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Modeling Potential Impacts of Future Climate Change in Mzimba District, Malawi, 2040-2070

An Integrated Biophysical and Economic Modeling Approach

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ABSTRACT

Historical data in Malawi indicates there has been climate change in the past and that farmer households have been affected. Climate models predict further changes in precipitation and temperature over Malawi in the future. However, most studies to understand the impacts of climate change in Malawi have focused on *ex post* assessments of weather events. Planning for future adaptations by Malawian farmers to a changed climate will require acknowledging that future climate patterns may deviate significantly from historical climate patterns. Little research has been done to assess *ex ante* (future) climate change and its potential impacts on and implications for farmer productivity, incomes, and poverty. This study investigates possible climate change patterns over the period 2040 to 2070 in order to assess the potential economic impacts for crop-livestock integrating and non-integrating farmers in Mzimba district in northern Malawi. Thirty year historical climate data were used with 20 Global Circulation Models (GCM) to generate plausible future climates. Future maize yields then were simulated using the APSIM crop model. The Trade-Off Analysis model for Multi-Dimensional Impact Assessment (TOA-MD) framework was used with the crop model results for economic analysis.

Results indicate that over the period 2040 to 2070 Mzimba district, relative to the present, will be warmer by between 1°C and 3°C and slightly drier by 1.1 percent, but with considerable uncertainty in the GCM models. Maize productivity is expected to increase by between 10 and 15 percent. On aggregate, 56 percent of farmers will register productivity gains – 55 percent of crop-livestock integrating farmers and 57 percent of non-integrating farmers. Mean net returns per hectare are expected to be higher among integrating farmers. Incomes per capita are predicted to increase by 5.2 percent – by 5.3 percent among integrating and by 5.1 percent among non-integrating farmers. Income-based poverty is predicted to decline by 4 percent – by 6 percent among integrating and by 2 percent among non-integrating farmers. The study recommends that in order to enable farmers in Mzimba to more effectively adapt to the changing climate, investment is needed in research to develop heat-tolerant maize varieties, and efforts should be made to enhance sustainable agricultural intensification, including crop-livestock integration.

I. INTRODUCTION

It is becoming increasingly evident that climate change will be a crucial player in Malawian agriculture in the future. A scan through scholarly work on climate change manifestations shows that many parts of the country already have been negatively affected by extreme weather events, such as floods and droughts. These have led to losses in the national gross domestic product (GDP) and in the consumption levels of households affected by these events (Pauw, et al. 2011; Arndt, et al. 2010). Climate models project general increases in warming of between 2°C and 3°C by 2050 and an overall decline in rainfall and water availability in Malawi (UNDP 2007; USAID 2013). Such climatic changes, as observed by Hassan and Nhemachena (2008), will affect food and water resources for crop and livestock production. The livelihoods of many smallholder farmers are likely to be disrupted as their rain-fed agricultural production systems are highly sensitive to climate variations and changes (GOM 2011). Associated direct effects on household consumption, poverty, and livelihoods in the long run are inevitable (Keller 2009; Lema & Majule 2009; Pauw et al. 2011; DFID 2004; Bie et al. 2008; Kinuthia 1997).

Many researchers have studied the impacts of climate change among different populations in Malawi. However, most have focused on the incidence and impact of adverse extreme weather events and their associated losses. A major oversight of these studies has been to imply that the weather events are directly related to climate change, thereby portraying a generally pessimistic assessment of the impact of climate change on the studied populations. As much as such events can be associated with climate change, the specific impact of climate change on individual households can be negative, positive, or neutral. Some gain due to the shifts in the average climate, while others lose out (Antle 2011). Thus, climate change will affect different areas and farmers differently due to heterogeneities in their characteristics.

As argued by Saka et al. (2013), the variation in Malawi's landscape has resulted in wide spatial differences in climates, hence the likelihood of qualitatively different impacts of climate change on farmers across Malawi. Area-specific analyses of the impact of climate change are required. Such subnational studies recognize that the impact of future climate change in Malawi is likely to be manifest differently in different agro-ecological zones. For example, Saka et al. (2013) consider the implications of two climate futures for maize yields in Malawi to 2050. The researchers found that maize yields are expected to increase by between 5 and 25 percent in the Northern and Central regions, while the Southern region is expected to experience maize yield declines. Such a finding highlights the need for contextualized or agroecologically specific studies of climate change impacts in order to identify locally-specific, best-bet adaptation packages that can work to respond to such impacts. Without such context-specific studies, "one-size-fits-all" policies and interventions may be recommended in response to climate change irrespective of expected impacts. This may exacerbate climate-related factors that threaten poverty eradication efforts in rural Malawi (De Wit & Stankiewicz 2006; IISD 2007).

While many policy studies have attempted to provide information on the impacts of climate change in Malawi, most of these reported on the historic or *ex post* impacts. Most concentrated on the impact of past droughts and floods (extreme events) on food and crop production while neglecting the potential impacts of future climate changes and their effects on adaptation strategies (Aggarwal et al. 2010; Akpalu et al. 2008; Hassan and Nhemachena 2008). While such historical analyses may be necessary to help design adaptation measures, examining how future climates may unfold and analyzing their potential impacts on current systems is crucial for effective mitigation, disaster preparedness, and adaptive technology development in readiness for future possibilities. Such future-oriented studies are not only critical to providing policy direction, but also to identify the sections of the population whose livelihoods may be significantly affected by climate change, whether positively or negatively.

Except for studies by Arndt et al. (2010) and Saka et al. (2013) that looked at the possible implications of future climate change on crop productivity and economic growth in the three regions of Malawi, no study has looked at the interactions of future climate change and smallholder sub-systems. There is scanty information on how resilient or vulnerable mixed farming systems in Malawi are to climate change. Nor has there been any enquiry into how different adaptation alternatives can help reduce or enhance the impact of climate change. Given these gaps in the research literature, this study seeks to assess the incidence and potential impacts of climate change on farmers within a mixed farming system context and to compare the different effects of climate change on crop-livestock integrating and on non-integrating households, respectively. Crop-livestock integration has been identified as one of the most important climate change adaptation strategies within agriculture, as it helps to diversify livelihood options and to spread climate change-related risks (Mendelsohn & Seo 2007).

We postulate that crop-livestock integration, also known as mixed farming, can increase resilience to the effects of climate change for farming households, and, secondly, that integrated farmers in Malawi will realize greater gains from the positive benefits of climate change than will non-integrated farmers. Mendelsohn & Seo show that mixed farmers in Africa will be adversely affected in the future by climate change, but less so than farmers engaged in crop only or livestock only farming systems. This article builds on this premise and endeavors to assess the climate change impacts on integrated and non-integrated farmers in Mzimba district in northern Malawi. Mixed farming is the dominant production system among farmers in Mzimba district, as livestock holds very important social, dietary, and economic value dimensions. We extend our study to quantify the potential deviations in yields, net farm earnings, and per capita incomes and the implications of these changes on household poverty under a future climate change environment. Lastly, the study provides policy implications and recommendations for future policy formulation and additional research.

Currently, Malawi does not have a national climate change policy in place, although a draft policy has been prepared (Saka et al. 2013). An *ex ante* evaluation of plausible future climate change impacts will contribute to better understanding and identifying potential points of policy intervention to manage future changes and risks under climate change. From the results of such analyses, policymakers will have a more informed basis upon which to plan adaptive interventions to build or maintain poor farmers' resilience to climate change and variability.

This article has three objectives: to assess the likely future incidence and extent of climate change in Mzimba district; to estimate its impacts on maize productivity; and, finally, to investigate the potential implications of climate change on incomes and income poverty in the period from 2040 to 2070.

The paper is organized as follows: Section 2 presents the methodology employed and describes the modelling framework and the biophysical and economic models used for the study. Section 3 provides a discussion of selected model findings. Lastly, section 4 provides the conclusions from the study and recommendations for policy and future research.

