

Climate change effects on crop productivity and welfare sensitivity analysis for smallholder farmers in Malawi

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Abstract

The effects of climate change on smallholder agriculture under different crop technologies, namely conservation agriculture, Falbedia albida, optimal fertilisation and intensive farming, were analysed against the conventional subsistence farming in Malawi. A biophysical economic modelling approach was used over a 60-year period to assess changes in crop productivity, total welfare and land-use options. The results indicate varying decreases in crop yield. For instance, when compared to the crop yield in 2010, maize yield decreased by -20% under subsistence farming and -0.1% under intensive farming in the seventh decade (2061 to 2070). Adaptation to climate change effects increased total welfare by 24% and producer revenues by 44% when compared to no adaptation. To optimise the welfare of smallholder farmers in Malawi, the study recommends increasing the adoption of intensive farming, conservation agriculture and Falbedia albida to at least 9.5%, 12% and 10% of total cultivated area in the 7th decade respectively. The study also reveals that farmers' inability to optimise land use has a higher negative impact on welfare when compared to the effect from climate change. This means that the optimisation of crop and technology choices may play a more vital role in improving farmers' welfare than mere adaptation to climate change.

Key words: climate change adaptation; crop technologies; welfare sensitivity analysis; Malawi

1. Introduction

The effects of climate change on the agricultural sector have been studied in many aspects involving different crops, crop technologies and geographical resolution. The actual combination of crops, crop technologies used and geographical resolution is vital to properly guide policy makers and farmers. Otherwise, the generalisation of results from any combination of crop, technology and geographical resolution is unhelpful, as different farmers have different potential to adapt to particular crop technologies (Feijt *et al.* 2016). In this case, specific guidance for both farmers and policy makers in a particular region requires consideration of the regional biophysical conditions, farmers' socioeconomic status, and crop and crop technology combination preferences (Vermeulen 2012). However, in many Sub-Saharan African (SSA) countries, such advice is usually generalised from scanty and low-resolution studies, which involve isolated crops and crop technologies. A synopsis of previous climate impact studies on SSA is presented in Table 1.

Even if advice generated from low-resolution climate impact studies may provide vital information for higher policy planning and general guidance to farmers, it may not justify adaptation needs or technological investments in a particular agroecological zone. Apart from geographical resolution, the actual crop selection is equally critical. In Malawi, cassava, cotton, groundnuts, maize, paprika, rice, sorghum, soybeans, sugarcane and tobacco are considered major crops, contributing to over 95% of the total cultivated area (Government of Malawi [GoM] 2014a). However, other than maize, not much is known regarding future climate change effects on the other listed crops (Cooper *et al.* 2008;

Schlenker & Lobell 2010). While many previous studies have justifiably focused on maize being a staple food crop, leaving out other crops derails the appreciation that cash crops make an important contribution to attaining food security and increasing farmers' income, which help to alleviate poverty (Barbier 2000; Masanjala 2006). For instance, not much is known about future climate change effects on the productivity of tobacco, which is the single most important cash crop in Malawi (Nakhumwa *et al.* 1999). Crop technology selection is also important to complement crop choices. However, a tendency has been evident from previous studies, in terms of which subsistence farming has been the most and at many times the sole crop technology analysed, which leaves farmers and policy makers with little or no advice on alternative technology options (Strauss *et al.* 2012; Gama *et al.* 2014).

The aim of this study was to fill the highlighted gaps in order to better understand the effects of climate change on crop productivity, optimal land-use options, total welfare and producer revenue in Malawi. Firstly, the study includes as many crops and technologies as are practised by smallholder farmers in Malawi. In this case, most of the major crops grown in Malawi under different crop technologies, like subsistence farming, conservation agriculture, *Falbedia albida*, optimal fertilisation and intensive farming, which have usually been missing from previous studies, are considered for analysis. Secondly, in this study, crop yield simulation is done at higher resolution, i.e. from 1 300 homogenous response units (HRUs) in Malawi. HRUs are areas with uniform slope range, soil type and altitude (Schmid *et al.* 2006). What distinguishes crop yield in a particular HRU is the crop technology used and the HRU climatic variables. Essentially, therefore, the study estimates adaptation options at the HRU level. However, for effective high-level planning purposes, a bottom-up regional aggregation approach is used, as presented in Figure 1, according to which crop yields, adaptation options and levels from 1 300 HRUs (Figure 1a) are aggregated into 184 agricultural extension planning areas (EPAs) (Figure 1b). EPAs represent the smallest and basic administrative planning units for agricultural activities in Malawi. From the EPA level, the land-use or adaptation levels are further aggregated into 28 districts (Figure 1c), then into eight agricultural development divisions (ADDs) (Figure 1d) and then into the entire country. In this way, diversification and adaptation options are not just estimated at the national level, but are also provided in all respective agroecological zones as well as all agricultural administrative planning regions.

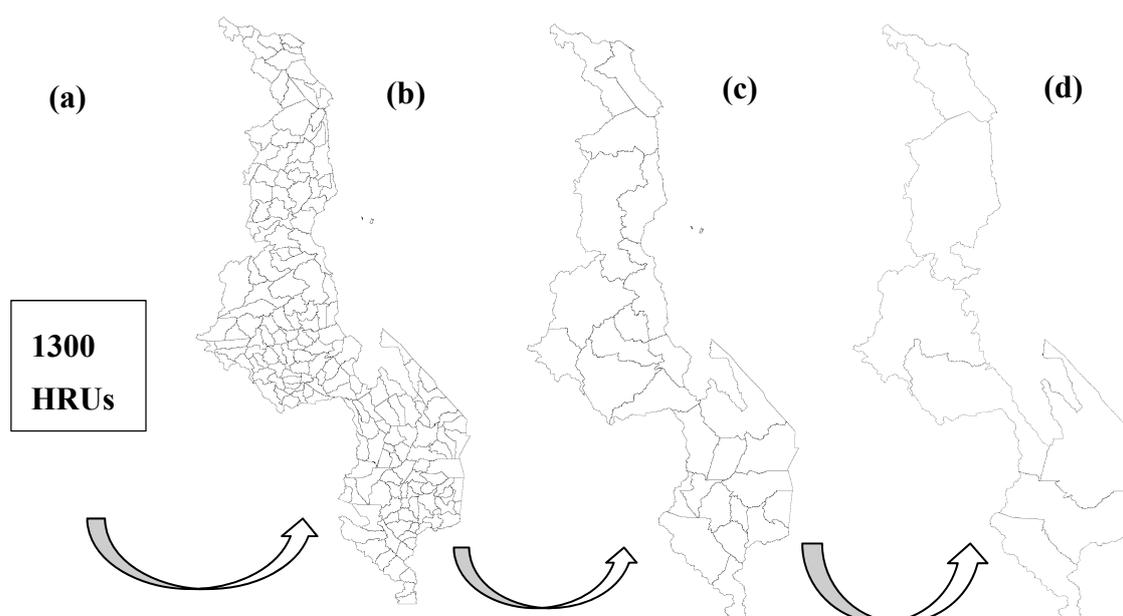


Figure 1: Regional aggregation approach for adaptation and land-use levels

(a) = 1 300 HRUs; (b) = 184 EPAs; (c) = 28 districts; (d) = eight ADDs.

