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Crop models simulations for evaluating maize adaptation practices under different climate change scenarios by Mid Century (2040-2069)

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Abstract

High risks and vulnerability to climate change remain the biggest threat to crop production in Sub-Saharan Africa. The impact of climate change on maize production was evaluated in Albert Rift in Uganda using climate and crop simulation models. The Decision Support System for Agro-technology Transfer (DSSAT) and Agricultural Productivity Systems Simulator (APSIM) models were calibrated and validated using observed climate, soil and agronomic data in the region. Historical data (1980-2009) and future projected climate were used for one time period 2040-2069 (MID century). We used 5 Global Circulation Models (GCMs) and the impact of climate change on yield was assessed for Mid Century, at 8.5 Representative Concentration Pathway (RCP). Results from the crop models demonstrated high yield variability in the region, mainly attributed to rainfall variability and model uncertainty in yield predictions. APSIM model simulated an increase in maize yield with all the 5 GCMS. The DSSAT model simulated yield decline with 2 GCMS (CCSM4 and GFDL-ESM2M). Other GCMS in both models showed that adaptation practices such as *longe* 9, N fertilizers, and changing planting date will result in double agricultural yield gain. Crop models demonstrated high uncertainty in predicting future crop productivity. Efforts are needed to improve model prediction capabilities to increase certainty in predicting climate change impacts on agricultural yield.

Key words

Maize Yield, Climate Change, Adaptation, Mid-Century, Crop Models

Introduction

Maize is a major food crop among smallholder farming systems in sub-saharan Africa, but yields remain low and per capital food production has declined since 1980 (Greenland *et al*., 1994; Sanchez *et al*., 1996; Muchena *et al*., 2005). Several factors influence crop production in the region. However, high risks and vulnerabilities linked to increased climate change impacts are becoming a major concern for food and income security for resource-poor farmers (Slingo *et al*., 2005; IPCC, 2007; Nelson *et al*., 2009). Farming systems are highly reliant on rainfall, and this makes agricultural production most vulnerable sector to climate change (Zhou *et al*., 2010). This is further aggravated by high soil degradation, poverty and poor infrastructure which remain key bottle necks to development (Fischer *et al*., 2005; IPCC 2007). According to the recent IPPC reports, negative impacts of climate change on agriculture outweigh the positive impacts. Increased evidence of climatic disasters such as drought and floods are increasingly becoming a threat to food security (Shongwe *et al*. (2009). Current estimates show that climate change of about 1°C warming is projected to result in 65% decline in maize yield (Lobell *et al*., 2011). Other studies in the East Africa have shown that by 20150, temperature may increase between 1.3 to 2.1^{o}C while some model predict annual precipitation increase by 1000 mm (Waithaka et al., 2013). These events call for the need to respond to climate change effects that could derail agricultural development. Adaptation strategies are essential to regulate such looming effects although these must be developed within an economic context (IPCC, 2007). Current management practices that are affordable by farmers are inefficient to respond to climate change adversity (Mudzonga 2011). Coping mechanisms to such impacts of climate change are required by identifying parsimonious adaptation strategies suited for vulnerable communities. In this regard, protocols and methods for an integrated assessment were developed by Agricultural Model Inter-comparison and Improvement Project (AgMIP), which aimed at developing accurate information on how the projected changes in climate might affect the smallholder farmers' crop productivity (Rosenzweig *et al*., 2013). The DSSAT and APSIM simulation models were suggested as potential tools in integrated assessment. The crop models have been widely used in several countries in the characterization of cropping system by integrating various processes and developing adaptation measures. However, there is limited knowledge on simulating the performance of existing adaptation options to respond to the current and future climatic threats in the fragile smallholder farming systems. Crop simulation models were was applied to simulate maize yield variability under current climate conditions, potential threats of projected climate change on maize production and assess adaptation practices that could be feasible for small holder farmers. It was hypothesized that there is significant difference in maize yield by adopting adaptation practices.

Materials and methods

Study sites

The study was conducted in two districts located in the Albertine region, namely Hoima and Masindi that straddle the Lake Albert bordering Uganda and DRC (Fig.1a). The two districts are located in the western Mid-Altitude Farmlands and Semliki Flats (MAFSF) Agro-ecological zone (Wortmann and Eledu, 1999). Generally, the districts are dominated by three soil types, namely, Ferralsols, Regosols, and Plinthisols (Figure 1b). The rainfall patterns are basically bi-modal. Maize is a major food and cash crop in the region, and major copping system in Uganda.

