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Droughts and Floods in Malawi

Assessing the Economywide Effects

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ABSTRACT

Malawi suffers frequent droughts and floods. In an economy that is heavily dependent on the agricultural sector, it is crucial to understand the implications of these extreme climate events. Not only are rural livelihoods affected due to the severe impacts on the agricultural sector, but nonfarm and urban households are also vulnerable given the strong production and price linkages between agriculture and the rest of the economy. This study uses a general equilibrium model to estimate the economywide impacts of drought- and flood-related crop production losses. Climate simulations are based on production loss estimates from stochastic drought and flood models. Model results show that the economic losses due to extreme climate events are significant: Malawi loses 1.7 percent of its gross domestic product on average every year due to the combined effects of droughts and floods. This is equivalent to almost US$22 million in 2005 prices. Given their crop choices, it is smaller-scale farmers and those in the flood-prone southern regions of the country who are worst affected. However, urban and nonfarm households are not spared. Food shortages lead to sharp price increases that reduce urban households' disposable incomes. This study makes an important contribution by estimating the economywide impacts of extreme climate events. However, this is only the first step toward designing appropriate agricultural and development strategies that explicitly account for climate uncertainty.

Keywords: droughts, floods, CGE modeling, poverty, Malawi

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1. INTRODUCTION

Malawi is a small, landlocked African country suffering frequent droughts and floods. These extreme weather events damage infrastructure and housing and occasionally displace significant portions of the population. However, it is their effect on agricultural production that is most detrimental to food-insecure Malawi. The country's largely rural population depends heavily on crop production for its livelihood, most notably the production of maize, which accounts for three-fifths of daily calorie consumption (Ecker 2009). Agriculture and downstream agroprocessing generate half of gross domestic product (GDP) and four-fifths of total export earnings and employment (Benin et al. 2008). Climate shocks therefore have a potentially profound direct effect on the agricultural sector and farm households while also indirectly affecting other economic sectors and nonfarm households through price and production linkages. Estimating impacts from and identifying policy responses to extreme climate events is therefore crucial for designing appropriate agricultural and development strategies. This is made more pressing by global climate change, which is likely to increase the severity and frequency of weather variability (Salinger 2005).

Analyses of the economywide impacts of abnormal hydrometeorological events (droughts and floods) often involve evaluating, ex post, changes in production levels, trade flows, prices, or household income and poverty rates in the period after the events (Pellinga, Özerdemb, and Barakatb 2002 provide a useful theoretical framework for conducting such ex post exercises). The difficulty with such analyses is, first, that they are time consuming: it may take years before all the required economic data become available. Second, when data are incomplete it may not always be possible to identify all the direct and indirect effects of the shock. For this reason economywide models such as computable general equilibrium (CGE) models, which formally define the linkages in the economy and require relatively few simulation inputs, have become popular tools for evaluating the economywide impacts of natural disasters.

Most CGE analyses of droughts and floods focus on the agricultural sector as the main channel through which the economy is affected. Whether these studies apply CGE models in the traditional ex ante manner to explore the impacts of hypothetical events (for example, Boyd and Ibarrarán 2009 and McDonald 2000) or to assess actual historical events (see Horridge, Madden, and Wittwer 2005), a common feature is the use of information on the biophysical impacts of extreme events (typically measured in terms of crop yield declines or agricultural land losses) in setting up the simulations. Such information may come from historical analyses of comparable events or from partial equilibrium crop production models.

This study also employs a CGE model to estimate the economywide impacts of drought- and flood-related crop production losses in Malawi. The simulations are based on production loss estimates from stochastic drought and flood models developed by RMSI (2009).[1] These models provide partial biophysical impacts of flood and drought events of different severities. They further attach a statistical probability of occurrence to each event of given severity. Thus, the economywide model enables us to identify the broader implications of partial crop losses, including their impacts on national income and household poverty (for the latter a microsimulation model complements the CGE model), while the stochastic element of the model makes this a useful planning tool by adding a probability distribution to the range of possible weather events and their impacts. This study also simulates drought mitigation scenarios involving more widespread adoption of drought-resistant maize varieties.

Our findings confirm earlier evidence of the severe detrimental effects that droughts and floods have on the broader Malawian economy and the constraints they place on future economic development (see Benson and Clay 2004; Devereux 2007). The analysis does not consider infrastructural losses (roads and railways) associated with floods, partly due to evidence that these are likely to be small relative to the

[1] RMSI is the registered name of a private consultancy and is no longer considered an acronym for "Risk Management Solutions, India," as the firm was previously known.

agricultural losses experienced (RMSI, 2009). The longer-term dynamic implications of extreme weather events, such as the effects of soil erosion or changes in investment behavior, are also not modeled.

The paper is organized as follows. Section 2 reviews the RMSI (2009) drought and flood risk models that were used in the estimation of crop-level production losses. Section 3 describes the structure of the Malawian economy and the CGE model. Sections 4 and 5 explain the simulations and present the results from the drought and flood scenarios. Section 6 summarizes the findings of the study.

2. DROUGHT AND FLOOD RISK MODELS

A recent study by RMSI (2009) uses probabilistic risk models to estimate the impact of extreme weather events on agricultural production in Malawi.[2] The CGE simulations in this study draw directly from the work by RMSI; hence in this section the RMSI models and the related literature are briefly described. The RMSI models capture two dimensions of drought and flood impacts: hazard and risk. Hydrometeorological *hazard* reflects the occurrence of an extreme climatic event and is defined by two parameters, namely, (1) the severity of an event and (2) the probability of an event's occurring within a specific time period (such as calendar year or crop season). It is standard practice in climate risk analyses to measure severity in terms of the return period (RP) of an event. The RP is the expected length of time between recurrences of two events with similar characteristics; thus, a 1-in-5-year (or RP5) flood is less severe than a 1-in-15-year (or RP15) flood. It follows that events with higher RPs are also less likely to occur in any given year; hence, the severity and probability of occurrence are inversely related to one another (see further detail below).

Risk, on the other hand, is the quantification of potential losses (here we focus on estimates of biophysical losses) and explicitly considers the exposure of different entities (in this instance farmers) to extreme weather events. Exposure—and hence risk—depends on a range of factors, including the severity of the weather event, 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 1-in-5-year flood line but below the 1-in-15-year flood line. Farmers' cropping patterns also matter since some crops are more drought tolerant than others given physiological characteristics or because certain crops are traditionally irrigated and hence less affected by droughts.

Identifying Drought Years

Several definitions of (meteorological) drought[3] exist in the literature, but there is agreement that it should be seen as an abnormal (in a statistical sense) event; thus, droughts should 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 less than the long-run mean. To facilitate the identification of droughts, a variety of drought indexes exist in the literature (Heim 2002 provides a review). The more complex of these, such as the widely used Palmer Drought Severity Index or one its variants (Palmer 1965), use precipitation and evaporation data (or temperature as a proxy) to determine soil moisture levels. Simpler indexes, such as the Standard Precipitation Index (SPI) developed by McKee, Doesken, and Kleist (1993), use only precipitation data. This is also the index used by RMSI (2009). Its use is justified on the basis of the SPI's simplicity and flexibility. The index further permits the measurement of drought intensity, magnitude, or severity as well as its duration. In addition to this, the probability of a particular event's occurring can be estimated on the basis of historical data (Heim 2002).

Precipitation data are collected in Malawi at 45 weather stations distributed across different climatic regions. RMSI's SPI-based drought risk model assumes that rainfall at each of these weather stations follows a gamma distribution; that is, $X_i \sim \Gamma(\alpha_i, \beta_i)$, where α_i and β_i are shape and scale parameters, respectively, of the stochastic rainfall variable X_i for weather station i. This particular probability distribution function is generally considered a good fit for precipitation distributions (RMSI 2009). The parameters are calibrated using maximum likelihood estimation, and the cumulative distribution function is then transformed into a standard normal random variable, Z_i, with a mean of 0 and

[2] Damages to housing as well as road and railway infrastructure were also estimated. In this study we focus only on the agricultural impacts.

[3] It is also possible to distinguish between different types of droughts, that is, meteorological, agricultural, and hydrological. In this study the term *drought* refers to a meteorological one, which relates to the relative degree of dryness experienced (see discussions below). Hydrological droughts consider groundwater supplies, whereas the concept of agricultural droughts links hydrological and meteorological factors to consider the impact of dry spells on agricultural production in particular. Most agriculture in Malawi is rainfed, which means a meteorological definition of drought is suitable.

a standard deviation of 1; that is, $Z_i \sim N(0,1)$. The Z-score of this distribution is the SPI. When rainfall levels drop below 1 standard deviation from the mean (meaning, Z-score of –1.0 or less) a drought event is declared. A drought is more severe when the Z-score is lower.

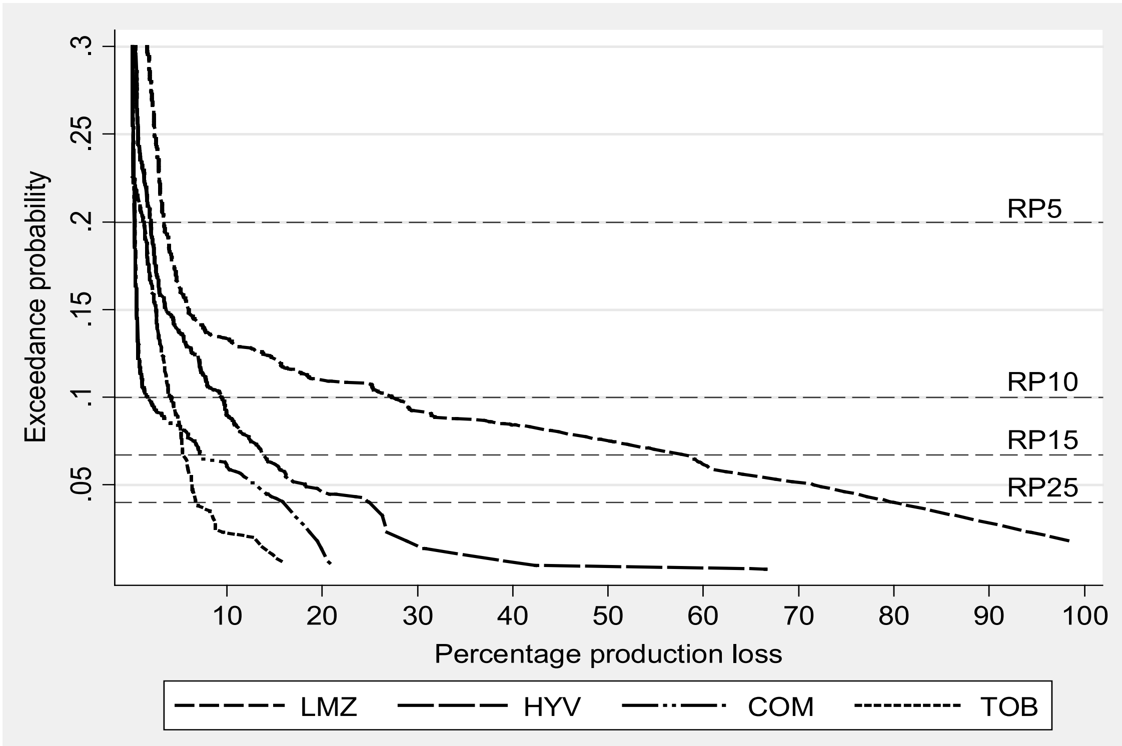
Measuring Production Losses during Droughts

Not all droughts of apparent similar severity have the same impact on crop production losses. 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, to compare different drought events in terms of their crop production effects, the SPI measure has to be adjusted to control for precisely when the historical drought event took place during the phenophase (see RMSI 2009 for details). Based on these regional adjusted SPIs, the RMSI study identifies the crop seasons 1986/87, 1991/92, 1993/94, 2003/04, and 2004/05 as significant droughts in Malawi. Regression models are then used to describe the statistical relationship between droughts of different severities (that is, as measured by their adjusted SPIs) and the associated crop production losses. Production losses are calculated as the difference between observed production and expected production. The latter is taken as the production level achieved during the closest normal year.