2. METHODOLOGY

2.1. Study area

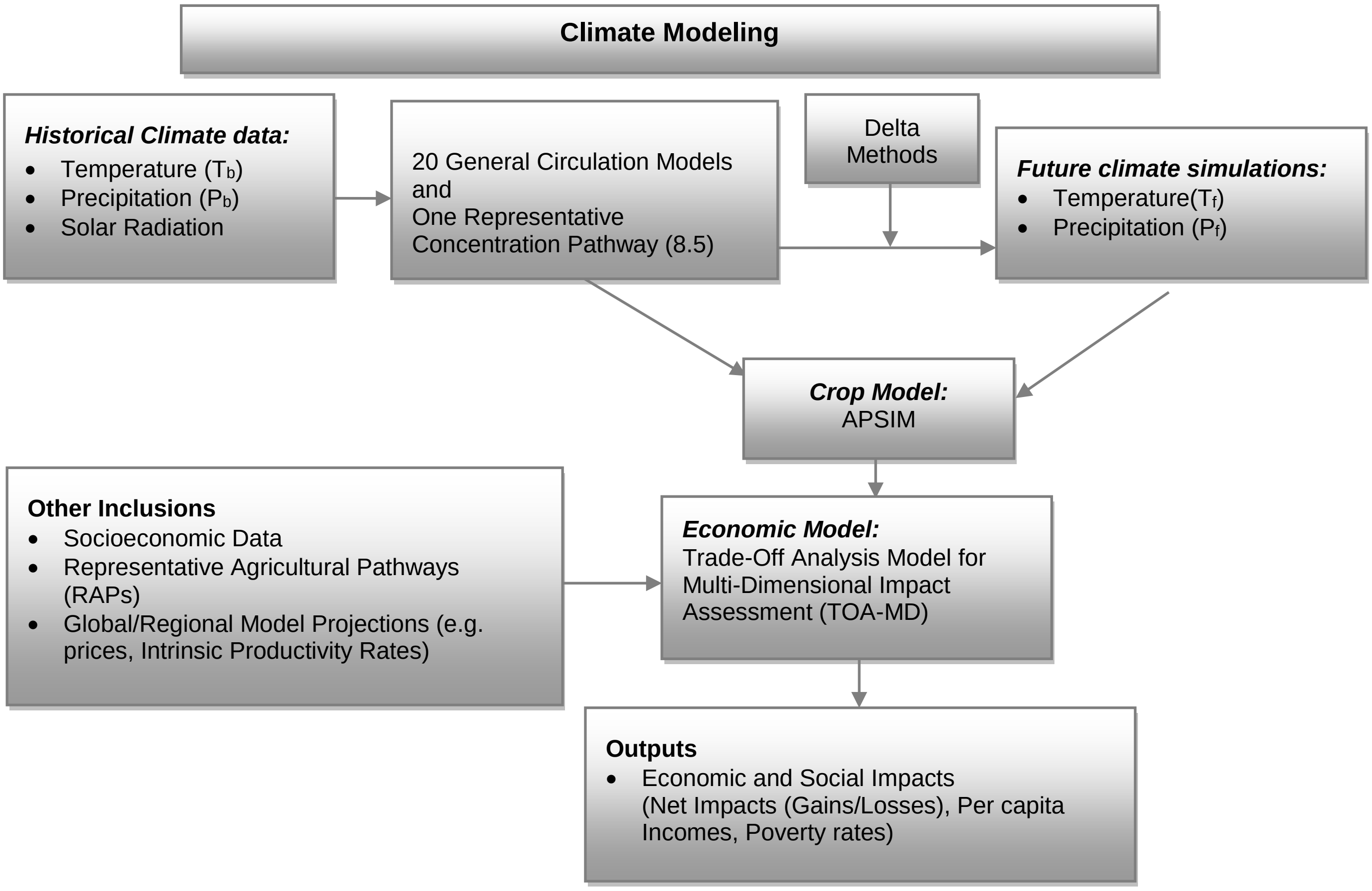
This study focused on Mzimba district in northern Malawi. Mzimba district is the largest district in the country. It has an estimated population of 870,000 and a population density of 70 persons per square kilometer (lower than the average national population density of 139 persons per square kilometer). The district is covered mainly with medium to light textured but moderately fertile soils with eutric-fersialic soil characteristics. The sandy-loam and loamy soils have moderate to good drainage and are suitable for growing tobacco and maize. The district has a warm tropical climate. The average monthly maximum temperature varies from 27°C to 33°C with the month of November being the hottest. The average monthly minimum temperatures range from 0°C to 10°C with June and July (winter season) being the coldest. The mean monthly temperature varies from 15.5°C to 19.8°C. Annual rainfall ranges from 650 to 1300 mm (Mzimba District Planning Department 2008). Although most climate change researchers have focused on extreme weather event-prone areas such as Nsanje, Chikwawa, and Karonga districts where floods and droughts are more common, our choice of Mzimba is motivated by the fact that future climate changes will affect different areas differently. *Ex ante* analysis for

all districts of Malawi are needed to provide a minimum of preparedness for all districts to design policies and programs that are best adapted for responding to a changing climate.

2.2. Climate change impacts modeling: the integrated assessment modeling framework

We employ an integrated assessment multi-modeling approach in which a climate model projects possible climate futures and passes on daily climate data under climate change conditions into a biophysical model (crop-growth model) to estimate crop yields. The crop model yield results enter into an economic model for the final economic assessment. The schema in Figure 1 depicts our modeling framework and data flow. In brief, historical data are obtained and used to simulate future projections for climate change using 20 General Circulation Models (GCMs, also known as Global Climate Models).[1] Future changes in the simulations are used to adjust the base series using a delta approach in order to impose a future distribution of climate across the GCMs. Daily simulated climate data under climate change conditions are used in a crop growth model to simulate crop productivity. The yields from the crop growth model are used in the economic model for an economic impact assessment. Socioeconomic data, socio-economic trends, and global and regional model projections are all inputs into the economic model to simulate farm returns, per capita incomes, and income poverty under climate change conditions. Further details of the modeling work are described in subsequent sections of this paper.

Figure 1—General modeling framework for analysis



2.3. Measuring future climate change

Modeling future climate change is a complex process which requires sophisticated tools and methods in order to cultivate a realistic representation of the future climate from what is known now. We downscaled 20 General Circulation Models to provide a representation of plausible future climates for the study site.

HISTORICAL DATASETS

The study acquired and utilized historical daily weather records covering the period 1980-2010 from the Department of Climate Change and Meteorological Services of the government of Malawi to structure the historical reference patterns for key variables of temperature and precipitation. Crop models require complete daily datasets. Consequently, every

[1] General Circulation Models are spatial numerical models representing physical processes in the atmosphere, ocean, cryosphere, and land surface and are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentration (IPCC 2014). Details at http://www.ipcc-data.org/guidelines/pages/gcm_guide.html.

historical dataset was patched for any missing values. The missing records were supplemented and filled using the best approximate AgMERRA[2] dataset available from the Agricultural Model Intercomparison and Improvement Project (AgMIP) to complete the series. Data on baseline solar radiation and potential evapotranspiration (ETo) were estimated at a daily time step relying on temperatures, latitude, and altitude in order to maintain inter-variable consistency.

FUTURE CLIMATE SCENARIOS PRODUCTION AND ASSUMPTIONS

In recognition of the uncertainty associated with future climates, to generate a plausible future climate for Mzimba district we used an ensemble of 20 downscaled GCMs and one Representative Concentration Pathway[3] (RCPs) based on the Coupled Model Intercomparison Project Phase 5 (CMIP-5) [4] from the Intergovernmental Panel for Climate Change (IPCC) Fifth Assessment Report (AR5). CMIP5 delta climate scenarios were created based on historical climate data with each day's weather variables perturbed using changes in climate model outputs for future time periods (2040-2070) (AgMIP 2013). The delta approach imposes a change factor from future simulated climates across the GCMs onto the base period climate series and produces distributions that are not very far from the baseline but display the expected deviations from the base observed in the climate model outputs. Table 1 lists the 20 GCMs used for the climate scenarios.

Table 1—List of Global Circulation Models used for simulations of future climate for Mzimba district

CMIP 5 Scenario ID	GCM Name	CMIP 5 Scenario ID	GCM Name	CMIP 5 Scenario ID	GCM Name
A	ACCESS1-0	H	GFDL-ESM2G	**O**	**MIROC5**
B	bcc-csm1-1	**I**	**GFDL-ESM2M**	P	MIROC-ESM
C	BNU-ESM	J	HadGEM2-CC	Q	MPI-ESM-LR
D	CanESM2	**K**	**HadGEM2-ES**	**R**	**MPI-ESM-MR**
E	**CCSM4**	L	inmcm4	S	MRI-CGCM3
F	CESM1-BGC	M	IPSL-CM5A-LR	T	NorESM1-M
G	CSIRO-Mk3-6-0	N	IPSL-CM5A-MR		

Note: The GCMs in bold are the five selected for the impact economic impact assessments.

Out of the 20 GCMs used in the climate analysis, only five GCMs in the mid-century (2040-2069) time period were used in the crop and economic impact assessment. The five GCMs – CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5 and MPI-ESM-MR – were selected for their rigor of processes and resolution, their being widely used in recent assessments, and their performance in monsoon regions (AgMIP 2013). Moreover, as this work was part of a model inter-comparison and improvement project that uses harmonized approaches, the choice of the five GCM models was done *a priori* in order to permit comparisons with other regions implementing different studies, but applying the same methods as ours. Unlike in forecasting studies or near-term studies that look to project from the current time-period into the near future e.g. 2010-2020 or 2010-2050, it is common practice in future climate change studies to look at impacts based on future time slices. Our study produced three time slices for future climate scenarios: near-term (2010-2040), mid-century (2040-2070), and end-of-century (2070-2100). The focus of this paper is on results for the mid-century period. As climate is a long term phenomenon (30-50 years), the mid-century period (2040-2070) also provides a period long enough to observe critical changes in climate.

In order to simulate maize yields for future periods of the projected climates, the Agricultural Production Systems Simulator (APSIM) model was used. This crop model was developed by the APSIM Initiative in Australia. It simulates biophysical processes in agricultural systems, including in the face of climate changes.[5] Calibrated using data from experiments conducted by the Ministry of Agriculture and Food Security in Njuyu EPA in 2012, APSIM simulated future yields for maize. The data acquired and utilized in the calibration included soil and crop management data such as planting dates, fertilizer application (type, quantities applied and dates of application), dates of weeding and harvesting, and production per unit area, among others. After calibration, general circulation model projections were then used as the daily weather input to simulate potential maize productivity under alternative climate futures relative to the historical climate environment in the APSIM model.

