Vol. 67: 87–97, 2016
doi: 10.3354/cr01357

CLIMATE RESEARCH
Clim Res

Published February 24

Impacts of climate change on agricultural household welfare in Kenya

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ABSTRACT: Natural and artificial (e.g. agricultural) ecosystems confer benefits in the form of provisioning, regulating, cultural and habitat/supporting goods and services. Degradation of ecosystems by natural and anthropogenic drivers compromises their ability to provide these goods and services. In Kenya, as in other regions worldwide, climate change and variability are driving weather pattern changes, and causing seasonal shifts. Such changing weather patterns and seasonal shifts act as stresses on agricultural ecosystems, compromising the production of agricultural goods and services, and leading to reduced farm returns, reduced household incomes, and increase in poverty levels. Using the example of Embu County in central Kenya as a case study, this study seeks to assess the impacts of climate change on household welfare (net farm returns, per capita incomes, and poverty) in current agricultural production systems. To address this objective we conducted a multi-disciplinary study involving climatologists, crop modellers and economic modellers. Primary data from 441 households were collected using a combination of stratified and multistage sampling. In climate modelling, 5 climate models were used to downscale future projected climate change scenarios for the mid-century timeframe of 2041–2070. Crop modelling for maize was done using DSSAT and APSIM crop models. Representative agricultural pathways were used to project the production of other non-modelled crops and dairy. Finally, economic analyses were done using the trade-off analysis multi-dimensional impact assessment tool. Results show that about 36 to 66% of the households in agro-ecological zones (AEZs) receiving limited rainfall are likely to lose from climate change. In addition, crop models indicate mixed results for net farm returns, per capita income and poverty levels in different AEZs, with poverty level declines being between 0.6 and 3.8% for APSIM, and between 0.7 and 11% for DSSAT. This therefore calls for adaptation, especially for households in AEZs likely to experience negative impacts from climate change.

KEY WORDS: Crop modelling · Economic modelling · Household welfare

1. INTRODUCTION

Natural and artificial (e.g. agricultural) ecosystems, confer benefits in the form of provisioning, regulating, cultural and habitat/supporting goods and services (Fisher & Christie 2010). Degradation of ecosystems compromises their ability to provide these goods and services. This change in the state of the ecosystem according to the DSPIR[1] framework is brought about by pressures such as changes in water flows, rainfall and evapotranspiration patterns (Kelble et al. 2013). The pressures are themselves a result of drivers; these have been classified as direct and indirect drivers (e.g. Brander et al. 2010). The IPBES[2] Framework classifies direct drivers as either

[1]Driver, pressure, state, impact, and response (DPSIR) model depicts how human society affects ecosystem state

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natural or anthropogenic, and indirect drivers include demographic factors, technological changes, economic changes etc. Climate change, which is the basis of this article, can be categorised under both natural and anthropogenic direct drivers (Diaz et al. 2015). However, anthropogenic drivers outweigh the natural drivers in contributing to climate change.

In Kenya (as with regions worldwide) climate change and variability drives changes in weather patterns and causes seasonal shifts (Republic of Kenya 2010). Changing weather patterns and seasonal shifts act as stresses on the agricultural ecosystems, compromising the production of agricultural goods and services. In Kenya, close to 70% of the population depends directly on agriculture for their livelihoods, and therefore any interference or disturbance to agricultural ecosystems is likely to have adverse impacts on the rural areas. Such impacts could include reduced farm returns, reduced household incomes, and increases in poverty levels. For instance, the country experienced in 2011 one of the worst droughts in the past 50 years, where poor rains greatly undermined the food security situation, leaving about 3.5 million people in need of food assistance (WFP 2012). Policy interventions from the government and other responses by individuals and organizations would be required to mitigate these impacts in the future.

Given this background, it is important to understand the potential impacts of climate change on current and future agricultural systems in the Kenya, and to propose plausible policy interventions. We measured the impacts of climate change using 4 welfare indictors of: (1) changes in the percentage of gainers or losers from climate change; (2) changes in net farm returns; (3) changes in per capita incomes; and (4) changes in poverty levels. We used a case study of Embu County in Central Kenya, and our hypothesis was that increased temperature and depressed rainfall, which are our indicators of climate change, would have a negative impact on all 4 welfare indicators.

2. METHODS

2.1. Study area

Embu County was chosen as a case study because of its diverse agro-ecological zones (AEZs) — totaling 11 in all. The county lies on the south-eastern slopes of Mount Kenya (Fig. 1) and covers the typical agro-ecological profile of the country, from cold and wet high altitude areas to the hot and dry low altitude areas (Jaetzold et al. 2007). The AEZs in the county are representative of most of the climatic conditions in Kenya, and it is therefore possible to infer productivity of most other regions in the country. The average annual rainfall varies from >2200 mm at an altitude of 2500 m to <600 mm near the Tana River at 700 m. The Upper Highlands (UH0) and Lower Highlands (LH0) are so wet and steep that forest is the best land use. In the Lower Highlands Zone (LH1) and Upper Midland Zone (UM1) precipitation is still 1800 mm or more, and average annual temperatures are <18°C, with the predominant cropping systems being tea and coffee. Compared to the Lower Midland (LM5) and Inner Midland (IL5) zones with 600–800 mm of rainfall, the productivity potential of LH1 or UM1 is more than ten times; and if the poor soils in LM5 and IL5 are considered, then the productivity potential of LH1 or UM1 is much higher than that of LM5 and IL5. The reason for this low potential in the low rainfall regions is the rapidly decreasing rainfall during the agro-humid periods (i.e. the growing periods for annual crops).