The average annual rainfall in Hoima and Masindi ranges between 700-1,000 and 800-1630 mm, respectively with a bi-modal distribution and peaks in March-May and August-November.

Majority of the people in the region are smallholder farmers. The dominant farming systems in the region are the western banana coffee cattle system and banana millet cotton system (Osiru, 2006). Major crops in the region under large-scale farming are maize, tea, sugarcane, while small-scale farming includes beans, ground-nuts, rice, sweet potatoes, cassava, millet, pigeon peas, banana, and simsim (Mubiru *et al*., 2007). However, the productivity of most smallholder farms vary from high to low potential and depends on soil type and management. Most of the farmers rarely use the inorganic fertilizers and only a few apply organic manure.

Soils characteristics. The dominant soils in the region include Hoima catena (Petric Plinthosols), Naitondo series (Dystric Regosols), and Kigumba series (Acric Ferralsol) (Figure 1). The Hoima catena covers a large part of south-west Bunyoro overlying the sedimentary beds predominated by tillites and phyllites with subsidiary counts of sandstones and conglomerates as basal members. The soils are usually very acid, poor in bases and available phosphorus and with lower amounts of organic material than their dark colour would suggest.

The Dystric Regosols are believed to be a variant of the Hoima catena overlying the valley slopes with deeper accumulation of soil material giving rise to reddish-brown clay loams. It occurs at lower altitude. Magnesium and potassium contents are rather variable and calcium seldom shows a deficiency. Soil reaction throughout is very acid which appears to be a fairly constant feature of these phyllite soils even when bases are present in adequate amounts. Crop growth is poor on the shallow acid members of this catena and intensive cultivation is confined mainly to the deeper soils on the valley slopes (Chenery, 1960).

The Acric Ferralsols (Kigumba series) are reddish-brown loams to clay loams. This soil lies with topography that appears as broad flat-topped or very slightly convex ridges separated by wide swamp tracts. The pH values are fairly steady around 5.0, bases are low, deficient in magnesium and the amounts reduce with depth (Chenery, 1960).

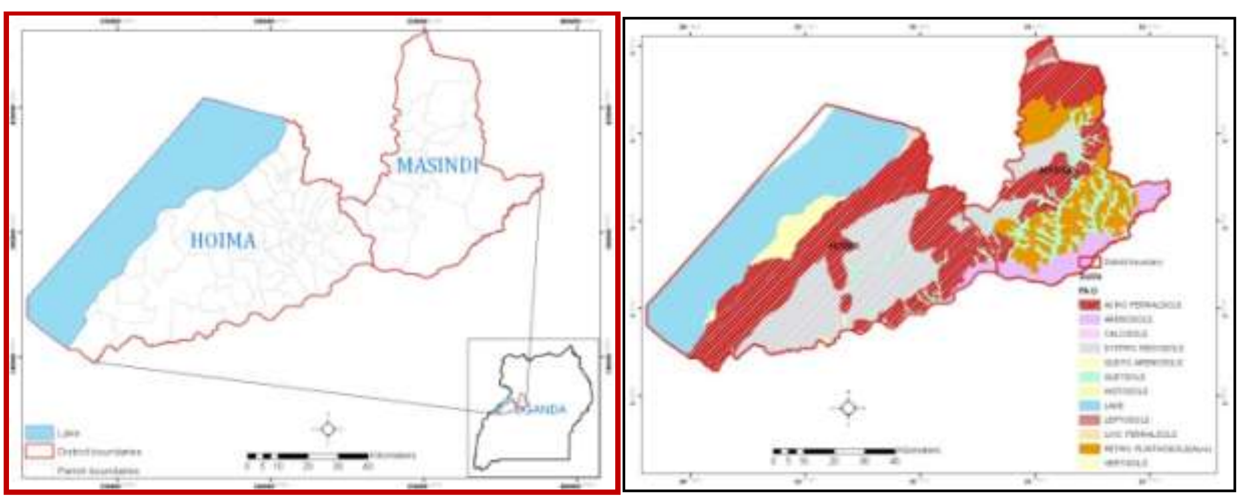


Figure 1. Target areas and the distribution of soils in Hoima and Masindi districts