However, due to lack of complete data for other crops and livestock, the study did not simulate their future production. Instead, projected (intrinsic) productivity growth rates and expected price trends from other regional integrated

[2] AgMERRA is the AgMIP climate forcing dataset based on the NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA). It corrects gridded temperature and precipitation, incorporates satellite precipitation, and replaces solar radiation with NASA/GEWEX SRB to cover the 1980-2010 period. See http://data.giss.nasa.gov/impacts/agmipcf/agmerra/ and http://www.agmip.org/ for details.

[3] RCPs are scenarios designed to help climate modelers explore the range of potential future greenhouse emissions and concentration pathways (van Vuuren et al. 2011).

[4] See www.ipcc.org

[5] Detailed information available at www.apsim.info

assessment model projects and expert opinions were used to estimate the most reasonable possible future yields and price trends in the period under study. The study benefitted from the work of Ringler et al. (2010) and Nelson et al. (2010), which helped align the un-modelled agricultural enterprises to possible future levels. The intrinsic productivity growth rate for cereals was pegged at 1.57 percent per annum, whereas other crop activities were adjusted by an average of 30 percent to the end of the mid-century period. Costs and prices for cereals and other crops were adjusted at 30 percent and 35 percent above base period, respectively. We did not take into consideration the effects of irrigation, which may significantly increase production per farmer per year. The effect of expansion in land allocated to crops also was not considered (land area kept constant), as studies indicate that either land expansion will remain almost the same (Saka et al. 2013) or the contribution of crop area expansion to yield growth will marginally contract in Southern Africa by 2050 (Ringler et al. 2010).

2.4. Measuring potential economic impacts of future climate change: Theoretical and analytical considerations

Climate change impacts on farmers are either positive or negative. Farmers' perceptions of climate change trigger action on their part to cushion or reduce the expected negative shocks brought about by climate change, while they act to derive maximum benefits from any positive shocks associated with climate change. We utilize the Trade-Off Analysis model for Multi-Dimensional Impact Assessment (TOA-MD) framework to analyze the economic impacts of climate change (Antle and Valdivia 2010). In this framework, farmers are postulated to be economically rational, and they make decisions to maximize their expected income The decision to engage in a particular activity in a given production system is informed by their expected income assessments. Farmers will, thus, choose a production system to maximize a function, v(*h*), where *h*=1, 2 indexes the production system and all attributes associated with it, including climate, prices and other factors affecting adoption of a system, such as institutions, geography, and infrastructure (Antle and Valdivia 2006). The farmers are presented with a simple binary choice: to continue producing in the current production system, *h=1* or to switch to an alternative system, *h=2* to maximize the function *v(h)*, which is assumed to be their returns.

In our climate change context, we treat farmers as operating a base technology under a base climate under specified socioeconomic conditions (Antle 2011). Assuming that there is climate change, *ceteris paribus,* farmers will act to enhance their resilience to impending negative effects (or expected shocks) associated with climate change. They choose to operate within a system that can potentially withstand certain climatic threats. Thus, we define a system as a pair *r k,* where *r* = (B, A) indexes the base and future (adapted)[6] technologies and *k* = (B, P) indexes the base and perturbed climates. Smallholder farmers, being heterogeneous, make decisions and choices differently based on the intensity of the climate change impacts. Changes in climate, thus, may increase returns to some farmers while reducing returns to others. There are both gains and losses and thus, all farmers are not necessarily adversely impacted (Claessens et al. 2012; Antle and Stoorvogel 2008; Claessens et al. 2009.). They can choose to adapt or not, conditional on whether they are better-off or worse-off with climate change. In this analysis, we assumed that the production technology and the environment (climate) within which a production system operates affects a system's productivity. Climate parameters are central to the productivity of a production system.

Following Antle (2011) and Claessens et al., (2012), we consider a farmer *j* at site *s* using production system *h* that gives returns per unit per time *t*, $v_t = v_t(s,h)$ for a given price and product price vector, *P.* Given *T* time periods and a relevant discount factor, δ_t, a system *h* would provide a discounted net return as:

$$V(s,h) = \sum \delta_t v_t(s,h) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Since the net returns from one system is a function of its technology and environment (climate), any changes in climate would also lead to changes in the expected returns for that farmer. Thus, the effect on farmer *j*'s returns operating under a new system *k*, e.g. new climate, from the initial system *r*, current climate, is:

$$\omega(s,r,k) = V(s,r) - V(s,k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

In essence, $\omega(s,r,k) > 0$ is the opportunity costs with climate change, whereas $\omega(s,r,k) < 0$ is the gain in net returns with a change to the current climate (system *r*). The distribution of the gains and losses in net returns in the farming population can be represented by the density function $\varphi(\omega|r,k)$. The area under the density function up to a given threshold amount, α, therefore represents the proportion of farmers that obtain returns less than or equal to α. Thus, the percentage of farmers that gain with climate change, i.e., $\omega(s, r, k) < \alpha$, would be given by:

[6] An adapted technology would refer to conscious adjustments to the current production technology in response to climate change.

$$\tau(\alpha, r, k) = 100\int_{-\infty}^{\alpha}\varphi(\omega|r,k)d\omega \qquad 0 \le \tau(\alpha) \le 1 \dots\dots\dots\dots (3)$$

As discussed, in the context of known climate change, we define system 1 as a case in which the current climate parameters and the production technology prevail. With a change in climate, farmers are forced to operate in a new system, but they are presented with a binary choice of whether to adapt or not. If farmers choose to operate in the new climate system but without adaptation, $\tau(\alpha, r, k)$ would represent the proportion of farmers whose losses are below α i.e. $(\omega|r,k) < \alpha$. In this case and letting $\alpha = 0, \tau(0,1,2)$ is the proportion of farmers gaining or positively impacted by the changed climate, whereas $1 - \tau(0,1,2)$ is the proportion of farmers that lose from climate change. If $\alpha > 0$, $\tau(\alpha, 1,2) - \tau(0,1,2)$ is the proportion of farmers with losses between zero and α, and if $\alpha < 0, \tau(0,1,2) - \tau(\alpha, 1,2)$.

In the case where farmers have felt the incidence of climate change and they choose to adapt, system 2 will be characterized by a new technology in a different climate context. The decision to choose to adapt will be informed by the expected returns (or opportunity cost) from the production technology choice of the farmers under the changed climates.

DERIVING THE OPPORTUNITY COST

As noted, the adoption choice of farmers or their conscious decision to switch to use a new technology in a new production system is basically based on opportunity cost. The opportunity cost of switching to a new technology due to climate change will come with its associated variable and fixed costs that the farmer initially did not need to meet. Thus, with time period, T; a relevant discount factor, δ_t; a periodic (e.g. annual) cost of adopting or using the new production technology, a_t, and a fixed cost associated with the technology in system 2 (changed climate and technology), F, the net present value of the returns becomes:

$$V(s,2) = \sum_{t=1}^{T}\delta_t(v_t(s,2) - a_t) - F \dots\dots\dots\dots (4)$$

Therefore, the opportunity cost with an adaptation technology adopted becomes:

$$\omega(s) = V(s,1) - V(s,2) = \sum_{t=1}^{T}\delta_t\{(v_t(s,1) - v_t(s,2) + a_t\} + F = \sum_{t=1}^{T}\delta_t\omega_t + F \dots\dots (5)$$

The difference in returns (or the opportunity cost of switching), ω_t is assumed to be independently and normally distributed over time, thus:

$$\omega_t = \mu_{1t} - \mu_{2t} + \sigma_{\omega_t}\varepsilon \qquad \varepsilon \sim N(0,1) \dots\dots\dots\dots (6)$$

$$\sigma_{\omega_t}^2 = \sigma_{1t}^2 + \sigma_{2t}^2 - 2\sigma_{12t} \dots\dots\dots\dots (7)$$

Where μ_{ht} (for all $h = 1, 2$), μ_{ht} and σ_{ht}^2 are the means and variance of v_t *(s, h)* v_t *(p, s, h)*, and σ_{12t}^2 is the covariance between $v_t(s,1)$ and $v_t(s,2)$.

From (5), (6) and (7), we get

$$\omega = \sum_{t=1}^{T}\delta_t\omega_t + F = \sum_{t=1}^{T}\delta_t\{\mu_{1t} - \mu_{2t} + \sigma_{\omega_t}\varepsilon\} + F = \mu_1 - \mu_2 + \sigma_\omega\varepsilon \dots\dots\dots\dots (7)$$

Where $\mu_1 = \sum_{t=1}^{T}\delta_t\mu_{1t}$, $\mu_2 = \sum_{t=1}^{T}\delta_t\mu_{2t} - F$, and $\sigma_\omega = \sum_{t=1}^{T}\delta_t\sigma_\omega$

The farmer will also adopt an adaptation technology if the differences in net returns are beyond a threshold value α. Thus, $\omega(s,r,k) = V(s,1) - V(s,2) < \alpha$, implying that $V(s,1) < V(s,2) + \alpha$. Equation 3 now can be taken to be the adoption rate or the percentage of farmers that adopt a given adaptive technology (conditional on $\omega < 0 \; or \; \omega > 0$).