Table 1: A synopsis of previous studies related to climate change effects on the agricultural sector in SSA

Author	Crops analysed										Technologies						Study focus	
	Cass	Cott	Gnut	Maiz	Papr	Rice	Sorg	Soyb	Suga	Toba	CA	FA	IF	OF	SF	MNR	Yield	Welfare
Akpalu <i>et al.</i> (2008)	X	X	X	✓	X	X	X	X	X	X	X	X	X	X	✓	X	✓	X
Arndt <i>et al.</i> (2012)	X	X	X	✓	X	X	X	X	X	X	X	X	X	X	✓	X	✓	✓
Gama <i>et al.</i> (2014)	X	X	X	✓	X	X	X	X	X	X	X	X	X	X	X	✓	✓	✓
Knox <i>et al.</i> (2010)	X	X	X	X	X	X	X	X	✓	X	X	X	✓	X	X	X	✓	X
Saka <i>et al.</i> (2003)	X	X	X	✓	X	X	X	X	X	X	X	X	X	X	X	X	✓	X
Schmid <i>et al.</i> (2006)	✓	✓	✓	✓	X	✓	✓	✓	✓	X	X	X	✓	✓	✓	X	✓	X
Zinyengere <i>et al.</i> (2014)	X	X	X	✓	X	X	X	X	X	X	X	X	X	X	✓	X	✓	X

✓ = Analysed; X = not analysed; Cass = cassava; Cott = cotton; Gnut = groundnuts; Maiz = maize; Papr = paprika; Sorg = sorghum; Soyb = soybean; Suga = sugarcane; Toba = tobacco; CA = conservation agriculture; FA = *Falbedia albida*; IF = intensive farming; OF = optimal fertilisation; SF = subsistence farming; MNR = manure application; Yield = climate change effect on crop yield; and Welfare = climate change effect on welfare of farmers.

2. Methods

2.1 Model structure

This study adopted and used the Malawi Agricultural Sector Model (MASM), developed by Kachulu (2017) through one of the algebraic modelling languages (AML) known as Generalised Algebraic Modelling Systems (GAMS). The MASM is an integration of a crop biophysical model and a partial economic equilibrium model, as presented in Figure 2. The model follows a documentation structure similar to the European Forest and Agricultural Sector Optimisation Model (Schneider & Schwab 2008). As already highlighted, the MASM is a bottom-up, country-based dynamic partial equilibrium model that covers a sixty-year period, from 2010 to 2070. The MASM depicts resource endowments, crops, crop technologies, agricultural markets, population growth and trade to analyse the effects of different policy decisions or scenarios on the Malawian agricultural sector.

2.2 Selected crops

As already stated, most of the major crops grown in Malawi were selected, including cassava, cotton, groundnuts, maize, paprika, rice, sorghum, soybean, sugarcane and tobacco. The selected crops contributed to more than 95% of historical crop area from 2005 to 2010 (GoM 2014a). It can be observed from the data that maize dominated the crop mix, accounting for over 70% of the total cultivated area under smallholder farmers in Malawi. This highlights the subsistence nature of growing one food crop for subsistence needs and the problems of crop diversification among smallholder farmers. Even though the selected crops represented over 95% of the cultivated area, only 59% of the total arable land was utilised. Low land utilisation could be attributed partly to unequal distribution of land among smallholder farmers (Chinsinga 2011) and the tendency among farmers with larger land holdings to underutilise land.

2.3 Selected crop technologies

As mentioned already, the selected crop technologies included subsistence, conservation agriculture, *Falbedia albida*, optimal fertilisation and intensive farming. In this study, subsistence farming represents a technology in which soils are tilled, they are dependent on rainfall, nitrogen is applied at 30% of what is otherwise recommended (GoM 2014b). Conservation agriculture represents no tillage, with soil cover of at least 30%, dependent on rainfall, with nitrogen applied as in subsistence farming but complemented with decomposed biomass from stock cover. *Falbedia albida* is an agroforestry type of technology and depicts conditions in which soils are tilled, that are dependent on rainfall, nitrogen is applied as in subsistence farming but complemented with decomposed biomass from *Falbedia albida* tree leaves. Under optimal fertilisation, soils are tilled, dependent on rainfall, nitrogen is applied as recommended (GoM 2014b), and hence faces no nitrogen stress. Intensive farming represents technology in terms of which soils are tilled, they are irrigated and nitrogen is applied as recommended by the Government of Malawi (GoM 2014b), hence crops experience neither water nor nitrogen stress.