Crop Model requirements

Climate data. Long-term daily observed historical climate data (1980-2010) were obtained from the Department of Meteorology in Uganda for Masindi district. For Hoima district (Kyangwali), the NASA's Modern Era-Retrospective Analysis for Research and Applications (MERRA) (Rienecker *et al*., 2011) was applied. MERRA is the NASA's climate model data repository. MERRA data are produced using their 4-Dimensional Variational (4D-Var) assimilation system and were provided in AgMIP extension (Ruane *et al*. 2014). MERRA data were used to fill temperature gaps for Masindi and its rainfall data from Kyangwali was adjusted using ten year data obtained from Bulindi weather station. The period 1980-2009 was considered as reference period because of the availability of complete MERRA climate data sets. The data collected include rainfall, minimum and maximum temperature, wind, relative humidity and solar radiation. This information was used to characterize the variability in the observed climate, develop future scenarios and also for use in DSSAT and APSIM.

Soil data. Soil parameters such as hydraulic conductivity, Drainage Upper Limit (DUL) and Lower Limit (DLL), air dry, saturation, bulk density were estimated using soil water characteristics Program (Rawls *et al*.,, 1982) based on soil texture, soil organic carbon content, gravel content, salinity and compaction. The physio-chemical characteristics of the soil profile in the models were arranged to a fixed depth per layer (Table 1). In APSIM, values of soil organic carbon pools (Fbiom, Finert, HumC, BiomC, InertC) as described in the model were dependant on soil organic carbon (SOC). In DSSAT, initial soil conditions of stable SOC were set at 44%. The C/N ratios in both models were derived by calculation.

In DSSAT, site descriptions such as slope per cent, run-off curve numbers, drainage rate, run-off potential, and soil fertility factor were estimated based on available literature (Chenery1960). All root growth factors were set at 1.0 as non-limiting in all soil profiles.

Table 1. Soil profile characteristics used in DSSAT and APSIM crop models in Uganda

		Depth	Drainage Lower Limit	Drainage Upper Limit	Plant available water	Bulk Density	SOC	Clay	Silt	Coarse	pH	CEC	Ksat (macro pore)
		cm	mm3/mm3	mm3/mm3	mm3/mm3	g/cm3	g[C] /100g	%	%	%		Cmol kg^{-1}	cm h^{-1}
Petro Plinthic	Good	15	0.155	0.366	0.512	1.29	2.770	23.0	8.00	0.00	5.5	3.50	0.10
		35	0.172	0.370	0.496	1.330	1.530	29.00	10.00	0.00	5.60	3.50	0.18
		70	0.205	0.400	0.503	1.32	1.100	37.0	8.00	0.00	4.4	3.50	0.13
		101	0.232	0.423	0.585	1.36	0.460	43.0	4.00	0.00	4.6	3.70	0.10
	Medium	15	0.153	0.359	0.502	1.32	2.355	23.0	8.00	0.00	5.5	3.50	0.10
		35	0.171	0.368	0.491	1.35	1.301	29.0	10.0	0.00	5.6	3.50	0.18
		70	0.204	0.399	0.598	1.33	0.935	37.0	8.00	0.00	4.4	3.50	0.13
		101	0.232	0.423	0.596	1.34	0.391	43.0	4.00	0.00	4.6	3.70	0.10
	Poor	15	0.150	0.351	0.490	1.35	1.939	23.0	8.00	0.00	5.5	3.50	0.10
		35	0.170	0.365	0.486	1.36	1.071	29.0	10.0	0.00	5.6	3.50	0.18

