et al. 2005; Yates et al. 2007).

It is worth noting that the climate change scenarios represent mean changes in future climate and so do not allow for a gradual evolution of climate change. The reason for this simplification is that we use the index sequential method (Prairie et al. 2006) to resample climate series and create the sequences used in our models. This implicitly assumes a stationary climate series. Moreover, we impose future climate changes in 2025 on economic scenarios for the period 2006–16. We implicitly assume that Zambia does not undergo major structural transformation between 2006 and 2020. For example, reducing agriculture’s share of the economy would lower the economy-wide effects of changes in agricultural production. However, our focus is on the *relative* size of the impacts from current climate variability and future climate change. We therefore do not need to run the CGE model forward to 2020 before imposing climate change impacts, as done in other studies (see, for example, Arndt et al. 2010; Yu et al. 2010).[4]

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[2] See www.ipcc-data.org/index.html (accessed April 2007).

[3] Growing consensus suggests that climate change may increase future weather variability. However, the global climate models cannot yet simulate climate variability adequately enough for us to use in our modeling analysis.

[4] Longer-run dynamic models might better capture exogenously determined structural change, although the basis of such predictions would require sensitivity analysis itself.

4 Results: current climate variability and extreme events

4.1 Baseline 'normal rainfall' scenario

The baseline scenario in the CGE model simulates a normal rainfall sequence for the period 2006–16, thus reflecting an optimistic growth scenario for Zambia (i.e., no yield losses from climate variability). Labor supply and capital stocks (including land and livestock) expand at 2 and 3percent per year, respectively. TFP increases by 2 and 3percent per year in agriculture and non-agriculture, respectively. Overall, total gross domestic product (GDP) in the baseline grows at an average 6.7 percent per year. Since agriculture grows more slowly, its contribution to total GDP falls from 20.5 in 2006 to 18.6 percent by 2016. Rising per capita GDP causes the national poverty headcount to decline from 67.9 to 52.2 percent by 2016. These growth and poverty trends are consistent with Zambia's strong economic performance prior to the recent global economic crises and so provides a reasonably 'optimistic' baseline against which we can compare the effects of climate variability.

4.2 Impacts on crop yields

Figure 2 shows decline in yields for zones 1–3 caused by historical climate variability during 1976–2007. Relative yields are the ratio of the simulated actual yield to the maximum yield achievable without water stress. Maize is chosen as an illustrative crop, but the yield responses of the other rain-fed crops follow similar patterns. For zones 1 and 2, the worst maize yield losses occurred in the 1991/92 season when estimated yields were 77 percent and 65 percent below normal yields, respectively. Large yield losses were also found in other seasons for the drier zones 1–3. These include 1994/95 for zones 1–3, 1976/77 for zones 2–3, and 1983/84, 1986/87, and 2001/02 for zone 2. Yield reductions during these seasons ranged between 30 and 50 percent. Zones 4 and 5 are not shown in the figure since they are less drought-prone than other parts of the country and so their drought-induced crop yield losses are both smaller and less frequent. For example, the largest yield loss in zone 5 was 14 percent in 1991/92.

Table 4 summarizes the severity and consequences of droughts and wet events (as defined by the Palmer Z score). The table shows the ranges of growing season rainfall, relative maize yield losses, and the frequency of weather events during the period 1976–2007. It also shows the water requirement satisfaction index (WRSI), which is the ratio of actual to potential ET during the maize growing season (Verdin et al. 2005). Each indicator is separated across zones and event categories. For example, the range of growing season rainfall in zone 1 for all severe drought years is 405–499mm.

For the drier zones 1–3, there were only 7 or 8 out of 32 years (i.e., 1976–2007) in which rainfall during the growing season was within the 'normal' range. This indicates a 75–80 percent chance that, in a given year, there is either a drought or too much rain in at least one of these three zones. Moreover, there is about a one-in-ten chance of a severe drought occurring in zones 1–2, during which yields fell by 14–77 and 21–65 percent, respectively. The average relative water deficit (i.e., 100 - WRSI) is usually not as high as yield losses during severe droughts. It is rather abnormally low rainfall during critical growing stages that causes substantial yield losses. The table clearly shows that zones 1–3 are drought-prone, whereas major drought damage is rare in zones 4–5. Moreover, despite being the wettest zone, very wet weather events are also rare in zone 5, with only one occurrence in 32 years.

It should be noted that our HC models are for drought impact assessments. Yield losses from floods and water-logging are not assessed, since floods are typically localized short-duration events and their assessment requires high-resolution data. However, drought damage is more important than flood damage for Zambian agriculture (World Bank 2009). Moreover, the analysis of wet events in Table 4 provides some measure of flood events and shows how yield losses occur during wet years due to the uneven distribution of rainfall.

4.3 Impacts on economic growth

Agricultural GDP rises in the baseline scenario from US$2.1 billion in 2006 to US$3.6 billion by 2016, implying a 5.7 percent annual growth rate (see ‘normal sequence’ in Figure 3). As described in Section 3, we simulate 32 possible weather sequences drawn from historical climate data. The reduction in agricultural GDP caused by climate variability varies by sequence. We report the mean outcome of all sequences (‘average sequence’) and the results of the worst sequence (defined below). Model results confirm the sensitivity of agricultural GDP to rainfall variability. On average, climate variability reduces agriculture’s GDP growth rate by one percentage point from the baseline. Accumulated agricultural GDP losses over this period equal US$2.2 billion (undiscounted and measured in 2006 prices). This is almost equal to agricultural GDP in an average year.

The worst rainfall sequence is identified using two criteria: the value of annual rainfall’s CV and the frequency of severe drought events. The worst 10-year rainfall sequence occurred between the 1985/86 and 1994/95 seasons. During this period the value of CV was highest in our historical climate data and the three most severe droughts occurred. The CGE model shows that if the rainfall patterns during 2006–16 replicated the worst historical sequence then the accumulated losses in agricultural GDP would be US$3.1 billion. This is almost 50 percent larger than the accumulated losses under the average rainfall sequence, and is a reduction in average annual agricultural GDP growth by 2.3 percentage points.