Therefore, to improve farm returns, household incomes and to reduce poverty rates in the face of climate change, households in the county have adopted various management practices, such as planting drought tolerant crop varieties, early planting and application of manure and fertilizers. The most popular improved maize varieties are the ‘Duma’ and ‘DK’ varieties which are planted by 32 and 27% of the households, respectively. About 26% of households also cultivate local maize varieties. In addition to improved varieties, households are also using inorganic fertilizers and manure. The main fertilizers used in the region are di-ammonium phosphate (DAP), nitrogen, phosphorus and potassium (NPK) and calcium ammonium nitrate (CAN). Apart from agriculture, other sources of income in the region vary from formal employment, businesses, and remittances from family members. The key source of non-agricultural income is from informal businesses followed by off-farm labour. Therefore, there are marked differences between the AEZs in the county with regard to crop varieties, management practices, and sources of income.

2.2. Conceptual framework and data

The conceptual framework employed in this study is based on the Agricultural Model Intercomparison and Improvement Project (AgMIP) regional integrated assessment framework (Rosenzweig et al.

[2]Intergovernmental platform on biodiversity and ecosystem services

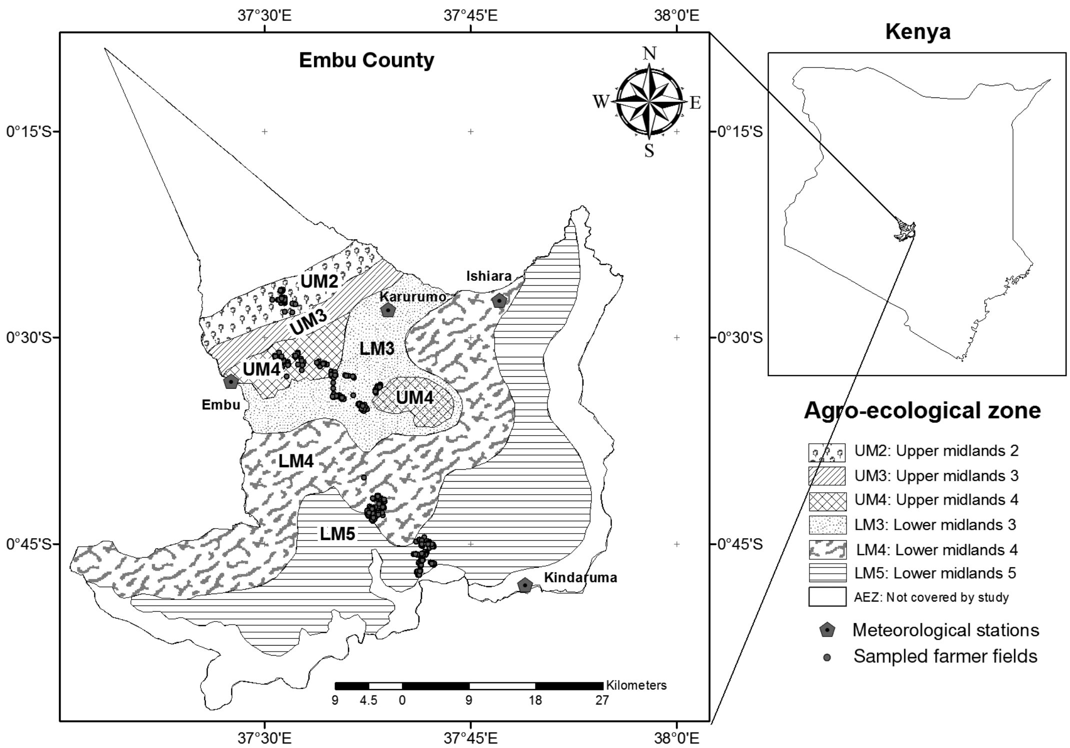

Fig. 1. Map displaying target agro-ecological zones (AEZs) of Embu County in Kenya. See Section 2.1 for descriptions of the AEZs

2013). This framework requires experiments, surveys and expert data for use in crop and economic modelling, including crop and livestock production data, costs of production of different enterprises, and household characteristics data, e.g. household size and non-farm income data. In crop modelling, crops and livestock production data are used to estimate the relative yield distributions under climate change. The crop modelling module uses downscaled climate data. For crops and livestock enterprises which could not be modelled, representative agricultural pathways (RAPs) are used to estimate these relative yields. The estimates from climate modelling are passed into an economic model and combined with prices and costs of different crops and livestock enterprises to estimate economic impacts of climate change, as shown in Fig. 2.

To collect the data required for the analysis, household surveys a from total of 441 households were collected using a combination of stratified and multistage sampling in 2013. The strata for the household survey were the AEZs in the county. Out of the 11 AEZs, 5 key AEZs were targeted for data collection. These were (1) Upper Midland 2 (UM2), which is the main coffee zone; (2) Upper Midland 3 (UM3), the marginal coffee zone; (3) Lower Midland 3 (LM3), the cotton zone; (4) Lower Midland 4 (LM4), the marginal cotton zone; and (5) Lower Midland 5 (LM5), the sorghum millet zone. In each AEZ, administrative regions (division, location and sub-location) were chosen, and one sub-location representing each AEZ was chosen for sampling. At the sub-location level, data collection from individual households was by simple random sampling. The data collected in these AEZs included: production of different varieties of crop and livestock, output prices and variable production costs of the different enterprises, non-farm incomes, and other