Using the adoption rate estimation, the TOA-MD model quantifies social, environmental, and economic outcome variables, identified as *z*(*h*) (Carleton 2012; Antle & Valdivia 2006). Since many outcomes of interest in the farm are

affected by the same factors that influence net returns, $z(h)$ and $v(h)$ must be jointly distributed. We therefore can use the joint distributions to generate heterogeneous outcome distributions for adopters, non-adopters, and the entire farmer population upon introduction of System 2.

The marginal distribution of an outcome variable, given the production system h, is defined as $\phi(k|h)$, where $k = v, z$. Antle (2011) demonstrates that the joint distribution of ω and the outcome $k = v, z$ in a population using both systems is a mixture of the distributions $\phi(k|h)$ under each system $h = 1, 2$ based on the proportion of adopters, r(2, a) and non-adopters, r(1, *a*). Given the production system h and conditional on the adoption threshold α, the outcome distribution for outcome k, defines $\chi(k|h, a)$ by integrating the distribution for System 1 over the interval $\omega > a$ and over $\omega < a$ for System 2. In this regard, $\chi(k|a)$ is the outcome distribution for the entire population, contingent on the threshold, α and the proportions of r(2, *a*) and r(1, *a*).

In economic analysis of producer welfare, net returns are sometimes referred to as the firm's producer surplus, and the change in producer surplus is used as a measure of the change in economic welfare of the firm. Thus, when systems r and k represent a change in climate, $\omega(s,r,k)$ measures the change in producer surplus associated with climate change. Since $\tau(\alpha,r,k)$ gives the percentage of farmers earning losses less than or equal to α, we can invert $\tau(\alpha,r,k)$ to obtain the function $\alpha(\tau,r,k)$ (Claessens 2012). This function tells us that τ percent of the population has losses less than or equal to α. The area under this function over an interval between 0 and 100 percent measures the change in producer surplus associated with that segment of the population. Thus:

$$PS(\tau_1, \tau_2, r, k) = \int_{\tau_1}^{\tau_2} \alpha(\tau, r, k)\, d\tau \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Setting $\tau_0 \equiv \tau(0, r, k)$, gainers will be better off by $PS(0, \tau_0, r, k)$, and losers will be worse off by $PS(\tau_0, 1, r, k)$. The total net gains or loss will be given by:

$$PS(0,1,r,k) = PS(0, \tau_0, r, k) + PS(\tau_0, 1, r, k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (9)$$

Overall vulnerability to climate change will, therefore, be measured by the proportion of farmers made worse off relative to a defined threshold, such as the poverty line (Antle et al. 2010).

3. RESULTS AND DISCUSSION

Here the key findings from the study are presented. The next section describes and discusses the results of the climate models for the future period (2040-2070) relative to observed historical patterns. Impacts of the resultant climate projections on crop productivity then are discussed, followed by a discussion of the economic impacts of future climate change. Terms such as 'historical,' 'current,' 'base' and 'baseline' period all refer to the same period of 1980-2010 which is our basis for comparison and measuring change.

3.1. Future climate incidence and GCM inter-comparison for 2040-2070

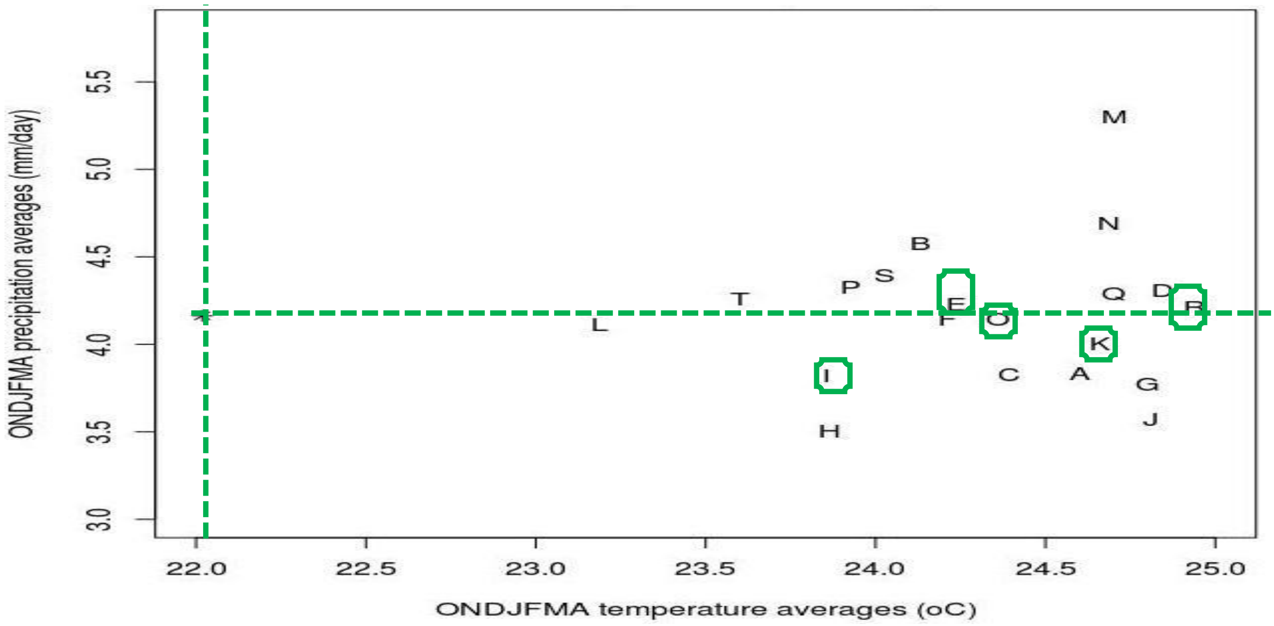
The following section presents the results from the climate models. Note that the results in subsequent subsections show results for all 20 GCMs first and later selects the 5 GCMs that have been used in the impact assessments. At this point, our approach only considers delta-based GCM projections in the future mid-century period (2040-2070) compared to the current base period (1980-2010).

TEMPERATURE CHANGE ACROSS GCMS

Evidence from the ensemble of 20 General Circulation Models under RCP 8.5[7] for Mzimba indicates potential increases in temperature in the future. Figure 2 shows that all 20 GCMs predict a warmer future with mean temperature increases ranging between +1°C and +3°C relative to base conditions (22°C) for the October to April season. Model INMCM4 (GCM L) predicts the lowest increase in the mean temperature, whereas model MPI-ESM-MR (GCM R) predicts the highest increase in the ensemble of models. The results agree with findings by Arndt et al. (2010) and Saka et al. (2013) who predicted expected rises of about 1.75°C and between 1°C and 3°C, respectively.

[7] Representative Concentration Pathway 8.5 (RCP 8.5) scenario assumes high population growth, more or less unabated emissions (no climate policy), 550 ppm carbon concentration, and uses the highest radiative forcing (8.5Watts/m^2) and of all the RCPs (Riahi et al. 2007; Moss et al. 2010).

Figure 2—Temperature and precipitation distributions for 20 GCMs under RCP 8.5

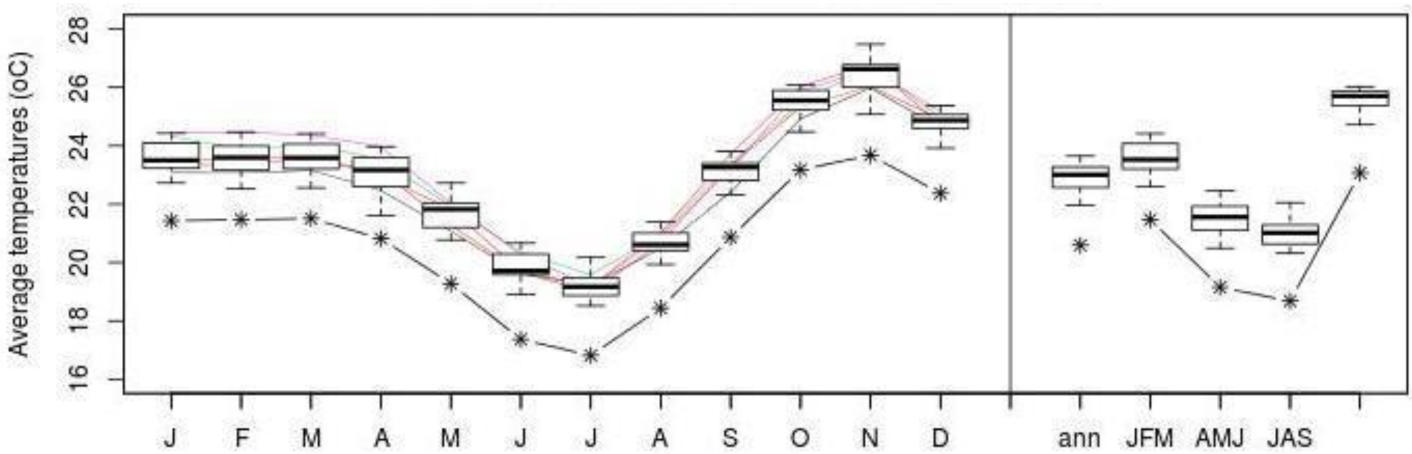


Source: Results from climate simulations

Note: The encircled GCMs (E, I, K, O, R) are used in the impact analysis. The dashed lines indicate current baseline temperature and precipitation averages.