The estimated coefficients are then used in a stochastic model in which a large number of random drought events are generated and from which a consistent and continuous relationship between production losses and droughts across a wide range of RPs can be extracted. The RP of an event is said to be inversely proportional to its exceedance probability (EP); that is, $EP = {}^{1}/_{RP}$. In the context of agricultural risk (or biophysical loss), an EP curve or loss exceedance curve (LEC) gives the likelihood that a certain level of crop loss (usually in percentage terms) will be exceeded during a particular drought event. Figure 1shows the estimated drought LECs for maize and tobacco crops in Malawi. The horizontal lines represent RPs of 5, 10, 15, and 25 years, with their inverses appearing on the vertical axis as EPs. In the LEC for tobacco, for example, an RP10 drought is associated with production losses of 4.1 percent; thus, there is a 1-in-10 or 10 percent chance that tobacco losses will be 4.1 percent or more during an RP10 drought.

The RMSI (2009) study estimates LECs for three types of maize crops, namely, local maize (LMZ), high-yield varieties (HYV), and composites (COM). Of the three varieties, COM, which include improved open-pollinated, drought-resistant varieties, display the greatest resilience to droughts (see Appendix A). Local varieties, on the other hand, suffer relatively large losses, especially during severe droughts. This implies that maize farmers' choice of seed variety determines their exposure to droughts. Tobacco is generally more drought tolerant than maize, particularly during severe droughts. Even during an RP25 drought, tobacco production losses are only 6.8 percent, which is well below 80.0, 24.9, and 15.9 percent losses for LMZ, HYV, and COM maize varieties, respectively.

Figure 1. Drought loss exceedance curves for maize (different varieties) and tobacco



Source: RMSI (2009).
Note: LMZ = local maize; HYV = high-yield varieties; COM = composites; TOB = tobacco; RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP15 = 1-in-15-year return period; RP25 = 1-in-25-year return period.

The occurrence of droughts is a stochastic process, and although LECs are useful for showing the minimum expected impact of a drought of a certain severity, future drought patterns remain highly uncertain. This is problematic from a short- to medium-term risk management perspective. There is, however, more certainty about the frequency and severity of events over a very long period of time; the average annual loss (AAL) provides a useful planning tool. It measures the expected losses during a long period of time and is obtained by multiplying the probability of an event's occurring by its expected loss and summing over the entire range of events (meaning, integration of the continuous LEC). The RMSI (2009) study estimates AALs for LMZ, HYV, and COM maize varieties at 7.3, 2.6, and 1.2 percent, respectively. The AAL for tobacco is 1.2 percent. These losses are roughly consistent with those experienced during an RP7 drought.

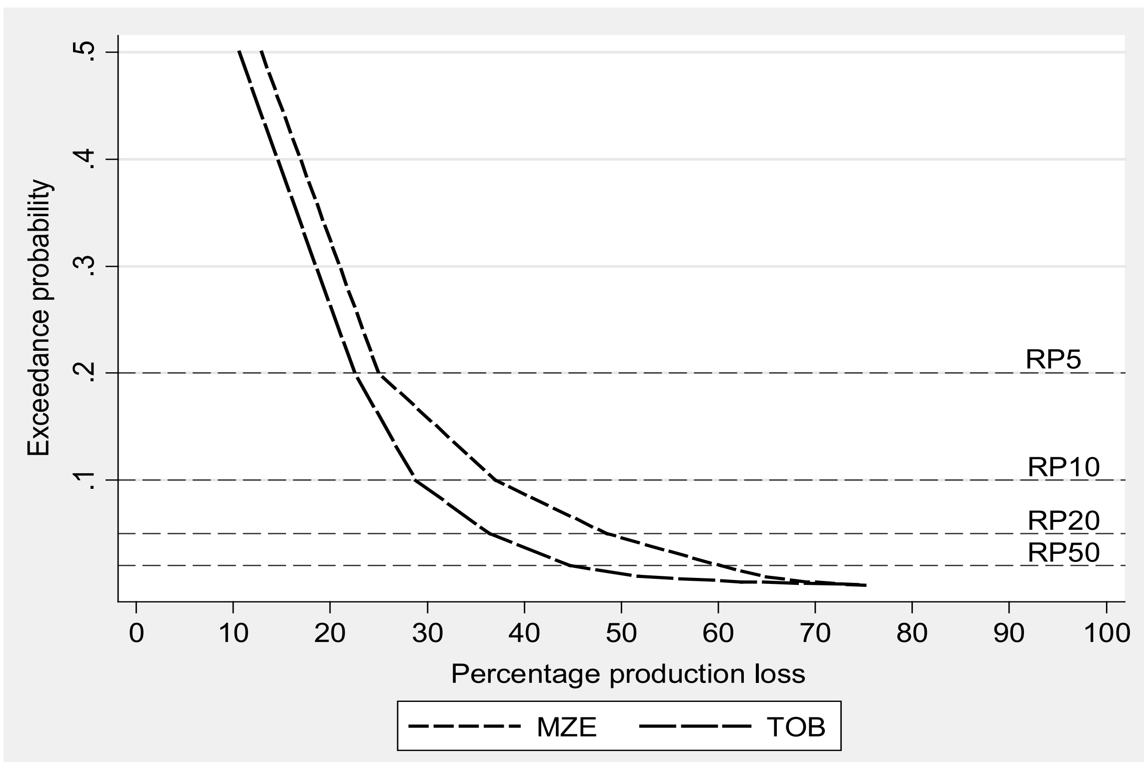
Identifying and Measuring Floods

The RMSI (2009) flood risk model adopts a similar approach as that used in the drought model in that the hazard is assessed on the basis of estimates of the probability of floods of different severities occurring within a given year. Given Malawi's topography, floods occur mostly in the Shire River basin in the southern part of the country; hence the RMSI study focuses exclusively on flood losses in this region. The probabilistic risk model is runoff based; that is, observed flood discharges are used in the identification of floods and the estimation of 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 level (meaning, at a 90-meter resolution).

The stochastic results from this model are validated using satellite images of historical flood events (floods occurred in 1982/83, 1991/92, 1997/98, 2000/01, 2001/02, and 2003/04). Agricultural losses are then determined on the basis of information about farmers' exposure to flood events. Such exposure depends on the portion of cropped areas in regions that are likely to become inundated during floods of given severity. As with the drought analysis, regression models are used to determine the relationship between production levels and historical flood events. Data from the regression models are then incorporated into a stochastic flood model to generate a complete set of data about production losses associated with floods with different RPs.

The relationship between flood events and production losses is once again captured in crop-specific LECs. Figure 2 shows the LECs generated for maize and tobacco. The three maize types are combined in the flood analysis since physiological differences have no bearing on the extent of production losses. As indicated, the horizontal lines represent RPs of 5, 10, 20, and 50 years. The AAL estimate for maize is 12.7 percent, whereas an average of 6 percent tobacco production is lost every year due to floods. This is equivalent to the loss experienced during an RP2 flood. Note these loss percentages are expressed relative to production in the southern region only.

Figure 2. Flood loss exceedance curves for maize and tobacco



Source: RMSI (2009).
Note: MZE = maize (same losses apply to all varieties); TOB = tobacco. RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP20 = 1-in-20-year return period; RP50 = 1-in-50-year return period.

3. ECONOMYWIDE MODELING FRAMEWORK

Basic Structure of Malawi's Economy

Agriculture and agroprocessing dominate the Malawian economy, generating almost half of GDP and four-fifths of total export earnings and employment. Within crop agriculture, maize and tobacco are by far the most important; hence, this section first examines the structure of Malawian agriculture, paying particular attention to these two crops. The information presented in Table 1 is drawn from the core database underlying the economywide model (see Benin et al. 2008).

Most farmers are smallholders, with a national average holding size of 1.13 hectares (first column of Table 1). Although most farmers allocate some land to maize, farmers working on less than 0.75 hectares of land do not grow tobacco (last three columns). We therefore separate out this group of small-scale farmers in the model. Around one-third of all households in Malawi are rural small-scale farmers, and two-thirds of these reside in the three southern regions of Machinga, Blantyre, and Ngabu. The average holding size for small-scale farms is 0.69 hectares, half of which is allocated to maize. Small-scale farmers' yields are typically less than the national average, and these households tend to have lower per capita expenditure and a higher incidence of poverty (poverty rates are presented later in Table 8).

Conversely, rural farmers with more than three hectares of land tend to be more heavily engaged in export-oriented crop production, such as production of sugar and tobacco. These large-scale farmers also form a separate household group in the model. The average large-scale farm is 8 hectares in size, although this is biased upward by a small number of very large farms, such that the median farm size for this group lies well below the mean. Large-scale farms have higher-than-average per capita expenditure, and their incidence of poverty is half that of small-scale farm households. With the exception of tobacco, which is widely grown, large-scale crop production is concentrated within a few agroecological zones.

Most Malawian farmers fall between the small- and large-scale groups (that is they harvest between 0.75 and 3.00 hectares of land). These medium-scale farmers, whose holdings average 1.44 hectares, tend to have more diverse cropping patterns, with similar shares of land allocated to maize and nonmaize food crops. These 1.2 million farm households also produce export-oriented crops, particularly tobacco. About 55 percent of the population living on medium-scale farms fall below the national poverty line, which is far above the poverty rate of large-scale farms and only slightly below that of small-scale farms. Medium-scale farmers are the third farm group identified in the model.

Finally, the model captures urban and rural nonfarm households as well as urban households engaged in agricultural production. Urban agriculturalists are an important part of Malawi's agricultural sector, accounting for 6 percent of harvested land. Urban farmers have cropping patterns similar to medium-scale rural farm households, although they allocate a slightly larger share of land to maize. However, urban farm households tend to be more heavily engaged in off-farm activities than rural households. Thus, although urban farm sizes and agricultural revenues are similar to those of medium-scale rural farmers, their average per capita income is substantially higher, and poverty is well below that of even large-scale farm and rural nonfarm households. Thus, apart from the detailed sector, factor, and household information usually captured by economywide models, the model used in this study also includes a detailed treatment of the constraints and opportunities facing different farmers across the regions of Malawi. The next section describes the basic workings of the model.