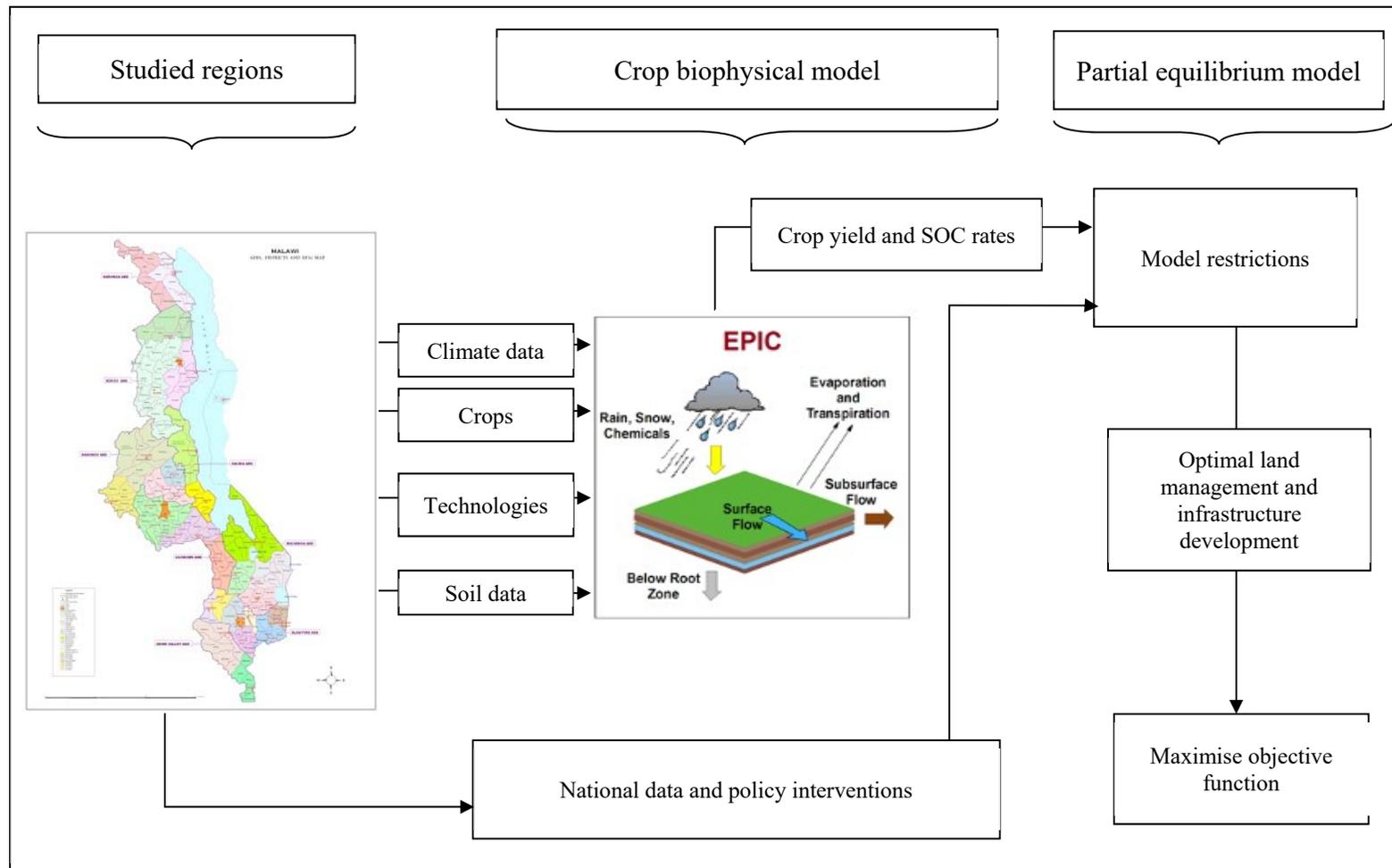


Figure 2: The Malawi Agriculture Sector Model (MASM) framework

MASM framework adopted from Kachulu (2017); EPIC diagram from Williams (1995); and EPA Map from Government of Malawi (GoM 1991a). National data obtained from product price data, consumption-level data, population data, income growth data, resource endowments data, resource and technology costs data; and SOC (soil organic carbon sequestration rates)

2.4 Data sources

Data on the national population, farming population, population growth rate and income levels were sourced from the Integrated Household Survey (GoM 2012a) and the National Census on Agriculture and Livestock (GoM 2012b). Data on technology costs were sourced through a farm budget survey conducted in 2013. Historical EPA crop areas and crop yield data, district consumption levels and product prices for 2010 were sourced from the Department of Agro Surveys under the Malawi Ministry of Agriculture (GoM 2014b) and the Malawi Agricultural Commodity Exchange (MACE 2014). The soil data were sourced from the Department of Land Resources and Conservation through the Land Resource Evaluation Project Database (GoM 1991b). In order to offer policy guidance under worst possible climate scenarios, the MASM uses the worst Representative Climate Pathway (RCP 8.5). Following a review by Gama *et al.* (2014), MIROC5 was found to be the best among the 20 evaluated GCMs in replicating Malawi's observed climate data. On this basis, MIROC5 was chosen for the study. The climate data with daily precipitation, maximum and minimum temperatures and relative humidity, downscaled from MIROC5 using self-organising maps (Hewitson & Crane 2006) under RCP 8.5 was provided by the Climate Systems Analysis Group of the University of Cape Town.

2.5 Crop biophysical simulation

For crop simulation, the Environmental Policy Integrated Climate (EPIC) model (Williams 1995), was selected for two basic reasons. Firstly, unlike some crop models that are developed for specific crops, like CERES for maize and wheat simulation (Ritchie *et al.* 1989) or SOYGRO for soybean simulation (Jones *et al.* 1989), EPIC is able to simulate multiple crops. Secondly, EPIC has previously been widely used on climate crop impact studies in SSA (Adejuwon 2005; Schmid *et al.* 2006). EPIC functions in daily time steps and simulates crop growth by predicting the combined effects of crop technologies, water and nutrient availability in the soil. The leaf solar radiation interception is converted into ground and above-ground biomass, from which the economic yield is deduced as a product of crop biomass and harvest index. Due to the unavailability of observed data for calibration or the practicability of certain crop and technology combinations, only feasible crop and technology combinations were simulated, as presented in Table 2.

Table 2: Crop and technology simulation combinations used in the study

Crop	Crop technology type				
	Conservation agriculture	<i>Falbedia albida</i>	Optimal fertilisation	Intensive farming	Subsistence farming
Cassava	X	X	✓	✓	✓
Cotton	X	X	✓	✓	✓
Groundnuts	X	X	✓	✓	✓
Maize	✓	✓	✓	✓	✓
Paprika	✓	✓	✓	✓	✓
Rice	X	X	✓	✓	✓
Sorghum	✓	✓	✓	✓	✓
Soybean	✓	✓	✓	✓	✓
Sugarcane	X	X	✓	✓	✓
Tobacco	X	X	✓	✓	✓

✓ = simulated crop and technology combinations, X = not simulated due to lack of observed data for calibration.

2.6 Aggregation of crop yield

As already stated, the homogenous response unit (HRU) concept of Schmid *et al.* (2006) was adopted, in terms of which an area with similar soils, a particular slope and a particular altitude range is

considered homogenous. Crop, crop technologies and climate data were coupled to HRUs to determine distinct crop simulation outcomes. The average EPA crop yield ($\bar{y}_{j,m,t,r}$) was estimated in Equation (1) as a product of HRU yields ($y_{j,m,t,r,h}$) and HRU areas ($\beta_{i,t,r,h}$) divided by respective EPA area ($\sum_h \beta_{i,t,r,h}$), where j is crop type, m is crop technology option, t is study period, h is HRU and β is the resource endowment (land), which was constant in all study periods.

$$\bar{y}_{j,m,t,r} = \sum_h (y_{j,m,t,r,h} \cdot \beta_{i,t,r,h}) / \sum_h \beta_{i,t,r,h} \quad \forall_{j,m,t,r} \quad (1)$$

2.7 Partial economic model

2.7.1 Objective function

In the MASM, all variables are endogenous and non-negative, except for the objective function (W), which may be positive or negative. The variables are estimated at the optimal level of agricultural activity, where economic and technological conditions are at an equilibrium. Total welfare (W_t) resulting from the decision to adapt or not to adapt, as (2), was estimated as a product of consumption ($Q_{j,t,r}$) and market prices ($p_{j,t,r}$), summed over all crop products (j) and regions (r), minus the cost of production ($c_{j,m,t,r} \cdot L_{j,m,t,r}$), cost of storage ($s_{j,t,r} \cdot S_{d,j,t,r}$) and cost of trade ($t_{r,\tilde{r}} \cdot T_{j,t,r,\tilde{r}}$). $c_{j,m,t,r}$ is the unit cost of production and $L_{j,m,t,r}$ is the actual hactarage used, $s_{j,t,r}$ is the unit cost of storage and $S_{d,j,t,r}$ is the level of storage, $t_{r,\tilde{r}}$ is the unit cost trade between regions and $T_{j,t,r,\tilde{r}}$ is the level of trade between regions.

$$\text{Max } W_t = \left(\begin{array}{l} \sum_{j,r} \left[\int p_{j,t,r} (Q_{j,t,r}) dQ_{j,t,r} \right] \\ - \sum_{j,m,r} (c_{j,m,t,r} \cdot L_{j,m,t,r}) \\ - \sum_{j,\tilde{r},r} (t_{r,\tilde{r}} \cdot T_{j,t,r,\tilde{r}}) \\ - \sum_{j,m,r} (s_{j,t,r} \cdot S_{j,t,r}) \end{array} \right) \quad \forall_t \quad (2)$$

Producer revenue (R_t) was estimated as a product of price ($p_{j,t,r}^*$) and demand ($Q_{j,t,r}^*$) at equilibrium point, as in Equation (3) below.