Economy-wide impacts are even larger than those on agriculture alone (see Table 5). On average, climate variability causes an accumulated loss in total GDP of US$4.3 billion, which is equivalent to reducing the total GDP growth rate by 0.4 percentage points. Ultimately, Zambia’s economy is 4percent smaller in 2016 than it would have been without climate variability. Current climate variability therefore has a profoundly negative impact on economic growth. Moreover, damages in the worst sequence are almost twice as large. This substantial contraction reflects the severe droughts that took place in the 1986/87, 1991/92, and 1993/94 seasons, which affected the entire economy.

Table 5 also reports changes in zonal agricultural GDP. The drought-prone zones 1–2 are an important part of the agricultural economy, generating half of national agricultural GDP and two-thirds of national maize production. However, damages from climate variability are largest in these zones. Almost 85 percent of agricultural GDP losses occur in zones 1–2, while zone 5 is largely unaffected by climate variability. The economic losses under the worst rainfall sequence are even more concentrated within zones 1–2, with almost 90 percent of agricultural GDP losses occurring in these two zones. These results highlight the spatial complexities of Zambia’s rainfall patterns and the importance of considering spatial variation when assessing the consequences of climate variability.

4.4 Impacts on household poverty

Climate variability has detrimental effects on household incomes and poverty. Figure 4 shows estimated national poverty headcount rates for 2006–16 (i.e., the share of the population with per capita consumption below the official poverty line). Poverty in the baseline falls from 67.9 to 52.2 percent during 2006–16, which is enough to offset population growth of 2percent per year so that the absolute number of poor people falls from 7.44 to 6.96 million. However, climate variability slows the rate of poverty reduction and, on average, causes the national poverty rate to be 2.3 percentage points higher by 2016. There are thus 300,000 more people living beneath the poverty line in 2016 than there would have been without climate variability. Under the worst rainfall sequence, the national poverty rate is 4.9 percentage points higher in 2016 and there are 648,000 more people below the poverty line compared to the baseline.

Although agriculture is the primarily impact channel for climate variability in Zambia, it affects poverty reduction in both rural and urban areas for two reasons. First, a third of Zambia’s urban population engages in agricultural production (Thurlow et al. 2008) and so climate variability will affect agricultural revenues and urban incomes. Second, food forms a large share of urban consumption baskets. So falling agricultural production causes food prices to rise and reduces real urban incomes. On average, our results indicate that two-fifths of the poverty caused by climate variability occurs in urban areas (i.e., 133,000 people out of 300,000 at the national level). This underscores the economy-wide nature of climate variability’s impacts, even though the primary impact is on agriculture.

4.5 Impacts during extreme weather events

The above results reported the impacts of climate variability over 10-year periods. Here we describe the losses occurring during major drought or flood years. We present the outcomes of a severe drought year (1991/92), a modest drought year (1994/95), and a severe flood year (2006/07). To ensure comparability, we adopt the same base year (i.e., the same level and structure of economic activity). Accordingly, in each scenario we impose the weather shock during the second simulation year (i.e., 2007). This means that we are not estimating the impact of the actual 1991/92 drought, which would require a model calibrated to the 1990/91 season. Rather, we are estimating what the impact would have been if a drought of similar magnitude were to have occurred in 2007.

The estimated impacts of extreme weather events on total and agricultural GDP are reported in Table 6. A severe drought of the same magnitude as one experienced in 1991/92 reduces national agricultural GDP by 22.7 percent compared to a normal rainfall outcome in the same year. This is mainly due to large declines in agricultural production in zones 1–3, which were worst affected by the drought. Falling production in agriculture and elsewhere in the economy causes total GDP to decline by 6.6 percent. A modest drought, like the one that occurred in

1994/95, also produces large negative outcomes, with national GDP falling by 4percent and with larger declines in zones 1–3. By contrast, a severe flood, similar to the one experienced in 2006/07, affects zones more evenly but has a less pronounced impact on the overall economy. Thus, while agricultural GDP in zone 5 declines the most under the severe flood, the impact on other zones is far smaller than under even the modest drought. Accordingly, total GDP declines by only 2.3 percent under the severe flood scenario.

While broadly consistent, the modeled decline in agricultural GDP during an extreme drought year is smaller than the observed decline in 1991/92 (i.e., 33 percent). One reason for this difference is the substantial change in the composition of agriculture that occurred between 1991 and 2006 (i.e., the base year for our analysis). Farmers in Zambia increased their production of drought-tolerant sorghum and millet and reduced maize production. This change in crop composition was due to the removal of unsustainable maize subsidies during the 1990s (see Thurlow and Wobst 2006). Moreover, non-traditional exports, including sugarcane and cotton, expanded dramatically, especially in the drought-affected zones 1, 2 and 4. These crops are more drought-resistant than traditional food crops and also benefit from irrigation. Given these changes, the agricultural sector as a whole has become more drought resistant over time, which is the main reason for the smaller GDP losses in our economic model.

Extreme weather events also have large impacts on poor households' incomes. The national poverty rate rises by 7.5 percentage points during the severe drought year. This implies an increase in the number of poor people by 836,000 compared to a normal year. Poverty also rises during a modest drought year by 3.9 percentage points or 435,000 people. Finally, the national poverty rate rises by 2.4 percentage points during a severe flood year, pushing 273,000 more people below the poverty line in that year.

In summary, current climate variability has a large detrimental impact on economic development in Zambia. It substantially reduces agricultural production, especially in the southern and central regions of the country. The importance of agriculture and the sector's strong linkages to the rest of the economy means that a significant share of the economic losses caused by climate variability occurs outside of agriculture and affects urban households. This underscores the importance of including economy-wide effects when evaluating climate variability. This is especially true for measuring the growth and poverty impacts of extreme weather events. The consequences of these events, particularly major droughts, overshadow the losses caused by average (or year-on-year) climate variability.