Table 1. Summary statistics by regions and farm households in the economywide model

	National	Urban		Rural											
		Urban farm	Urban non-farm	Rural farm households by region								Rural farm households by farm size (hectares / ha)			Rural non-farm
				Karonga	Mzuzu	Kasungu	Salima	Lilongwe	Machinga	Blantyre	Ngabu	Small (<0.75ha)	Med. (0.75-3.00ha)	Large (>3.00ha)	
Population (1,000)	12,173	654	727	358	814	1,282	661	2,523	2,033	1,972	693	3,731	6,240	363	458
Number of households	2,694	133	189	71	163	246	143	537	465	474	137	942	1,241	54	134
Small-scale (<0.75 ha)				30	44	69	72	203	237	217	70				
Per capita expenditure ($US)	150.8	286.2	308.6	116.7	132.0	152.8	130.9	145.4	110.3	125.3	101.0	121.6	130.1	203.7	185.8
Poverty rate (%)	52.4	30.0	21.2	62.8	55.0	43.0	56.3	47.0	67.7	61.4	70.6	61.0	55.6	30.6	37.5
Share of poor (%)	100.0	3.1	2.4	3.5	7.0	8.7	5.8	18.6	21.6	19.0	7.7	35.7	54.4	1.7	2.7
Harvest area (1,000 ha)	3,050	174	-	81	295	525	128	591	482	599	175	647	1,792	437	-
Maize	1,538	132	-	38	130	266	58	315	270	238	90	343	863	200	-
Tobacco	133	5	-	0	28	54	0	28	14	6	0	0	31	97	-
Average farm land (ha)	1.13	1.31	-	1.13	1.80	2.13	0.89	1.10	1.04	1.26	1.28	0.69	1.44	8.02	-
Maize	0.57	0.99	-	0.54	0.80	1.08	0.41	0.59	0.58	0.50	0.66	0.36	0.70	3.67	-
Other cereals	0.05	0.01	-	0.10	0.06	0.01	0.04	0.03	0.06	0.09	0.22	0.04	0.08	0.09	-
Root crops	0.12	-	-	0.28	0.36	0.20	0.18	0.09	0.10	0.17	-	0.09	0.18	0.36	-
Pulses and nuts	0.26	0.23	-	0.12	0.34	0.56	0.05	0.29	0.20	0.40	0.17	0.16	0.36	1.17	-
Horticulture	0.03	0.03	-	0.05	0.07	0.06	0.02	0.04	0.03	0.03	0.03	0.02	0.05	0.13	-
Tobacco	0.05	0.04	-	-	0.17	0.22	-	0.05	0.03	0.01	-	-	0.03	1.79	-
Other export crops	0.04	0.02	-	0.04	0.01	0.01	0.20	0.01	0.04	0.05	0.20	0.01	0.05	0.81	-

Source: Benin et al. (2008). Calculations use official agricultural production data (MOAFS 2007) and the Integrated Household Survey (IHS) of 2004/05 (NSO, 2005).
Note: Per capita expenditure is mean expenditure unadjusted for adult equivalence; poverty rate is the poverty headcount based on the national basic needs poverty line (approximately MWK16,165 or US$115 per person per year in 2005).

A Simple CGE Model

Table 2 presents the equations of a simple CGE model illustrating how extreme climate events may affect economic outcomes in our analysis. Producers in each sector s and region r produce a level of output Q by employing the factors of production F under constant returns to scale (exogenous productivity α) and fixed production technologies (fixed factor shares δ) (equation 1). Profit maximization implies that factor payments W are equal to average production revenues (equation 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 (equation 10). National capital market equilibrium implies that capital is mobile across both sectors and regions and earns a national rental rate (meaning regional capital returns are equalized) (equation 11). Finally, given the rapid onset of droughts and floods, we assume that land is allocated at the start of the crop season and is not reallocated across crops in response to climate shocks (equation 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 simple 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 (equation 3). Conversely, if domestic prices fall below world export prices w^e, then export demand X increases (equation 4). To ensure macroeconomic consistency, we assume a flexible exchange rate and a fixed current account balance b (in foreign currency) (equation 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 (equation 5). Total household incomes Y are then either saved (based on marginal propensities to save υ) or spent on consumption C (according to marginal budget shares β) (equation 6). Household savings and foreign capital inflows are collected in a national savings pool and used to finance investment demand I (meaning savings-driven investment closure) (equation 7). Finally, a national price P equilibrates product markets, thus avoiding the necessity of modeling interregional trade flows (equation 8).

The model's variables and parameters are calibrated to data from a regional social accounting matrix constructed by Thurlow, Diao, and McCool (2008) that captures the equilibrium structure of the Malawian economy in 2005. Parameters are then adjusted to reflect extreme climate shocks. The hydrocrop models estimate reductions in crop productivity and land availability caused by floods and droughts, which are imposed on the model by adjusting the parameters π and λ (equations 1 and 12). Lowering the value of these parameters to less than one reduces production and raises product prices and the returns to factor resources. This may then change international trade flows and affect households' real incomes depending on their income and expenditure patterns.

Table 2. Simple computable general equilibrium model equations and variables

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 (agroclimatic)
- 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 parameters
- λ Land loss adjustment factor ($0 < \lambda \leq 1$)
- π Productivity loss adjustment factor ($0 < \pi \leq 1$)

Extensions to the Full Malawi Model

The simple model described above illustrates how changing climate conditions are translated into production and income effects. However, the full model actually used in our analysis drops certain restrictive assumptions (see Löfgren, Robinson, and Harris 2001). Constant elasticity of substitution production functions allow factor substitution based on relative factor prices (meaning δ is no longer fixed).

The model identifies 36 sectors (that is, 17 in agriculture, 9 in industry, and 10 in services). Agricultural crops and livestock sectors are further disaggregated across eight agroclimatic regions (see Figure D1 in Appendix D), urban areas, and small-, medium-, and large-scale farmers. Intermediate demand in each sector (excluded from the simple model) is determined by fixed technology coefficients. Based on the Integrated Household Survey (IHS) of 2004/05 (NSO 2005), labor markets are further segmented across three skill groups: (1) elementary workers and family labor; (2) workers in professional, managerial, and technical professions; (3) workers in other lower-skilled professions. Farmland in each region is divided into (1) small-scale farms with less than 0.75 hectares; (2) medium-scale farms of between 0.75 and 2.00 hectares; and (3) larger-scale farms of more than 2.00 hectares. All factors, except for unskilled labor, are assumed to be fully employed with labor immobile across regions and agricultural land immobile across both regions and sectors. Nonagricultural capital is fully mobile, but agricultural capital is, like land, fixed by sector.

Although agricultural production is specified at a regional level, the full model still assumes national product markets. However, international trade is now 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 differs from the simple CGE model described in the previous section, which assumed perfect substitution between domestic and foreign goods (meaning, homogeneous products). This treatment captures differences in domestic and foreign products and allows for two-way trade. The full model still assumes that Malawi is a small economy such that world prices are fixed and the exchange rate (meaning, the price index of tradable-to-nontradable goods) adjusts to ensure a fixed current account balance. Production and trade elasticities are drawn from Dimaranan (2006).

Households maximize a Stone-Geary utility function such that a linear expenditure system determines consumption and permits nonunitary income elasticities. Consumption patterns and income elasticities were econometrically estimated using the IHS 2004/05. Households are disaggregated across rural farm and nonfarm groups and small urban and metropolitan centers. Farm households in each region are separated into small-, medium-, and large-scale land groups. There are a total of 28 distinct representative households in the full CGE model. These household groups pay taxes to the government based on fixed direct and indirect tax rates. Tax revenues finance exogenous recurrent spending, resulting in an endogenous fiscal deficit. This implies that government recurrent spending and employment are maintained during droughts and floods but public investment may contract.

In summary, the full Malawi model captures the detailed sector and labor market structure of Malawi's economy as well as the linkages among production, employment, and household incomes. Moreover, the results from the hydrocrop models are explicitly integrated within the economic analysis. The impact channels captured by the CGE model thus provide a reasonable approximation of the economic costs of droughts and floods in Malawi.

4. THE IMPACT OF NATIONAL-LEVEL DROUGHTS AND DROUGHT MITIGATION

Simulation Design

Drought Impact Scenarios

The drought LECs in Figure 1 provide the basis for the CGE simulations. These LECs show the expected maize and tobacco production losses for nationwide droughts. The LECs further specify losses separately for three types of maize seed, namely, LMZ, HYV, and COM. The CGE model, on the other hand, includes only a single maize crop,[4] whereas agricultural producers are disaggregated across several regions. We therefore calculate a weighted average maize loss factor for each region included in the CGE model using regional maize crop shares as weights. The crop shares, which are obtained from the Ministry of Agricultural and Food Security's crop production data for 2004/05 (MOAFS 2007), and the weighted average losses modeled are shown in Table 3 (note 2005 is the base year of the model). Tobacco losses are assumed to be uniform across the agricultural regions and are read directly off the LEC for tobacco.

Table 3. Maize crop shares and simulated losses

	Maize Crop Shares (*row sum* = 1)			*Region-specific Weighted Average Maize Losses (%)*				
Agricultural Regions	LMZ	HYV	COM	*RP5*	*RP10*	*RP15*	*RP25*	*AAL*
Karonga	0.42	0.16	0.42	–1.83	–13.34	–29.05	–43.11	–3.88
Mzuzu	0.57	0.23	0.20	–2.15	–15.73	–33.12	–47.57	–4.36
Kasungu	0.44	0.28	0.27	–1.78	–12.52	–26.18	–38.56	–3.54
Salima	0.45	0.26	0.30	–1.80	–12.81	–26.99	–39.74	–3.63
Lilongwe	0.61	0.22	0.17	–2.34	–17.23	–36.24	–51.74	–4.75
Machinga	0.50	0.25	0.24	–2.69	–19.37	–40.68	–59.17	–5.42
Blantyre	0.46	0.27	0.27	–2.66	–18.86	–39.57	–58.08	–5.32
Ngabu	0.47	0.20	0.33	–2.98	–21.62	–46.26	–67.88	–6.17
Urban	0.51	0.25	0.25	–2.59	–18.68	–39.30	–57.10	–5.23
National average	*0.51*	*0.25*	*0.25*	*–2.30*	*–16.61*	*–34.95*	*–50.79*	*–4.65*

Source: Authors' estimates based on MOAFS (2007) and RMSI (2009).
Notes: LMZ = local maize; HYV = high-yield varieties; COM = composites; RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP15 = 1-in-15-year return period; RP25 = 1-in-25-year return period; AAL = average annual loss. Urban crop shares unavailable, hence assumed to be the same as the national average crop shares.

The RMSI (2009) analysis covered only maize and tobacco crop losses. Although these two crops account for a substantial share of agricultural GDP (see Table 6), the full effect of droughts on the agricultural sector and the rest of the economy can be determined properly only by including production losses for other agricultural crops in the analysis. Rather than replicating the stochastic analysis of RMSI, we impute production losses for nonmaize crops on the basis of a comparison of nonmaize and maize crop losses during key drought events. This correlation analysis is conducted on the basis of national crop data published by the Food and Agricultural Organization (FAO 2008). On average, during Malawi's major drought events, production losses in rice, other cereals, and cotton were found to be of a similar magnitude to the weighted average maize loss experienced. Groundnut production losses were about half

[4] The maize activities in the social accounting matrix are not disaggregated into the three types of maize, since detailed information on inputs required for different maize varieties is not available.

that of maize losses, whereas losses in root crops, pulses, and tea were about one-quarter. Vegetable and fruit production losses were only about 5 percent of the loss in maize, whereas sugarcane losses were negligible, most probably due to the extensive use of irrigation. These correlations are shown in Table 4; that is, the percentages listed show the percentage by which each of the nonmaize crops (excluding tobacco) declines for every 1 percent drop in maize production as a result of drought. The correlations are assumed to remain constant at all RPs.

Table 4. Average percentage decline in nonmaize crops for every 1 percent decline in maize during key drought events

Crop	Correlation Factor	Crop	Correlation Factor
Rice	1.00	Vegetables	0.05
Other cereals	1.00	Fruits	0.05
Root crops	0.25	Cotton	1.00
Pulses	0.25	Sugar	0.00
Groundnuts	0.50	Tea	0.25

Source: Authors' estimates based on FAO (2008).

