The economic costs of extreme weather events: A hydro-meteorological CGE analysis for Malawi

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Abstract – Extreme weather events, such as droughts and floods, have potentially damaging implications for developing countries. Previous studies have estimated economic losses during hypothetical or single historical events, and have relied on historical production data rather than explicitly modeling climate. However, effective mitigation strategies require knowledge of the full distribution of weather events and their isolated effects on economic outcomes. We combine stochastic hydro-meteorological crop-loss models with a regionalized computable general equilibrium model to estimate losses for the full distribution of possible weather events in Malawi. Results indicate that, based on repeated sampling from historical events, at least 1.7 percent of Malawi's GDP is lost each year due to the combined effects of droughts and floods. Smaller-scale farmers in the southern region of the country are worst affected. However, poverty amongst urban and nonfarm households also increases due to national food shortages and higher domestic prices.

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1. Introduction

Extreme weather events, such as droughts and floods, can severely undermine economic growth and poverty reduction, especially in food-insecure, low-income countries. Such events usually have higher-order or 'economywide' implications beyond directly-affected sectors or regions, as production chains are disrupted, assets depreciate and consumer demand declines (Van der Veen, 2004). A number of studies have estimated the economywide losses occurring during extreme events, but these studies typically consider either a hypothetical event (e.g., Arndt and Bacou, 2000; Narayan, 2003; Boyd and Ibarrarán, 2008) or a specific historical event (e.g., Horridge *et al*., 2005). However, a range of possible events should ideally be considered when designing disaster relief programs or large-scale investments (Rose, 2004a). Moreover, future climate change may alter the frequency and severity of historical events (Salinger 2005). This uncertainty underlines the importance of considering the full distribution of possible extreme weather events when evaluating mitigation options (Freeman *et al*., 2004).

Existing studies usually rely on deviations in historical production data to determine direct losses during an event, rather than isolating purely climate-related effects (e.g., Horridge *et al*., 2005). However, it is essential to disentangle climate shocks from other influences on production, such as policies and world commodity prices. This limitation is likely to be most binding in lower-income countries, especially those that have undergone significant policy reforms, or where the public sector dominates climate-sensitive sectors, such as agriculture (Rose, 2004b).

Given these gaps in the literature, we develop an integrated analytical framework that evaluates the economic losses for the full distribution of extreme weather events. We apply this framework to Malawi, which is a typical low-income country that depends heavily on rain-fed agriculture for the livelihoods of its largely rural population. We first estimate direct crop production losses using stochastic drought and flood models that isolate the effects of climate shocks from other influencing factors. We focus on agriculture when estimating direct losses given its importance for national income and household poverty in Malawi. To estimate both direct and indirect impacts, we develop a regionalized computable general equilibrium (CGE) model (Section 3). This model is linked to a survey-based micro-simulation module, which measures changes in the distribution of household incomes and poverty—another overlooked dimension in the literature

(Rose, 2004b). We then report the simulation results for both floods and droughts in Malawi (Section 4). We conclude by summarizing our findings and identifying areas for further research.

2. Estimating direct production losses

2.1 Hydro-meteorological hazard and risk

We develop probabilistic models to estimate the direct impact of weather events on agricultural crop production. These models capture two aspects of drought and flood impacts: hazard and risk. Hydro-meteorological 'hazard' is defined by (i) the severity of an event and (ii) the probability of that event occurring within a given year. This is measured by an event's 'return period' (RP), which is the expected length of time between the reoccurrence of two events with similar characteristics. An event's RP is inversely proportional to its so-called 'exceedance probability' (i.e., EP = 1/RP), which gives the likelihood of an event of certain severity or worse occurring (see below). Thus, an RP5 (or 1-in-5 year) event occurs more frequently but is less severe than an RP15 (or 1-in-15 year) event. In our analysis we evaluate weather events across the full spectrum of return periods.

'Risk' is the quantification of potential losses during a particular event. It explicitly considers the exposure of different entities, such as farmers, to weather events. Exposure or risk depends on many factors, including the severity of weather events, the location of farmers, and their cropping patterns. For example, farmers above a floodplain are not exposed to floods and hence are unaffected by flooding. Some farmers may, however, be above the RP5 flood line but below the RP15 line. Farmers' cropping patterns also matter since some crops are more drought-tolerant than others given their physiological characteristics. Similarly, some crops may be irrigated and thus less affected by periods of low rainfall. We consider each of these aspects of exposure when estimating crop production losses.

2.2 Measuring drought impacts

Although several definitions of meteorological drought exist in the literature, there is agreement that it should be seen as an 'abnormal' event. Droughts should therefore not be confused with normal desiccation caused by dry spells (Agnew, 2000). For an event to be declared a drought the precipitation or soil moisture levels must be sufficiently below the long-run mean. In order to facilitate the identification of droughts, a variety of indices exist in the literature (Heim, 2002, provides a review). We use the Standard Precipitation Index (SPI) developed by McKee *et al*. (1993), which is based on precipitation data. This index permits the measurement of drought intensity, magnitude or severity as well as its duration. Moreover, the probability of an event occurring within a certain year can be estimated on the basis of historical data (Heim, 2002).

Precipitation data is taken from 45 weather stations distributed across Malawi's eight agro-ecological zones. We assume that rainfall at each station follows a gamma distribution $X_i \sim \Gamma(\alpha_i, \beta_i)$ where α_i and β_i are shape and scale parameters of rainfall (X_i) at weather station i. This probability distribution function is generally considered a good fit for precipitation distributions (McKee et al., 1993). The parameters are estimated using maximum likelihood estimation and the cumulative distribution function is then transformed into a standard normal random variable Z_i with a zero mean and a standard deviation of one (i.e., $Z_i \sim N(0,1)$). The Z-score of this distribution is the SPI. In the analysis here a drought is declared when rainfall levels drop below 75 percent of the long run mean at a particular weather station; the lower the Z-score the more severe the drought.