Future rising temperatures (Figure 3) are reflected in the mean monthly, seasonal and annual temperature estimates. A close examination of the graphs reveals that major shifts in mean monthly temperature are predicted to occur in the months of May and November. For seasonal (quarterly) temperatures, the highest increase is depicted to occur during the October, November and December (OND) period. However, different general circulation models show varied level of increase for all months, as shown by the box plots and the superimposed GCM schedules on each data point.

Figure 3—Mean temperature distributions for 20 GCMs relative to baseline conditions



Source: Results from climate simulations

Note: The graph at left shows predicted average monthly temperature, while the graph at right presents predicted annual (ann) and seasonal (Jan-Mar, Apr-Jun, Jul-Sep and Oct-Dec) average temperature. Box and whisker plots identify how the 20 GCMs are spread on the temperature prediction space above the base-period (baseline: 1980-2010). Boxes show the median, 25th and 75th percentiles, whereas the whiskers are endpoints. Stars (*) are baseline period (1980-2010) average temperatures.

Projected changes in the minimum and maximum temperature changes are shown in Table 2. In terms of maximum temperatures, the average for the five selected GCMs is predicted at 28.7°C with temperatures ranging from an average minimum of 25.8°C to an average maximum of 32.6°C. UK's Hadley Centre for Climate Prediction and Research's general circulation model, HadGEM2-ES, projects the highest increase in average maximum temperature from 26.2°C during the historical (base) period to 29.2°C in the future period, whereas MPI-ESM-MR predicts the highest increase in the average minimum temperatures (from 15.0°C to 17.8°C).

Table 2—Projected minimum and maximum temperatures

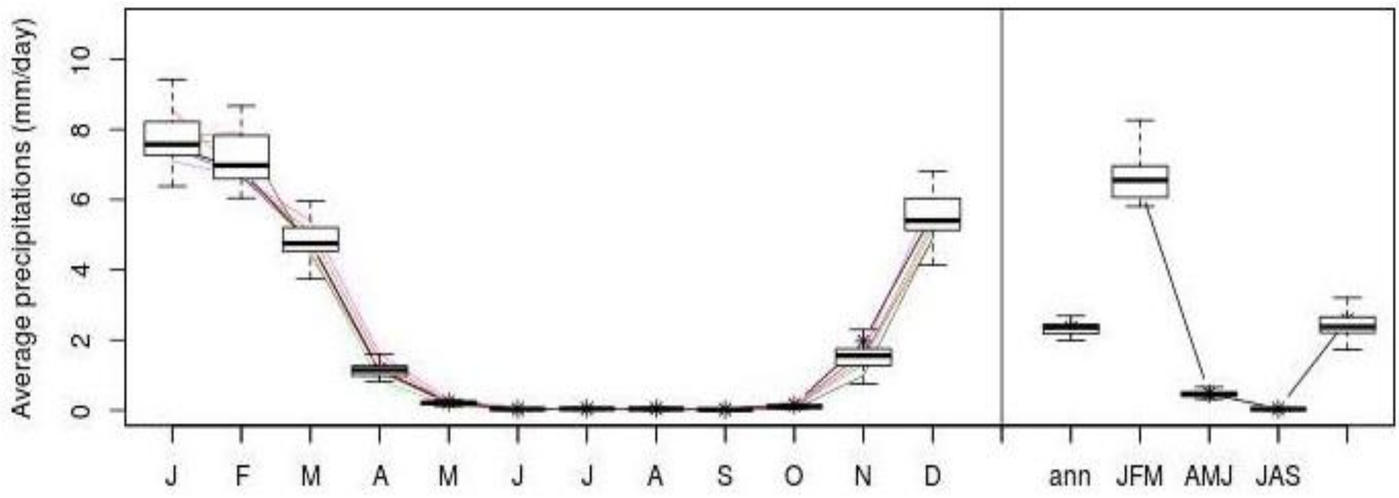
Name of Model	Maximum Temperatures				Minimum Temperatures			
	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max
Base Period	*26.2*	*1.95*	*23.2*	*29.5*	*15.0*	*2.61*	*10.4*	*17.9*
CCSM4 (E)	28.5	2.02	25.3	32.0	17.1	2.59	12.6	20.1
GFDL-ESM2M (I)	28.2	2.05	25.8	32.4	16.8	2.44	12.6	19.6
HadGEM2-ES (K)	29.2	2.00	26.4	33.4	17.3	2.64	12.7	20.1
MIROC5 (O)	28.8	2.27	25.6	33.0	17.2	2.58	12.7	20.6
MPI-ESM-MR (R)	29.0	2.07	25.6	32.6	17.8	2.71	12.7	20.7
Mean of 5 GCMs	28.7	2.06	25.8	32.6	17.2	2.58	12.7	20.2

Source: Model Results

PRECIPITATION CHANGE ACROSS GCMS

As is frequently observed in climate change integrated modeling, precipitation projections tend to be more uncertain and varied than are temperature projections (for example, see Saka et al. 2013; Solomon et al. 2007; Arndt et al. 2010; Hachigonta et al. 2013). Our precipitation results reveal uncertainty across the GCMs. A slight majority of the GCMs considered indicates a marginal decline in precipitation in the future period relative to the current baseline period. From Figure 2, mean precipitation is predicted to range between 3.5 mm/day and 5.5 mm/day among the 20 GCMs, compared to about 4.2 mm/day in the historical period. Conditions are predicted to be slightly wetter during the months of January, February, and March as median mean precipitation of the 20 GCMs for this period of the year is seen to slightly increase above the historical level (Figure 4). November and December are predicted to be drier than the historical median precipitation. In essence, we observe a marginal decline at the beginning of the crop growing season and an incremental increase during the critical crop growing period.

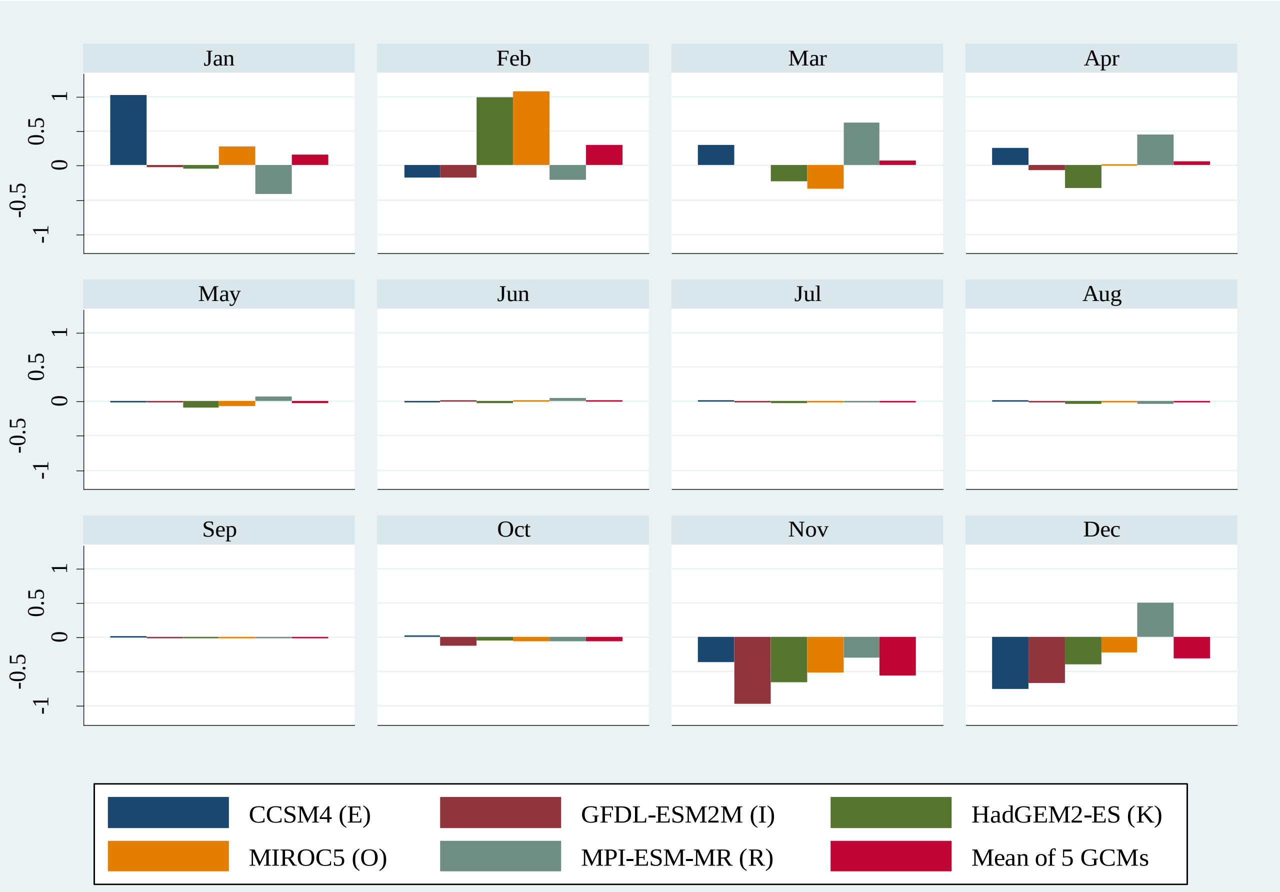
Figure 4—Precipitation projections distributions for 20 GCMs under RCP8.5



Note: Lines depict the estimated precipitation for the five selected GCMs. The stars (*) represent base-period conditions. Note that in some months or seasons, base conditions are anticipated to prevail in the future period (no significant change), e.g. May, June, July. Hence, the stars (*) may be masked by the box-whiskers.