		70	0.204	0.398	0.593	1.34	0.770	37.0	8.00	0.00	4.4	3.50	0.13
		101	0.232	0.423	0.593	1.34	0.322	43.0	4.00	0.00	4.6	3.70	0.10
Dystric regosols	Good	15	0.160	0.406	0.561	1.16	3.228	23.0	10.0	0.00	5.4	15.13	0.10
		43	0.189	0.408	0.524	1.26	1.176	33.0	20.0	0.00	4.8	10.86	0.18
		81	0.216	0.425	0.530	1.25	1.092	39.0	14.0	0.00	4.8	9.04	0.13
		117	0.235	0.444	0.613	1.29	0.492	43.0	14.0	0.00	4.7	10.88	0.10
		173	0.195	0.403	0.593	1.34	0.372	35.0	18.0	0.00	4.8	5.65	0.10
		203	0.138	0.335	0.448	1.46	0.060	23.0	20.0	0.00	4.9	5.65	0.18
	Medium	15	0.164	0.399	0.553	1.19	2.690	23.0	10.0	0.00	5.4	15.13	0.13
		43	0.188	0.405	0.515	1.29	0.980	33.0	20.0	0.00	4.8	10.86	0.10
		81	0.216	0.424	0.525	1.26	0.910	39.0	14.0	0.00	4.8	9.04	0.10
		117	0.235	0.444	0.610	1.20	0.410	43.0	14.0	0.00	4.7	10.88	0.18
		173	0.194	0.403	0.591	1.35	0.310	35.0	18.0	0.00	4.8	5.65	0.13
		203	0.138	0.335	0.448	1.45	0.050	23.0	20.0	0.00	4.9	5.65	0.10
	Poor	15	0.159	0.384	0.534	1.23	2.152	23.0	10.0	0.00	5.4	15.13	0.10
		43	0.187	0.403	0.510	1.30	0.784	33.0	20.0	0.00	4.8	10.86	0.18
		81	0.215	0.422	0.616	1.28	0.728	39.0	14.0	0.00	4.8	9.04	0.13
		117	0.235	0.444	0.605	1.31	0.328	43.0	14.0	0.00	4.7	10.88	0.10
		173	0.194	0.402	0.588	1.36	0.248	35.0	18.0	0.00	4.8	5.65	0.10
		203	0.138	0.335	0.448	1.46	0.040	23.0	20.0	0.00	4.9	5.65	0.18
Acric Ferralsol	Good	13	0.175	0.405	0.564	1.15	3.336	26.0	6.00	0.00	5.1	12.20	0.13
		46	0.219	0.411	0.525	1.26	1.104	40.0	4.00	0.00	4.8	9.63	0.10
		84	0.229	0.427	0.613	1.29	0.612	42.0	8.00	0.00	5.0	7.62	0.10
		122	0.228	0.426	0.604	1.31	0.420	42.0	8.00	0.00	5.3	6.38	0.18
		152	0.208	0.396	0.587	1.36	0.264	38.0	4.00	0.00	5.0	5.83	0.13
		183	0.181	0.364	0.471	1.40	0.240	32.0	4.00	0.00	4.8	7.50	0.10
		213	0.182	0.367	0.479	1.38	0.384	32.0	4.00	0.00	4.6	6.30	0.10
	Medium	13	0.175	0.402	0.561	1.16	2.780	26.0	6.00	0.00	5.1	12.20	0.18
		46	0.219	0.410	0.518	1.28	0.920	40.0	4.00	0.00	4.8	9.63	0.13
		84	0.228	0.426	0.609	1.30	0.510	42.0	8.00	0.00	5.0	7.62	0.10
		122	0.228	0.426	0.601	1.32	0.350	42.0	8.00	0.00	5.3	6.38	0.10
		152	0.208	0.395	0.585	1.37	0.220	38.0	4.00	0.00	5.0	5.83	0.18
		183	0.181	0.363	0.468	1.41	0.200	32.0	4.00	0.00	4.8	7.50	0.13
		213	0.182	0.366	0.476	1.39	0.320	32.0	4.00	0.00	4.6	6.30	0.10
	Poor	13	0.171	0.388	0.543	1.21	2.240	26.0	6.00	0.00	5.1	12.20	0.10
		46	0.218	0.409	0.511	1.29	0.736	40.0	4.00	0.00	4.8	9.63	0.18
		84	0.228	0.426	0.604	1.31	0.408	42.0	8.00	0.00	5.0	7.62	0.13
		122	0.228	0.425	0.599	1.33	0.280	42.0	8.00	0.00	5.3	6.38	0.10
		152	0.208	0.395	0.582	1.37	0.176	38.0	4.00	0.00	5.0	5.83	0.10
		183	0.181	0.363	0.468	1.41	0.160	32.0	4.00	0.00	4.8	7.50	0.15
		213	0.181	0.363	0.470	1.41	0.256	32.0	4.00	0.00	4.6	6.30	0.16

Crop management

Crop management parameters used in setting up simulations for individual farms were derived from the results of the survey conducted in Hoima and Masindi districts. Parameters used in setting up on-farm simulations were also derived from data collected in the survey. Varieties that are most dominant in the region are local traditional, *Longe* 5, and *Longe* 9 (Table 2). Detailed Information on *Longe* 5 and *Longe* 9 varieties was obtained from NASECO seeds. For the local traditional variety, *Katumani* information was used because of similarities in physiology, phenology and yield potential.