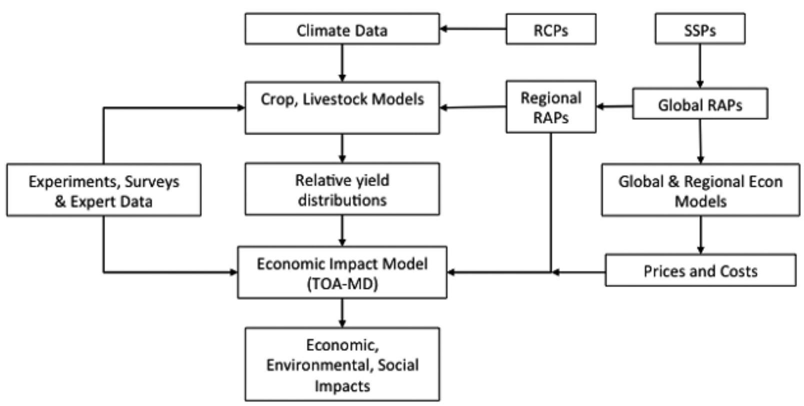

Fig. 2. The AgMIP regional integrated assessment framework. Source: Rosenzweig et al. (2013). RCP = representative concentration pathway; SSP = shared socio-economic pathway; RAP = representative agricultural pathway; TOA-MD = trade-off analysis model for multi-dimensional impact assessment

household characteristics. All AEZs had maize and dairy activities but UM2 and UM3 also had coffee. The other AEZs had pigeon peas and sorghum/millet enterprises which were not in UM2 and UM3. In total there were 5 crop activities and dairy. There are marked differences in the household characteristics among the AEZs. For instance, UM2 has the smallest geographical area and lowest mean household size. Other AEZ household characteristics are as shown in Table 1.

In UM2, the key crops are maize and beans, but households also grow coffee as a cash crop. They also plant bananas, vegetables, sweet potatoes, etc. for private consumption and sale to markets. UM3 has similar crops to UM2, but the mean farm size is larger (as shown in Table 1). Households in LM3 plant the same crops as in UM2 and UM3 (except for coffee), plus sorghum and millet in some households. Households in LM4 and LM5 plant the same crops as grown in LM3. All AEZs produce milk but at varying quantities, with the highest production in UM2 (Table 2). The prices of farmers' produce are fairly similar in all the AEZs, as shown in Table 3. The mean crop and livestock outputs and mean prices are indicators of mean gross revenues in the AEZs.

The net farm returns in different farms in the AEZs are determined by the costs of production. Table 4 shows the mean costs of production for different enterprises. These costs vary across the different enterprises and across the AEZs. Maize has the highest cost of production in all AEZs except in UM2, where dairy and coffee production recorded higher costs of production.

2.3. Climate, crop and economic modeling

This being a multi-disciplinary study, it involved climate, crop and economic modelling. Five climate models — CCSM4, GFDL-ESM, HadGEM2-ESM, MIROC-5 and MPI-ESM — were used to downscale future projected climate change scenarios for the mid-century timeframe of 2041–2070. Crop modelling for maize was carried out using the Decision Support System for Agrotechnology Transfer (DSSAT) and Agricultural

Table 1. Characteristics of AEZs and households (HHs; HH size is no. of people). Ksh: Kenyan shillings. Source: Jaetzold et al. (2007) and household survey data (this study)

AEZ	Geographical area (ha)	Mean HH size	Mean annual non-agric. income (Ksh)	Mean farm size (ha)	Mean dairy herd size
UM2	4370	4.3	114 411	0.9	2.29
UM3	8400	5.7	67 902	2.21	1.79
LM3	18 020	5.8	148 525	1.86	1.83
LM4	60 420	6.5	146 671	2.44	2.2
LM5	105 500	6.9	118 877	1.74	1.88

Table 2. Mean yield of different crops (kg ha^{-1} yr^{-1}) and dairy (kg farm^{-1} yr^{-1}) in AEZs. Source: household survey data (this study)

AEZ	Maize	Beans	Coffee	Pigeon pea	Sorghum and millet	Milk
UM2	2191.20	1113.09	1836.80	0.00	0.00	1938.39
UM3	2273.20	1275.41	1850.93	0.00	0.00	679.52
LM3	1935.09	1481.33	0.00	890.47	643.49	1019.95
LM4	1675.40	1254.99	0.00	1154.20	921.76	1153.30
LM5	877.04	645.61	0.00	674.45	626.75	781.29

Table 3. Mean prices (in Kenyan shillings, Ksh) of different crops (Ksh kg^{-1}) and dairy (kg l^{-1}) in AEZs. N/A: not applicable. Source: household survey data (this study)

AEZ	Maize	Beans	Coffee	Pigeon pea	Sorghum and millet	Dairy (milk)
UM2	32.00	58.89	28.70	N/A	N/A	30.20
UM3	30.70	55.35	22.67	N/A	N/A	31.20
LM3	31.40	60.82	N/A	58.94	43.15	38.40
LM4	31.40	54.24	N/A	58.29	45.38	42.50
LM5	31.30	80.00	N/A	59.64	43.89	38.20

Table 4. Mean cost of production (in Kenyan shillings, Ksh) for different crops and dairy (Ksh farm^{-1} yr^{-1}) in AEZs. N/A: not applicable. Source: household survey data (this study)

AEZ	Maize	Beans	Coffee	Pigeon pea	Sorghum and millet	Dairy (milk)
UM2	6952.06	2718.13	6977.03	N/A	N/A	18 110.24
UM3	19 255.25	4098.46	17996.13	N/A	N/A	9436.22
LM3	20 980.85	3079.52	N/A	1232.66	725.01	8407.54
LM4	14 046.51	3733.04	N/A	1182.81	1160.19	7731.88
LM5	6506.86	2147.13	N/A	776.86	1301.59	982.50

Production Systems sIMulator (APSIM) crop models. RAPs were used to project the impacts of, and adaptations to, climate change for other farm activities, which could not be modelled using crop models. These were beans, coffee, pigeon peas, sorghum and millet, and dairy. Economic analyses were performed using the Trade-off Analysis Multi-Dimensional (TOA-MD) impact assessment tool (Antle & Valdivia 2010, 2011, Antle 2011, Claessens et al. 2012).