Projections from the five GCMs that were selected for the impact assessment are consistent with the estimates from the ensemble of 20 GCMs. In Figure 5, except for the MPI-ESM-MR model, all the models show a slightly drier (lower rainfall) than the base (historical) period at the onset of the rainy season in November and December (GCMs projecting a decrease in the precipitation). This signal would suggest a delayed rain onset, hence a shortening of the rainy season since no delayed cessation is suggested. The result agrees with USAID (2013), which predicts declining rainfall during December. Such a future has crucial implications for farmers, including that planting dates for crops may shift later.

Figure 5—Predicted monthly precipitation deviations from historical mean for five GCMs used in impact analysis, mm/day



TOTAL ANNUAL PRECIPITATION PREDICTED BY THE FIVE SELECTED GCMS

Generally, most of the five selected GCMs project a drier future relative to the current period (Table 3). Two GCMs, I and K, show a negative percentage change, indicating a drier future (7.3 percent and 3.4 percent, respectively), while the rest depict a modestly wetter future of between 0.3 percent and 2.1 percent above historical precipitation patterns. Averaging the five GCMs, the mean prediction entails that Mzimba district will likely experience a 1.4 percent decline in rainfall to 2070. However, in common with many studies of future precipitation patterns under climate change, we cannot imply any certainty to this occurrence.

Table 3—Percentage change in mean annual precipitation for future period from base period

GCM Name	Deviation from baseline	Standard Deviation	Minimum	Maximum
Base Period	858.1 mm	148.01 mm	606.3 mm	1339.4 mm
CCSM4 (E)	1.1 %	2.4 %	-3.3 %	5.5 %
GFDL-ESM2M (I)	-7.3 %	3.4 %	-18.8 %	-2.3 %
HadGEM2-ES (K)	-3.4 %	3.1 %	-10.1 %	2.7 %
MIROC5 (O)	0.3 %	2.7 %	-6.6 %	6.0 %
MPI-ESM-MR (R)	2.1 %	2.6 %	-3.9 %	7.7 %
Mean for 5 GCMs	-1.4 %	2.2 %	-8.5 %	1.8 %

Source: Results from climate simulations.

Note: Deviations from baseline are predicted percentage changes in annual precipitation for 2040-2070 as a percentage of the mean annual precipitation in the current period (1980-2010).

However, over time the series reveal a declining trend in seasonal and annual precipitation. Farmers in Mzimba are likely to face the lowest rainfall patterns at the end of the mid-century period towards 2070 where annual precipitation trend has a clear negative slope. However, this result differs from the Northern region assessments reported in Saka et

al. (2013) using A1B[8] greenhouse gas emission scenarios which predict an increase in mean annual precipitation of 50-100 millimeters by 2050. Our study, however, uses the Representative Concentration Pathway 8.5 (RCP 8.5) which is the worst case scenario that assumes high population growth, more or less unabated emissions (no climate policy), a 550 ppm carbon concentration, and uses the highest radiative forcing[9] (8.5Watts/m^2) of all the RCPs (Riahi et al. 2007; Moss et al. 2010; van Vuuren et al. 2011). The RCP 8.5 is a scenario that provides an extreme of future projections, as it embodies the most pessimistic case associated with present rates of emissions of greenhouse gases and no mitigation. This scenario provides an estimate of temperature and rainfall conditions if nothing is done, i.e. without forcing an intermediate limit to greenhouse gas emissions.

3.2. Impact on maize productivity

As noted, the results of five of the climate models from the 20 initially considered were used as climate data input to the biophysical model, APSIM, in order to assess the implications of climate change on crop productivity. This section focuses on the impact of climate change in the future period on maize yields among both integrating and non-integrating farmers.

Table 4 reports the impact of climate change on maize yields among integrating and non-integrating farmers across different GCM climate projections. The APSIM results indicate that all models predict a brighter future for both integrating and non-integrating farmers, as mean maize yields are expected to be higher in future. Average mean yields for all GCMs in the future period is expected to be 2094 kg/ha, against a baseline yield of 2060 kg/ha in the historical period. The average mean for integrating farmers is significantly lower than the average for non-integrating households by one percent. However, the percentage change in median average yields is higher among integrating households (2.6 percent) than among non-integrating households (1.2 percent). The HadGEM2-ES GCM predicts the highest future yield for all farmers, whereas MIROC5 predicts the lowest yield per farmer for the future.

Table 4—Comparison of mean maize yields between current and future period, kg/ha

	Non-integrating farmers		Integrating farmers		All farmers	
GCM Name	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Base period	2,137	1,148.1	1,958	1,075.7	2,060	1,121.1
CCSM4 (E)	2,160	1,081.4	2,002	1,018.4	2,092	1,057.7
GFDL-ESM2M (I)	2,164	1,090.0	2,006	1,016.5	2,097	1,061.9
HadGEM2-ES (K)	2,169	1,060.8	2,021	996.8	2,106	1,036.4
MIROC5 (O)	2,145	1,077.8	1,991	1,010.1	2,079	1,052.1
MPI-ESM-MR (R)	2,161	1,065.7	2,012	1,006.6	2,097	1,043.3
5 GCM mean	2,159	1,074.6	2,006	1,008.7	2,094	1,049.5
5 GCM median	2,162	1,075.0	2,009	1,008.4	2,097	1,049.6

Source: APSIM crop model results

VARIATIONS IN MEAN MAIZE YIELDS

There is consistency in the predicted year to year variation in mean yields across all the models and years. As can be seen in Figures 6 and 7, all models agree on variation in year to year mean maize yields and predict a generally positive mean maize yield change. There is declining productivity in the late 2060's for all GCMs. This decline in maize productivity coincides with declining precipitation during the same years. There is declining productivity in the late 2060's for all GCMs. This decline in the annual productivity coincides with the declining precipitation realizations during the same years. Thus negative effects of increased temperatures and declines in precipitation begin to be clearly seen from the 2060's. In terms of relative yields[10] (Figure 7), the distributions decline to below 1.0 after 2060 relative to years prior. This confirms that at the current rate of change of climate without abating greenhouse gas emissions or without farmers properly adapting to the effects of climate change, the long run picture in maize productivity may not be entirely positive.

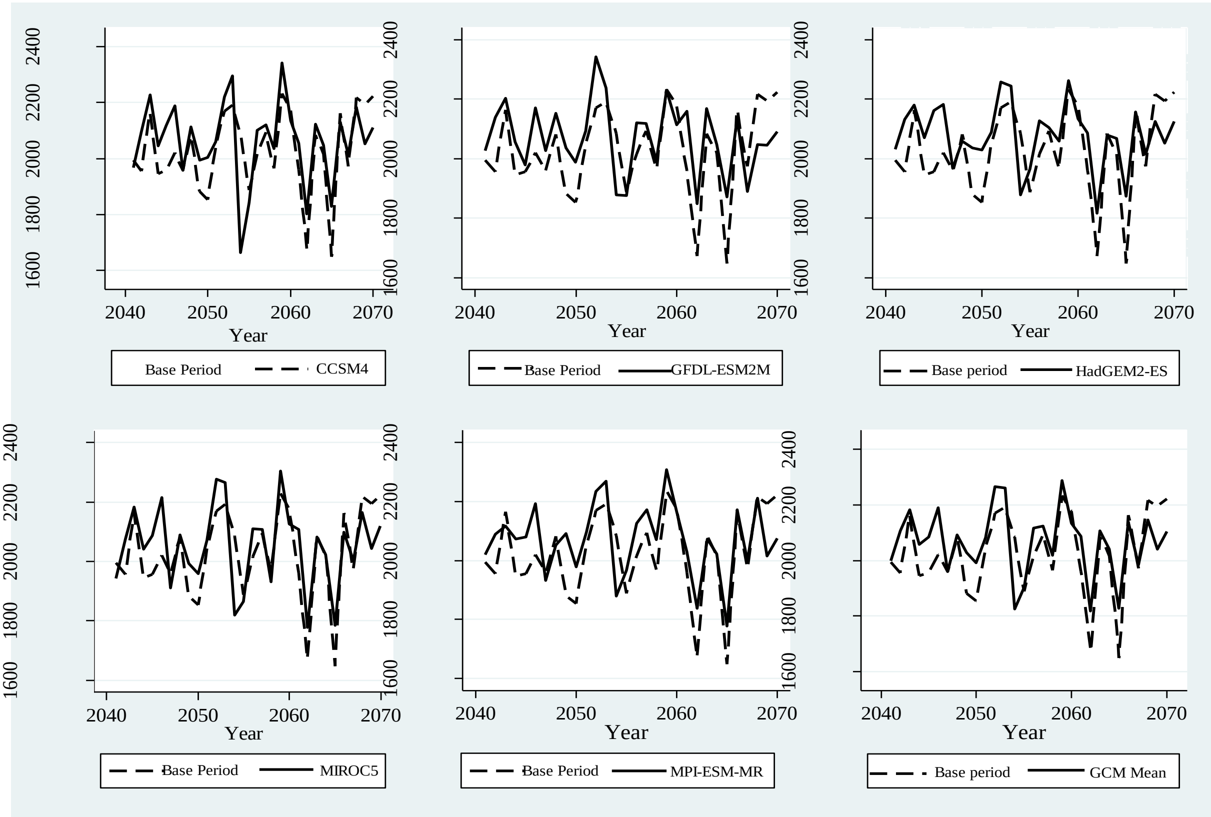
[8]The A1B SRES scenario assumes fast economic growth, a population that peaks mid-century and the development of new and efficient technologies with balanced use of energy sources.