$$R_t = \sum_{j,r} (p_{j,t,r}^* \cdot Q_{j,t,r}^*) \quad \forall_t \quad (3)$$

2.7.2 Model constraints

2.7.2.1 Commodity balance constraints

The commodity balance equation, Equation (4), ensured that the sum of consumption ($Q_{j,t,r}$), exports ($T_{j,t,r,\tilde{r}}$) and quantity added to storage ($S_{j,t,r}^+$) did not exceed the sum of production ($y_{j,t,r,m} \cdot L_{j,t,r,m}$), imports ($T_{j,t,\tilde{r},r}$) and quantity subtracted from storage ($S_{j,t,r}^-$).

$$Q_{j,t,r} + \sum_{\tilde{r}} T_{j,t,r,\tilde{r}} + \sum S_{j,t,r}^+ - \sum_m (y_{j,t,r,m} \cdot L_{j,t,r,m}) - \sum_{\tilde{r}} T_{j,t,\tilde{r},r} - \sum S_{j,t,r}^- = 0 \quad \forall_{j,t,r} \quad (4)$$

2.7.2.2 Resource constraints

The availability of arable land and labour restricted agricultural activity levels

(5)). The product of unit resource use, $\alpha_{i,j,t,r,m}$, and activity level, $L_{j,t,r,m}$, summed over all crops (j) and crop technologies (m), could not exceed resource endowments ($\beta_{i,t,r}$) in each region (r) and study period (t).

$$\sum_{j,m} (\alpha_{i,j,t,r,m} \cdot L_{j,t,r,m}) \leq \beta_{i,t,r} \quad \forall_{i,t,r} \quad (5)$$

2.7.2.3 Crop mix restrictions

Farmers' decisions were further constrained by a crop-mix equation

(6)), which forced all activity levels ($\sum_m L_{j,t,r,m}$) to fall within a convex combination of historical crop ratios ($\eta_{j,\hat{t},r}$) and historical crop levels ($X_{\hat{t},r}$) (Chen & Önal 2012), where \hat{t} are observed years, i.e. 2005 to 2010.

$$\sum_m L_{j,t,r,m} - \sum_{\hat{t}} (\eta_{j,\hat{t},r} \cdot X_{\hat{t},r}) = 0 \quad \forall_{j,t,r} \quad (6)$$

2.7.2.4 Storage level

The outstanding product storage level, ($S_{j,t,r}$, (7)) was the sum of the previous storage level, $S_{j,t-1,r}$, and the current quantity added to storage, $S_{j,t,r}^+$, minus the quantity subtracted from storage, $S_{j,t,r}^-$.

$$S_{j,t,r} = S_{j,t-1,r} + S_{j,t,r}^+ - S_{j,t,r}^- \quad \forall_{j,t,r} \quad (7)$$

2.7.3 Model calibration

Model calibration is an adjustment of a particular parameter within the model in order to reproduce a response accuracy specified by some criteria (Refsgaard & Henriksen 2004). The model was calibrated by adjusting the cost of production where a shadow price of a parameter, i.e. land ($\xi_{j,t,r,m}$)

(8)), was added to the original production costs in order to force the model to replicate observed, historical crop-activity levels ($\hat{L}_{j,t,r,m}$). This adjustment reduced deviation between the observed welfare (\hat{W}_t) and the model welfare output (W_t) in the base year. While highlighted here separately, the cost of adjustments ($\xi_{j,t,r,m}$) in the model is essentially part of the production costs.

$$\xi_{j,t,r,m} = \frac{\partial W_t}{\partial \hat{L}_{j,t,r,m}} \quad \forall_{j,t,r,m} \quad (8)$$

2.7.4 Model calibration report

The model calibration report is presented in Table 3. The calibration results are presented for the base year, i.e. 2010. The model performance is estimated as a ratio of model solution to observed levels. On cultivated areas, the model performance ranged from 92.9% under tobacco to 99.6% under cotton and cassava, resulting in an average model performance of 96.6%. While consumption levels were for both national and foreign regions, only national consumption levels are presented for comparison. Crops like tobacco and paprika are mostly produced for external markets and were therefore assumed to have zero consumption levels in Malawi. The model performance for consumption ranged from 82.7% for sugarcane to 99.2% for maize, resulting in an average model performance of 94.3%.

Table 3: MASM calibration report

Crop	Crop area levels (million hectares)		Model performance (%)	Crop consumption levels (million tons)		Model performance (%)
	Observed	Model		Observed	Model	
Cassava	0.1632	0.1625	99.6	2.012	2.335	86.2
Cotton	0.063	0.0627	99.6	0.016	0.017	90.4
Groundnuts	0.1853	0.1915	96.8	0.064	0.061	93.7
Maize	1.9018	1.9953	95.4	1.683	1.697	99.2
Paprika	0.003	0.0031	95.1	0.000	0.000	100.0
Rice	0.0378	0.0353	92.9	0.069	0.071	97.6
Sorghum	0.1015	0.1019	99.7	0.051	0.053	95.9
Soybean	0.1238	0.1286	96.4	0.049	0.048	97.4
Sugarcane	0.0165	0.0162	98.3	0.076	0.065	82.7
Tobacco	0.1065	0.1146	92.9	0.000	0.000	100.0
Average model performance			96.6%			94.3%

3. Results

Before the presentation of the results, a review of climate variables aggregated at the national level is presented in Figure 3. Mean annual precipitation is expected to decrease by -31 mm from the second decade (2011 to 2020) to the seventh decade (2061-2070). This, however, does not explain the annual precipitation variability or distribution. The average number of annual rain days over the two decades was almost the same, at 103 and 104 days respectively. Both the mean maximum and minimum temperatures increased by 1.9°C from the second to the seventh decade. All the climate variables over the two decades were found to be significantly different at $p = 0.05$. These significant changes, as shown in the preceding sections, affected crop productivity over the two decades.