Not all droughts of apparent similar severity have the same impact on crops. This is because crop production losses depend on when a drought occurs during a crop’s phenophase or growing cycle. For example, maize is relatively tolerant to water deficits during the vegetative and ripening stages, but less so during the flowering stages. Therefore, in order to make different drought events comparable, the measured SPI was adjusted to control for when the event took place during the growing cycle (i.e., November to March).

Based on the adjusted SPIs, we identify crop seasons 1986/87, 1991/92, 1993/94, 2003/04 and 2004/05 as significant drought years in Malawi. We then used regression models to identify whether a statistical, non-linear relationship exists between historical drought events of different severities (i.e., as measured by their adjusted SPIs) and the associated crop production losses for different crops observed during those years. Production losses are calculated as the difference between observed production and expected production, where the latter reflects the production level achieved during the closest 'normal' or non-drought year.[1]

The regression coefficients are then used in a stochastic model that randomly generates a large number of possible drought events across the full range of RPs. From this a consistent and continuous relationship between different drought events and their associated production losses is defined. This relationship is represented by a 'loss exceedance curve' (LEC), which, in the context of agricultural risk, gives the likelihood or probability that a certain level of crop loss will be exceeded during a particular drought event (recall that the EP and RP are inversely related).

Figure 1 shows the estimated drought LECs for maize and tobacco in Malawi.[2] Instead of indicating the EP values on the vertical axis as is customary, RPs of 5, 10 and 20 years (i.e., EPs of 0.2, 0.1 and 0.05, respectively) are shown for ease of reference. Thus, for example, the tobacco LEC (TOB) shows that production falls by at least 4.1 percent during an RP10 drought event. We estimate separate LECs for different maize varieties, namely local maize (LMZ), high yield varieties (HYV) and composites (COM). Our results indicate that composite seeds are more drought-tolerant than other varieties, which is consistent with expectations (Denning *et al*., 2009).[3]

[Figure 1: Loss exceedance curves for droughts]

The LECs allow us to attach a precise probability of occurrence to each possible weather event. Thus, while future weather patterns are uncertain, expected long-term losses can be predicted with greater certainty. This expected long-term loss is the 'average annual loss' (AAL), which is obtained by multiplying the probability of an event by its expected loss and summing over all possible events (i.e., integration of the LEC). The drought AAL for LMZ, HYV and COM maize

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[1] Detailed regression results are reported in World Bank (2009).
[2] LECs for droughts (and floods) were only estimated for maize and tobacco. These two crops account for almost half of crop agriculture's gross domestic product (GDP) in Malawi. Section 3.3 explains how direct losses for other crops were estimated for the CGE simulations.
[3] Denning *et al*. (2009) explain that local maize is traditionally-grown, open-pollinated and can be reused each year. Hybrid varieties are cross-bred and cannot be recycled. Composites are improved open-pollinated varieties that can be recycled, and are bred scientifically to enhance suitability to local environments, including drought-resistance.

varieties is 7.3, 2.6 and 1.2 percent, respectively, and 1.2 percent for tobacco. These production losses are roughly consistent with those experienced during an RP7 drought.

2.2 Measuring flood impacts

The flood risk model adopts a similar approach to the drought model in that hazard is assessed using estimates of the probability of floods of different severities occurring. Given Malawi's topography, floods mostly occur in the Shire River basin in the southern part of the country, and so we only estimate production losses for this region. The probabilistic risk model is based on runoff, which means that observed flood discharges are used to identify floods and estimate their probability of occurrence. Stochastically generated discharges are then routed through a Digital Elevation Model of the affected floodplain to determine flood extents and depths at a detailed 90 square meter resolution.

The stochastic results from this model were validated using satellite images of historical flood events (i.e., 1982/83, 1991/92, 1997/98, 2000/01, 2001/02 and 2003/04). Agricultural losses are determined on the basis of information about farmers' exposure to flood events. This depends on the portion of cultivated land in geographic areas likely to be inundated during floods of different severities. As with the drought analysis, regression models are used to estimate the relationship between production levels and historical flood events. Data from the regression models were then incorporated into a stochastic flood model in order to generate production losses under the complete distribution of flood events (i.e., for all RPs).

The relationship between flood events and production losses is once again reflected by crop-specific LECs. Figure 2 shows flood LECs for maize and tobacco (the three maize varieties are combined in the flood analysis since physiological differences have little bearing on the extent of production losses). The AAL due to floods is estimated at 12.7 and 6.0 percent for maize and tobacco, respectively. This is roughly equivalent to the loss experienced during an RP2 flood. Note that these percentage declines only apply to production in the southern region, an area that accounts for about a third of maize and a quarter of tobacco grown in Malawi.

[Figure 2: Loss exceedance curves for floods]

3. A regionalized CGE model of Malawi

Cochrane (2004) reviews the methods used to estimate indirect losses from natural hazards. CGE models have a number of limitations, such as the assumption of functioning markets and the inability to capture non-market losses, such as leisure. However, they are the preferred method for estimating net losses (Rose 2004a). CGE models capture all income and expenditure flows in an economy within a consistent accounting framework, and thus avoid the ‘double-counting’ that often occurs when combining partial equilibrium approaches. Moreover, CGE models provide a simulation laboratory for conducting counterfactual analysis. This allows us to isolate climate effects from other influencing factors, a common problem associated with *ex post* methods. Regionalized CGE models can also capture direct and indirect losses at national and local levels, which is an advantage over purely macroeconomic models (e.g., Freeman *et al*., 2004). Finally, CGE models can capture distributional effects and thus identify vulnerable population groups. In this section we describe the workings and structure of the Malawian CGE model.