2.4. Climate modeling

Since it is not practical to assess impacts of climate change on agricultural systems at the local scale with coarse data from coupled atmosphere–ocean general circulation models (AOGCMs), location-specific climate change scenarios were developed using the delta[3] method. Using this method, monthly changes in temperature and precipitation from AOGCMs, calculated at the grid scale, were added to the corresponding observed station data. Climate change scenarios for mid-century (2041–2070) and end-century (2071–2100) periods were developed for 20 AOGCMs from the Coupled Model Inter-comparison Project phase 5 (CMIP5) for 2 Representative Concentration Pathways (RCPs), 4.5 and 8.5. The climate change scenarios were developed and analyzed for all the stations used in this assessment. Future projected climate change scenarios were downscaled with the delta method for 20 CMIP5 climate models. However, note that in this study we are considering 5 GCMs (CCSM4, HadGEM2ES, MIROC5, MPI ESM and GFDL); the mid-century (2041–2070) scenario; and RCP 8.5 presents a higher carbon dioxide concentration compared to RCP 4.5.

2.5. Crop modeling

Long-term historical climate data for the baseline period 1980–2010 for 4 locations in the target county were collected from the archives of the Kenya Meteorological Department (KMD). Efforts were made to collect daily observations on all parameters — rainfall, maximum temperature, minimum temperature and solar radiatio — that are required to operationalize the crop models. Two plot-specific crop simulation models, DSSAT and APSIM were selected for the study. The data on maize[4] (H511, H513 and 'Katumani' varieties) crop phenology, biomass, yields and management practices for the long- and short-range seasons over 2 years (2000 and 2001) were obtained from Kenya Agricultural and Livestock Research Organization (KALRO). Yield experimental data were selected that represented the 3 major maize varieties and the major crop growing seasons. In addition to crop experimental data, historical daily weather data (rainfall, maximum and minimum temperatures, solar radiation and relative humidity) for the period 1980 to 2012, and soil data (including albedo, surface runoff curve number, texture; water-holding capacity at drained lower and upper limits and at saturation; bulk density; pH; and organic carbon for 4 to 5 layers of soil) and site information were collected. Varieties were calibrated for 4 main parameters — days to flowering, days to maturity, and grain and biomass yields at harvest. For some varieties such as 'Katumani', default parameters that are available in APSIM and DSSAT models needed no further adjustments. For other varieties, parameters were derived by manipulating the thermal time required to complete various growth stages until the simulated phenology matched the observed phenology. Simulations with a final set of parameters by both models indicated a good relationship between observed and simulated days to flowering and days to maturity. The model-simulated biomass and grain yield were closely related to the observed data.

2.6. Economic modeling

For the analysis of impacts of climate change on current agricultural systems we used the TOA-MD. The TOA-MD model is a parsimonious, generic model for analysis of technology adoption and impact assessment, and ecosystem services analysis (Antle 2011). In this model, households are presented with a simple binary choice: they can operate with a current or base production System 1 (current climate, current technology), or they can switch to an alternative system (Claessens et al. 2012). The empirical model is therefore based on the random utility theory where a household is assumed to maximize a welfare-

[3]The delta method assumes that future model biases for both mean and variability will be the same as those in present day simulations (Mote & Salathé 2009)

[4]Note that only maize was simulated using APSIM and DSSAT. For other crops such as beans, coffee, pigeon peas, sorghum/millet, future production, price and variable costs of production were estimated using RAPs based on expert opinion

enhancing factor such as utility (McFadden 1973). The random utility model theory posits that the utility U that an individual or household i gains from participating in system h is made up of an observable deterministic component V (of observable attributes) and a random component ε . Thus, the random utility function is represented as (Greene 2003):

$$U_{ih} = V_{ih} + \varepsilon_{ih} \tag{1a}$$

Therefore, an individual or a household is assumed to maximize utility from a given system if the utility derived from participating in the system (U_h) is greater than the individual/household utility before participation in this system. This equation can be presented as (Maddala 2001):

$$U_{ih} = V(X_h) + \varepsilon_{ih} \tag{1b}$$

where, for any individual or household i, a given level of utility U will be associated with participation in a certain system h. Thus, system h will be chosen over some other system k if $U_h > U_k$. The utility derived from participation in a project is assumed to depend on the attributes of the system X_h and the attributes of the individual Z_i (Maddala 2001).

This theoretical foundation can be empirically translated into the TOA-MD, which has been used for the analysis of technology adoption (Claessens et al. 2008, 2010); payments for environmental services (Antle & Valdivia 2006, Immerzeel et al. 2008, Antle et al. 2010); and evaluating climate change adaptations (Claessens et al. 2012). To motivate the TOA-MD model, assume a household at a site s using a production system h which is defined as a combination of technology, climate and a certain RAP. The returns per hectare (V) in a certain period t — usually a year — for this household is equal to $v_t = v_t(s, h)$. If this household was to earn this annuity over T time periods, the discounted net return for this system h would be given as:

$$NR(s,h) = \sum_{t=1}^{T} \delta_t v_t(s,h) \Rightarrow v_t(s,h)\left[\frac{1-\delta^{-T}}{r}\right] \tag{2}$$

where, $NR(s,h)$ is the discounted net return for system h over time T; δ_t is the discount factor; and r is the interest rate. If there is a change in technology or climate or both, then the production in system h is also expected to change and so are the expected returns of the system. This change ushers in a new system of production which we christen system k. The effect of changing from system h to the new system k on household's returns can be expressed as:

$$\omega(s,h,k) = NR(s,h) - NR(s,k) \tag{3}$$

where NR are the net farm returns. If $\omega(s,h,k)$ is positive it means that the net farm returns in the old system are higher than in the new system and hence a loss or opportunity cost is associated with switching from system h to system k. If the figure is negative, it represents the gain in switching to system k. If we were to define the spatial distribution of gains or losses in the population of farms indexed by s using the density function $\varphi(\omega|h,k)$; then the percent of farms with $\omega(s,h,k) < a$ (where a is an amount in dollars per ha or acre) is given by:

$$r(a,h,k) = 100\int_{-\infty}^{a} \varphi(\omega|h,k)\mathrm{d}\omega \tag{4}$$

If we assume that climate changes and households do not adapt, then their only option is to use the same technology with the new climate (say System 2). The task, therefore, is to compare the performance of farm-level indicators under System 1 with current technology and current climate, and System 2 where climate has changed but households retain the same technology (i.e. not adapted to climate change). In this case, Eq. (4) above is interpreted as showing the proportion of farms with losses less than a, i.e. $\omega(s,1,2)$. Therefore, $r(0,1,2)$ can be interpreted as the proportion of farms that are positively impacted by climate change and $1 - r(0,1,2)$ is the proportion of farms that is negatively impacted by climate change.

Although it is possible for farmers to adapt to new technologies, this study does not extend to the impacts of adaptation to climate change, but restricts itself to the impacts of climate change on farmers in the case where climate changes but farmers fail to adapt, or what we would call the 'pure climate change impact'. The comparison is therefore between a scenario of current climate with current production technology against a future climate but still using current technology. To capture this pure climate change impact it is assumed that the climate will change but in terms of technology, households will continue with 'business as usual'. This comparison can be presented as: (a) System 1 = current climate, current technology; and, (b) System 2 = future climate, current technology.

For the purposes of this study, current climate is defined as what exists now, i.e. as influenced by present direct drivers e.g. prevailing rainfall and temperatures as currently experienced by farms. Current technology is comprised of existing management practices, crop varieties, farm sizes etc. To capture the pure climate change impact on production, we assume that this present technology does not change in the different AEZs. We however assume that cli-

Table 5. Simulated and observed maize yields in different agro-ecological zones (AEZs). <1 and >1 indicate that climate change has a negative or positive impact, respectively, on maize production. $r = S_2/S_1$ is the relative yield, where S_2 is the future simulated yield (System 2) and S_1 is the base simulated yield (System 1)

AEZ	Observed yield (kg ha^{-1})	Time-averaged relative yield ($r = S_2/S_1$)									
		APSIM					DSSAT				
		CCSM4	GFDL	HadGEM	MIROC	MPI	CCSM4	GFDL	HadGEM	MIROC	MPI
UM2	2191.20	0.97	1.06	1.07	1.06	1.03	1.12	1.17	1.07	1.11	1.23
UM3	2273.20	1.00	1.02	0.98	1.02	0.99	1.35	1.39	1.27	1.28	1.44
LM3	1935.09	1.02	1.03	1.00	1.02	1.00	1.32	1.51	1.63	1.24	1.41
LM4	1675.40	0.75	1.05	1.06	0.91	0.88	0.98	1.12	1.30	0.92	1.06
LM5	877.04	0.98	1.06	1.07	1.02	0.89	1.13	1.27	1.27	1.29	1.23

mate does change (as indicated by relative crop yields and as estimated by crop modellers and RAPS). This would give rise to a future climate with changes in rainfall and temperature which are expected to change the levels of crop production. Indirect drivers such as technology are held constant, but economic factors such as prices of inputs are expected to change. If one wanted to capture the impact of adaptation, then both climate and technology would change, but this is beyond the scope of this study. For our analysis, the present production system under current climate and current technology (System 1) is shocked with future (2041–2070) climate (System 2) to determine how it responds to such a shock.

3. RESULTS

3.1. Relative yield distributions

The relative yield distributions in Table 5 were obtained from crop modelling, both in APSIM and DSSAT models. They depict the expected changes in maize production based on the different climate models in all the 5 AEZs. For instance, in APSIM, CCSM4 indicates a 25% decline in maize production in LM4, and minor declines or increments in the other AEZs. The other models yield changes in production ranging from a 12% decline in LM4 to a 7% increase in UM2 and LM5. In DSSAT, the increments are much larger and range from 6 to 63% increase in maize production while the declines are between 2 and 8% (Table 5).

Based on results from the maize simulation, historical data and expert opinion, we made certain assumptions on expected changes in other crops in the system which were not simulated using APSIM or DSSAT. For instance with climate change, bean production is expected to increase by 10% in UM2, UM3 and LM3, and decline by 10% in LM4 and LM5. Coffee is grown in UM2 and UM3, both of which gain from climate change, hence its production is expected to increase by 20% in both AEZs. Pigeon pea and sorghum are drought-tolerant crops grown in marginal areas and are not expected to be adversely affected by climate change. In fact, the simultaneous increment in rainfall and temperature in the region is expected to boost pigeon pea and sorghum production by 20 and 15%, respectively, in LM3, and decrease production of both crops by 10% in LM4 and LM5 (Table 6). Dairy production is also expected to increase by 10% in all AEZs.