5 Results: future climate change

5.1 Impacts on crop yields

Our three climate change scenarios do not explicitly introduce changes in variability into observed meteorological data, but rather cause changes in mean climate. The impact of these mean climate changes on crop yields are analysed using the HC model. Table 7 reports the mean and average standard deviation of changes in maize yields relative to the estimated yields for 1976–2007 under each climate change scenario. In the HadCM3-B1a scenario, maize yields decline relative to the estimated historical trend of 1976–2007 for all agro-climatic zones except zone 3, where yields increase slightly. Since rainfall generally declines in the HadCM3-B1a scenario, this slight increase in zone 3's maize yield is mainly due to slight increases in rainfall in zone 3 under the HadCM3-B1a scenario. However, this result should by no means be over-interpreted since it is so small.

From our results we conclude that, compared to the historical period, climate change with less rainfall and higher temperature (i.e., the HadCM3-B1a scenario) leads to a one percent reduction in maize yields by 2025 for zones 1, 2, and 4 and to very small yield changes in zones 3 and 5. Since the HadCM3-B1a scenario does not capture the changes in the patterns of rainfall variation, the standard deviations of maize yields from historical trends have a similar magnitude to the changes in the mean. Although the HadCM3-B1a scenario causes only small changes in mean maize yields relative to historical trends, impacts within a particular year can be much larger. For example, in a severe drought year, such as that of 1991/92, maize yields are four percent lower than they were in 1991/92 when future climate change effects were not incorporated.

In the T2P-15 scenario, mean maize yields decline by 4–6 percent relative to historical trends in all zones except zone 5, where yields decline by only 1.4 percent. Again, the magnitude of standard deviations is consistent with the mean change at the zonal level. This implies that there will be an average 4–6 percent drop in maize yields throughout most of Zambia if rainfall in the future declines by 15 percent and temperature rises by 2 ºC. In the T2P+15 scenario mean maize yields increase by 3–4 percent relative to historical trends for zones 1–3. There is a 2percent increase for zone 4 and a slight increase for zone 5. In both hypothetical climate change scenarios, the wetter zone 5 remains fairly resilient to climate changes in terms of crop yield responses to changing rainfall. By contrast, the remaining drier zones experience larger changes in crop yields.

5.2 Impacts on economic growth and poverty

In Section 4 we used the CGE model to estimate the economy-wide impact of current climate variability by simulating 32 possible 10-year rainfall patterns drawn sequentially from historical data for the period 1977–2007. We now use a similar method to estimate how climate change affects the broader economy via its impact on crop yields. Corresponding to each climate change scenario, we adjust historical rainfall data to reflect new weather conditions. The three synthetic datasets now contain the effects of both historical climate variability and future climate change. We then redraw the 32 sequences from each synthetic dataset and compare the average outcomes under these new climate change scenarios with the average outcomes from the previous section which only included the effects of current climate variability. The differences between these average outcomes can be solely attributed to climate change.

The results from the climate change scenarios are reported in Table 8. The top half of the table shows deviations in the mean of all rainfall sequence scenarios from the results of the normal rainfall scenario. As discussed in Section 4, if climate variability follows historical patterns without any future climate changes, then the average decline in the annual total GDP growth rate of is 0.4 percentage points. Incorporating the effects of climate change produces mixed results.

The decline in total GDP growth is only slightly larger under the HadCM3-B1a scenario, but is substantially larger under the T2P-15 scenario. Conversely, higher rainfall under the T2P+15 scenario dampens the adverse effects of climate variability, such that the decline in GDP growth is smaller than in the case without climate change. These results indicate that if climate changes cause less rainfall every year, then annual economic growth would decline further by between 0.05 percentage points (HadCM3-B1a scenario) and 0.20 percentage points (T2P-15 scenario). However, if climate changes cause more rainfall then GDP growth would increase slightly by 0.14 percentage points (T2P+15 scenario).

The implications of these seemingly small changes in total GDP's growth rate become more substantial once the effects are accumulated over the ten-year simulation period (i.e., 2006–16). For instance, cumulative declines in total GDP under the T2P-15 scenario are US$6 billion (i.e., US$1.7 billion more than that without climate change effects) compared to US$3 billion under T2P+15 scenario (i.e., US$1.3 billion less than that without climate change effects). Even under the more modest HadCM3-B1a scenario, climate change raises the damages already caused by current climate variability by an additional US$0.37 billion over a 10-year period. Thus while the economic implications of climate change may appear inconsequential at any given point in time, its gradual impact on GDP becomes more significant over time.

The final two columns of the table report the impact of climate change on national poverty rates and on the absolute number of poor people in 2016. Since climate change affects agricultural production and food prices directly, there is a significant difference in poverty outcomes across the three scenarios. Even in the modest HadCM3-B1a scenario the national poverty rate in 2016 is 0.24 percentage points higher than it would without climate change. Thus even the small changes in climate expected by 2025 will increase the absolute number of poor people by 32,000 over ten years. Deviations in poverty rates are also much larger for the two hypothetical climate scenarios.

Overall, the additional impact of future climate change on economic growth and poverty in Zambia is smaller than that of current climate variability, at least until well after 2025. Even the damages caused by the more pessimistic climate change scenarios are less than half those of the current climate variability scenarios. However, it should be noted that the climate change scenarios in this study did not capture possible changes in climate variability and hence can only provide illustrative results for potential climate change impacts in Zambia. Thus, while average changes over the longer-term are relatively small, there may be large impacts during specific years, especially if there is even less rainfall than during the severe drought years observed in Zambia's history.