Agricultural production (*P*) is defined as the product of area planted (*A*) and yield (*Y*). Production is endogenously determined in the CGE model, and hence changes in production are simulated by changing land use or yield parameters (see λ and π in Table 2) in the model. Droughts may affect either land area or yields. If, for example, the drought occurs during the sowing season, farmers may decide not to plant at all, and hence by default the area harvested will be smaller. Land losses may also be a result of a complete abandonment of planted lands during extreme droughts. Given these complexities and the fact that no two drought events are the same, RMSI (2009) was unable to uncover any statistical relationship between land/yield losses and different drought events. However, a clear pattern between overall production and drought events was evident. In our analysis we assume that production losses are entirely attributable to yield losses, which is equivalent to assuming that the drought events compared in these analyses all occur after the sowing season. Agricultural land is fixed in this short-run specification of the model.

Before moving on to the mitigation scenarios, it is necessary to consider two further issues. The first concerns adaptation by farmers. The model aggregates the three maize varieties into a single maize-producing activity. The implicit assumption is that farmers cannot change their cropping patterns in response to a drought. This is consistent with an assumption that the drought is sudden or unexpected and takes place only after planting decisions (with respect to maize varieties and other crops planted) had been made. This rigidity in the model is therefore an appropriate assumption for our analysis. Moreover, the assumption is actually beneficial when mitigation scenarios are modeled later in this paper since it is possible to exogenously impose adoption rates of different maize varieties.

A second issue that warrants attention is the impact of droughts on the livestock sector. McDonald (2000) notes that livestock is often more resilient to droughts than crops, provided drinking water supplies can be maintained. However, as a serious shortage of fodder develops, farmers must respond by selling livestock. Income from livestock sales therefore serves as a buffer against crop income losses. During the postdrought recovery period farmers need to build up their livestock numbers again, which leads to a shortage of meat supply and a decline in livestock income. The implication is that relative crop and livestock price changes during and after drought periods as well as the household income or welfare effects associated with livestock management are important considerations in analyses of drought impacts. This is especially true in a country such as Botswana, where livestock accounts for almost two-thirds of agricultural supply (McDonald 2000). In Malawi, however, livestock's share in agricultural supply is only 8 percent (or 6 percent of agricultural GDP). Consequently, our analysis does not consider livestock stock changes, but we do capture important indirect effects such as rising feed (maize) costs during droughts. This, as we shall see, has important consequences for Malawi's poultry sector, which makes up almost half of the livestock sector in the country.

Mitigation Scenarios: Drought Scenarios with Crop Adoption (Maize Only)

In addition to the impact analyses, we model various crop adoption scenarios. Each of the three maize varieties planted in Malawi possesses unique yield and drought resistance properties. Malawian crop data (MOAFS 2007) for the past decade (1998–2007) show that yields for HYV were, on average, 2.60 times that of LMZ, whereas COM yields were 1.78 times higher. Research suggests that HYV and COM varieties have a consistent yield advantage over LMZ "*at all levels of fertilizer use, including in a drought year*" (see Denning et al. 2009), a finding that is underscored by the RMSI (2009) LECs in Figure 1 (also see discussion in Appendix A). Adoption of more drought-tolerant and higher-yielding maize varieties could therefore produce double dividends of higher yields and lower production losses during drought years and could therefore be an important mitigation strategy against droughts.

In our mitigation scenarios we focus exclusively on maize. Particularly, we consider the combined effect of yield losses due to droughts and yield gains due to adoption of COM. Three adoption scenarios are considered in which the share of land area in each region that is under local varieties (LMZ) is reduced by 10, 20, or 30 percentage points relative to the base (compare Table 3) and reallocated to COM. For instance, in the model's base year (2005), 25 percent of agricultural land allocated to maize was under COM. This increases to 55 percent under the 30 percent adoption scenario. The share of HYV remains constant at 25 percent.

Table 5 shows the matrix of the possible combinations of yield gains associated with COM adoption and production losses associated with droughts. Based on historical yield data, our estimates suggest that 10 percent adoption, in the absence of droughts, will cause average yields to grow by 6.5 percent. Similarly, yield gains are 13.1 and 19.6 percent in the 20 and 30 percent adoption scenarios, respectively. The first column, in turn, shows the yield losses under current cropping patterns (meaning, this is similar to the impact scenarios before; compare Table 3). Yield gains from adoption will therefore offset all or some of the production losses due to droughts, depending on the severity of the drought. The rest of the entries in the table are obtained by simply subtracting the yield loss of a particular drought from the yield gain due to adoption. These changes, shown here at the national level, are once again disaggregated across the agricultural regions before they are applied in the CGE simulations.

Table 5. Drought mitigation: Adoption yield gains versus drought production losses

		Adoption Scenarios			
		No Adoption	*10 Percent Adoption*	*20 Percent Adoption*	*30 Percent Adoption*
	Normal year	0.0	6.5	13.1	19.6
Drought severity	*RP5*	–2.3	4.2	10.8	17.3
	RP10	–16.6	–10.1	–3.6	3.0
	RP15	–35.0	–28.4	–21.9	–15.4
	RP25	–50.8	–44.3	–37.7	–31.2

Source: Authors' estimates based on MOAFS (2007) and RMSI (2009).
Note: RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP15 = 1-in-15-year return period; RP25 = 1-in-25-year return period.

Importantly, in our mitigation scenarios, we do not consider the costs associated with each adoption scenario, whether the cost is in the form of a government subsidy (for example, Malawi's current maize subsidy program) or whether farmers themselves incur higher costs (such as adoption costs associated with changes in the production system or increased fertilizer and seed costs). The adoption scenarios in the CGE model therefore focus on how the impact of droughts would have differed if rates of adoption of improved maize varieties were higher. It is further important to bear in mind that the yield gain from adoption is once-off; that is, the results show only the net effect if adoption takes place in the same year as the drought.

Results: Drought Impacts

Table 6 shows the economic impact of droughts on maize and tobacco production and, by extension, on GDP. The model estimates that an RP5 drought (column 2) reduces maize and tobacco GDP by 2.12 and 1.49 percent, respectively. These two crops account for more than a third of the agricultural sector. Other export crops also contribute significantly to the overall agricultural GDP decline of 1.12 percent during an RP5 drought. The more severe the drought, the larger is the estimated loss in agricultural GDP. During an RP25 drought year, for example, agricultural GDP declines by as much as 21.53 percent, driven largely by the large fall in maize production. Since two-fifths of Malawi's economy is in agriculture, the decline in agricultural GDP causes total or national GDP to fall substantially. For example, during an RP25 drought, total GDP declines by as much as 10.42 percent, which in 2005 prices is equal to a total economic loss of US$135.1 million.

Table 6. Impact of droughts on gross domestic product (GDP)

	Initial Share (%)	Change in Real GDP under Droughts of Different Return Periods, All Crops (%)				Average Annual Losses (AALs) and Partial Crop Loss Scenarios		
	2005	RP5 Drought	RP10 Drought	RP15 Drought	RP25 Drought	AAL (All Crops)	AAL (Maize and Tobacco)	AAL (Maize Only)
Total GDP (factor cost)	100.00	–0.53	–3.48	–7.16	–10.42	–0.97	–0.63	–0.53
Agriculture	40.15	–1.12	–7.27	–14.88	–21.53	–2.02	–1.36	–1.15
Maize	10.07	–2.12	–15.88	–34.55	–51.24	–4.34	–4.34	–4.37
Other food crops	14.18	–0.73	–5.33	–11.18	–16.12	–1.49	–0.56	–0.56
Tobacco	5.89	–1.49	–4.25	–4.35	–4.26	–1.28	–1.38	0.12
Other export crops	4.28	–1.16	–4.65	–7.03	–8.79	–1.37	–0.74	0.10
Livestock	2.46	–0.45	–3.45	–7.87	–12.33	–0.91	–0.79	–0.78
Other agriculture	3.27	0.05	0.13	0.03	–0.26	0.05	–0.02	–0.05
Industry	16.47	0.02	0.03	0.25	0.72	–0.01	0.18	0.14
Food processing	3.88	–0.38	–3.32	–7.64	–11.72	–0.89	–0.19	–0.29
Services	43.38	–0.20	–1.31	–2.83	–4.36	–0.35	–0.26	–0.21
Crops and livestock	36.87	–1.22	–7.92	–16.21	–23.42	–2.21	–1.47	–1.25
Karonga	1.15	–1.22	–8.98	–19.41	–28.68	–2.53	–0.97	–0.98
Mzuzu	4.45	–1.25	–7.05	–13.59	–19.17	–1.96	–1.53	–1.03
Kasunga	6.89	–1.11	–6.11	–11.84	–17.23	–1.71	–1.30	–0.84
Salima	2.37	–0.39	–2.97	–6.27	–9.06	–0.84	–0.30	–0.34
Lilongwe	7.47	–1.24	–8.01	–16.31	–23.30	–2.20	–1.64	–1.36
Machinga	4.20	–1.66	–11.48	–23.85	–34.53	–3.20	–2.16	–2.02
Blantyre	6.28	–1.08	–7.69	–16.13	–23.45	–2.15	–1.12	–1.11
Ngabu	1.42	–1.97	–14.35	–30.45	–44.28	–4.04	–1.61	–1.62
Urban	2.63	–1.34	–9.32	–19.61	–28.74	–2.58	–2.35	–2.23
Crop agriculture	34.41	–1.19	–7.69	–15.68	–22.60	–2.15	–1.42	–1.20
Small scale	6.92	–1.49	–10.62	–22.31	–32.34	–2.97	–2.18	–2.15
Medium scale	17.25	–1.35	–9.43	–19.75	–28.66	–2.62	–1.59	–1.50
Large scale	10.24	–1.00	–4.63	–8.13	–11.24	–1.30	–0.97	–0.33

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP15 = 1-in-15-year return period; RP25 = 1-in-25-year return period; Drought scenarios include impacts on maize and tobacco production only.

The AAL in GDP is 0.97 percent or US$12.5 million. This represents the average amount that the Malawian economy loses in foregone production every year due to droughts. Two additional AAL scenarios are included in the final two columns to illustrate how maize and tobacco production losses during drought years dominate the overall economic impact. As shown, when only maize and tobacco losses are accounted for (that is, other crop production levels are assumed to be unaffected), the average annual GDP loss is 0.63 percent. In the maize-only scenario it drops to 0.53 percent. Thus, maize losses account for more than half of the overall economic losses.

The model also captures the impact of falling crop production on downstream sectors. In particular, food-processing sectors contract by as much as 11.72 percent in the RP25 drought scenario (see column 5 in Table 6). Reduced supply of maize, which is used as animal feed, also adversely affects the poultry sector, causing livestock GDP to fall dramatically.

The overall decline in food availability in the country causes a sharp increase in the demand for imported foods and an increase in the consumer price index. This is shown in Table 7, which reports the macroeconomic impacts of droughts. There is a large increase in demand for imported maize during major droughts, with maize imports more than tripling (256 percent increase) during an RP25 drought. At the same time there is a decline in tobacco exports, which in 2005 generated around one-third of all of Malawi's foreign earnings.