Table 2: Maize varieties used by farmers and the equivalent cultivar in the cropmodel

Variety used by farmer	Duration (days)	Grain Yields (t ha^{-1})	Variety in the Model
Nafa, Ndele, *Longe* 1, *Longe* 4	100-105	1.5-1.8	Local traditional (Katumani)
Longe 5, dk	115	4-5	*Longe* 5
Longe 2H, *Longe* 6H, *Longe* 10H	120	7-8	*Longe* 9
Others	Considered as local		Local- traditional Katumani

Source: NASECO seeds Ltd, Kampala, Uganda

Plant population that were estimated for each individual farms were set based on farmers' practice. The plant population normally ranged between 40,000 to 60,000 plants per hectare. Three major categories of plant population were used on three major soil types (Table 3). In the survey, it was noted that majority of the farmers do not apply inorganic fertilizers. While setting up the models for individual farmers, 5 kg N fertilizer amounts was applied to allow for model sensitivity. All model runs for the survey data was conducted using AgMIP tools namely QuadUIi and ACMO UI that can be availed at www.tools.agmip.org.

Table 3: Number of farmers using different plant populations in the three soil types in Uganda

Plant population (plants/ha)	Acric Ferralsols	Petric Plinthisols	Dystric Regosols	Total
40,000	60	69	53	162
50,000	18	16	32	66
60,000	20	18	21	59

Source: Uganda AGMIP survey data, 2012

Crop Model calibration and validation

Both the DSSAT and APSIM Models were calibrated for *Longe* 5 and *Longe* 9 using experimental data from Bulindi Zonal Agricultural Research Institute in Hoima (Kaizzi *et al*., 2012). Validation of model outputs was done using information from National Agricultural Research Laboratories, Kawanda (NARL). Both experiments were conducted for the two rain seasons of 2010. Crop management and growth measurements over the seasons and growing period were conducted as described by Kaizzi *et al*., (2012).

All model parameter coefficients for DSSAT were derived after adjusting existing varieties typical of tropical conditions (Table 4 and Table 5) and also by manipulating various growth parameters until the simulated phenology and yields matched the observed. Models were run and the relationship between observed and simulated data was demonstrated using observed and simulated days to flowering, days to maturity, stover and grain yield. All DSSAT model runs were compared to the observed using the highest fertilizer rates of 100 and 150 kg N ha^{-1} since model runs were under non-limiting conditions of phosphorus, acidity, micronutrients and pH, thus providing highest yield potential.

Table 4: Data for calibration and validation of the crop models (*Longe* 5) in Uganda

		Trt (N kg/ha)	Stover wt	Grain wt	TOP wt	P_date (2009)	A_date	PMDate	H_date
2009B							Julian Days		
Long rain (*longe* 5)	1	0	3.83	1.32	5.15	252	306	2(2010)	40 (2010)
	2	50	4.69	2.96	7.65	252	306	2(2010)	40 (2010)
	3	100	4.86	3.43	8.29	252	306	2(2010)	40 (2010)
	4	150	5.23	3.54	8.77	252	306	2 (2010)	40 (2010)
2010A									
Short rain (*Longe* 5)	5	0	4.55	1.47	6.02	78	136	203	234 (2010)
	6	50	7.25	3.66	10.91	78	136	203	234 (2010)
	7	100	7.35	3.5	10.85	78	136	203	234 (2010)
et al									

Source: Kaizzi et al. (2012)

Table 5. Data for calibration and validation of the crop models (*Longe* 9 and *local traditional* varieties) in Uganda

2010A		Treatment (N kg/ha)	Stover weight	Grain weight	TOP weight	Planting date (2009)	Anthesis date	Physiological maturity date	Harvesting date
			--------------kg ha^{-1}-----------				-----Julian Days----		
Long rain (*longe* 9)	1	0	5.25	4.16	9.41	78	136	199	230 (2010)
Long rain (*longe* 9)	2	100	5.15	5.20	11.35	78	136	199	230 (2010)
Sourced from NASECO seeds Ltd									
Long rain (Local tradition)	1	0	3.25	1.16	4.31	78	137	208	236 (2010)
Long rain (local tradition)	2	100	4.33	3.02	7.35	78	138	208	238 (2010)
Sourced from AGMIP on-farm survey									

Where A represents long rain season and B short rain season.