6 Conclusion

We developed an integrated hydro-crop and CGE modeling framework, and used this to compare the economic impacts of current climate variability and future climate change. Simulation results indicate that, on average, current variability reduces Zambia's agricultural and total GDP by 9 and 4percent, respectively, over a ten-year period. The resulting income losses to households mean that an additional 300,000 people will remain below the national poverty line as a result of current variability (i.e., 2.3 percent of the population in 2016). Socio-economic damages during extreme weather event years are particularly severe. Results indicate that total GDP falls by 6.6 percent during a severe drought (i.e., similar to the one experienced in 1991/92), and the national poverty rate rises by 7.5 percentage points pulling an additional 836,000 people into poverty during the drought year. These results confirm that current climate variability already presents a significant challenge to future development in Zambia, particularly in the country's southern and central regions.

We also examined whether climate change will exacerbate or dampen the negative impacts of current variability. Here considerable uncertainty exists, especially regarding changes in future rainfall patterns. Accordingly, we not only used a modest GCM projection, but also simulated two more extreme hypothetical scenarios. We found that the damages from climate change will be much smaller than those from current climate variability, at least until well after 2025. However, differences in rainfall projections influence the size, and to a lesser extent, the direction of economic impacts. For example, if mean rainfall were to fall by 15 percent throughout Zambia, then climate change would increase the economic losses from current climate variability by 50 percent. Therefore, even though current climate variability will continue to dominate anthropogenic climate changes over the next few decades, our results suggest that there are still large incentives to address climate change concerns, especially since most anthropogenic climate change is expected to occur after 2025 (IPCC 2007).

There are at least three areas where our study can be extended. First, we focused on agricultural impacts via crop yields. Recent studies, such as Arndt et al. (2010), find that agriculture may not be the main impact channel for climate change damages, even in low-income African countries. Further work is therefore needed to incorporate other biophysical impact channels, especially flooding, which was not adequately addressed in our study. Second, we considered a wide range of possible climate change outcomes. However, designing robust adaptation strategies requires knowledge of the full distribution of GCM projections (and ideally the relative probability of them being realized). Finally, we allowed only limited autonomous adaptation opportunities, which we felt were appropriate for small-scale farmers' land allocation decisions. However, forward-looking adaptation behavior may be needed in sectors (and countries) that are more developed than Zambia's smallholder agriculture.

Appendix: Specification of the HC and CGE models

Table A1: Variables, parameters, and equations in the HC model

Parameters					
λ_t	Crop water sensitivity index	-	p	Fraction of active tension water capacity in root zone below which crop experiences stress	-
θ_f	Field capacity	mm m^{-1}			
θ_w	Wilting point	mm m^{-1}			
γ	Pychrometric constant	kPa °C^{-1}	S_{max}	Max. tension water capacity in root zone	mm m^{-1}
K_c	Crop coefficient	-			
K_{Rs}	Radiation adjustment coefficient	-	Y_{max}	Maximum yield without water stress	t ha^{-1}
K_y	Yield response factor	-			
			Z_r	Root zone depth	m
Variables					
e_s	Saturation vapor pressure	kPa	PET	Potential evapotranspiration	mm
Δ	Slope vapor pressure curve	kPa °C^{-1}	R_a	Extraterrestrial radiation	MJ m^{-2} day^{-1}
μ_2	Wind speed at 2 m height	m s^{-1}	R_n	Net radiation at the crop surface	MJ m^{-2} day^{-1}
AET	Adjusted actual crop evapotranspiration	mm	R_s	Incoming solar radiation	MJ m^{-2} day^{-1}
			S	Soil water content in root zone	mm
AET^*	Predicted actual crop evapotranspiration	mm	T	Mean air temp. at 2m height	°C
			T_{max}	Max. air temp. at 2 m height	°C
ET_o	Reference evapotranspiration	mm	T_{min}	Min. air temp. at 2 m height	°C
G	Soil heat flux density	MJ m^{-2} day^{-1}	Y_a	Actual crop yield	t ha^{-1}
P	Rainfall	mm			

Crop water requirement model		
$ET_o = \dfrac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} \mu_3 (e_s - e_a)}{\Delta + \gamma(1 + 0.34\mu_2)}$	FAO Penman-Monteith equation for calculating reference evapotranspiration (Allen et al., 1998)	A1
$R_s = K_{Rs} \cdot (T_{max} - T_{min})^{0.5} \cdot R_a$	Hargreaves' radiation formula for when radiation data is unavailable (Allen et al. 1998)	A2
$PET_t = K_c \cdot ET_o$	Crop potential evapotranspiration (Allen et al. 1998)	A3
Soil water balance model		
$S_{max} = \left(\theta_f - \theta_w\right) \cdot Z_r$	Active tension water capacity in root zone	A4
$AET_t^* = \begin{cases} \frac{S_{t-1} + P_t}{p \cdot S_{max}} \cdot PET_t, S_{t-1} + P_t < p \cdot S_{max} \\ PET_t, \quad S_{t-1} + P_t \geq p \cdot S_{max} \end{cases}$	Predicted actual crop evapotranspiration	A5
$AET_t = \min\langle AET_t^*, \quad S_{t-1} + P_t \rangle$	Adjusted crop actual evapotranspiration	A6
$S_t = \begin{cases} S_{t-1} + P_t - AET_t, S_{t-1} + P_t - AET < S_{max} \\ S_{max}, \quad S_{t-1} + P_t - AET \geq S_{max} \end{cases}$	End of period soil water content	A7
Crop water production function		
$Y_a = Y_{max} \cdot \left[1 - K_y \cdot \left(1 - \frac{\sum_t AET_t}{\sum_t PET_t}\right)\right]$	FAO yield response function	A8
$Y_a = Y_{max} \cdot \prod_{t \in T} \left(\frac{AET_t}{PET_t}\right)^{\lambda_t}$	Crop water production function (Jensen 1968)	A9