3.1 Core CGE model specification

The full model specification can be found in Löfgren *et al*. (2002). However, Table 1 presents the equations of a simplified model that illustrates how weather events affect economic outcomes in CGE analyses. Producers in each sector s and region r produce output Q by employing factors of production F under constant returns to scale (exogenous productivity α) and fixed production technologies (fixed factor shares δ) (eq. [1]). Profit maximization implies factor returns W equal average production revenues (eq. [2]). Labor supply l, land supply n and capital supply k are fixed, implying full employment of factor resources. Labor market equilibrium is defined at the regional level, so labor is mobile across sectors but wages vary by region (eq. [10]). National capital market equilibrium implies that capital is mobile across both sectors and regions and earns a national rental rate (i.e., capital returns are equalized) (eq. [11]). Finally, given the rapid onset of weather events, we assume that land is allocated at the start of the crop season and cannot be reallocated across crops in response to weather shocks (eq. [12]). Land therefore earns sector- and region-specific rents under this short-run specification.

International trade is determined by comparing domestic prices to world prices. The latter are fixed under a small-country assumption. The core model treats trade as a complementarity problem. If domestic prices exceed world import prices w^m (adjusted by exchange rate E), the quantity of imports M increases (eq. [3]). Conversely, if domestic prices fall below world export prices w^e then export demand X increases (eq. [4]). To ensure macroeconomic consistency, we assume a flexible exchange rate and fix the current account balance b in foreign currency (eq. [8]). This implies that short-term foreign borrowing cannot replace production losses and external price adjustments are necessary to offset rising import demand or falling export supply.

Factor incomes are distributed to households in each region using fixed income shares θ based on the households' initial factor endowments (eq. [5]). Total household incomes Y are either saved (based on marginal propensities to save υ) or spent on consumption C (according to marginal budget shares β) (eq. [6]). Household savings and foreign capital inflows are collected in a national savings pool and used to finance investment demand I (i.e., savings-driven investment closure) (eq. [7]). Finally, a national price P equilibrates product markets, thus avoiding having to model interregional trade flows (eq. [8]).

The model's variables and parameters are calibrated to the social accounting matrix (SAM) constructed by Benin *et al*. (2008) that captures the equilibrium structure of the Malawian economy in 2005. Parameters are then adjusted to reflect extreme climate shocks. The hydro-meteorological crop models estimate reductions in crop productivity and land availability during droughts and floods, which are imposed on the model by adjusting the parameters π and λ (eq. [1] and [12]). Lowering the value of these parameters below one reduces production and affects product prices and factor resources. This then influences households' real incomes depending on their resource endowments and employment patterns.

[Table 1: Core model equations]

3.2 Extensions to the full CGE model

The actual model used in our analysis drops some assumptions in the core model. Constant elasticity of substitution production functions allow factor substitution (i.e., δ is no longer fixed), and intermediate demand is captured via fixed technology coefficients. The model identifies 36 sectors (17 agriculture, 9 industry and 10 services). Agriculture is disaggregated across eight agro-ecological zones, urban areas, and small, medium and large-scale farmers. Labor markets are segmented into three skill groups. Farm land in each region is divided into small-scale farms (less than 0.75 hectares); medium-scale farms (between 0.75 and 2 hectares); and larger-scale farms (more than 2 hectares). Unskilled labor is underemployed and earns a fixed real wage.

International trade is captured by allowing production and consumption to shift imperfectly between domestic and foreign markets, depending on the relative prices of imports, exports and domestic goods. This captures differences in domestic and foreign products and allows for two-way trade. Production and trade elasticities are drawn from Dimaranan (2006).

Household consumption is based on a linear expenditure system that permits non-unitary income elasticities, which were econometrically estimated using the 2004/05 household survey (NSO 2005). Households are split into rural farm/nonfarm groups and small urban and metropolitan centers. Farm households in each region are further divided into small, medium and large-scale land groups. This implies 28 representative households in the full model. Households pay taxes at fixed rates, and these revenues finance exogenous recurrent spending leaving an endogenous fiscal balance. Recurrent spending is thus fixed during weather events, but public investment can contract. Finally, each respondent in the survey is linked to their corresponding household group in the CGE model. Changes in real commodity consumption in the model are passed down to the survey, where per capita expenditure levels and poverty measures are recalculated.

3.3 Simulation design

The CGE simulations are based on the LECs in Section 2. Production losses are imposed on the model via changes in crop productivity or land availability. Since farmers cannot reallocate agricultural land or capital, changes in crop yields cause proportional changes in production. In reality production may fall because farmers abandon land once it is inundated or productivity falls below a threshold. However, we did not find a consistent statistical relationship between land or yield losses and different drought events.[4] This may be because no two historical drought events are comparable, especially in their intra-annual timing. Therefore, for convenience, we

[4] A crop's yield is the level of production per unit of land. It is a partial measure of productivity affecting only land. However, in the CGE model we shock total factor productivity (i.e., the shift parameter on the production function).

assume that production losses in the drought LECs are solely attributable to yield losses. The same problem was not experienced in the flood analysis; hence for the flood scenarios we reduce both productivity and land availability to achieve target production losses as shown in the LECs. This is shown in Table 2 for selected weather events.

[Table 2: Simulated yield and land losses]

Drought LECs were estimated for different maize varieties, but only an aggregate maize crop is modeled in each agro-ecological zone. In line with fixed land allocations, we assume that farmers cannot switch between maize varieties in response to a climate shock. For example, farmers cannot switch to drought-tolerant composite varieties during a low rainfall season. We can therefore weight production losses for each variety by base year variety adoption rates from MOAFS (2007) to derive aggregate maize LECs for each zone. Zonal variation in drought impacts therefore results from different adoption rates and cropping patterns. Tobacco losses are assumed to be uniform across zones. Finally, flood losses only apply to producers in the three flood-prone southern zones (i.e., Machinga, Blantyre, and Ngabu).