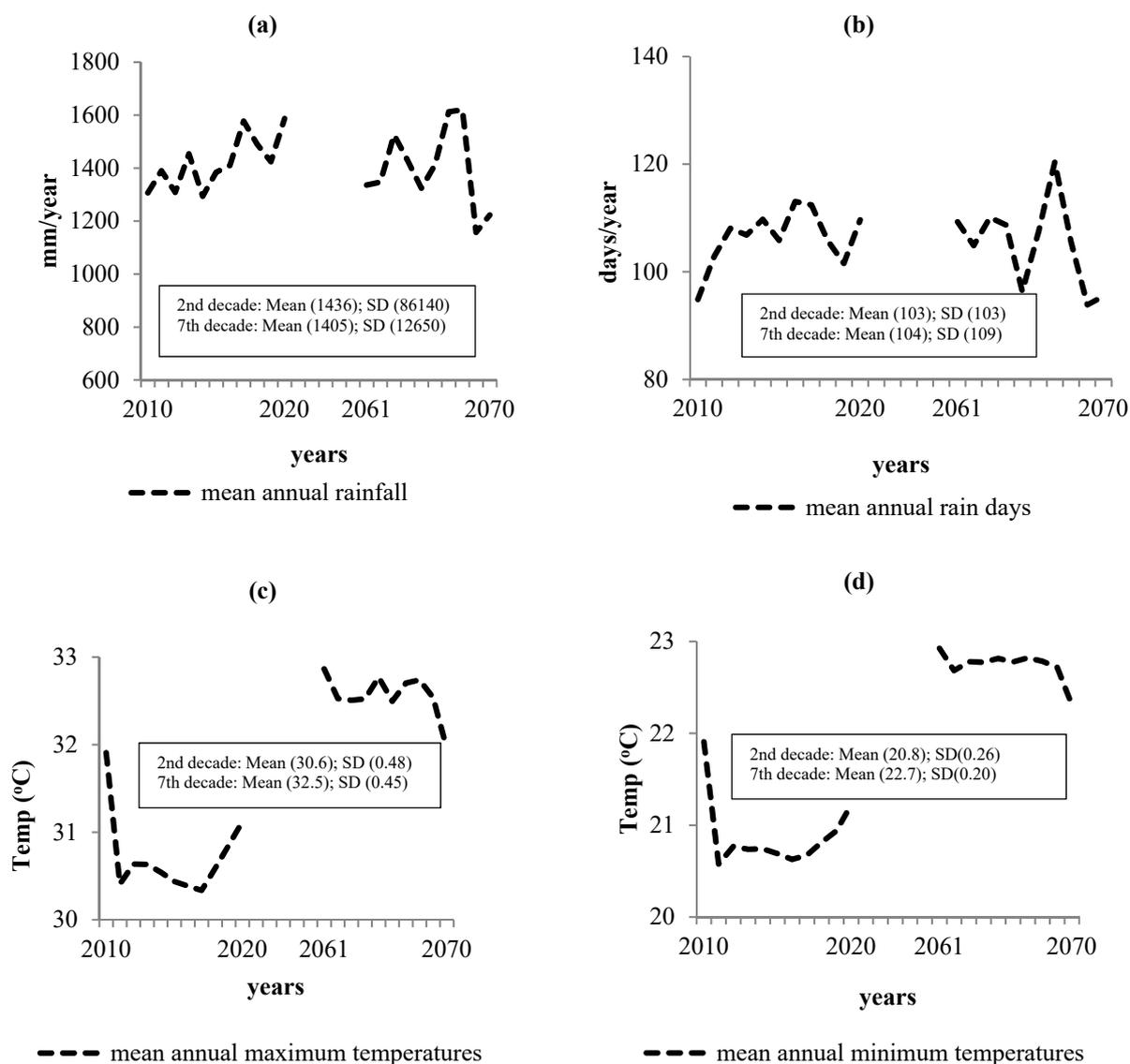


Figure 3: Comparison of decadal climate variables (2011 to 2020 and 2061 to 2070)

3.1 Climate change effects on crop yield

Different climate variables have different influences on crop yield and crop yield changes. In this section, the coefficient of determination (R^2) was selected to analyse the extent to which rainfall variability in the seventh decade explained crop yield changes under different crop technologies, using regression analysis. The results, as shown in Table 4, indicate that rainfall variability could explain the maize yield variability of 63% under optimal fertilisation ($R^2 = 0.63$) and 64% under subsistence farming ($R^2 = 0.64$), but could only account for 1% of maize yield variability under intensive farming ($R^2 = 0.01$). This indicates that rainfall variability influenced crop yield variability more under subsistence and optimal fertilisation, whereas intensive farming, which is irrigated, was least affected by rainfall variability.

Table 4: Rainfall and yield coefficient of determination

Crop technology	Crop type								
	Cotton	Groundnuts	Maize	Paprika	Rice	Sorghum	Soybean	Sugarcane	Tobacco
Conservation agriculture	--	--	0.34	0.18	--	0.37	0.14	--	--
<i>Falbedia albida</i>	--	--	0.63	0.14	--	0.28	0.08	--	--
Intensive farming	0.02	0.05	0.01	0.001	0.17	0.12	0.06	0.07	0.08
Optimal fertilisation	0.18	0.15	0.63	0.10	0.18	0.22	0.22	0.23	0.22
Subsistence farming	0.17	0.16	0.64	0.10	0.22	0.23	0.22	0.25	0.23

The results for crop yield and crop yield changes aggregated at the national level are presented in Figure 4 and

Figure 5 respectively. The crop yield changes are in references to the base year of 2010. All crops, with the exception of paprika – as shown in

Figure 4d – experienced yield losses. Average crop yield changes ranged from +10% to -30% for most crops and management options. The highest yield losses, of up to -52%, were observed for maize under *Falbedia albida* (

Figure 5c) and for soybeans, at -48%, also under *Falbedia albida* (

Figure 5g). All crops under intensive farming had the lowest changes in crop yield, where the maximum crop yield decrease was -1% for groundnuts.