Table A2: Indices, variables, and parameters in the CGE model

Indices			
c	Commodities and activities	h	Representative households
f	Factors (land, labor, and capital)	t	Time periods
Exogenous parameters (Greek characters)			
α^p	Production function shift parameter	θ^v	Value-added share of gross output
α^q	Import function shift parameter	π	Foreign savings growth rate
α^t	Export function shift parameter	ρ^p	Production function substitution elasticity
β	Household marginal budget share	ρ^q	Import function substitution elasticity
γ	Non-monetary consumption quantity	ρ^t	Export function substitution elasticity
δ^p	Production function share parameter	σ	Rate of technical change
δ^q	Import function share parameter	τ	Foreign consumption growth rate
δ^t	Export function share parameter	υ	Capital depreciation rate
ε	Land and labor supply growth rate	φ	Population growth rate
θ^i	Intermediate share of gross output	ω	Factor income distribution shares
Exogenous parameters (Latin characters)			
ca	Intermediate input coefficients	pwm	World import price
cab	Current account balance	qfs	Total factor supply
cd	Domestic transaction cost coefficients	$qgov$	Base government consumption quantity
ce	Export transaction cost coefficients	$qinv$	Base investment demand quantity
ci	Capital price index weights	rf	Factor foreign remittance rate
cm	Import transaction cost coefficients	sh	Marginal propensity to save
cpi	Consumer price index	tf	Factor direct tax rate
cw	Consumer price index weights	th	Personal direct tax rate
ga	Government consumption adjustment factor	tm	Import tariff rate
gh	Per capita transfer from government	tq	Sales tax rate
pop	Household population	wh	Net transfer from rest of world
pwe	World export price		
Endogenous variables			
AR	Average capital rental rate	QG	Government consumption quantity
FS	Fiscal surplus (deficit)	QH	Household consumption quantity
IA	Investment demand adjustment factor	QI	Investment demand quantity
PA	Activity output price	QK	New capital stock quantity
PD	Domestic supply price with margin	QM	Import quantity
PE	Export price	QN	Aggregate intermediate input quantity
PM	Import price	QQ	Composite supply quantity
PN	Aggregate intermediate input price	QT	Transaction cost demand quantity
PQ	Composite supply price	QV	Composite value-added quantity
PS	Domestic supply price without margin	WD	Sector distortion in factor return
PV	Composite value-added price	WF	Economy-wide factor return
QA	Activity output quantity	YF	Total factor income
QD	Domestic supply quantity	YG	Total government revenues
QE	Export quantity	YH	Total household income
QF	Factor demand quantity	X	Exchange rate

Table A3: Equations in the CGE model

Prices	
$PM_{ct} = pwm_c \cdot (1 + tm_c) \cdot X + \sum_{c\prime} PQ_{c\prime t} \cdot cm_{c\prime c}$	B1
$PE_{ct} = pwe_c \cdot X_t - \sum_{c\prime} PQ_{c\prime t} \cdot ce_{c\prime c}$	B2
$PD_{ct} = PS_{ct} + \sum_{c\prime} PQ_{c\prime t} \cdot cd_{c\prime c}$	B3
$PQ_{ct} \cdot (1 - tq_c) \cdot QQ_{ct} = PD_{ct} \cdot QD_{ct} + PM_{ct} \cdot QM_{ct}$	B4
$PX_{ct} \cdot QX_{ct} = PS_{ct} \cdot QD_{ct} + PE_{ct} \cdot QE_{ct}$	B5
$PN_{ct} = \sum_{c'} PQ_{c't} \cdot ca_{c'c}$	B6
$PA_{ct} \cdot QA_{ct} = PV_{ct} \cdot QV_{ct} + PN_{ct} \cdot QN_{ct}$	B7
$cpi = \sum_{c} cw_c \cdot PQ_{ct}$	B8
Production and trade	
$QV_{ct} = \alpha_{ct}^{p} \cdot \sum_{f} \left(\delta_{fc}^{p} \cdot QF_{fct}^{-\rho_c^p}\right)^{-1/\rho_c^p}$	B9
$WF_{ft} \cdot WD_{fct} = PV_{ct} \cdot QV_{ct} \cdot \sum_{f\prime} \left(\delta_{f\prime c}^{p} \cdot QF_{f\prime ct}^{-\rho_c^p}\right)^{-1} \cdot \delta_c^p \cdot QF_{fct}^{-\rho_c^p - 1}$	B10
$QN_{ct} = \theta_c^i \cdot QA_{ct}$	B11
$QV_{ct} = \theta_c^v \cdot QA_{ct}$	B12
$QA_{ct} = \alpha_c^t \cdot \left(\delta_c^t \cdot QE_{ct}^{\rho_c^t} + (1 - \delta_c^t) \cdot QD_{ct}^{\rho_c^t}\right)^{1/\rho_c^t}$	B13
$\frac{QE_{ct}}{QD_{ct}} = \left(\frac{PE_{ct}}{PS_{ct}} \cdot \frac{(1 - \delta_c^t)}{\delta_c^t}\right)^{1/(\rho_c^t - 1)}$	B14
$QQ_{ct} = \alpha_c^q \cdot \left(\delta_c^q \cdot QM_{ct}^{-\rho_c^q} + \left(1 - \delta_c^q\right) \cdot QD_{ct}^{-\rho_c^q}\right)^{-1/\rho_c^t}$	B16
$\frac{QM_{ct}}{QD_{ct}} = \left(\frac{PD_{ct}}{PM_{ct}} \cdot \frac{\left(1 - \delta_c^q\right)}{\delta_c^q}\right)^{1/\left(1 + \rho_c^t\right)}$	B17
$QT_{ct} = \sum_{c\prime} (cd_{cc\prime} \cdot QD_{c\prime t} + cm_{cc\prime} \cdot QM_{c\prime t} + ce_{cc\prime} \cdot QE_{c\prime t})$	B18
Incomes and expenditures	
$YF_{ft} = \sum_{c} WF_{ft} \cdot WD_{fct} \cdot QF_{fct}$	B19
$YH_{ht} = \sum_{f} \omega_{hf} \cdot \left(1 - tf_f\right) \cdot \left(1 - rf_f\right) \cdot YF_{ft} + gh_h \cdot pop_{ht} \cdot cpi + wh_h \cdot X$	B20
$PQ_{ct} \cdot QH_{cht} = PQ_{ct} \cdot \gamma_{ch} + \beta_{ch} \cdot \left((1 - sh_h) \cdot (1 - th_h) \cdot YH_{ht} - \sum_{c\prime} PQ_{ct\prime} \cdot \gamma_{c'h}\right)$	B21
$QI_{ct} = IA_t \cdot qinv_c$	B22
$QG_{ct} = ga_t \cdot qgov_c$	B23