[9]Radiative forcing is a measure of the influence a factor has in altering the balance of incoming and outgoing energy in the earth-atmosphere system and is measured in watts per square meter.

[10] We measure Relative Yield, r_j, as a ratio of average yield simulated under conditions of a future climate and the average yield simulated under conditions of the current climate and this relates the average yields under climate change. It ranges between 0 and infinity. If r_j<1, a system is worse off with climate change as productivity declines, if r_j=1 then climate change does not affect productivity since productivity is indifferent with or without climate change, and lastly, if r_j>1 then climate change improves productivity (yield per hectare) as yield is higher under climate change conditions relative to the current climate conditions. Thus, the relative yield will represent the effects of climate change on productivity. (See AgMIP 2013 for details).

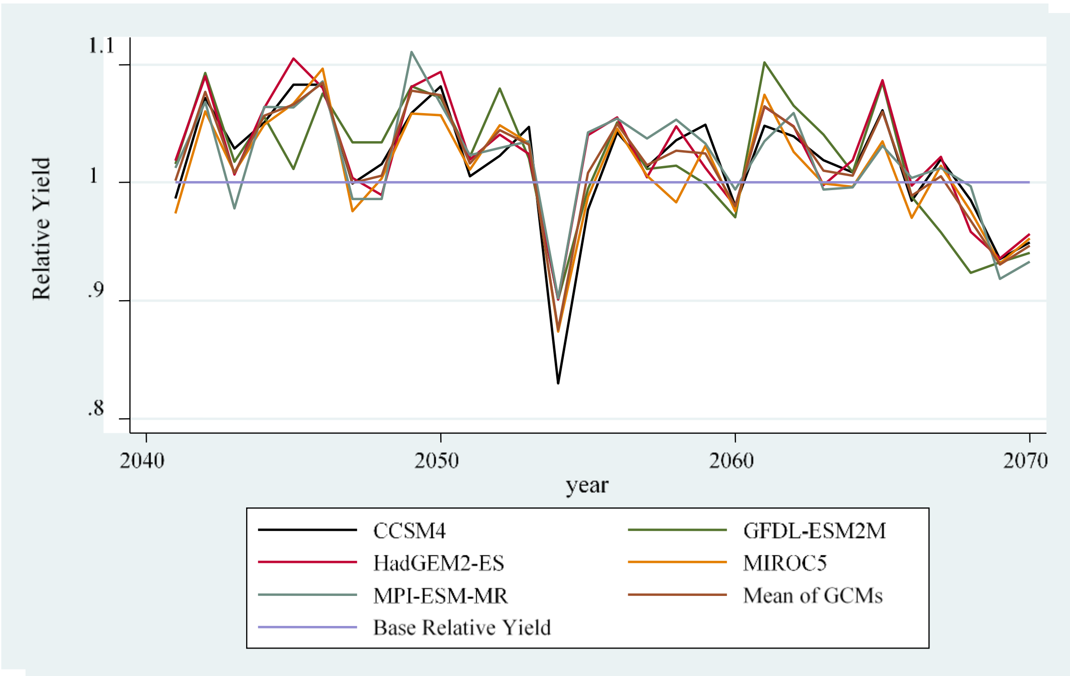
Such declines present a warning message to smallholder farmers in Mzimba to initiate system adaptations to climate change to ensure that the effects of a warmer and drier future do not affect their entire livelihood system.

Figure 6—Predicted maize yield response to climate change by GCM, 2040-2070, kg/ha



Source: APSIM crop model results

Figure 7—Relative yield comparison for base and future period by GCM, 2040-2070



Source: APSIM crop model results

As shown in Table 5, model HadGEM2-ES predicts that, all things being equal, with climate change farmers will gain 15.1 percent above current period mean maize yields. However, there are considerable variations in the changes in yields within the model (CV=100 percent). Wider variations in the period are predicted under the GFDL-ESM2M GCM (12 percent increase in mean maize yields with CV of 108 percent).

Table 5—Mean change and coefficient of variation in mean maize yields under climate change relative to current maize yields by GCM, 2040 -2070, , percent

GCM	Mean Maize Yield Change	Coefficient of variation
CCSM4 (E)	+12.1	83.2
GFDL-ESM2M (I)	+12.0	108.3
HadGEM2-ES (K)	+15.1	100.1
MIROC5 (O)	+10.1	88.0
MPI-ESM-MR (R)	+14.3	90.3

Source: APSIM crop model results

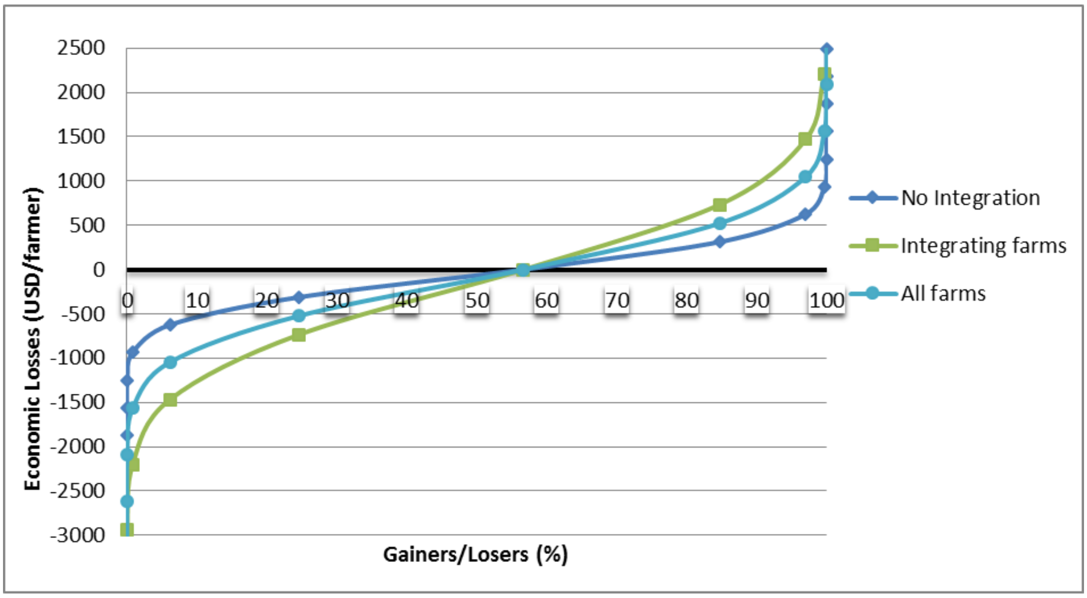
3.3. Economic gainers and losers under future climate change in Mzimba

As explained in the analytical framework, the opportunity cost due to climate change, (ω), in our analysis is used to measure who gains or who loses and the magnitude of their gain or loss. It is measured by the difference in the mean gains between system 1 from the base-period (current production system where there is no climate change) and system 2 from the future period with climate change. System 2 consists of a plausible future production system where climate change is imposed and economic values are estimated for the whole farm using simulated productivity and current socio-economic values adjusted with trends from regional models such as CGE and IMPACT models.

Figure 8 shows the cumulative distribution curves of gainers and losers due to climate change ranked based on their degree of loss or gain. The y-axis represents the economic losses (the opportunity cost), (ω), due to the perturbed climate, whereas the x-axis represents the proportion of the population that is affected. Farm households that gain as a result of climate change have negative losses, while those that lose have positive losses. Where the cumulative distribution curve crosses the x-axis demarcates economic gainers from losers.