Table 6. DSSAT model calibration crop coefficients for the three varieties in Uganda

Cultivar ID	Variety name	P1	P2	P5	G2	G3	PHINT
IC0005	*Longe* 5	200.8	. 0.500	508.5	450.0	10.50	45.60
IC0006	*Longe* 9	208.6	0.500	554.0	460.0	10.50	45.00
IC0007	Local tradition (Katumani)	180.0	0.600	600.0	680.0	8.70	40.0

Where P1 = Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8 °C) during which the plant is not responsive to changes in photoperiod.
P2=Is the extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours
P5= is the Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8 °C).
G2 = Maximum possible number of kernels per plant
G3 is the Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).
PHINT is the Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.

Table 7. APSIM model calibration crop coefficients for the three varieties in Uganda

	Katumani (local)	*Longe* 5	*Longe* 9
hi_incr (1/days)	0.018	0.018	0.018
hi_max_pot (g/g)	0.55	0.55	0.55
Head grain number - maximum ()	450	610	750
Grain growth rate (mg/grain/day)	10.5	9.17	8.0
tt_emerg_to_endjuv (°C day)	150	210	240
est_days_endjuv_to_init ()	20	20	20
pp_endjuv_to_init	10	10	10
tt_endjuv_to_init (°C day)	0.0	0.0	0.0
photoperiod_crit1 (hours)	12.5	12.5	12.5
photoperiod_crit2 (hours)	24.0	24.0	24.0
photoperiod_slope (°C/hour)	10.0	10.0	0
tt_flower_to_maturity (°C day)	660	660	980
tt_flag_to_flower (°C day)	10	10	50
tt_flower_to_start_grain (°C day)	120	120	120

tt_maturity_to_ripe (^{o} C)	1	1	1

Testing model sensitivity

Model sensitivity to various environmental parameters was examined by conducting a matrix of simulations designed to understand the response of DSSAT and APSIM crop models to changes in maximum and minimum temperatures, precipitation and atmospheric CO2 concentrations. Climate data for 30 years (1980- 2010) was used for the sensitivity analysis. We tested using the following climatic parameters; Base Climate, Base + 1 ^{0}C, Base + 3 ^{0}C, Base + 5 ^{0}C, Base + 1 ^{0}C + 10%RF, Base +3 ^{0}C + 10% RF, Base + 5 ^{0}C+ 10% RF, Base + 1 ^{0}C-10%RF, Base + 3^{0}C-10%RF, Base+5 ^{0}C-10%RF.

Model simulation for impacts of Mid and End climatic scenarios on crop yields

Climate change scenarios for mid-century (2041-2070) and end-century (2071-2100) periods were developed for 20 AOGCMS (Coupled Atmosphere-Ocean General Circulation Models) for two Representative Concentration Pathways (RCPs) 4.5 and 8.5. Since it is not practical to assess impacts of climate change on agricultural systems at local scale with coarse data from coupled atmosphere-ocean general circulation models (AOGCM), location specific climate change scenarios were developed using a simple Delta Method in which monthly changes in temperature and precipitation from an AOGCM, calculated at the grid scale, are added to the corresponding observed station data. The delta method assumes that future model biases for both mean and variability will be the same as those in present day simulations (Mote and Salathe, 2010). Climate change scenarios for mid-century (2041-2070) and end-century (2071-2100) periods were developed for 20 AOGCMS. For this paper, we extracted five GCMs since they have been widely used to assess the impacts of climate change. The 5 GCMS include, CCSM4; GFDL-ESM2M; HadGEM2-ES; MIROC5 and MPI-ESM-MR.