$$YG_t = \sum\nolimits_h th_h \cdot YH_{ht} + \sum\nolimits_f tf_f \cdot YF_{ft} + \sum\nolimits_c (tm_c \cdot pwm_c \cdot QM_{ct} \cdot X + tq_c \cdot PQ_{ct} \cdot QQ_{ct}) \tag{B24}$$

Equilibrium conditions

$$qfs_{ft} = \sum\nolimits_c QF_{fct} \tag{B25}$$

$$QQ_{ct} = \sum\nolimits_{c'} ca_{cc'} \cdot QN_{c't} + \sum\nolimits_h QH_{cht} + QG_{ct} + QI_{ct} + QT_{ct} \tag{B26}$$

$$\sum\nolimits_c pwm_c \cdot QM_{ct} + \sum\nolimits_f \left(1 - tf_f\right) \cdot rf_f \cdot YF_{ft} \cdot X_t^{-1} = \sum\nolimits_c pwe_c \cdot QE_{ct} + \sum\nolimits_h wh_h + cab_t \tag{B27}$$

$$YG_t = \sum\nolimits_c PQ_{ct} \cdot QG_{ct} + \sum\nolimits_h gh_h \cdot pop_{ht} \cdot cpi + FS_t \tag{B28}$$

$$\sum\nolimits_h sh_h \cdot (1 - th_h) \cdot YH_{ht} + FS_t + cab_t \cdot X_t = \sum\nolimits_c PQ_{ct} \cdot QI_{ct} \tag{B29}$$

Capital accumulation and allocation

$$AR_{ft} = \frac{YF_{ft}}{qfs_{ft}} \tag{B30}$$

$$QK_{fct} \cdot \left(\sum\nolimits_{c'} PQ_{c't} \cdot ci_{c'}\right) = \left(\frac{QF_{fct}}{qfs_{ft}} \cdot \frac{WF_{ft} \cdot WD_{fct}}{AR_{ft}}\right) \cdot \left(\sum\nolimits_{c'} PQ_{c't} \cdot QI_{c't}\right) \tag{B31}$$

$$QF_{fct+1} = QF_{fct} \cdot (1 - \upsilon) + QK_{fct} \tag{B32}$$

Land and labor supply, technical change, population growth, and other dynamic updates

$$qfs_{ft+1} = qfs_{ft} \cdot \left(1 + \varepsilon_f\right) \tag{B33}$$

$$\alpha_{ct+1}^{p} = \alpha_{ct}^{p} \cdot (1 + \sigma_c) \tag{B34}$$

$$pop_{ht+1} = pop_{ht} \cdot (1 + \varphi_h) \tag{B35}$$

$$ga_{t+1} = ga_t \cdot (1 + \tau) \tag{B36}$$

$$cab_{t+1} = cab_t \cdot (1 + \pi) \tag{B37}$$

Table A4: Activities, factors, and households in the CGE model

Activities	Maize,sorghum and millet,other cereals,root crops,pulses and oilseeds,groundnuts,vegetables,fruits,cotton,sugar,tobacco,other export crops,cattle,poultry,other livestock,forestry,fishing,mining,food processing,textiles and clothing,wood and paper,chemicals,machinery and metals, other manufacturing,energy and water,construction,trade,hotels and catering,transport and communication,financial services,government services,education,health,community services.
Regions	Agriculture across five agro-ecological zones, large-scale farms, and urban farms (total 6 regions).
Factors	Farm labor in each region; unskilled labor; semi-skilled labor; skilled labor; crop land and livestock numbers in each region; agricultural, mining and non-agricultural non-mining capital.
Households	Rural small-scale farmers; rural large-scale farmers; rural non-farmers; small urban center farmers; small urban centers non-farmers; metropolitan area farm; metropolitan area non-farmers.

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Table 1: Characteristics of Zambia's agro-climatic zones, 1976–2007

	Annual average (mm)		Coefficient of variation	
	Precipitation	Reference Evapotranspiration	Precipitation	Reference Evapotranspiration
Zone1	786	1,689	0.180	0.036
Zone 2	818	1,624	0.203	0.032
Zone 3	941	1,847	0.171	0.031
Zone 4	930	1,619	0.152	0.035
Zone 5	1,228	1,546	0.094	0.021

Table 2: Occurrences of extreme climate events in Zambia, 1976–2007

	Number of agro-climatic zones simultaneously affected				
	5	4	3	2	1
Severe dry ($Z \leq -1.5$)	0	0	1(92: 1-3)	2(95: 1-2; 05: 1-2)	1(87: 2)
Moderate dry ($-1.5 < Z \leq -0.5$)	1(94:1-5)	4	4	4	7
Normal ($-0.5 < Z \leq 0.5$)	0	0	6	11	10
Moderate wet ($0.5 < Z \leq 1.5$)	0	4	5	2	9
Very wet ($Z > 1.5$)	0	1(78: 1-4)	0	1 (81: 1,3)	4(79: 5; 89: 2; 97: 2; 04: 3)

Note: Averaged monthly Palmer Z Index in maize growing period (November to March);terms in parentheses indicate the year and zones in which events occurred (e.g., '1 (92: 1-3)' means one event occurred in 1992 affecting zones 1-3).