LECs were only estimated for maize and tobacco. We impute direct losses for other crops by analyzing the correlation between maize and non-maize production trends during event years using national production data from FAO (2009). The correlation coefficients used in our simulations are shown in Table 3. We assume correlation coefficients remain constant across RP values.

[Table 3: Crop correlation coefficients]

We focus on agriculture when estimating direct losses. Crop agriculture is Malawi's most climate-sensitive sector due to inadequate irrigation and water management. Moreover, agriculture and food processing generate half of national GDP and four-fifths of export earnings and employment. Even though our analysis covers most expected losses during extreme events, we exclude certain impact channels. For instance, we do not model livestock stock changes or livestock losses seen during droughts. However, most of Malawi's livestock is poultry, which is less affected by droughts than cattle, goats and sheep. We also do not capture infrastructure damages during floods as these are generally small relative to total economic losses, as is evident from historical events such as the 2001/02 floods (World Bank, 2009). Thus, despite these omissions, our results should provide a near approximation of the economic losses incurred during extreme events.

4. Total economic losses during extreme events

4.1 Impacts on domestic production

Table 4 reports the impact of droughts and floods on national production or GDP measured at factor cost. Results are reported for agricultural subsectors, industry and services, while the first column shows initial GDP shares in the base year of the model (i.e., 2004/05). Maize suffers the largest declines in GDP during droughts, with an average annual loss of 4.34 percent. Average tobacco production losses during droughts are significantly smaller at 1.28 percent. This reflects the net value of long-term losses in the maize and tobacco sectors caused by weather events. The production of other crops also declines, based on the correlation coefficients from Section3. Overall, agricultural production is significantly lower due to extreme weather events, with annual GDP losses averaging 2.02 and 1.43 percent for droughts and floods, respectively.

[Table 4: National production results]

The table also reports agricultural GDP losses for droughts with different RPs. Losses increase significantly during more severe droughts. For example, agricultural GDP declines by 1.12 percent during an RP5 drought, but by 18.75 percent during an RP20 drought. Figure 3 shows the decline in agricultural GDP for the full distribution of drought events. Expected damages are significantly higher for less frequent but more severe droughts, with losses in excess of 20 percent of agricultural GDP for droughts of RP20 or higher. Damages eventually taper off as crop production losses reach maximum levels (see Figure 1). However, our assumption that crop correlation coefficients remain constant across RPs explains at least some of the tapering effect. For example, the coefficient of 0.5 for groundnuts means that production of this crop cannot decline by more than half, even if maize production were to fall to zero. For this reason, we focus on economic losses associated with those drought events that are less severe, more frequent and for which better historical climate data exists.[5]

[Figure 3: Distribution of drought impacts]

Table 4 also demonstrates the importance of measuring indirect economic losses during extreme events. For example, even though we did not include direct losses for the livestock sector, the decline in maize production and subsequent increase in maize prices causes average annual livestock GDP to fall by 0.91 percent because of the importance of maize as a feedstock for poultry in particular. Similarly, falling agricultural production has knock-on effects for the food processing sectors, which rely on the domestic supply of raw intermediate products. Services also decline during droughts as demand for trade and transport services falls along with agricultural production. Overall, average annual total GDP losses equal 0.97 and 0.70 percent, respectively. These are average losses incurred over long time periods (i.e., 500 random annual events simulated in the stochastic models described in Section 2). Accordingly, we can combine these annual damages to arrive at an expected annual loss caused by general weather variability (i.e., floods and droughts) of 1.67 percent of total GDP.

Table 5 shows that agricultural GDP is negatively affected by droughts in all regions of Malawi. However, there is significant variation in damages across agro-ecological zones due to differences in regions' dependencies on drought-sensitive crops, such as local variety maize. For example, farmers in the central regions are less affected by droughts because it is here that most of the country's relatively drought-tolerant tobacco and composite maize is grown. By contrast, farmers in the southern region of Machinga and Ngabu experience the largest declines in crop and livestock GDP due to their greater reliance on local maize and poultry. The southern region is also where flood damages are likely to occur and where declining land availability due to water inundation has profoundly negative consequences for agricultural production during severe floods.

[Table 5: Regional production results]

[5] The 1991/92 drought has been classified as an RP40 drought, and was followed in 1993/94 by another severe RP20 drought. With the exception of these two highly unlikely events occurring within such a short space of time, all other major drought events over the last 40 years were RP10 events or less.

The increase in crop and livestock GDP for the northern and central regions during floods is driven by the assumption that national product markets function in Malawi. When production losses only occur within certain regions, then overall supply shortages in the economy ensure that unaffected regions experience an increase in demand for their output at higher prices. Thus, while the overall impact on GDP is negative during floods, the northern and central regions experience marginal gains in production.

Finally, Table 4 reports agricultural impacts for different farm types. Small- and medium-scale farmers are worst affected by droughts and floods. Small-scale farmers lose almost 2.97 percent of annual production due to droughts and 2.67 percent due to floods. By contrast, large-scale farmers experience production losses of only 1.30 percent during droughts, and actually benefit slightly (0.03 percent) from floods in the southern region. Larger impacts for small- and medium-scale farmers are due to their greater reliance on maize production, especially local varieties, which heightens their vulnerability to droughts and floods. Large-scale farmers, on the other hand, grow more drought-tolerant crops, such as tobacco and sugarcane, and are more heavily concentrated in the less flood-prone northern and central regions. They also benefit from the macroeconomic effects of extreme weather events.