3.2. Losers from climate change

Once again, note that the aim of our analysis is to assess the impact of future climate on current agricultural systems, i.e. to shock the current system with climate change and observe changes in welfare indicators. Therefore, output prices, both for crops and livestock (dairy), were held constant (Table 3). However, production costs for all enterprises are expected to change, as production changes, e.g. an increase (decrease) in bean output is expected to increase (decrease) variable costs of production. Other household characteristics such as farm size, herd size, non-agricultural income, etc. are also assumed to remain

Table 6. Expected relative yields ($r = S_2/S_1$) of non-modelled crops using representative agricultural pathways (RAPs). N/A: not applicable

Crop	Beans	Coffee	Pigeon pea	Sorghum	Dairy
UM2	1.1	1.2	N/A	N/A	1.1
UM3	1.1	1.2	N/A	N/A	1.1
LM3	1.1	N/A	1.1	1.15	1.1
LM4	0.9	N/A	0.9	0.9	1.1
LM5	0.9	N/A	0.9	0.9	1.1

constant. Any change between the two systems is therefore purely the effect of climate on the current system. For impact analysis, the household and farm characteristics highlighted earlier, production levels of different crops and diary, output prices, and costs of production for the current system were keyed-in the TOA-MD model and compared with a future system where production levels and costs of production are changed due to climate change. Results from analysis indicate that if the current production system in Embu County is subjected to climate change shock, then LM4 and LM5 will have the highest number of losers. This is because climatic changes in these two AEZs is expected to have adverse effects on crop production and other ecosystems goods and services from the farms. From APSIM simulations, about 36–56% of the households in LM5 and 39–66% in LM4 are expected to be worse off than they are today if the current system was to be subjected to climate change. The figures are lower using DSSAT estimations (Table 7). Losses in UM3 and LM3 are lower in both APSIM and DSSAT for all GCMs.

3.3. Impact of climate change on net farm returns

The impact of climate change on net farm returns is as shown in Table 8 both for APSIM and DSSAT, respectively. In the APSIM analysis, for all the AEZs (except CCSM4 for LM4; and MPI-ESM for LM4 and LM5), climate change will have a positive impact on net farm returns. In some GCMs, declines in maize production were recorded as reported in Table 6. Therefore, the positive net farm returns could be explained by net farm returns from other crops (coffee, beans, pigeon peas, and sorghum), which are expected to increase in yields in some AEZs due to climate change. Examples of this are in UM2 for CCSM4 and LM4 for MIROC-5, which record a decline in maize production but increased net farm returns. In instances where loss in maize production and loss in other crops was recorded, net farm returns also recorded a decline, e.g. CCSM4 for LM4, and MPI-ESM for LM4 and LM5. The gains in net returns are highest in LM3 and UM3 and lowest in LM5. Results from the DSSAT model indicate gains in net farm returns in all AEZs, and the trends are similar to those of APSIM, though higher.

The total gains and losses from climate change were expressed as a percent of net farm returns for the different models (Fig. 3). APSIM simulations indicate minimal net impact from climate change, with GFDL recording the highest net gains of 53.2%, while MPI-ESM recorded a net gain of 0.45% (Fig. 3a). The net impacts under DSSAT (Fig. 3b) are almost uniformly spread across the different models, with the least (CCSM4) recording 5.6% net gains, while HADGEM recorded the highest net gains of 9.1%.

Table 7. Percentage of households expected to be worse-off ('losers') with climate change

AEZs	APSIM					DSSAT				
	CCSM4	GFDL	HadGEM	MIROC-5	MPI-ESM	CCSM4	GFDL	HadGEM	MIROC-5	MPI-ESM
UM2	31.62	28.77	27.79	28.04	29.15	26.19	24.82	28.15	28.24	22.95
UM3	33.05	31.94	33.81	32.00	33.70	21.70	20.56	23.22	27.50	20.94
LM3	29.56	39.03	31.24	29.67	30.33	21.73	19.48	18.62	24.78	20.24
LM4	56.41	44.43	38.80	45.26	51.90	43.56	34.84	26.89	47.74	38.06
LM5	40.10	37.43	39.94	36.05	56.09	36.95	33.81	37.75	34.26	35.67
Mean	43.65	39.30	38.26	37.95	50.89	36.70	32.05	31.83	37.11	34.08

Table 8. Change in net farm returns (US\$ farm^{-1} yr^{-1}) with climate change (APSIM and DSSAT)

AEZs	APSIM					DSSAT				
	CCSM4	GFDL	HadGEM	MIROC-5	MPI-ESM	CCSM4	GFDL	HadGEM	MIROC-5	MPI-ESM
UM2	82	99	106	103	97	116	124	102	122	145
UM3	104	116	98	112	99	315	335	274	276	372
LM3	120	178	108	119	115	265	357	414	223	311
LM4	-67	115	92	107	-8	35	95	165	12	68
LM5	24	29	27	33	-20	30	39	29	103	34
Mean	17	70	56	65	5	68	97	110	100	85

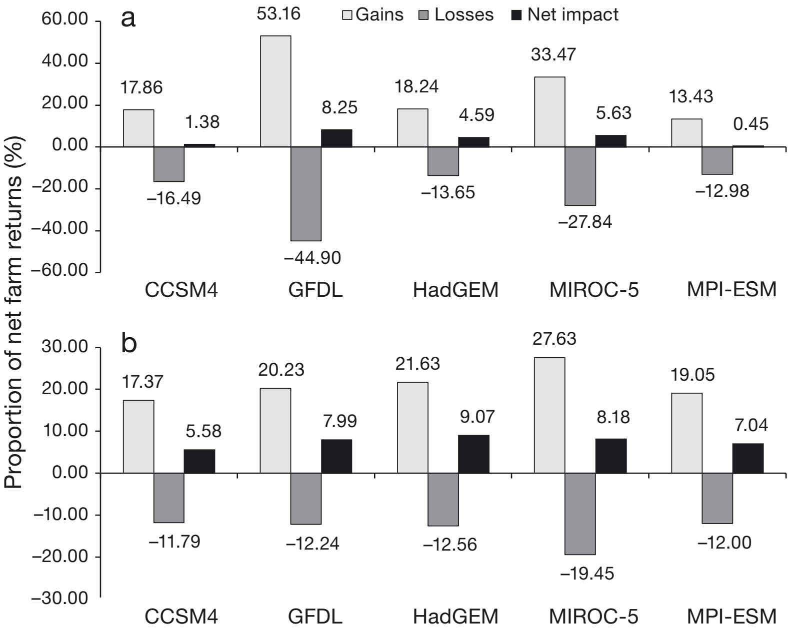

Fig. 3. Gains, losses and net impact as percent of net farm returns for all agroecological zones. (a) APSIM, (b) DSSAT