Table 3: Impact channels in the CGE model

Impact channel	Affected sectors	
All 10 years in each of 32 weather sequences		
Crop yields	Rain-fed crops	Yields are reduced based on annual HC model results.
Severe drought years (1983/84, 1986/87, 1991/92, 1994/95 and 2001/02)		
Crop land expansion	Rain-fed crops	Crop land expansion that would take place in a normal year is eliminated in the drought year and remains at zero in the immediate post-drought year.
Livestock numbers	Livestock	Livestock capital declines in drought year and stock growth gradually returns to normal year rates with two-period diminishing lagged effects.
Physical capital accumulation	All sectors	Capital depreciation increases in drought year and gradually returns to normal year levels with two-period diminishing lagged effects.
Major flood years (2006/07)		
Crop land expansion	All crops	Cultivated land area falls in flood year and only returns to pre-flood levels in the subsequent year.

Table 4: Maize results from the HC Models, 1976–2007

	Palmer Z drought index-based weather classification				
	Severe dry	Moderate dry	Normal	Moderate wet	Very wet
Zone 1					
Growing period rainfall (mm)	405-499	481-624	632-751	746-902	971-1031
Maize WRSI (%)[a]	70-96	94-100	96-100	97-100	100
Maize yield loss (%)[b]	14-77	1-15	0-8	0-10	0
Frequency[c]	3	8	8	11	2
Zone 2					
Growing period rainfall (mm)	401-506	505-623	711-781	761-887	961-1008
Maize WRSI (%)[a]	75-95	83-100	94-100	92-100	96-100
Maize yield loss (%)[b]	21-65	0-48	7-19	1-23	0-14
Frequency[c]	4	9	7	9	3
Zone 3					
Growing period rainfall (mm)	585	578-766	765-858	927-1085	1079-1125
Maize WRSI (%)[a]	86	86-100	88-100	95-100	97-100
Maize yield loss (%)[b]	40	0-44	1-34	0-21	0-10
Frequency[c]	1	13	7	8	3
Zone 4					
Growing period rainfall (mm)	-	635-781	765-954	910-1058	1113
Maize WRSI (%)[a]	-	97-100	95-100	95-100	99
Maize yield loss (%)[b]	-	1-11	0-17	0-20	2
Frequency[c]	-	11	10	10	1
Zone 5					
Growing period rainfall (mm)	-	875-987	960-1158	1136-1314	1290
Maize WRSI (%)[a]	-	98-100	97-100	100-100	100
Maize yield loss (%)[b]	-	0-9	0-13	0	0
Frequency[c]	-	7	18	6	1

Note: (a) 'WRSI' is the ratio of actual to potential ET during growing season; (b) Maize yield losses estimated by HC model; (c) Number of annual occurrences during 1976–2007.

Table 5: Growth and poverty results under current climate variability, 2006–16

	Average rainfall sequence		Worst rainfall sequence	
	Change in annual growth rate (%-point)	Accumulated 10-year losses (US$ mil.)	Change in annual growth rate (%-point)	Accumulated 10-year losses (US$ mil.)
Total GDP	-0.43	4,278	-0.90	7,088
Agricultural GDP	-1.01	2,213	-2.29	3,132
Zone 1	-1.28	172	-4.63	302
Zone 2	-1.58	1,682	-3.52	2,442
Zone 3	-0.86	5	-2.44	9
Zone 4	-0.93	182	-1.64	175
Zone 5	-0.37	158	-0.94	169
	Change in poverty rate in 2016 (%-point)	Absolute poverty change (1000s)	Change in poverty rate in 2016 (%-point)	Absolute poverty change (1000s)
Poverty	2.25	300	4.85	648
Rural	2.05	167	4.25	346
Urban	2.56	133	5.79	303

Note:Ten-year losses are undiscounted cumulative losses for the 10-year period. Since zonal agricultural GDP excludes forestry, total zonal impacts are below national impacts.

Table 6: Extreme weather event results, 2006–16

	Percentage point change in growth or poverty rate during extreme event year		
	Severe drought	Modest drought	Severe flood
Total GDP	-6.6	-4.0	-2.3
Agricultural GDP	-22.7	-15.7	-9.4
Zone 1	-60.1	-30.8	-7.8
Zone 2	-40.8	-24.0	-13.5
Zone 3	-22.4	-17.3	-5.6
Zone 4	0.1	-12.0	-14.1
Zone 5	2.6	-5.3	-5.7
National poverty	7.5	3.9	2.4
Zone 1	5.6	2.3	0.1
Zone 2	8.2	1.4	0.6
Zone 3	6.5	4.1	1.4
Zone 4	2.8	2.1	3.3
Zone 5	-1.3	-1.0	-0.8

Note:Severe drought reflects climate conditions from 1991/92; modest drought is 1994/95; and severe flood is 2006/07.

Table 7: Yield responses under climate change scenarios

	Changes in maize yields relative to historical yield trends (%)					
	HadCM3-B1a		T2P-15		T2P+15	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Zone 1	-0.9	1.3	-5.8	6.9	3.2	4.4
Zone 2	-1.0	1.4	-5.7	5.8	4.2	5.6
Zone 3	0.1	0.5	-4.5	4.2	3.2	4.5
Zone 4	-1.3	1.3	-3.8	4.1	1.8	2.2
Zone 5	-0.2	0.5	-1.4	2.2	0.5	1.5

Note:HadCM3-B1a is SRES B1a scenario from HadCM3 GCM; T2P-15 and T2P+15 scenarios assume that temperatures rise by 2 percent and rainfall either rises or falls by 15 percent.