4.2 Macroeconomic effects

One of the strengths of CGE models is that their consistent accounting framework ensures that macroeconomic constraints are respected. For example, Table 6 shows how falling domestic production during drought years increases demand for imported food products, with maize imports more than doubling in an RP20 drought year. However, at the same time, there is a drop in tobacco exports, which generated a third of total export earnings in 2005. This results in a declining capacity to pay for imports—a situation that places considerable pressure on Malawi's current account balance. We assume that the country cannot increase its external deficit via increased public sector borrowing or additional foreign aid receipts. Accordingly, the real exchange rate must depreciate in order to encourage exports from those sectors less affected by droughts. This benefits larger-scale farmers, who account for most of Malawi's export agriculture, as well as industrial producers, who do not experience direct losses from the drought.

This explains the small increase in industrial GDP during some of the simulated drought events (see Table 4).

[Table 6: Macroeconomic results]

Taking macroeconomic balances into account is crucial for measuring the overall impacts of extreme weather events. For example, the depreciating exchange rate raises the locally-denominated value of foreign grants, which allows government expenditure to expand slightly. This is more than offset by falling GDP and national income, which reduces the level of savings during a drought or flood year, and in turn lowers investment demand. However, it is private consumption spending that declines the most during extreme events, as household's real disposable income levels fall with declining production and the rise in consumer prices. Such adverse price and income changes may cause households at the lower end of the income distribution to drop below the poverty line.

4.3 Poverty outcomes

The CGE model estimates changes in real commodity expenditure for each household group, and these are then passed down to the survey on which the model is based. After recalculating per capita expenditures in the survey, standard poverty measures are computed. Table 7 reports the impact of droughts and floods on household poverty. The results show how national poverty worsens under all drought and flood scenarios. On average, the national poverty headcount rate increases by 1.26 and 0.91 percentage points as a result of droughts and floods, respectively. This is equivalent to an additional 265,000 people dropping below the poverty line every year due to the combined effect of droughts and floods (out of a total population of 12.2 million in 2004/05). During particularly severe events, such as an RP20 drought, the poverty rate is expected to increase by 14.35 percentage points, pulling an additional 1.75 million people into poverty.

[Table 7: Poverty outcomes]

CGE models can also distinguish impacts between household groups. While all household groups reported in the table experience increasing poverty, it is nonfarm households that are worst affected. As net consumers of agricultural products, these households are especially vulnerable to rising food prices (i.e., unlike farm households who produce their own foods, nonfarm households cannot offset the negative welfare effects associated with rising prices). Moreover, declining nonfarm wages and rising unemployment caused by migration of farm workers to the nonfarm economy due to falling farm revenues further contributes to income losses for existing nonfarm workers.

Nonfarm households, however, account for only 15 percent of the total population and an even smaller share of the poor population. In fact, over 90 percent of the poor live in rural farm households. As such, changes in poverty for these households largely dictate what happens at the national level. In this regard, results show relatively large increases in poverty among small- and medium-scale farm households compared to large-scale farm households. In absolute terms, 90 percent of people that become poor as a result of either droughts or floods reside in small- or medium-scale farm households.

4.4 Comparison with observed events

To partially validate the model's results, Table 8 compares the economic impact of the modeled RP20 drought year with the observed outcome in 1993/94, which was also classified as an RP20 drought. Similarly, we compare the RP10 flood scenario with the observed outcome during the 2002/03 flood.

[Table 8: Comparing modeled and observed events]

The modeled and observed results are broadly consistent. However, it is difficult to directly compare modeled and observed impacts for three reasons. Firstly, the structure of the economy changed between 1994 and 2004 (the latter being the base year of the CGE model). Agriculture's share of the economy has increased since 1994, implying that observed impacts at the national level should be higher than modeled impacts. Secondly, by 2004 Malawi's government had successfully encouraged more farmers to use drought-tolerant composite and hybrid varieties, which would lessen the impact of droughts.

Finally, the CGE model isolates the impact of the drought, while observed data includes other changes taking place at the same time. For example, the 1994 drought was preceded by an even more severe drought in 1992 (RP40), while the 2002 flood was preceded by an RP5 flood in the previous year. The aftershocks of these earlier events are likely to have affected observed changes, which are reported here as year-on-year changes rather than relative to the closest normal year. Such difficulties further emphasize the importance of using CGE models to estimate economic losses during extreme weather events.

5. Conclusion

We developed an integrated analytical framework that imposed the direct production losses estimated by stochastic flood and drought models on a regionalized CGE model. We used this framework to estimate economywide damages for the full distribution of possible weather events in Malawi. This is an advance over existing studies, which have evaluated either hypothetical or single historical events, and have therefore limited their ability to inform future mitigation strategies. Moreover, we examined the impact of extreme weather events on the distribution of incomes and poverty across different regions and population groups. This enabled us to identify vulnerable sections of the population. Our methodology could therefore be usefully applied to a wide range of contexts to inform both development policy and disaster management programs.

Results for Malawi indicate that, on average, droughts and floods together reduce total GDP by about 1.7 percent per year. However, damages vary considerably across weather events, with total GDP declining by at least 9 percent during a severe 1-in-20 year drought. Such severe outcomes place a significant constraint on Malawi's development prospects. Smaller-scale farmers in the southern regions of the country are especially vulnerable to declining agricultural revenues and rising poverty during drought and flood years. However, urban households also experience increased poverty due to higher food prices and declining nonfarm wages. Indeed, the disruption of supply chains during extreme events causes indirect losses in downstream food processing and upstream services. This result underlines the potential economywide impacts of extreme weather events and the advantages of using a CGE model to measure indirect losses.