3.4. Impact of climate change on per capita income

The sensitivity of per capita income to climate change is estimated by considering the difference in per capita income (in US\$ d^{-1}) between System 1 and System 2 (Table 9). The results indicate that climate change will cause a change of varying degrees in per capita income in different AEZs, with the highest gains made in UM2, UM3 and LM3. In LM4, CCSM4 under APSIM predicts a decline in per capita income, while the gains in LM5 are very marginal. This illustrates that climate change will have negative impacts on households in LM4 and LM5. The predictions under DSSAT tell a similar story, though no AEZ under DSSAT reported negative change, and households in LM4 and LM5 gained the least from climate change while those in UM3 and LM3 gained the most.

3.5. Impact of climate change on poverty

Another important indicator of household welfare is poverty level. Changes in poverty levels from the APSIM and DSSAT models are shown in Table 10. From the APSIM estimates, changes in poverty levels indicate that climate change will reduce poverty levels in all AEZs for all GCMs (except CCSM4 in LM4 and MPI-ESM in LM5). However, the levels do vary, as seen from the distribution of results across the AEZs. The highest re-

Table 9. Change in per capita income (US\$ d^{-1}) with climate change (APSIM and DSSAT)

AEZs	APSIM					DSSAT				
	CCSM4	GFDL	HadGEM	MIROC-5	MPI-ESM	CCSM4	GFDL	HadGEM	MIROC-5	MPI-ESM
UM2	0.07	0.08	0.09	0.08	0.08	0.09	0.10	0.08	0.10	0.12
UM3	0.06	0.07	0.06	0.06	0.06	0.18	0.19	0.16	0.16	0.21
LM3	0.07	0.10	0.06	0.07	0.07	0.15	0.21	0.24	0.13	0.18
LM4	−0.03	0.06	0.05	0.05	0.00	0.02	0.05	0.08	0.01	0.03
LM5	0.01	0.01	0.01	0.02	−0.01	0.01	0.02	0.01	0.05	0.02
Aggregate	0.03	0.06	0.05	0.06	0.04	0.09	0.11	0.11	0.09	0.11

Table 10. Percent decline in poverty levels (APSIM and DSSAT)

AEZs	APSIM					DSSAT				
	CCSM4	GFDL	HadGEM	MIROC-5	MPI-ESM	CCSM4	GFDL	HadGEM	MIROC–5	MPI-ESM
UM2	−1.4	−1.7	−1.8	−1.8	−1.7	−2.0	−2.1	−1.8	−2.1	−2.5
UM3	−3.4	−3.8	−3.2	−3.7	−3.3	−9.6	−10.2	−8.5	−8.6	−11.1
LM3	−1.8	−1.6	−1.6	−1.8	−1.7	−3.8	−4.8	−5.4	−3.1	−4.2
LM4	1.4	−2.2	−1.6	−1.1	0.2	−0.7	−1.7	−2.9	−0.2	−1.3
LM5	−0.6	−0.8	−0.7	−0.8	0.5	−0.8	−1.01	−0.7	−2.7	−0.9
Aggregate	−1.2	−2.0	−1.8	−1.8	−1.2	−3.4	−4.0	−3.9	−5.1	−4.0

duction in the poverty rate is in UM3, where APSIM projected reductions in poverty of up to 3.8% while DSSAT projected poverty declines of >11% in UM3. In both models the smallest poverty rate reduction was in LM4 and LM5.

4. DISCUSSION

Our results indicate that climate change will have mixed impacts on maize production (Table 4) in different AEZs based on the GCM and the crop model used. For instance, using APSIM, climate change will have a negative impact on maize production in LM4 and LM5 for CCSM4 and MPI-ESM. Losses are also recorded in LM4 for MIROC-5 and UM3 for HadGEM. The other GCMs indicate gains from climate change under APSIM. Overall, APSIM shows a negative impact of climate change on current production systems for some GCMs, while DSSAT shows an overall increase in maize production due to climate change. APSIM results show that ~36–56% of the households in LM5 and 39–66% in LM4 are projected to be worse off than they are today were the current system subjected to climate change. The figures are lower for DSSAT estimations. According to the DSSAT results there are positive net farm returns and per capita income for all GCMs, but these are low for UM2, LM4 and LM5, and APSIM results indicate very low or negative net farm returns and per capita income with climate change for LM4 and LM5, while the other AEZs show gains for all GCMs. This indicates that households in LM4 and LM5 are more vulnerable to climate change compared to the other AEZs. There are also mixed results regarding the impacts of climate change on poverty levels from the APSIM and DSSAT estimates.

Climate change is therefore likely to have negative impacts on maize production in the LM4 and LM5 AEZs of Embu County. This is expected because although these 2 AEZs are not ideal for maize production, quite a large number of households still grow it. In the other AEZs, climate change is likely to have a positive impact on maize production. Note that Embu County is on the slopes of Mount Kenya, and temperatures in the upper AEZs (UM2, UM3 and LM3) are sub-optimal for maize. Therefore an increase in temperature might boost maize production in the AEZs. Increases or decreases in maize production in the different AEZs influence the levels of the welfare indicators. The other crops, along with dairy production, also determine the levels of welfare indicators. For instance, certain AEZs report a decline in maize production, but with positive net farm returns and per capita income, an indication that the contribution of the other crops outweighs the negative impact of climate change on maize production in that particular AEZ. This suggests that all crops and livestock in the farming systems in the County are potentially important in determining the overall welfare of households under climate change.