Table 7. Macroeconomic impacts of droughts

	Initial Value (MWK Billion) 2005	Change in Real GDP under Droughts of Different Return Periods, All Crops (%)				Average Annual Losses (AALs) and Partial Crop Loss Scenarios		
		RP5 Drought	RP10 Drought	RP15 Drought	RP25 Drought	AAL (All Crops)	AAL (Maize and Tobacco)	AAL (Maize Only)
GDP (market prices)	207.2	–0.5	–3.5	–7.7	–11.9	–1.0	–0.6	–0.5
Consumption	192.9	–0.6	–3.8	–8.2	–12.4	–1.0	–0.7	–0.6
Government	35.0	0.2	1.1	2.2	2.9	0.3	0.2	0.2
Investment	29.7	–0.2	–1.2	–3.0	–5.3	–0.3	–0.2	–0.1
Exports	48.6	–0.6	–2.3	–2.6	–1.9	–0.7	–0.2	0.3
Tobacco	14.4	–1.8	–5.5	–6.8	–8.5	–1.6	–1.8	–0.1
Imports	–98.9	–0.3	–1.1	–1.3	–0.9	–0.4	–0.1	0.1
Maize	–4.2	6.3	57.2	150.2	256.1	13.8	14.7	15.2
Real Exchange Rate (2005 = 100)	100.00	0.5	3.0	6.6	10.6	0.8	0.5	0.3
Consumer Price Index (2005 = 100)	100.00	0.2	1.4	3.0	4.8	0.4	0.2	0.1

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: GDP = gross domestic product; RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP15 = 1-in-15-year return period; RP25 = 1-in-25-year return period. Drought scenarios include impacts on maize and tobacco production only.

Although there is growing demand for imported maize during drought years, there is also a declining capacity to pay for these maize imports due to falling tobacco production. This places considerable pressure on the country's current account balance, which we assume cannot run a larger deficit. Accordingly, the real exchange rate depreciates (for example, by 10.6 percent during an RP25 drought) to encourage greater exports and discourage import demand. This benefits some agricultural but particularly nonagricultural exporters, such that overall exports actually decline less during more severe droughts than during moderate droughts, despite the increasing decline in tobacco exports. Thus, improved export competitiveness from the depreciating exchange rate allows production to rise in sectors not adversely affected by the drought. For example, there is an increase in industrial GDP during major drought years (see Table 6). This slight industrial expansion is observed in historical drought years in Malawi (see Appendix B). Rising import demand might be offset by inflows of foreign food aid, although the macroeconomic effect of declining tobacco production would still depreciate the exchange rate.

Drought impacts vary across regions. Table 6 reports changes in crop and livestock GDP for each of the eight regions identified in the model. The overall size of these agricultural shocks depends on a region's initial cropping patterns. For example, the largest agricultural GDP losses are in the southern Machinga and Ngabu regions because they rely more heavily on maize revenues than do other regions (meaning, more than half of agricultural lands in these regions are allocated to maize production—see Table 1). By contrast, losses are much smaller in the central Kasungu and Mzuzu regions, despite their larger tobacco sectors. This is because farmers in these regions rely more heavily on nonmaize food crops, which are susceptible to droughts (see Table 1). Finally, agricultural GDP in the Salima region along the coast of Lake Malawi falls only slightly during drought years because almost a quarter of this region's agricultural land is allocated to nontobacco export crops, such as sugarcane, which benefit from the depreciated real exchange rate. In addition to this, production losses for sugarcane are small due to irrigation.

Small-scale farms are worst affected by droughts. Total earnings (or value added) generated on small farms from crop agriculture fall by 32.34 percent under the RP25 scenario, compared to 11.24 percent for large-scale farmers (see Table 6). Moreover, it is their greater reliance on maize production that makes smallholder farmers particularly vulnerable to droughts. By contrast, large-scale farmers' agricultural revenues fall more as a result of declining tobacco production rather than maize. This is evident from the final two columns, which show the outcomes under the AAL scenarios with and without tobacco losses (compare Table 1).

The CGE model estimates changes in expenditures for each household group, and these are then passed down to the household survey (IHS 2004/05) on which the model is based. After recalculating per capita expenditures in the survey, standard poverty measures are computed. The impact of droughts on household poverty is shown in Table 8. The results show that poverty worsens under the various drought scenarios. For example, the national poverty headcount rate increases by 16.9 percentage points (not percent) during the RP25 scenario. Based on 2005 population levels, this means that an additional 2.1 million people fall under the poverty line as a result of an RP25 drought (out of a total population of 12.1 million). The poverty increase under the AAL scenario is 1.3 percentage points, suggesting that on average, every year, 154,000 people are poor because of droughts.

Poverty increases the most for rural nonfarm households. These households are hurt by rising food prices and by declining labor wages and rising unemployment among lower-skilled workers, as farm workers migrate to urban centers and the nonfarm economy to offset falling farm revenues. By contrast, farm households are hurt by falling farm production, which is only partially offset by rising agricultural prices. Small- and medium-scale farmers are most vulnerable to droughts, with their poverty rates rising by around 18 percentage points during an RP25 drought. Poverty among large-scale farmers, on the other hand, rises by only 4.8 percentage points both because of smaller declines in production and because these households are less likely to be in the vicinity of the poverty line.

Table 8. Impact of droughts on the poverty headcount rate (P_0)

	Initial Poverty Rate (%)	Change in P_0 under Droughts of Different Return Periods, All Crops (Percentage Points)				Change in P_0 under Average Annual Loss (AAL) Scenario		
	2005	RP5 Drought	RP10 Drought	RP15 Drought	RP25 Drought	AAL (All Crops)	AAL (Maize and Tobacco)	AAL (Maize Only)
National	52.41	0.67	4.87	10.91	16.92	1.26	0.81	0.70
Urban	25.40	0.49	4.60	9.36	13.25	0.96	0.78	0.63
Farm	30.03	0.24	3.83	7.42	11.40	0.55	0.55	0.24
Nonfarm	21.23	0.72	5.30	11.11	14.91	1.33	0.99	0.99
Rural	55.86	0.69	4.90	11.10	17.39	1.30	0.81	0.71
Farm	56.68	0.70	4.87	11.05	17.42	1.27	0.80	0.69
Karonga	62.83	0.00	3.03	9.38	14.85	0.00	0.00	0.00
Mzuzu	54.99	0.89	4.00	9.82	16.13	1.01	0.89	0.56
Kasunga	43.04	0.40	3.87	7.25	13.18	0.78	0.40	0.32
Salima	56.33	1.21	6.03	11.51	17.53	2.41	1.35	1.12
Lilongwe	46.97	0.58	4.77	11.96	20.37	1.35	0.60	0.42
Machinga	67.72	0.96	5.08	10.75	16.55	1.43	1.19	1.15
Blantyre	61.40	0.59	5.06	11.32	16.55	0.97	0.76	0.76
Ngabu	70.56	0.83	6.79	16.79	22.39	2.04	0.95	0.95
Nonfarm	37.50	0.56	5.53	12.27	16.59	2.10	1.18	1.18
Small-scale farm	61.03	0.62	4.72	11.11	17.56	1.26	0.91	0.88
Medium-scale farm	55.60	0.74	5.15	11.49	18.08	1.30	0.74	0.62
Large-scale farm	30.60	0.66	1.64	2.85	4.77	0.66	0.66	0.04

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP15 = 1-in-15-year return period; RP25 = 1-in-25-year return period. The poverty headcount is based on the national basic needs poverty line (approximately MWK16,165 or US$115 per person per year in 2005). Drought scenarios include impacts on maize and tobacco production only.

Results: Drought Mitigation

In the crop adoption mitigation scenarios we first focus on the benefits from higher yields under expanded adoption. Table 9 shows the impact of increasing COM adoption rates in a normal climate year. The second column in the table shows how maize GDP increases by 5.4 percent under the 10 percent adoption scenario. This raises farm incomes and generates additional demand for other products, such that GDP rises for all subsectors. Higher maize production also benefits downstream producers, such as livestock and food processing, since falling maize prices reduce their costs of production.

Table 9. Impact of greater adoption of higher-yield maize varieties

	No Change in Adoption Rates (A0)	10 Percent Adoption Scenario (A10)	20 Percent Adoption Scenario (A20)	30 Percent Adoption Scenario (A30)
	Initial share (%)	Change in real GDP (%)		
Total GDP (factor cost)	100.00	0.71	1.40	2.06
Agriculture	40.15	1.53	3.01	4.44
Maize	10.07	5.35	10.55	15.59
Other food crops	14.18	0.81	1.60	2.37
Tobacco	5.89	0.03	0.08	0.14
Other export crops	4.28	0.04	0.09	0.15
Livestock	2.46	1.23	2.33	3.30
Other agriculture	3.27	0.10	0.18	0.24
Industry	16.47	0.02	0.05	0.08
Food processing	3.88	0.71	1.34	1.92
Services	43.38	0.22	0.43	0.62
	Initial (MWK billion)	Change from base (%)		
Exports	48.58	–0.02	0.00	0.06
Imports	98.94	–0.01	0.00	0.03
Maize	4.21	–10.78	–19.85	–27.51
Real Exchange Rate	100.00	–0.18	–0.33	–0.46
Consumer price index	100.00	–0.14	–0.26	–0.36
	Initial rate (%)	Change in poverty headcount rate (percentage point)		
National poverty rate	52.41	–0.66	–1.32	–1.97
Urban	25.40	–1.27	–1.87	–2.71
Rural	55.86	–0.58	–1.25	–1.88

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: GDP = gross domestic product. Drought scenarios include impacts on maize and tobacco production only.

Lower domestic prices also reduce demand for imported maize. This relieves some of the pressure on the trade balance and causes a slight real appreciation of the real exchange rate, thus benefiting nonfood agricultural exports. Overall, total GDP rises by 0.71 percent under the 10 percent adoption scenario, which is equal to US$9.6 million (measured in 2005 prices). Economic gains are larger with higher levels of adoption (see columns 3 and 4). Increased national income also reduces poverty, with the national poverty headcount rate falling by as much as 2 percentage points under the 30 percent adoption scenario (meaning, 240,000 people). These results indicate that there are substantial benefits to expanding the use of improved crop technologies in Malawi. These results are consistent with the official evaluation of Malawi's input subsidy program (see Appendix C).

We now consider the drought-mitigating effects of increasing adoption of COM. Table 10 shows the economic gains from raising adoption rates under droughts of different severities. The first rows in parts 1 and 2 of the table report changes in total GDP under each of the adoption scenarios without the losses incurred during drought years (meaning, a normal year). Results suggest that raising COM adoption rates to 30 percent increases total GDP by 2.1 percent or US$27.8 million (in 2005 prices).

Table 10. Changes in gross domestic product (GDP) and poverty under alternative adoption scenarios

	No Change in Adoption Rates (A0)	10 Percent Adoption Scenario (A10)	20 Percent Adoption Scenario (A20)	30 Percent Adoption Scenario (A30)
Part 1: Change in total GDP from base value (%)				
Normal year	0.00	0.71	1.40	2.06
RP5	–0.26	0.46	1.16	1.83
RP10	–1.95	–1.17	–0.41	0.31
RP15	–4.31	–3.45	–2.62	–1.81
RP25	–6.52	–5.59	–4.69	–3.82
Part 2: Change in total GDP (US$ million in 2005 prices)				
Normal year	0.00	9.60	18.86	27.78
RP5	–3.50	6.23	15.60	24.64
RP10	–26.29	–15.75	–5.59	4.22
RP15	–58.10	–46.49	–35.27	–24.42
RP25	–87.83	–75.33	–63.20	–51.44
Part 3: Change in poverty headcount rate from 2005 base year (percentage point)				
Normal year	0.00	–0.66	–1.32	–1.97
RP5	0.30	–0.41	–1.06	–1.74
RP10	2.41	1.35	0.53	–0.10
RP15	5.85	4.56	3.48	2.32
RP25	9.95	8.29	6.63	5.32
Part 4: Change in poor population from 2005 base year (1,000s)				
Normal year	0	–80	–161	–240
RP5	37	–50	–129	–212
RP10	293	164	65	–13
RP15	712	555	424	282
RP25	1,212	1,009	807	648

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP15 = 1-in-15-year return period; RP25 = 1-in-25-year return period. The poverty headcount is based on the national basic needs poverty line (approximately MWK 16,165 or US$115 per person per year in 2005). Drought scenarios include only impacts on maize.