Our analysis is by no means exhaustive. First, our objective was to measure the immediate impact of extreme weather events via market channels, which justifies the use of a comparative static CGE model. However, the longer-term, dynamic implications of climate shocks, such as soil erosion, infrastructure losses or investment behavior, should also be considered. Secondly, we focused on direct losses within agriculture. However, while agricultural losses dominate in Malawi, other impact channels may prove as important in other countries, such as hydropower and road infrastructure. Finally, while our findings highlight the need to account for weather risk when designing policies, we did not evaluate any specific mitigation measures (see Devereux, 2007). However, our integrated framework would be a suitable tool for assessing the climate resilience of alternative policies or investments, such as crop insurance, improved seed varieties, and enhanced flood management practices.

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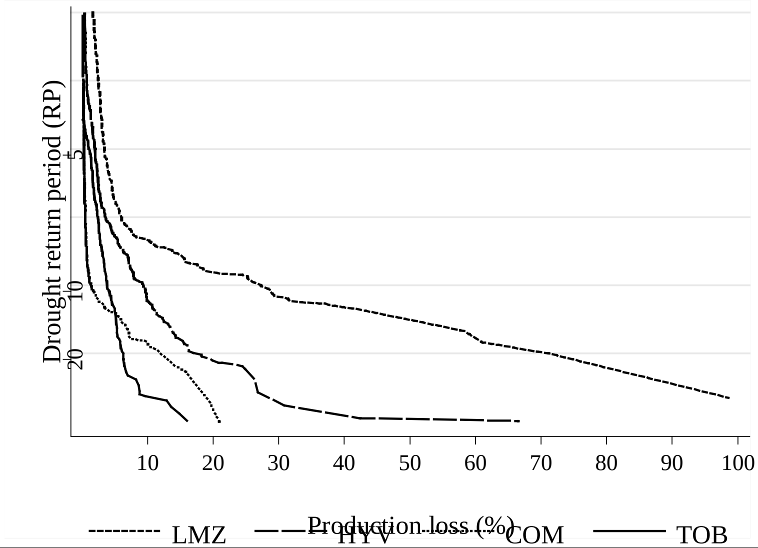
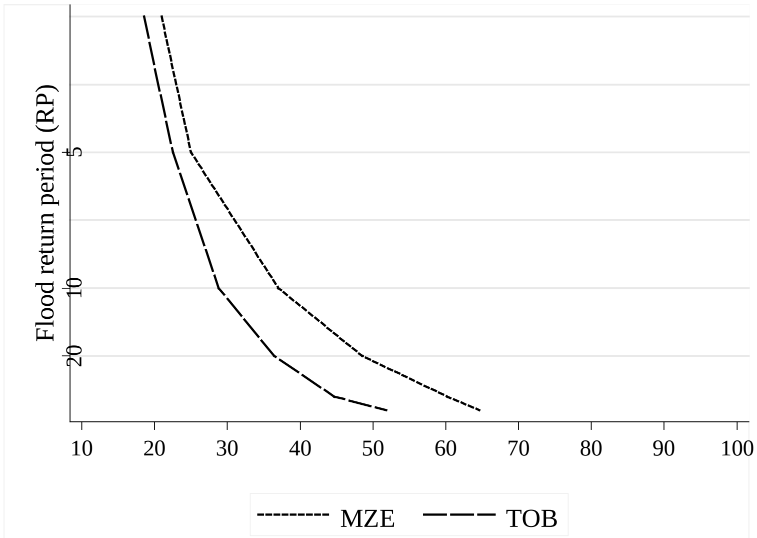
Figure 1: Drought loss exceedance curves (LEC) for maize and tobacco



Source: Results from the stochastic drought model.

Notes: A drought's return period (RP) is the inverse of its exceedance probability (EP). 'TOB' is tobacco; 'LMZ' is local variety maize; 'COM' is composite variety maize; and 'HYB' is hybrid variety maize.

Figure 2: Flood loss exceedance curves (LEC) for maize and tobacco in the southern region



Source: Results from the stochastic flood model.

Notes: A flood's return period (RP) is the inverse of its exceedance probability (EP). 'TOB' is tobacco; 'MAZ' is maize of all varieties.

Table 1: Core CGE model equations

Production function	$Q_{sr} = \alpha_{sr} \cdot \pi_{sr} \cdot \prod_f F_{fsr}^{\delta_{fsr}}$		(1)
Factor payments	$W_{fr} \cdot \sum_s F_{fsr} = \sum_s \delta_{fsr} \cdot P_s \cdot Q_{sr}$		(2)
Import supply	$P_s \leq E \cdot w_s^m \perp M_s \geq 0$		(3)
Export demand	$P_s \geq E \cdot w_s^e \perp X_s \geq 0$		(4)
Household income	$Y_{hr} = \sum_{fs} \theta_{hf} \cdot W_{fr} \cdot F_{fsr}$		(5)
Consumption demand	$P_s \cdot D_{hsr} = \beta_{hsr} \cdot (1 - \upsilon_{hr}) \cdot Y_{hr}$		(6)
Investment demand	$P_s \cdot I_s = \rho_s \cdot \left(\sum_{hr} \upsilon_{hr} \cdot Y_{hrt} + E \cdot b\right)$		(7)
Current account balance	$pw_s^m \cdot M_s = pw_s^e \cdot X_s + b$		(8)
Product market equilibrium	$\sum_{hr} D_{hsr} = \sum_r Q_{sr} + I_s$		(9)
Labor market equilibrium	$\sum_s F_{fsr} = l_{fr}$	*f is labor*	(10)
Capital market equilibrium	$\sum_{rs} F_{fsr} = k_f \quad and \quad W_{fr} = W_{fr'}$	*f is capital*	(11)
Land market equilibrium	$F_{fsr} = n_{fsrt} \cdot \lambda_{sfr}$	*f is land*	(12)