Outputs from these climatic models will be used for running both the DSSAT and APSIM models to evaluate impacts of climate change on maize yield under the three soil types, local varieties, normal planting date and without mineral fertilizer applications.

Simulating adaption practices under the Mid Century climatic scenarios (8.5 RCP)

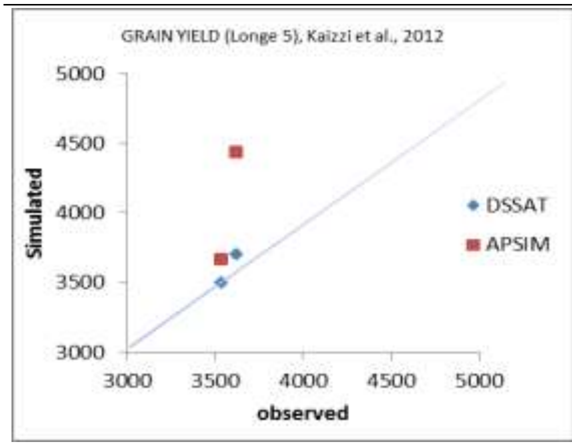
Using the same outputs from these climatic models, both DSSAT and APSIM models evaluated the impacts of adaptation practices on maize yield response in three soil types. The adaptation practices that were tested include use of improved variety (*Longe* 9) (changing from local varieties), application of 50 kg N ha^{-1} (changing from practice of no fertilizer use); applying late planting (15th march for the short season and 15th September for long season) all established at plant population at 50,000 plants per hectare.

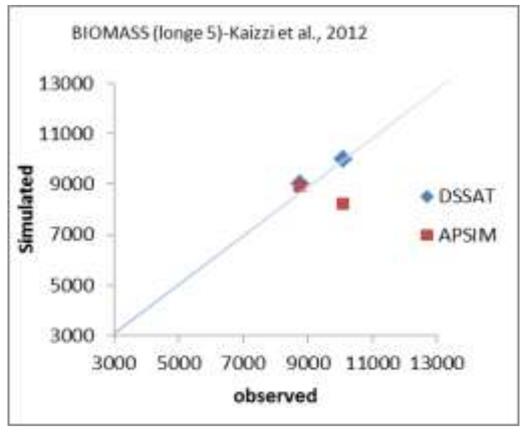
RESULTS

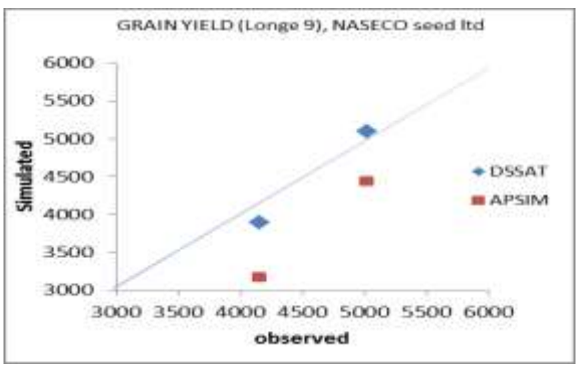
(a) Model calibration and sensitivity analysis

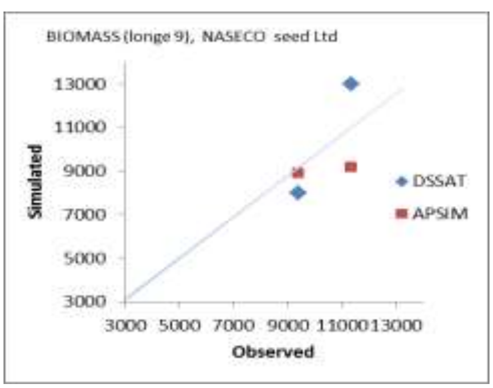
Model calibration. The response of APSIM and DSSAT models to the calibration varied for both maize grain yield and total biomass for the three production datasets, that is, Kaizzi et al. (2012), NASECO and local on-farm survey (Figure 2). For Kaizzi et al. (2012) dataset with

Longe 5, APSIM did not perform very well as compared to the DSSAT. The former over-estimated *Longe* 5 maize yield over the observed while the simulation by DSSAT fitted the observed yields. Unlike the grain yield, the biomass simulation by the two models did not differ significantly. When the calibration of the models using NASECO maize data, APSIM under-estimated implying that the observed yields were more that the simulated. Although APSIM and DSSAT varied slightly, the observed and simulated and observed maize grain yields were similar.