However, apart from higher yields, COM have the added benefit of being more drought resistant than local varieties. Increasing adoption rates therefore offset some of the losses incurred during drought years. For example, total GDP declines by 6.5 percent (US$87.83 million) when adoption rates remain unchanged but by only 3.8 percent (US$55.4 million) when adoption rates increase by 30 percentage points during the same year (see Table 11). The difference between these outcomes is US$36.4 million, which is greater than the purely yield-based gains during a RP1 year (meaning, US$27.8 million). This gap of US$8.6 million is the additional gain from adopting more drought-resilient maize varieties.

Table 11 decomposes the economic gains from adopting COM into the portions of economic gains that are attributable to higher yields and to greater drought resistance. As expected, the additional resilience gains are relatively small under less severe droughts. For example, the additional gains are only US$0.4 million under an RP5 drought and with 30 percent higher COM adoption. This means that the drought resilience of COM increases economic gains by 1.3 percent beyond what is obtained from their having higher yields. The share of these additional gains (or, more accurately, reduced losses) in overall gains rise to as much as 31 percent during a severe RP25 drought. Expanding the adoption of COM and hybrid varieties therefore has a profound mitigating effect during drought years. Taking these additional benefits into account would greatly improve the benefit-cost ratio of Malawi's current and future maize input subsidy programs.

Table 11. Decomposing yield and drought-resilience gains from adoption scenarios

	10 Percent Adoption Scenario (A10)	20 Percent Adoption Scenario (A20)	30 Percent adoption Scenario (A30)
	Change in total GDP (US$ million in 2005 prices)		
Gains from using higher-yield COM varieties	9.60	18.86	27.78
Additional gains from greater drought resilience			
RP5	0.13	0.25	0.37
RP10	0.93	1.84	2.73
RP15	2.00	3.97	5.90
RP25	2.89	5.77	8.61
	Change in poverty headcount rate (percentage point)		
Gains from using higher-yield COM varieties	–0.66	–1.32	–1.97
Additional gains from greater drought resilience			
RP5	–0.06	–0.04	–0.08
RP10	–0.40	–0.55	–0.54
RP15	–0.64	–1.05	–1.56
RP25	–1.00	–2.00	–2.66

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: GDP = gross domestic product; RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP15 = 1-in-15-year return period; RP25 = 1-in-25-year return period; COM = composites. Higher-yield gains assume a normal climate year (meaning, no drought conditions). Resilience gains are the difference between adoption and nonadoption outcomes under alternative drought years less the normal year yield gains. The poverty headcount is based on the national basic needs poverty line (approximately MWK 16,165 or US$115 per person per year in 2005).

Finally, expanding adoption rates is also an effective mitigation strategy in terms of poverty. For example, a 30 percent adoption scenario reduces the national poverty headcount rate by 2 percentage points under normal climate conditions (see the second half of Table 11). However, this excludes any additional benefits from COM's enhanced drought resilience. Accounting for this additional benefit, drought resilience under a 30 percent adoption scenario would reduce poverty by a further 2.7 percentage points during an RP25 drought year, which is equivalent to 323,000 fewer people's falling below the poverty line. This means that the drought resistance of COM increases the poverty gains from higher adoption by as much as 134 percent. Ignoring drought resilience when evaluating input subsidy programs in Malawi would thus exclude a large share of these programs' benefits, especially in terms of reducing the vulnerability of the poor to major droughts.

5. THE ECONOMYWIDE IMPACT OF FLOODS IN MALAWI'S SOUTHERN REGION

Simulation Design

The RMSI (2009) flood risk model established a relationship between crop losses and floods of increasing severity. Production losses were estimated for maize (all three types combined) and tobacco. The analysis was restricted to the flood-prone southern region, which includes the Machinga, Blantyre, and Shire Valley (or Ngabu) districts. Compared to droughts, flood events are more consistent in terms of the way they affect crop production levels in that it was possible to decompose the production losses into land and yield losses. Hence, in the CGE simulations, land and yield losses are applied to the relevant parameters in the CGE model (meaning, λ and π in Table 2) to generate production losses comparable to those in the LECs in Figure 2. The land and yield losses applied are shown in Table 12. Note that the exact same loss factors are applied to all three regions in the southern region. However, regional differences in cropping patterns and the contribution of agriculture to regional GDP will cause some regional variation in the economic impact of floods.

Table 12. Flood scenarios: Simulated land and yield losses for maize and tobacco (in Percentages)

	Maize			Tobacco		
	Loss in Area	*Yield Loss*	*Loss in Production*	*Loss in Area*	*Yield loss*	*Loss in Production*
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
RP50	–40.4	–33.1	–60.2	–28.8	–22.3	–44.7
AAL	–8.0	–4.3	–12.0	–5.6	–3.7	–9.2

Source: Authors' estimates based on RMSI (2009)
Note: RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP20 = 1-in-20-year return period; RP50 = 1-in-50-year return period; AAL = average annual loss. Production losses shown can be read of directly from the LECs in Figure 2. The relationship between production (p), yield (y), and land (a) losses is given by the equation $\mathrm{P}(1-\mathrm{p}) = \mathrm{A}(1-\mathrm{a}).\mathrm{Y}(1-\mathrm{y})$.

As is the case with the drought scenarios, we extend the analysis to include losses in other crops as well. We assume that losses in rice and other cereals in the southern region are similar to those experienced for maize. This assumption also extends to roots, groundnuts, vegetables, and other crops. Fruits are assumed to be unaffected by floods, whereas cotton losses are similar to tobacco losses. Sugarcane and tea crops are also unaffected by floods. Although these assumptions may seem crude, a statistical analysis of correlation did not yield useful results. A lack of spatial cropping data further makes it difficult to determine which crops might become inundated during floods. Similar problems were experienced by RMSI (2009).

Results: Flood Impacts

Although they are similar in terms of simulation design, the important difference between the earlier drought impact scenarios and the flood impact scenarios is the fact that flood losses are now modeled only for the southern region of Malawi. This region accounts for about 40 percent of the land area under maize (see Table 1) but only contributes 30 percent to overall maize production, reflecting the lower-than-average maize yields obtained in this region.[5] The region also accounts for 20 percent of the land area

[5] The high concentration of less-commercialized small farmers in this region partly explains this outcome. Also, the fact that this area has historically been more prone to droughts and floods compared to the rest of the country may explain lower yields achieved here.

under tobacco and one-quarter of tobacco production in the economy (note that there is virtually no tobacco production in the Ngabu district). Thus, although maize and tobacco production levels were found to be quite vulnerable to floods, the national production effects are relatively smaller than what the LECs in Figure 2 suggest because the impact channel of the shock is much narrower.

A feature of the CGE model that is of relevance for interpreting the flood results is the fact that the model assumes a single national market for all commodities. When production losses occur only in a certain region there will be an overall shortage of that commodity in the domestic market, which causes domestic prices to rise. The implication is that those regions that are not directly affected by floods will experience an increase in demand for their output at higher prices. At the existing world prices, imported goods will be more attractive, but rising imports will only offset some of the domestic price increase. Ultimately, we expect producers and households in the central and northern regions to benefit from floods occurring exclusively in the southern region, if not in absolute terms, then at least in relative terms. The overall impact on GDP, however, is likely to be negative.

The discussion here follows the same basic structure as the discussions in the previous sections. We focus on the RP5 to RP50 scenarios, although results for the AAL scenarios (which are comparable to an RP2 flood) are also presented. Starting with the GDP effects, Table 13 shows that maize production falls by almost 6.3 percent during an RP5 flood. These losses more than double during an RP50 flood (15.4 percent). Tobacco production losses are much smaller, ranging from 5.89 percent during an RP5 flood to 3.8 percent during an RP50 flood. This is expected given slightly smaller losses modeled for tobacco but also because the southern region is not the dominant tobacco-producing region in Malawi. In fact, more than half the tobacco is produced in Lilongwe and Kasungu, which are at a higher altitude where floods are a less likely event.

The small contribution of tobacco losses to overall economic losses is even more evident in the final three columns of Table 13. Although the AAL in GDP is about 0.7 percent when all crops are included in the analysis, the loss declines to 0.4 percent when only maize and tobacco losses are modeled. Thus, almost half of the loss is explained by losses in maize and tobacco. When tobacco is excluded, the GDP loss declines only marginally to 0.3 percent, which suggests that of the two crops, maize is the important driving factor in these results. The 0.7 percent AAL in GDP is equivalent to US$9 million (in 2005 prices). During a particularly severe RP50 flood, losses are US$52.2 million.

Table 13. Impact of floods in the southern region on gross domestic product (GDP)

	Initial Share (%)	Change in Real GDP under Floods of Different Return Periods, All Crops (%)				Average Annual Losses (AALs) and Partial Crop Loss Scenarios		
	2005	RP5 Flood	RP10 Flood	RP20 Flood	RP50 Flood	AAL (All Crops)	AAL (Maize and Tobacco)	AAL (Maize Only)
Total GDP (factor cost)	100.00	–1.73	–2.52	–3.19	–4.03	–0.70	–0.36	–0.31
Agriculture	40.15	–3.54	–5.13	–6.49	–8.15	–1.43	–0.77	–0.68
Maize	10.07	–6.37	–9.51	–12.25	–15.48	–2.66	–2.71	–2.72
Other food crops	14.18	–3.16	–4.67	–5.91	–7.39	–1.29	–0.28	–0.29
Tobacco	5.89	–1.81	–2.20	–2.59	–3.21	–0.61	–0.67	0.04
Other export crops	4.28	–2.20	–2.70	–3.13	–3.85	–0.75	–0.32	0.08
Livestock	2.46	–1.31	–1.99	–2.63	–3.44	–0.52	–0.47	–0.46
Other agriculture	3.27	0.11	0.14	0.15	0.15	0.05	–0.04	–0.06
Industry	16.47	–0.55	–0.87	–1.17	–1.56	–0.23	0.11	0.09
Food processing	3.88	–1.99	–3.14	–4.20	–5.54	–0.81	–0.10	–0.15
Services	43.38	–0.51	–0.72	–0.91	–1.15	–0.20	–0.15	–0.12

Table 13. Continued

	Initial Share (%)	Change in Real GDP under Floods of Different Return Periods, All Crops (%)				Average Annual Losses (AALs) and Partial Crop Loss Scenarios		
	2005	RP5 Flood	RP10 Flood	RP20 Flood	RP50 Flood	AAL (All Crops)	AAL (Maize and Tobacco)	AAL (Maize Only)
Crops and livestock	36.87	–3.87	–5.60	–7.08	–8.89	–1.56	–0.84	–0.74
Karonga	1.15	0.38	0.57	0.73	0.91	0.16	0.03	0.03
Mzuzu	4.45	0.50	0.74	0.95	1.20	0.21	0.11	0.11
Kasunga	6.89	0.69	1.03	1.32	1.67	0.29	0.20	0.21
Salima	2.37	0.37	0.54	0.69	0.88	0.15	0.07	0.05
Lilongwe	7.47	0.57	0.85	1.08	1.37	0.24	0.12	0.12
Machinga	4.20	–16.86	–24.40	–30.93	–38.95	–6.79	–4.03	–3.36
Blantyre	6.28	–9.68	–14.20	–17.99	–22.52	–3.96	–2.04	–1.88
Ngabu	1.42	–15.03	–21.09	–26.39	–33.14	–5.91	–2.33	–2.33
Urban	2.63	–0.82	–1.24	–1.62	–2.12	–0.32	–0.32	–0.31
Crop agriculture	34.41	–3.78	–5.46	–6.90	–8.66	–1.52	–0.81	–0.70
Small scale	6.92	–6.32	–9.39	–12.06	–15.18	–2.67	–1.48	–1.49
Medium scale	17.25	–5.44	–7.90	–10.01	–12.58	–2.20	–1.09	–1.01
Large scale	10.24	–0.17	–0.01	0.17	0.29	0.03	–0.08	0.17

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP20 = 1-in-20-year return period; RP50 = 1-in-50-year return period. Modeled flood scenarios include impacts on maize and tobacco only.