About 56 percent of farmers in Mzimba district realize economic gains as a result of climate change in the future period, 2040-2070. About 57 percent of non-integrating farmers gain compared to 55 percent of integrating farmers. Observing the slope of the gain/loss curve, however, the distribution of gains is wider among those with an integrated crop-livestock farming system. The mean losses are larger among integrating farmers compared to the mean losses for non-integrating farmers across the distribution of farmers. The level of net gains per farmer is higher among integrating farmers than non-integrating (only producing crops or only producing livestock) and the variance in the losses and gains increases with integration. Integration of crops and livestock would be expected to enhance the benefits received as a result of the change in climatic conditions expected in Mzimba district.

Figure 8—Cumulative distribution of economic gainers and losers in Mzimba district due to climate change

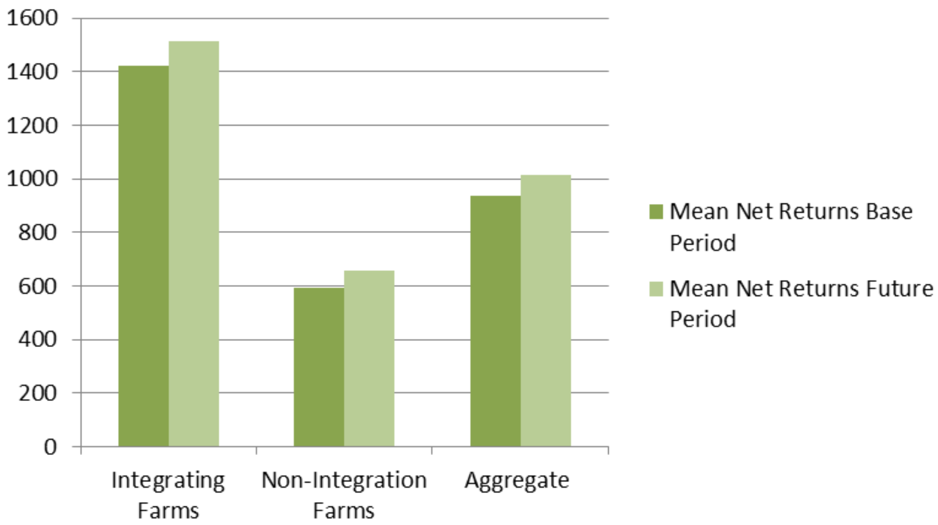


Source: Results from TOA-MD model

In terms of net farm returns (Figure 9), the results of the analysis project an increase in the mean returns per farmer as a result of the net positive gains in yield (productivity). On average, farm earnings increase from US$938 per year in the base period to US$1015 per year in the future period. Integrating farmers earn considerably more on average than those specialized in crop production or in livestock production. In the mid-century period, integrated farms earn about US$1512 in mean net returns compared to US$1420 per year observed in the current period representing a 10.6

percent improvement. For non-integrating farms, mean net earnings increase from US$592 per year in the base period to US$655 per year in the future period, representing an increase of 6.5 percent. On average, for all farm there is an improvement of about 8 percent in economic returns above current baseline conditions – about 10.6 percent for integrating farmers and 6.5 percent for non-integrating farmers.

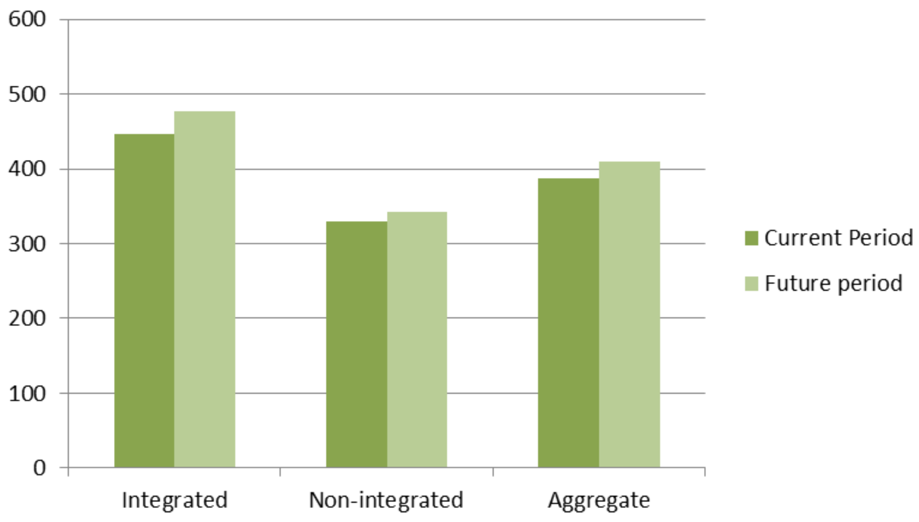
Figure 9—Effects of climate change on mean net returns per farmer in Mzimba district



Source: TOA-MD model result

On the basis of estimated effects of climate change on per capita incomes, all farmers gain (Figure 10). The average income per person per year is likely to move from US$388 during the current (base) period to US$409 per person per year (5.4 percent change) in the future mid-century period. Among integrating farm households, annual per capita incomes will potentially jump from US$447 during the base period to US$477 during the future period (6.7 percent increase over the base mean per capita income), while annual per capita incomes among non-integrating farm households indicate a potential per capita increase from US$330 to US$342 (3.6 percent increase).

Figure 10—Effects on per capita incomes in Mzimba district under climate change



Source: TOA-MD model result

Due to the rise in per capita incomes, we expect a reduction in poverty rates on the basis of a $1.25/person/day (MK 456.25/person/per year) poverty line (Table 6). Greater declines in poverty are anticipated among farmers that integrate crops and livestock into their farming system, as the availability of more livestock feed under changed climatic conditions will likely accelerate livestock productivity and, consequently, farmer incomes. The overall poverty rate is predicted to decline from 64 percent in the current (base) period to 60 percent in the future among all the farmers. Among integrated farm households, about 54.2 percent are expected to be classified poor in the future period relative to 60 percent in the base period. Among non-integrated farm households, poverty rates are expected to decline to 66.5 percent from 68 percent.

Table 6—Population of Mzimba district that is poor under climate change, percent

Stratum	Base period	Future	Net Change
Integrating Households	60.0	54.2	-5.8
Non-Integrating Households	68.0	66.5	-1.5
Aggregate	64.0	60.0	-4.0

Source: TOA-MD model results

The implication is that if farmers are encouraged to stock or increase their stock of ruminant livestock and are able to integrate their farming systems, they may be better able to improve their welfare with climate change and, for those now in poverty, move out of poverty. It should be borne in mind, however, that these figures are only indicative of the potential implications on poverty of climate change effects.

4. CONCLUSION AND RECOMMENDATIONS

This study assessed the potential impacts of future climate change among smallholder farmers in mixed farming systems in Mzimba district. The results reveal that in the future mid-century period between 2040 and 2070 there will be significant changes in temperatures (1-3°C). There are uncertainties as to the expected changes in precipitation levels for the 20 GCMs considered, but the average change in rainfall observed in five selected GCMs used in the analysis show an average decline of 1.1 percent.

As much as most studies of the likely impact of climate change on agriculture in Malawi have viewed climate change as always bad, we find higher productivity benefits largely associated with the anticipated changes in temperature. Relative to the current base period, maize productivity is predicted to increase. The yield gains due to climate change are in the range of 10 percent under the MIROC5 GCM to 15 percent under the HadGEM2-ES GCM. All five selected GCMs used in the analysis show an increase in maize yields over the future mid-century period, but with an eventual decline post-2065. The decline in maize yields coincides with an anticipated decline in annual precipitation.

In terms of economic returns, an estimated 56 percent of all farmers gained in net income due to climate change. The percentage gains in mean net farmer returns were however skewed more towards farmers with no integration of crop and livestock in their farming system. Per capita incomes were found to be higher among integrating farmers than among non-integrating farmers. The resultant effects on poverty indicate that the proportion of the population of Mzimba district that is poor may decline slightly due to climate change.

The study concludes that the future changes in the climate of Mzimba district are likely to bring benefits, on average, to farmers in the district for the period in question. The gains due to climate change are likely to decline towards the end of the future mid-century period unless farmers implement systemic adaptations in their farming practices in light of anticipated changes in the local climate.

We make several recommendations for policy action and future research:

- Since the study predicts a warmer and marginally drier future, investing in research to develop new heat-tolerant maize varieties would be crucial to maintain the productivity gains registered. Promoting early maturing drought-tolerant maize varieties can also enable farmers to cut losses emanating from higher temperatures and less rain.
- We recommend promoting the adoption of ruminant production and increasing the integration of crop and livestock production to improve or maintain farmers' resilience to disruptive climate change threats. Sustainable intensification can help increase farmers' output per unit area without endangering the environment or contributing significantly to climate change.

Much as the study attempted to perform a whole-system analysis from one crop, it utilized intrinsic productivity growth rates and future prices drawn from other comprehensive studies conducted in the region by institutions such as IFPRI and AgMIP, coupled with expert opinions, to generate future productivity data for other farm activities (crops and livestock). We recommend that a full system modelling study be undertaken which fully calibrates and models additional crops and livestock under many GCMs and RCPs to assess a range of futures and responses to climate. This will help provide a closer picture of the distribution of the impact on farmer productivity and welfare under plausible future conditions in the system. An economy-wide but context disaggregated study can also be done using state-of-the-research models to assess effects on different agro-ecological zones to get a picture of the potential impacts in Malawi.

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