Subscripts
- f Factor groups (land, labor and capital)
- h Household groups
- r Regions (agro-climatic)
- s Economic sectors

Endogenous variables
- B Foreign savings balance
- D Household consumption demand quantity
- F Factor demand quantity
- I Investment demand quantity
- M Import supply quantity
- P Commodity price
- Q Output quantity
- W Average factor return
- X Export demand quantity
- Y Total household income

Exogenous variables
- e Exchange (local/foreign currency units)
- k National capital supply
- l Regional labor supply
- n Sector and region-specific land availability
- w World import and export prices

Exogenous parameters
- α Production shift parameter (factor productivity)
- β Household average budget share
- δ Factor input share parameter
- θ Household share of factor income
- ρ Investment commodity expenditure share
- υ Household marginal propensity to save

Climate shock parameter
- λ Land loss adjustment factor ($0 < \lambda \leq 1$)
- π Productivity loss adjustment factor ($0 < \pi \leq 1$)

Table 2: Simulated land and yield losses for selected droughts and floods

	Maize			Tobacco		
	Land loss (%)	Yield loss (%)	Production loss (%)	Land loss (%)	Yield loss (%)	Production loss (%)
Droughts						
RP5	-	-2.3	-2.3	-	-1.3	-1.3
RP10	-	-16.6	-16.6	-	-4.1	-4.1
RP20	-	-44.1	-44.1	-	-6.3	-6.3
AAL	-	-4.7	-4.7	-	-1.2	-1.2
Floods						
RP5	-11.0	-15.7	-25.0	-10.1	-13.8	-22.5
RP10	-18.0	-23.2	-37.0	-16.2	-15.1	-28.8
RP20	-30.0	-26.4	-48.5	-22.8	-17.6	-36.4
AAL	*-8.0*	*-4.3*	*-12.0*	*-5.6*	*-3.7*	*-9.2*

Source: Results from the stochastic drought and flood models.
Notes: An event's return period (RP) is the inverse of its exceedence probability (EP). 'AAL' is the average annual loss. 'Yield' is a crop's output per unit of land.

Table 3: Crop correlation coefficients

	Drought	Flood
Rice	1.00	1.00
Other cereals	1.00	1.00
Root crops	0.25	1.00
Pulses	0.25	0.00
Groundnuts	0.50	1.00
Vegetables	0.05	1.00
Fruits	0.05	0.00
Cotton	1.00	1.00*
Sugarcane	0.00	0.00
Tea	0.25	0.00

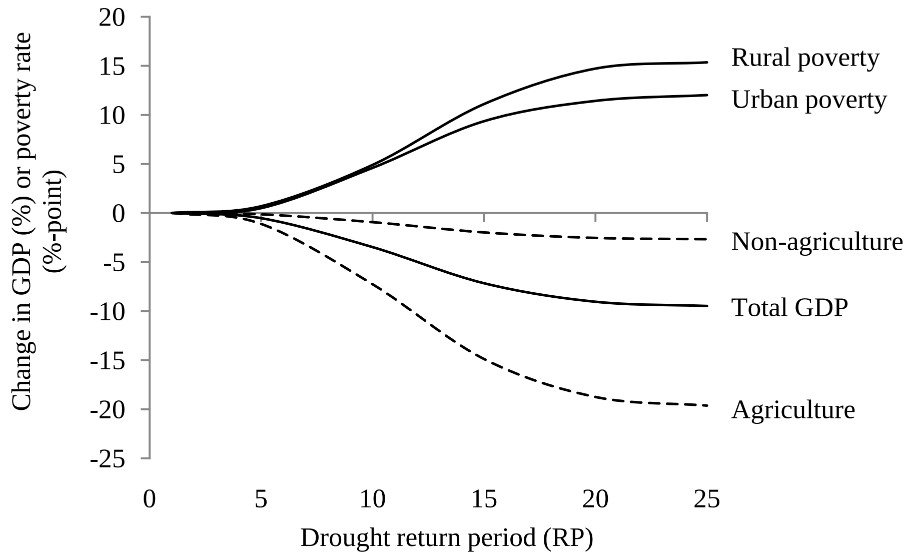
Source: Own calculation using FAO (2009).
Notes: Crop production changes during major event years relative to maize production change (except for cotton losses during floods (*), where the loss factor is expressed relative to tobacco production).

Table 4: Production results for selected events

	Initial share (%)	Change from base value (%)							
		Droughts				Floods			
		RP5	RP10	RP20	AAL	RP5	RP10	RP20	AAL
Total GDP	100.00	-0.53	-3.48	-9.05	-0.97	-1.73	-2.52	-3.19	-0.70
Agriculture	40.15	-1.12	-7.27	-18.75	-2.02	-3.54	-5.13	-6.49	-1.43
Maize	10.07	-2.12	-15.88	-44.18	-4.34	-6.37	-9.51	-12.25	-2.66
Other food crops	14.18	-0.73	-5.33	-14.06	-1.49	-3.16	-4.67	-5.91	-1.29
Tobacco	5.89	-1.49	-4.25	-4.44	-1.28	-1.81	-2.20	-2.59	-0.61
Other export crops	4.28	-1.16	-4.65	-8.15	-1.37	-2.20	-2.70	-3.13	-0.75
Livestock	2.46	-0.45	-3.45	-10.37	-0.91	-1.31	-1.99	-2.63	-0.52
Forestry/fishing	3.27	0.05	0.13	-0.11	0.05	0.11	0.14	0.15	0.05
Industry	16.47	0.02	0.03	0.50	-0.01	-0.55	-0.87	-1.17	-0.23
Food processing	3.88	-0.38	-3.32	-9.96	-0.89	-1.99	-3.14	-4.20	-0.81
Services	43.38	-0.20	-1.31	-3.69	-0.35	-0.51	-0.72	-0.91	-0.20
Crop agriculture	34.41	-1.19	-7.69	-19.72	-2.15	-3.78	-5.46	-6.90	-1.52
Small-scale	6.92	-1.49	-10.62	-28.15	-2.97	-6.32	-9.39	-12.06	-2.67
Medium-scale	17.25	-1.35	-9.43	-24.93	-2.62	-5.44	-7.90	-10.01	-2.20
Large-scale	10.24	-1.00	-4.63	-9.98	-1.30	-0.17	-0.01	0.17	0.03

Source: Results from the CGE model.
Notes: GDP is measured at factor cost.