Table 8: Growth and poverty results under climate change scenarios

	Deviation from the results of the normal rainfall scenario					
	Change in annual growth rate (%-point)		Accumulated 10-year GDP losses (US$ bil.)		Change in poverty rate (%-point)	Absolute poverty change (1000s)
	Total GDP	Agric. GDP	Total GDP	Agric. GDP		
Mean of 32 rainfall sequences						
No climate change	-0.43	-1.01	-4.32	-2.21	2.25	300
HadCM3-B1a	-0.48	-1.07	-4.69	-2.34	2.49	332
T2P-15	-0.63	-1.32	-6.02	-2.86	3.25	433
T2P+15	-0.29	-0.76	-3.00	-1.69	1.55	207
Worst rainfall sequence						
No climate change	-0.90	-2.29	-7.13	-3.13	4.85	648
HadCM3-B1a	-1.01	-2.55	-7.84	-3.36	5.41	722
T2P-15	-1.31	-3.35	-9.91	-4.07	7.23	965
T2P+15	-0.61	-1.51	-5.08	-2.41	3.16	422

Notes:HadCM3-B1a is SRES B1a scenario from HadCM3 GCM; T2P-15 and T2P+15 scenarios assume that temperatures rise by 2 percent and rainfall either rises or falls by 15 percent.

Figure 1: Agro-climatic zones, weather stations and Thiessenpolygons

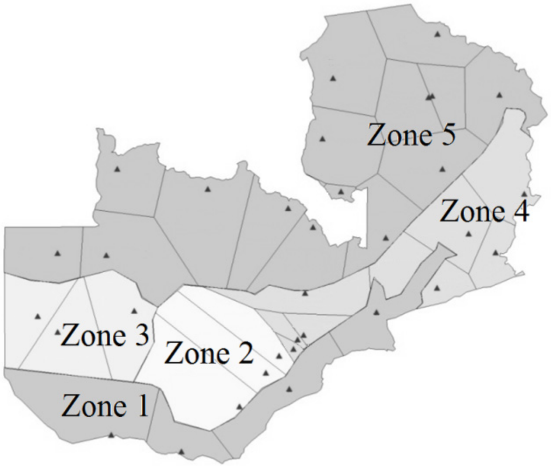

Figure 2: Maize relative yields by agro-climatic zone, 1976–2007

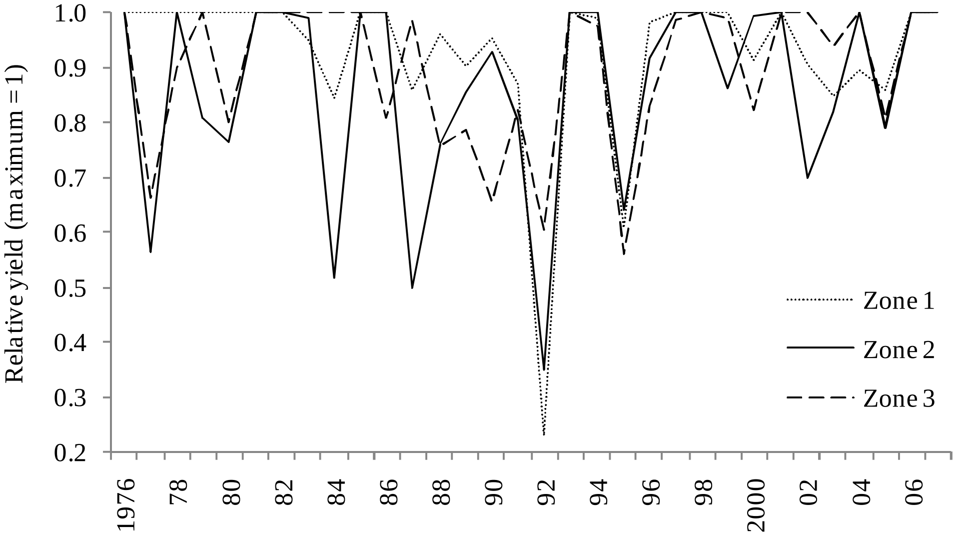

Figure 3: Agricultural GDP losses due to climate variability, 2006–16

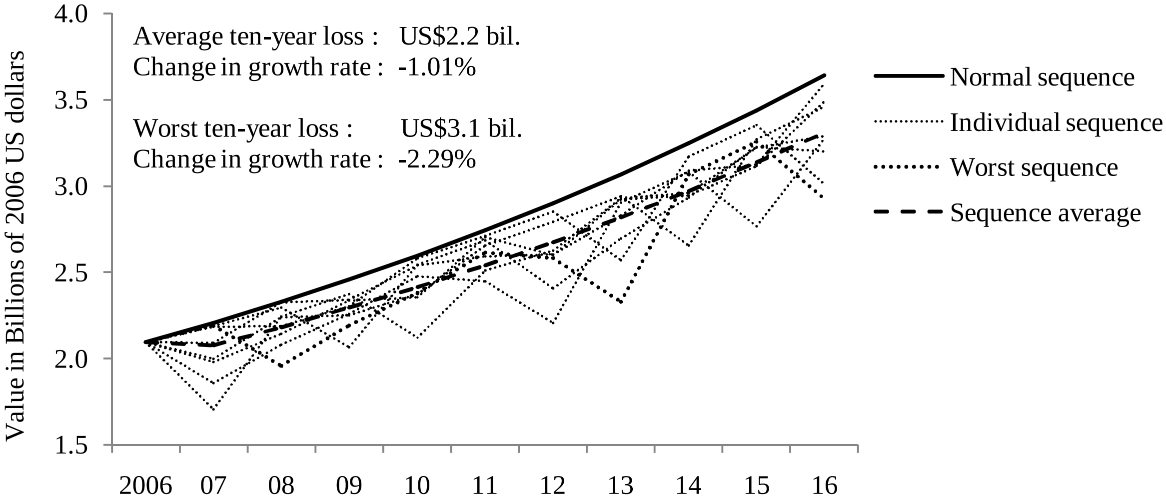

Figure 4: Change in national poverty headcount due climate variability, 2006–16