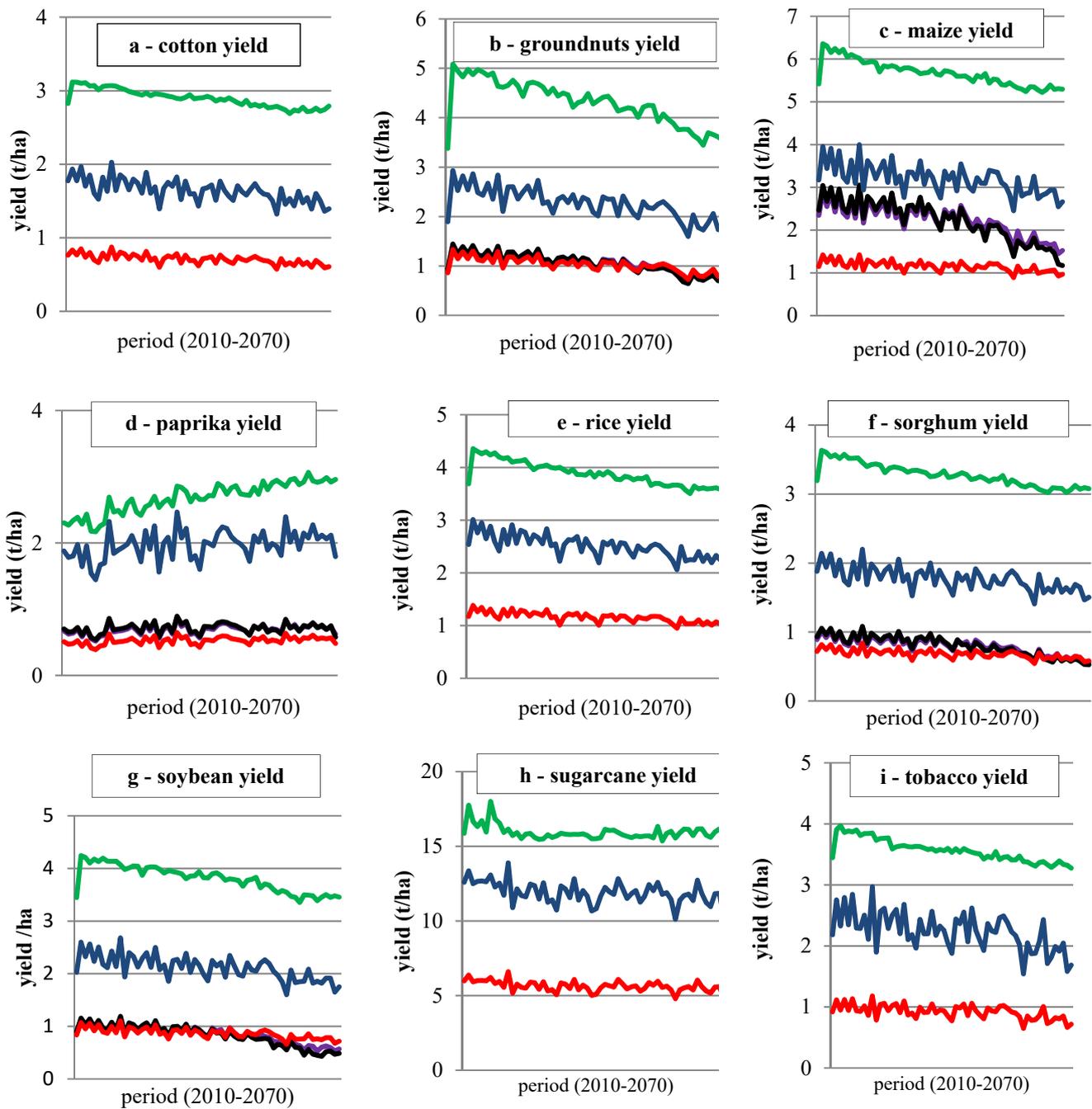


Figure 4: Crop yield under different crop technology practices from 2010 to 2070

Green = intensive farming; blue = optimal fertilisation; amber = *Falbedia albida*; black = conservation agriculture; red = subsistence farming

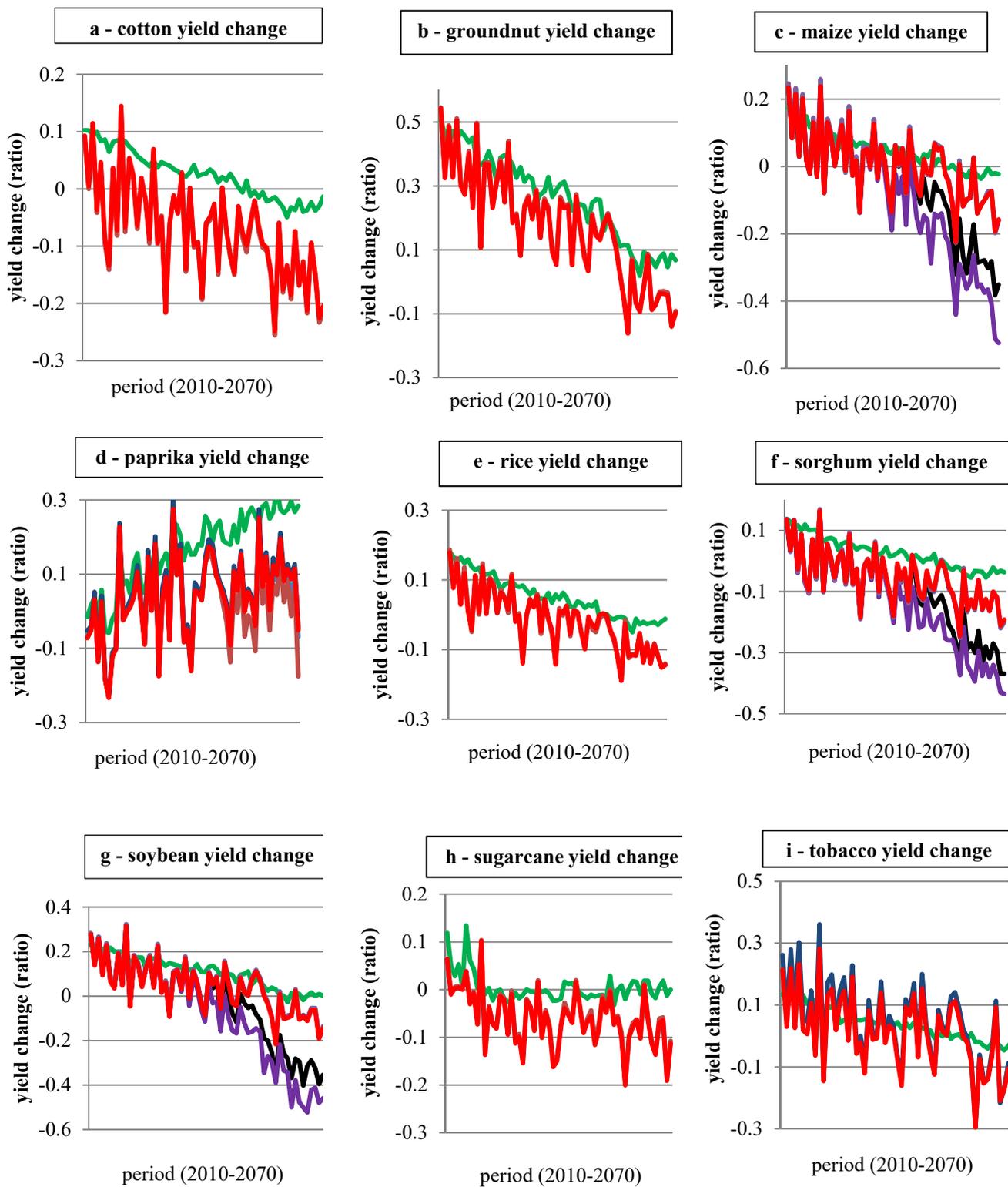


Figure 5: Change in ratio of crop yield in comparison to 2010 yields

Green = intensive farming; blue = optimal fertilisation; amber = *Falbedia albida*; black = conservation agriculture; red = subsistence farming

3.2 Effect of technology shifts on change in crop yield

Changes in crop yield due to shifts in technology were calculated as a ratio of crop yield from alternative technologies to crop yield under subsistence farming. Shifting from subsistence farming

to any alternative technology had a positive effect on crop yield, as presented in Figure 6. In the second decade, intensive farming had the highest maize yield ratio, of up to 4.8, whereas conservation agriculture had the least increase, at 2.1. The results also show that the crop yield ratio changed from the second to the seventh decade. Intensive farming resulted in an increased maize yield ratio of 5.1 in the seventh decade, whereas the maize yield ratio under conservation agriculture decreased to 1.6.