As with the drought scenarios, downstream food-processing sectors decline, in this instance by between 1.9 and 5.5 percent in the RP5 and RP50 scenarios, respectively. The services sector also declines by between 0.5 and 1.6 percent. The AAL industrial and services losses are 0.2 and 0.2 percent, respectively, which is small compared to the agricultural GDP loss.

Table 14 presents the macroeconomic results. The decline in domestic maize supply leads to sharp increases in maize imports, ranging from 20.2 percent (RP5) to 57.4 percent (RP50). Although these are large in percentage terms, the absolute impact on overall imports is relatively small since maize accounts for only about 4 percent of overall imports in the base. On average, though, Malawi has to increase maize imports by about 8.1 percent due to flood losses (AAL scenario). Although tobacco losses are fairly small in these scenarios, we do observe declines in tobacco exports of between 1.7 and 2.7 percent. Increased import demand and declining exports place pressure on the current account balance, which causes the exchange rate to depreciate in all the scenarios considered. For example, during an RP50 flood, the exchange rate depreciates by 3.7 percent.

Table 14. Macroeconomic impacts of floods in the southern region

	Initial Value (MWK Billion) 2005	Change in Real GDP under Floods of Different Return Periods, All Crops (%)				Average Annual Losses (AALs) and Partial Crop Loss Scenarios		
		RP5 Flood	RP10 Flood	RP20 Flood	RP50 Flood	AAL (All Crops)	AAL (Maize and Tobacco)	AAL (Maize Only)
GDP (market prices)	207.2	–1.8	–2.6	–3.4	–4.4	–0.7	–0.4	–0.3
Consumption	192.87	–2.0	–2.9	–3.8	–4.9	–0.8	–0.4	–0.3
Government	34.99	0.7	1.0	1.3	1.7	0.3	0.1	0.1
Investment	29.71	–0.4	–0.6	–0.8	–1.1	–0.1	–0.1	0.0
Exports	48.58	–1.5	–1.9	–2.2	–2.7	–0.5	0.0	0.2
Tobacco	14.36	–1.7	–2.0	–2.2	–2.7	–0.5	–0.9	–0.1
Imports	98.94	–0.7	–0.9	–1.1	–1.3	–0.3	0.0	0.1
Maize	4.21	20.2	31.9	43.1	57.4	8.1	9.1	9.4
Real Exchange Rate (2005 = 100)	100.00	1.5	2.2	2.8	3.7	0.6	0.2	0.2
Consumer Price Index (2005 = 100)	100.00	0.7	1.1	1.4	1.8	0.3	0.1	0.1

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: GDP = gross domestic product; RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP20 = 1-in-20-year return period; RP50 = 1-in-50-year return period. Modeled flood scenarios include impacts on maize and tobacco only.

Returning to the regional production results in Table 13, we note some variation in agricultural production losses (crops and livestock) across Machinga, Blantyre, and Ngabu despite the fact that the same land and yield loss factors were applied. This variation is explained mainly by differences in cropping patterns; that is, in both Machinga and Ngabu, more than half of agricultural land is allocated to maize, compared to 40 percent in Blantyre. As a result overall agricultural production losses, which are essentially weighted here by crop shares, are also lower in Blantyre.

Real GDP levels increase in all the other agricultural districts (central and northern regions), reflecting the fact that producers in these regions benefit from increased demand for their output (particularly maize) given the adverse supply shock in the southern region. One exception is the decline in urban agriculture. Closer inspection reveals that urban farmers benefit from increased demand for maize. However, livestock production levels decline sharply due to the increase in feed costs, and since livestock accounts for almost 40 percent of urban agricultural output, this causes overall urban agricultural GDP to decline. Although similar livestock declines are experienced on rural farms as well, livestock on these farms accounts for only about 5 percent of agricultural output.

Small- and medium-scale farmers are worst hit by the floods (see bottom three rows in Table 13), with AALs in GDP of 2.7 and 2.2 percent, respectively. This relates to smallholder farmers' greater reliance on maize production. The maize and tobacco only and the maize only AAL scenarios further highlight the differential impact of maize and tobacco production shocks, with tobacco losses almost exclusively affecting large farmers. Thus, when tobacco losses are accounted for, large-scale farmers experience losses, whereas when only maize losses are modeled, these farmers actually benefit.

The impact of floods on poverty levels is shown in Table 15. At the national level the combination of higher food prices and lower economic activity ultimately causes the percentage of poor people in Malawi to increase. These increases range from 2.7 percentage points during an RP5 flood to 6.3 percentage points during an RP50 flood. Poverty increases in urban areas are generally lower than the national average. Urban agricultural households are less affected than nonfarm urban households since their incomes are somewhat buoyed by the domestic maize shortage. Therefore, like their rural counterparts in the central and northern regions, they are able to increase production levels as floods hit the southern region.

Table 15. Impact of floods on the poverty headcount rate (*P_0*)

	Initial Poverty Rate (%) 2005	Change in P_0 under Floods of Different Return Periods, All Crops (Percentage Point)				Change in P_0 under Average Annual Loss (AAL) Scenario		
		RP5 Flood	RP10 Flood	RP20 Flood	RP50 Flood	AAL (All Crops)	AAL (Maize and Tobacco)	AAL (Maize Only)
National	52.41	2.67	4.10	5.09	6.29	0.91	0.50	0.47
Urban	25.40	1.90	3.62	4.50	5.64	0.78	0.41	0.41
Farm	30.03	1.38	2.85	3.62	4.23	0.55	0.07	0.07
Nonfarm	21.23	2.38	4.31	5.30	6.91	0.99	0.72	0.72
Rural	55.86	2.76	4.16	5.16	6.37	0.93	0.51	0.48
Farm	56.68	2.71	4.11	5.13	6.28	0.91	0.52	0.49
Karonga	62.83	0.00	0.00	0.00	–0.33	0.00	0.00	0.00
Mzuzu	54.99	0.00	–1.00	–1.74	–1.96	0.00	0.00	0.00
Kasunga	43.04	–0.26	–0.57	–1.14	–2.16	–0.08	–0.08	–0.08
Salima	56.33	0.98	1.44	1.62	1.62	0.75	0.43	0.43
Lilongwe	46.97	0.19	0.13	0.07	–0.06	0.03	–0.10	–0.10
Machinga	67.72	6.22	9.91	11.89	15.12	2.21	1.52	1.43
Blantyre	61.40	5.14	7.92	10.85	13.04	1.36	0.88	0.76
Ngabu	70.56	6.42	10.02	13.04	17.37	2.51	0.95	0.95
Nonfarm	37.50	3.91	5.24	5.93	8.42	1.31	0.25	0.25
Small-scale farm	61.03	3.18	5.05	6.44	7.86	1.25	0.82	0.76
Medium-scale farm	55.60	2.56	3.75	4.61	5.67	0.75	0.38	0.35
Large-scale farm	30.60	0.51	0.55	0.55	0.55	0.04	0.04	0.04

Source: Results from the Malawi computable general equilibrium and microsimulation model.
Notes: RP5 = 1-in-5-year return period; RP10 = 1-in-10-year return period; RP20 = 1-in-20-year return period; RP50 = 1-in-50-year return period. Modeled flood scenarios include impacts on maize and tobacco only.

Among the rural farm households, those in the southern region are obviously affected the worst. The poverty rates in Machinga, Blantyre, and Ngabu rise by as much as 15.1, 13.0, and 17.4 percentage points, respectively, during an RP50 flood. However, among the rest of the rural farming households, poverty levels remain largely unchanged, whereas in some areas poverty actually declines marginally. Nonfarm rural households face a very similar plight to their nonfarm urban counterparts, with their only direct link to floods being the commodity market where they now face significantly higher prices and lower levels of welfare. The poverty results for small-, medium-, and large-scale farming households largely follow expectations. Floods mainly affect small- and medium-scale maize farmers given their increased exposure to flood risk, and this is reflected in the relatively larger poverty increases among these farmers compared to large-scale farmers. These farmers are also generally closer to the poverty line and hence are more vulnerable to changes in income. On average, the poverty rate increases by 0.9 percentage points every year due to floods (AAL scenario), which is equivalent to about 111,000 people out of a population of 12.1 million in 2005 (IHS 2004/05).

6. SUMMARY AND CONCLUDING REMARKS

The objective of this paper was to quantify the economic losses associated with droughts and floods of different severities as they might occur in Malawi. Although drought and flood risk models such as those developed by RMSI (2009) are extremely valuable to our understanding of the short-term impact of extreme climate events on crop production, they tell only a partial story. In a country such as Malawi, where agriculture plays a major role in the economy, it is important to also consider the effects that crop losses might have on international trade, production in nonagricultural sectors, labor employment, and household incomes and poverty.

Model results estimate that droughts, on average, cause GDP losses of almost 1 percent every year. This is equivalent to US$12.5 million per annum (2005 prices). Economic losses are much higher during extreme droughts; for example, during a 1-in-25-year drought (RP25), which is similar to that experienced in 1991/92 in Malawi, GDP contracts by as much as 10.4 percent. Droughts also exacerbate Malawi's already high levels of income poverty. On average, droughts cause a 1.3 percentage point increase in poverty, but this rises to almost 17.0 percentage points during an RP25 drought. This is equivalent to an additional 2.1 million people's falling below the poverty line. Importantly, when droughts do occur, their impacts vary considerably across regions and population groups, with smaller-scale farmers most vulnerable to drought-induced economic losses. Nonfarm and urban households are also vulnerable, especially poor households that spend a large proportion of their income on food.

A drought mitigation scenario that involves replacing local varieties with higher-yielding and more drought-resistant COM maize varieties was also considered in this paper. Average annual GDP losses associated with droughts may already be offset by replacing only 10 percent of land under LMZ by COM maize in the same year that the drought occurs. We find that gains from drought resilience may be as much as one-third of overall economic gains from implementing an input subsidy program, such as the existing Agricultural Input Subsidy Program in Malawi. Extending COM also lowers the large increase in poverty that would normally take place during major drought years. The adoption of COM therefore generates double dividends of higher yields and greater drought resilience, which suggests that climate uncertainty should be taken into account when analyzing the costs and benefits of agricultural programs.

The paper also estimates the impact of floods in the southern region of Malawi. The average annual GDP loss due to floods is about 0.7 percent or US$9 million, thus making the average impact of floods slightly less than that of droughts. However, considering that this is the national-level impact of an event that is highly localized, that is, one that only affects production levels in the southern region directly, the economywide effects are in reality quite severe. These national-level losses occur despite the fact that agricultural production in the central and northern regions may increase during floods. These benefits arise from higher national food prices during southern floods. The implications for farming households in the southern region are, however, severe. Average annual crop and livestock losses range from 4.0 percent in Blantyre to 6.8 percent in Machinga. Floods are further found to mainly affect small- and medium-scale farmers. By contrast, large-scale farmers and those growing export crops in the central and northern regions may actually benefit more during flood years.