5. CONCLUSIONS AND POLICY IMPLICATIONS

This study analysed the sensitivity of current Kenyan agricultural production systems to climate change. Climate change is expected to have mixed impacts in Embu County, with some AEZs gaining and others losing from climate change. The IPCC (2014) WGII report indicates that negative impacts of climate change on crop yields are more common than positive impacts. The higher-elevation AEZs in Embu County present an example of where climate change is expected to have positive impacts on agricultural production. The lower-elevation AEZs, which are make up >80% of Kenya's farmlands, are expected to be negatively affected by climate change. We recommend that farmers both from higher- and lower-elevation AEZs take steps to adapt to climate change. Though we have shown that farmers in higher AEZs would gain from climate change, adaptation to climate change will boost their expected returns. Farmers in lower AEZs need to adapt to climate change to boost production and mitigate the potential negative impacts of climate change. This adaptation can be autonomous, where individual farms choose different adaptations based on available information. However, planned adaptation led by government or government agencies and non-governmental organizations (NGOs) would probably be a better strategy, as it would benefit from government or donor funding and resources.

Finally, note that for the non-modelled crops, estimates from expert opinions were used. Modelling these crops using APSIM, DSSAT or other crop models would give a more complete picture of impact of climate change on current agricultural system in the county. It would also be interesting to model the impact of adaptations to climate change on these welfare indicators.

LITERATURE CITED

Antle JM (2011) Parsimonious multi-dimensional impact assessment. Am J Agric Econ 93:1292–1311

Antle JM, Valdivia RO (2006) Modelling the supply of ecosystem services from agriculture: a minimum-data approach. Aust J Agric Resour Econ 50:1–15

Antle JM, Valdivia RO (2010) TOA-MD Version 4: Minimum-Data Tradeoff Analysis Model. http://tradeoffs.oregonstate.edu/climate/agmip

Antle J, Valdivia R (2011) Methods for assessing economic, environmental and social impacts of aquaculture technologies: adoption of integrated agriculture-aquaculture in Malawi. Oregon State University, Corvallis, OR

Antle JM, Diagana B, Stoorvogel JJ, Valdivia RO (2010) Minimum-data analysis of ecosystem service supply in semi-subsistence agricultural systems: evidence from Kenya and Senegal. Aust J Agric Resour Econ 54: 601–617

Brander L, Gómez-Baggethun G, Martín-López B, Verma M (2010) The economics of valuing ecosystem services and biodiversity, In Kumar P (ed) TEEB: The economics of ecosystems and biodiversity. Ecological and Economic Foundations, Earth Scan, London. Chapter 5, p 1–133

Claessens L, Stoorvogel JJ, Antle JM (2008) Ex ante assessment of dual-purpose sweet potato in the crop-livestock system of western Kenya: a minimum-data approach. Agric Syst 99:13–22

Claessens L, Stoorvogel JJ, Antle JM (2010) Exploring the impacts of field interactions on an integrated assessment of terraced crop systems in the Peruvian Andes. J Land Use Sci 5:259–275

Claessens L, Antle JM, Stoorvogel JJ, Valdivia RO, Thornton PK, Herrero M (2012) A method for evaluating climate change adaptation strategies for small-scale households using survey, experimental and modeled data. Agric Syst 111:85–95

Diaz S, Demissew S, Carabias J, Joly C and others (2015) The IPBES conceptual framework — connecting nature and people. Current Opinion Env Sustainability 14:1–16

Fisher B, Christie M (2010) Integrating the ecological and economic dimensions in biodiversity and ecosystem service valuation. In Kumar P (ed) TEEB: the economics of ecosystems and biodiversity. Ecological and Economic Foundations, Earth Scan, London. Chapter 1, p 1–40

Greene WH (2003) Econometric analysis, 5th edn. Prentice Hall, Upper Saddle River, NJ

Immerzeel W, Stoorvogel JJ, Antle JM (2008) Can payments for ecosystem services secure the water tower of Tibet? Agric Syst 96:52–63

IPCC (2014) Climate change 2014: impacts, adaptation and vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the IPPC. Part B: Regional aspects. Cambridge University Press, Cambridge.

Jaetzold R, Schmidt H, Hornetz B, Shisanya C (2007) Farm management handbook of kenya: natural conditions and farm management information, Vol. II, 2nd edn, Part C. East Kenya: Subpart C1, Eastern Province. Ministry of Agriculture, Nairobi.

Kelble CR, Loomis DK, Lovelace S, Nuttle WK and others (2013) The EBM-DPSER conceptual model: integrating ecosystem services into the DPSIR framework. PLoS ONE 8:e70766

Maddala AS (2001) Limited dependent and quantitative variables in econometrics. Cambridge University Press, Cambridge

McFadden D (1973) Conditional logit analysis of qualitative choice behaviour. In: Zarembka P (ed) Frontiers in econometrics. Academic Press, New York, NY

Mote PW, Salathé EP Jr (2010) Future climate in the Pacific Northwest. Clim Change 102:29–50

Republic of Kenya (2010) National climate change response strategy. Government Press, Nairobi

Rosenzweig C, Jones J, Hatfield J, Antle J (2013) Guide for regional integrated assessments: handbook of methods and procedures, Version 5. Agricultural Model Intercomparison and Improvement Project (AgMIP). www.agmip.org/refbase/uploads/cynthiarosenzweig/2013/170_CynthiaRosenzweig2013.pdf

WFP (World Food Programme) (2012) Countries: Kenya — overview. https://www.wfp.org/node/3497/2608/279525

Editorial responsibility: Eduardo Zorita, Geesthacht, Germany

Submitted: March 16, 2015; Accepted: November 21, 2015
Proofs received from author(s): January 26, 2016