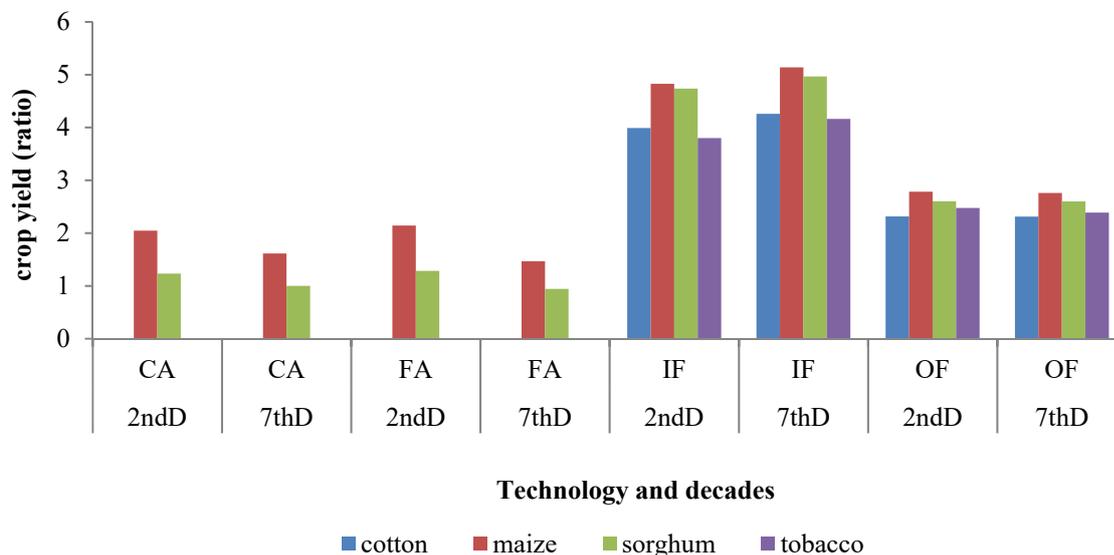


Figure 6: Effect of technology shifts on crop yield ratio (compared to subsistence farming)

CA = conservation agriculture; FA = *Falbedia albida*; IF= Intensive farming; OF = optimal fertilisation

3.3 Technology crop yield and cost of production

The ratio of crop yield to cost of production per hectare for each technology is presented in Figure 7. In the second decade, maize under intensive farming had the highest crop yield per cost of production, at 12.2 kg/\$, followed by *Falbedia albida*, at 10.2 kg/\$, with subsistence farming being the lowest, at 5.7 kg/\$. However, the ratio of maize yield to cost of production decreased in the seventh decade to 10.4 kg/\$ for intensive farming, 5.6 kg/\$ for *Falbedia albida* and 4.11 kg/\$ for subsistence farming. This simply shows the effect of climate change on crop productivity over the two decades.

3.4 Optimal land use options

3.4.1 Crop choices

Crop choices for the second and seventh decades are presented in Table 5. While there were changes in terms of crop area for all crops in the different decades, the changes were insignificant, at $p = 0.05$. This is partly due to the influence of the crop-mix equation in the model and the shift in technology adoption by the farmers. If technology adoption rates were held constant, total cultivated area would be expected to increase significantly due to an increase in demand for agricultural products as a result of population growth over the decades. However, due to farmers shifting from subsistence to more productive technologies (see section 3.4.2), there is not much of an increase in total cultivated area in future decades. This shows that adaptation may also be used as a solution to relieve the pressure of land scarcity among smallholder farmers in Malawi.

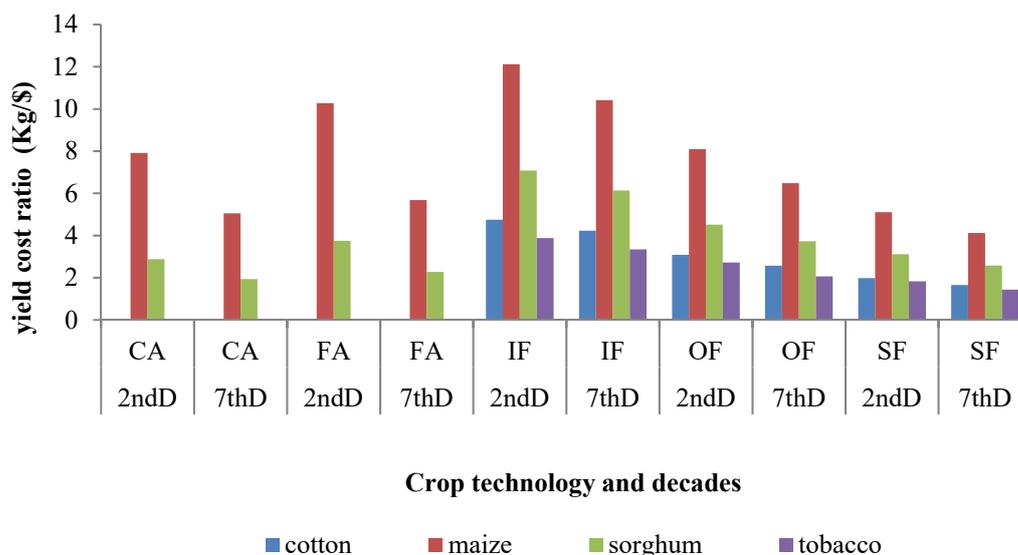


Figure 7: Technology yield cost ratio (compared to subsistence farming costs)
 CA = conservation agriculture; FA = *Falbedia albida*; IF= Intensive farming; OF = optimal fertilisation;
 SF = subsistence farming

Table 5: Optimal crop choice levels aggregated at the national level

Crop type	Crops area (000 ha)			Crop mix ratios (%)		
	Observed (2010)	Optimal (2 nd decade)	Optimal (7 th decade)	Observed (2010)	Optimal (2 nd decade)	Optimal (7 th decade)
Cassava	162.421	166.884	163.46	5.78	5.73	5.74
Cotton	62.672	64.535	60.807	2.23	2.22	2.14
Groundnuts	191.464	202.702	197.054	6.82	6.96	6.92
Maize	1 995.267	2 044.445	2 005.057	70.98	70.13	70.39
Paprika	3.100	3.513	3.305	0.12	0.13	0.12
Rice	35.256	37.560	39.657	1.26	1.29	1.4
Sorghum	101.812	105.793	100.586	3.63	3.63	3.54
Soybean	128.537	120.036	123.391	4.58	4.12	4.34
Sugarcane	16.152	20.046	18.548	0.58	0.69	0.66
Tobacco	114.587	149.819	136.894	4.08	5.14	4.81
Total	2 811.268	2 915.333	2 848.759	100	100	100

3.4.2 Technology choices

Technology choices for the different decades are presented in Table 6. Changing from observed crop area levels to optimal adaptation levels resulted in reduced adoption of subsistence farming, from 60.3% in 2010 to 47.9% in the second decade and 41.33% in the seventh decade. Instead, subsistence farming was replaced by more productive technologies, like conservation agriculture and *Falbedia albida*, which in total contributed to more than 22% of the total cultivated area in both the second and the seventh decades.