The impacts of droughts and floods are often discounted or ignored given the infrequent nature of these events. However, these events are costing the Malawian economy 1.7 percent of its GDP every year in terms of production forgone. Indications are that drought and flood events are becoming more frequent (RMSI 2009), which suggests that the average annual impact might become even greater in the future. It is therefore crucial that policymakers take heed of the severe implications of climate variability, especially for the most vulnerable in society, such as resource-poor small-scale farmers and poorer urban households.

This study outlined a methodology in which hydrological and meteorological risk models and economic models can be integrated to facilitate better understanding of the economic costs of climate uncertainty. The explicit aim was to capture only the immediate impacts of extreme climate events during the same year in which the event occurs, which justifies the use of a comparative static model framework.

The analysis is, however, by no means exhaustive. As data become available, the longer-term dynamic implications of extreme climate events, such as the effects of soil erosion, infrastructure losses, or investment behavior, should also be analyzed.

It is clear from this analysis, though, that climate uncertainty is important. Although it is imperative to quantify the potential economic losses associated with climate uncertainty as we have done here, this is merely the first step. Further research is needed that explicitly considers the risk and uncertainty in designing and evaluating agricultural development policies in low-income countries like Malawi.

APPENDIX A: LOCAL MAIZE, HYBRIDS, AND COMPOSITES

There are three broad maize varieties in Malawi. The first, local maize (LMZ) is an open-pollinated variety (OPV), which means the plants produce seeds through random pollination (Heisey and Smale 1995). LMZ seed can be saved and reused from year to year, which implies input cost savings compared to other alternatives. However, yields are typically low. A second variety is known as hybrids or high-yielding varieties (HYV). HYV are produced in controlled environments by crossing inbred lines. Although yields are much higher compared to LMZ, HYV are more expensive to produce. Private-sector control also keeps market prices high (Denning et al. 2009). HYV seeds also cannot be successfully recycled. A third variety, composites (COM), can be classified as improved OPVs. These also are bred using scientific processes (such as selection) to make them suited to local environments, but in contrast to hybrids, the seeds can be recycled for several seasons despite cross-pollination (Denning et al. 2009). Often COM varieties will be more drought tolerant compared to LMZ or HYV (as our earlier results also suggest), but yields are typically lower than those of hybrids.

Ultimately, the choice between LMZ, HYV, and COM is a complex decision involving yield and cost considerations. In this study we argue that a third dimension needs to be added, namely, the drought tolerance of each variety. As far as Malawian farmers' choices, historical trends have shown a steady decline in the area of land under LMZ. HYV grew strongly in the late 1980s and early 1990s, whereas COM varieties have gained prominence since the late 1990s. Whereas only three years ago LMZ still covered half the planted area in Malawi, latest figures suggest that roughly equal shares of land are now allocated to each of the three varieties.

Both HYV and COM are available under the Malawian Agricultural Input Subsidy Program (AISP). Seed coupons enable recipients to obtain 3 kilograms of COM or 2 kilograms of HYV, depending on farmers' choices and seed availability (Denning et al. 2009). An evaluation of the AISP by Dorward et al. (2008) reveals that 76 percent of farmers opted for HYV. Although it is not clear whether this outcome was driven more by seed availability than by farmers' preferences, it is somewhat unexpected considering the recent surge in the area of land under COM since the inception of the AISP in 2005/06. It may, however, be that these trends were driven by farmers outside of the subsidy program.

As for future trends, recent reports announced the development of two new OPVs (called ZM309 and ZM523) with potential yields in excess of 5 tons per hectare (see Neondo 2009). Developed in partnership by Malawi's Ministry of Agriculture and Food Security and the International Maize and Wheat Improvement Center, the new varieties are suitable for growing in drought-prone areas. ZM309 will be available under the next round of the AISP, with a government representative's claiming that it is "*only a matter of time before* [farmers] *will be demanding seed of these new varieties*" (Neondo 2009). Increased adoption of COM rather than HYV under the AISP may therefore become a reality in the near future.

APPENDIX B: COMPARING MODELED AND OBSERVED 1-IN-25-YEAR RETURN PERIOD DROUGHTS

To partially validate the model's results, Appendix Table B.1 below shows the impact of the modeled 1-in-25-year return period drought year and the observed drought that took place during 1991/92. This drought can be classified as a 1-in-25-year return period drought. It is difficult to directly compare model and observed impacts for three reasons. First, the structure of the economy changed between 1991/92 and 2005 (the base year of the computable general equilibrium model). Agriculture was a larger share of the economy by 2005, so simulated droughts in the 2005 have larger impacts on total gross domestic product. Second, by the 2004/05 crop season Malawi had shifted maize production toward more drought-resistant composite and hybrid varieties, which lessens the impacts of droughts.

Table B.16. Modeled and observed drought impacts

Share of Total before Drought Year (%)			Change from Base Year (%)		
	2004/05	1990/91		Modeled (RP25)	Observed (1991/92)
Total GDP	100.00	100.00	Total GDP	–9.05	–7.92
Agriculture	40.15	27.92	Agriculture	–21.53	–25.12
Industry	16.47	20.15	Industry	0.72	2.43
Services	43.38	51.93	Services	–4.36	–2.68
Total maize production	100.00	100.00	Maize production	–51.24	–58.80
Local varieties	32.51	65.50	Tobacco production	–4.26	–20.60
Composite varieties	26.98	1.68			
Hybrid varieties	40.51	32.82			

Source: Results from the Malawi computable general equilibrium and microsimulation model and historical production data.
Note: RP25 = 1-in-25-year return period; GDP = gross domestic product.

Finally, the computable general equilibrium model isolates the impact of the drought, whereas observed data include other changes taking place during 1991/92 (such as agricultural policy changes and world price movements). Given these caveats, the model produces impacts that are only broadly consistent with observed data for similar drought years. Importantly, however, the slight rise in industrial gross domestic product is observed in 1991/92 despite declines for both agriculture and services.

APPENDIX C: THE 2005/06 AGRICULTURAL INPUT SUBSIDY PROGRAM

Malawi's Agricultural Input Subsidy Program (AISP) was implemented during 2005/06 and was similar in size to the modeled 10 percent adoption scenario (see Table C.1 below). It is difficult, however, to compare the modeled economic gains with what was actually observed. This is because the crop year preceding the AISP (2004/05) was a 1-in-15-year return period drought year, whereas the implementation year (2005/06) was a normal year. The observed increase in production following the subsidy was therefore a combination of higher adoption rates and improved climate conditions.

Overall, the model's estimated gain in total gross domestic product (GDP) between the two years is US$67.7 million. This comprises US$9.6 million from using higher-yielding composite seeds (see row 1 in Table 11) and US$58.1 million due to the ending of the 1-in-15-year return period drought (see column 1 in Table 11).

Table C.1. Modeled and observed outcomes under the Agricultural Input Subsidy Program

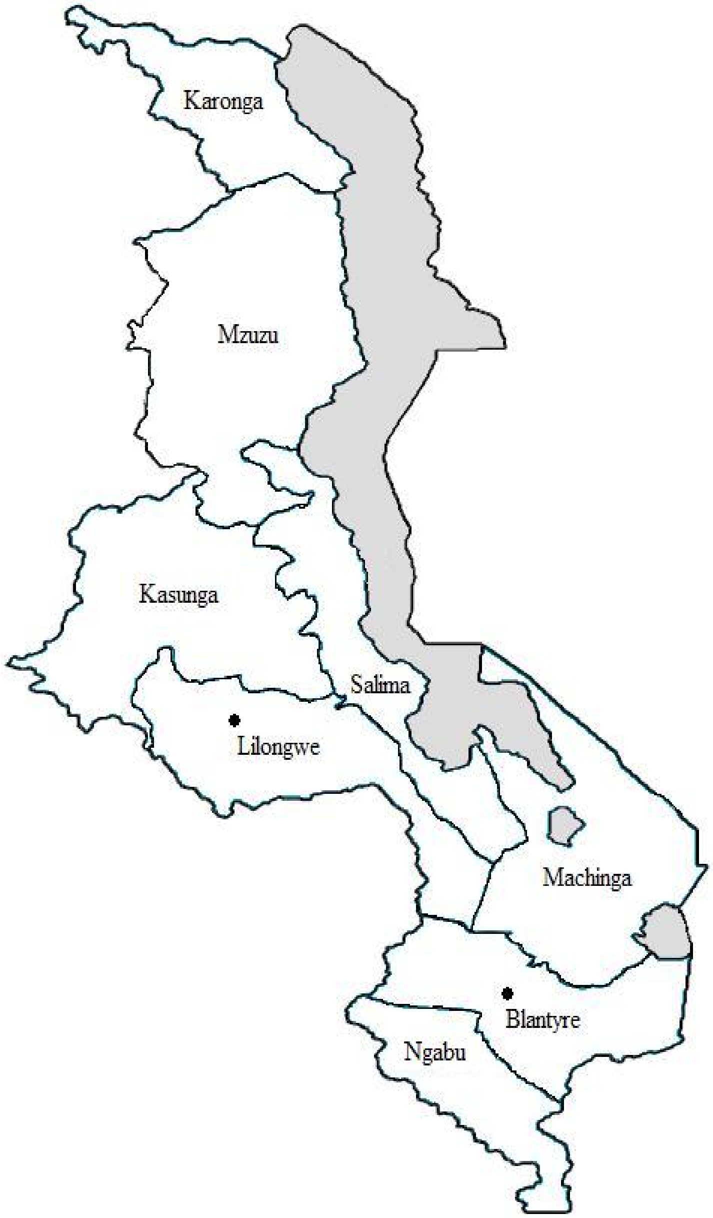
	Modeled (RP10:A0 to RP1:A10)	Observed/Estimated (2004/05–2005/06)
Change in land share (percentage point)		
Local varieties	–10.00	–10.49
Composite varieties	10.00	8.98
Hybrid varieties	0.00	1.50
Change in maize production (%)	53.13	98.7
Change in GDP (US$ million)		
Total GDP	67.70	
Maize GDP	50.20	45.98–82.28
Cost of AISP (2005 US$ million)		58.50
Benefit-cost ratios		
Total GDP	1.16	
Maize GDP	0.86	0.76–1.36

Source: Dorward et al. (2008) and results from the Malawi computable general equilibrium model.
Note: RP10 = 1-in-10-year return period; RP1 = 1-in-1-year return period; GDP = gross domestic product. The modeled scenario is the difference between the results for the RP10 drought scenario without additional adoption (meaning, A0) and the RP1 scenario with 10 percentage points' additional adoption (meaning, A10). This is roughly equivalent to the conditions in 2004/05 and 2005/06, respectively. The observed increase in maize production is net of increases in harvested land area to be comparable with the model scenario.

Similarly, the increase in maize GDP in the model was US$50.2 million, which is close to the program's cost of US$58.5 million (Dorward et al. 2008). This implies a benefit-cost ratio of 0.86, which falls within the lower range identified in official bottom-up program evaluations (see Dorward et al. 2008). However, once economywide effects are taken into account (by using total GDP rather than just maize GDP) then the benefit-cost ratio rises to 1.16. Economywide linkages may therefore increase the measured benefits of AISP by one-quarter compared to solely maize-based estimates of benefits.

APPENDIX D: SUPPLEMENTARY FIGURE

Figure D.1. Agricultural development districts in Malawi



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