Figure 3: Distribution of economic losses during droughts



Source: Results from the CGE model.
Notes: 'Poverty rate' based on the basic needs poverty line (US$115 per person per year in 2004/05).

Table 5: Regional production results for selected events

	Initial share (%)	Change from base value (%)							
		Droughts				Floods			
		RP5	RP10	RP20	AAL	RP5	RP10	RP20	AAL
Crops and livestock	36.87	-1.22	-7.92	-20.41	-2.21	-3.87	-5.60	-7.08	-1.56
Karonga (north)	1.15	-1.22	-8.98	-24.83	-2.53	0.38	0.57	0.73	0.16
Mzuzu (north)	4.45	-1.25	-7.05	-16.87	-1.96	0.50	0.74	0.95	0.21
Kasunga (center)	6.89	-1.11	-6.11	-14.95	-1.71	0.69	1.03	1.32	0.29
Salima (center)	2.37	-0.39	-2.97	-7.90	-0.84	0.37	0.54	0.69	0.15
Lilongwe (center)	7.47	-1.24	-8.01	-20.40	-2.20	0.57	0.85	1.08	0.24
Machinga (south)	4.20	-1.66	-11.48	-30.06	-3.20	-16.86	-24.40	-30.93	-6.79
Blantyre (south)	6.28	-1.08	-7.69	-20.38	-2.15	-9.68	-14.20	-17.99	-3.96
Ngabu (south)	1.42	-1.97	-14.35	-38.55	-4.04	-15.03	-21.09	-26.39	-5.91
Urban	2.63	-1.34	-9.32	-24.89	-2.58	-0.82	-1.24	-1.62	-0.32

Source: Results from the CGE model.
Notes: GDP is measured at factor cost.

Table 6: Macroeconomic results for selected events

	Initial value (US$ mil.)	Change from base value (%)							
		Droughts				Floods			
		RP5	RP10	RP20	AAL	RP5	RP10	RP20	AAL
Total GDP	1,474	-0.53	-3.54	-10.05	-0.96	-1.77	-2.63	-3.40	-0.70
Consumption	1,372	-0.56	-3.82	-10.60	-1.04	-1.96	-2.91	-3.77	-0.78
Government	249	0.16	1.12	2.60	0.32	0.70	1.04	1.34	0.29
Investment	211	-0.20	-1.20	-4.25	-0.29	-0.44	-0.63	-0.82	-0.15
Exports	346	-0.63	-2.31	-2.32	-0.74	-1.49	-1.89	-2.21	-0.53
Tobacco	102	-1.78	-5.48	-7.83	-1.60	-1.71	-1.96	-2.20	-0.52
Imports	-704	-0.31	-1.13	-1.14	-0.36	-0.73	-0.93	-1.09	-0.26
Maize	-30	6.30	57.22	208.55	13.77	20.18	31.92	43.14	8.14
Real exchange rate	100	0.47	2.96	8.79	0.77	1.49	2.18	2.81	0.57
Consumer price index	100	0.21	1.36	3.99	0.36	0.71	1.05	1.36	0.28

Source: Results from the CGE model.
Notes: GDP is measured at market prices.

Table 7: Poverty results for selected events

	Initial poverty rate (%)	Number of poor (1000)	Point change from base rate (%-point)							
			Droughts				Floods			
			RP5	RP10	RP20	AAL	RP5	RP10	RP20	AAL
National	52.41	6,380	0.67	4.87	14.35	1.26	2.67	4.10	5.09	0.91
Urban	25.40	351	0.49	4.60	11.43	0.96	1.90	3.62	4.50	0.78
Farm	30.03	196	0.24	3.83	9.46	0.55	1.38	2.85	3.62	0.55
Non-farm	21.23	154	0.72	5.30	13.21	1.33	2.38	4.31	5.30	0.99
Rural	55.86	6,029	0.69	4.90	14.72	1.30	2.76	4.16	5.16	0.93
Farm	56.68	5,858	0.70	4.87	14.72	1.27	2.71	4.11	5.13	0.91
Small	61.03	2,277	0.62	4.72	14.89	1.26	3.18	5.05	6.44	1.25
Medium	55.60	3,470	0.74	5.15	15.24	1.30	2.56	3.75	4.61	0.75
Large	30.60	111	0.66	1.64	3.98	0.66	0.51	0.55	0.55	0.04
Non-farm	37.50	172	0.56	5.53	14.78	2.10	3.91	5.24	5.93	1.31

Source: Results from the CGE model.

Table 8: Comparing model results and observed outcomes

	Share of total GDP (%)			1994/95 drought		2002/03 flood	
	1993	2001	2005 (model base)	Modeled	Observed	Modeled	Observed
Total GDP	100.00	100.00	100.00	-9.05	-11.59	-2.52	-3.76
Agriculture	31.36	38.78	40.15	-18.75	-28.92	-5.13	-6.32
Industry	18.73	16.69	16.47	0.50	2.41	-0.87	-10.27
Services	49.91	44.53	43.38	-3.69	-5.95	-0.72	0.91

Source: Historical GDP data from World Bank (2008) and results from the CGE model.