Table 6: Optimal technology choice levels aggregated at national level

Technology	Crops area (000 ha)			Technology mix ratio (%)		
	Observed levels (2010)	Optimal (2 nd decade)	Optimal (7 th decade)	Observed levels (2010)	Optimal (2 nd decade)	Optimal (7 th decade)
Conservation agriculture	13.599	329.307	360.818	0.49	11.3	12.67
<i>Falbedia albida</i>	13.514	335.803	287.179	0.49	11.52	10.09
Intensive farming	119.082	142.943	159.241	4.24	4.91	9.59
Optimal fertilisation	968.509	708.7	721.975	34.46	24.31	25.35
Subsistence farming	1 696.564	1 398.578	1 319.544	60.35	47.98	41.33
Total	2 811.268	2 915.333	2 848.759	100	100	100

3.5 Welfare sensitivity analysis

The results of the welfare sensitivity analysis results are presented in Table 7. The sensitivity analysis considered welfare changes under farmers' decisions to adapt or not to adapt to climate change effects, and also under a scenario in which it was assumed that there were no climate change effects. Under no adaptation, the model assumed that the farmers maintained the observed crop and technology levels of the base year throughout the study period. The assumption of no climate change meant that there were no changes in crop yield over the entire study period. As such, the model was forced to adopt the crop yields of the base year, i.e. 2010, throughout the study period. It should be noted that crop yields in the second decade (2011 to 2020) were relatively higher than in 2010, whilst crop yields in the seventh decade were relatively lower than in 2010. The results show that, in the second decade, the decision not to adapt or to operate at non-optimal land-use levels under no climate change led to total welfare loss of -9%. This is understandable, since crop yields in the second decade were higher than in 2010, and as such climate change in second decade had a positive influence on total welfare even under no adaptation. However, when farmers adapted or operated at optimal levels under the no climate change scenario in the second decade, this increased farmers' welfare by 5.0%. This shows that adaptation does not just avert the negative effects of climate change, but also increases farmers' production efficiency even without climate change effects. The decision to adapt to climate change in the seventh decade also had a positive effect on welfare when compared to the decision not to adapt.

Table 7: Welfare sensitivity analysis under different scenarios of adaptation and no adaptation, climate change and no climate change in the different decades (2011 to 2020 and 2061 to 2070)

Decision	Climate outcome	Type of welfare			
		Total welfare change (%)		Producer revenue change (%)	
		2 nd decade	7 th decade	2 nd decade	7 th decade
Observed levels (no adaptation)	Climate change (yield changes)	0.00	0.00	00.00	0.00
	No climate change (constant yields)	-0.09	0.09	-0.13	0.22
Optimal land use (adaptation)	Climate change (yield changes)	0.02	0.24	0.10	0.44
	No climate change (constant yields)	0.05	1.02	0.86	1.36

4. Discussion

In the preceding section, the results of the effects of climate change on crop productivity, land-use options and welfare sensitivity analysis were presented. The following section discusses the significance of these results. While it is not possible to discuss all crop yield results due to the unavailability of comparable studies in SSA, a few crop yield results are discussed. The crop yield results mostly indicate a general decrease under each crop and crop technology. Rainfall variability had a higher coefficient of determination on maize yield – of 0.64 under subsistence farming and 0.63 under optimal fertilisation, while maize yield under intensive farming had the lowest coefficient of determination – of 0.01. This is to be expected, as intensive farming is practised under irrigation and therefore is least affected by rainfall variability. The crop yield changes under intensive farming may emanate from other factors, like changes in temperature and relative humidity. Conservation agriculture had a lower coefficient of determination when compared to subsistence farming. This supports the argument expressed by many authors that conservation agriculture improves soil water conservation (Hatfield *et al.* 2001; Bossio *et al.* 2010; Thierfelder *et al.* 2015).

The results for the change in aggregated crop yield agree with the findings of Saka *et al.* (2003), who also noted a crop yield decrease in maize, ranging from -5% to -25%. However, the results are different from the findings of Gama *et al.* (2014), whose results portrayed an increase in maize yield ranging from +5% to +10%. The difference from the results of Gama *et al.* (2014) may be attributed to a number of factors. Firstly, the difference may arise due to different geographical resolutions used in the two studies. Gama *et al.* (2014) did not consider the HRU approach, but instead analysed a particular EPA, without any differentiation of soil type, slope and altitude within the EPA. Secondly, the difference in the results may also be attributed to the level of aggregation of the results. In this study, the results, even though generated from a higher geographical regional resolution, viz. 1 300 HRUs, are presented as aggregates at the national level for ease of discussion, whereas the results of Gama *et al.* (2014) were only for one particular EPA. Yield crop and cost of production ratios in all decades were found to be the highest under intensive farming. This suggests that, despite higher production costs, intensive farming has higher returns on investment. The increase in crop yield in relation to cost of production for intensive farming in the seventh decade is mainly due to the negative effects of climate change on crop yields under subsistence farming.

In order to maximise total welfare, technology adoption rates for conservation agriculture and *Falbedia albida* need to be increased from the observed levels of 0.48% in 2010 to around 12% for conservation agriculture and 10.5% for *Falbedia albida* in the seventh decade. Such adoption levels, although optimal, may be argued as being too high to be easily achieved by smallholder farmers. Smallholder farmers are known to face a number of challenges in adopting such technologies on a larger scale (Mfune 2014). Apparently, only 3% of cultivated area has been estimated to be under conservation agriculture in Southern Africa (Ngwira *et al.* 2014). The results also show that it would be advisable to increase the proportion of intensive farming from the observed levels of 4.23% in 2010 to 9.5% by the seventh decade. This would require increasing the area equipped with irrigation infrastructure from the current 110 000 hectares to 248 000 hectares. The study's findings on the required increase in irrigated area is lower, but within the 650 000 hectares estimated by Ferguson and Mulwafu (2005) to be easily irrigable using gravity-fed irrigation. However, when compared to the Greenbelt Initiative, an initiative of the government of Malawi that aims to develop two million hectares under irrigation (GoM 2011), such a target would be deemed too high and therefore economically inefficient with reference to the findings of this study. The results also show that a shift in crop technology would reduce the total cultivated area that would otherwise have increased significantly assuming there was no technology shift or adaptation by farmers. This entails that adaptation to climate change effects may be a solution to relieve pressure on the already dwindling land-holding sizes among smallholder farmers in Malawi.

The results of the welfare sensitivity analysis show that climate change in the seventh decade will have negative effects on welfare, as indicated by the welfare differences between the no climate change and climate change scenarios. Secondly, the welfare sensitivity analysis also shows that adaptation improves welfare when compared to no adaptation, especially in the seventh decade. What is also important under these results is the need to operate at optimal level, even without the envisaged climate change effects. Many subsistence farmers were noted to operate at non-optimal land-use levels, regardless of climate change effects. Adjusting to optimal land use or adaptation would not only avert the negative climate change effects, but would also improve productivity, even under the no climate change scenario or the absence of climate change effects. The literature review did not find any previous studies related to climate change and welfare analysis in the Malawian agricultural sector. However, the results on producer revenue are in agreement with the findings of Gama *et al.* (2011), who also found that farmers who adapted to climate change effects had 5.1% more revenue compared to those who did not adapt, even though they analysed only the maize crop from one EPA.

While the study considered almost all the important crops and technology used by smallholder farmers in Malawi, it is not certain that farmers would continue to grow or use the selected technologies in the future. As it is difficult to know which crop and technology preferences farmers may actually have, the results and discussions in this study, as in many other similar studies, are based on the assumption that farmers would stick with what are currently observed to be the most important crops and technologies.

5. Conclusion

In this study, the effect of climate change on the crop productivity and welfare of smallholder farmers under different crops and crop technologies was analysed. Most crops experienced crop yield decreases under all technologies, but alternative technologies provided better crop yields and crop yield returns when compared to subsistence farming. For policy planning, it has been shown that adaptation is not just necessary to improve farmers' productivity and offset the future negative effect of climate change, but it may also be used as a solution to relieve the pressure on total available arable land. The study has also shown that, in order to achieve optimal land-use levels, policy makers and smallholder farmers in Malawi should focus more on technology adoption than on changing crop preferences.

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