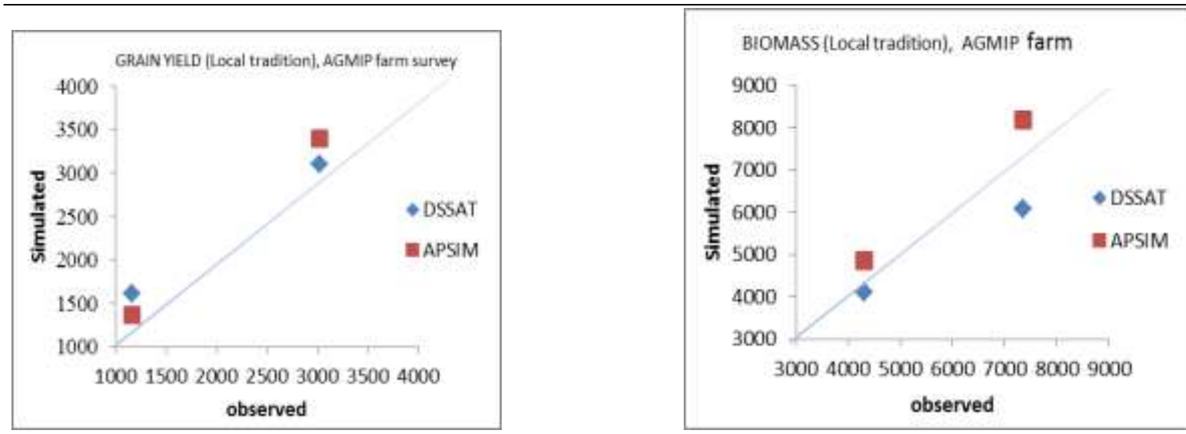


Figure 2. Simulated and observed yield and top weight for *Longe* 5, *Longe* 9 and local traditional variety

(b) Testing model sensitivity

The sensitivity of DSSAT and APSIM models in simulating maize yield is presented in Table 8. APSIM simulated high grain yield as compared to DSSAT. Both models were sensitive to changes in temperature and rainfall. Simulations with APSIM showed an increase in yield parameters with increase in temperature and rainfall compared to the baseline. However, DSSAT showed an opposite trend.

Table 8: Model sensitivity to changes in climatic conditions in Uganda: Effect of temperature and rainfall

Treatment	Biomass Yield (kg/ha)(CV)	Grain Yield (kg/ha)(CV)	Biomass Yield (kg/ha) (CV)	Grain Yield (kg/ha)(CV)
Base Climate	5748 (18.9)	2753.72 (15.13)	11087 (6.8)	3126 (12.2)
Base+1^{0}C	9007 (7.2)	4755.15 (12.4)	10716.8 (7.4)	2924 (12.1)
Base+3^{0}C	7901(8)	4136(15)	10579 (6.9)	2825 (15.3)
Base+5^{0}C	6926(9)	3431(19)	9139 (11.52)	1971 (20)
Base+1^{0}C+10%RF	9060 (5.5)	4843(11.5)	7774 (7)	2270.8 (9.3)
Base+3^{0}C+10%RF	7976 (6.4)	4227 (12.9)	7678 (7)	2088 (10.6)
Base+5^{0}C+10%RF	7020 (7.4)	3486 (17.2)	7334 (8)	1666 (12.2)
Base+1^{0}C-10%RF	8948 (10.9)	4659 (18)	8310 (41.7)	2061.3 (59.8)
Base+3^{0}C-10%RF	7793 (11)	4070 (17)	853 1 (38.5)	2174.9 (52.7)
Base+5^{0}C-10%RF	6833 (11)	3378 (20.4)	9342 (22)	2664.5 (22.8)

c) DSSAT and APSIM model runs for On-farm yield

After the calibration, APSIM and DSSAT model were used to simulate the yields of 307 household farms and comparing with their harvests in the studied agro-ecological zone in Uganda. The on-farm survey was conducted that considered specific on-farm climate, soil, crop and agronomic management practices. In all, simulated yields of APSIM (Figure 3) were much lower than that of DSSAT (Figure 4). For both models, the simulated values were too much higher that the observed. Therefore, there was no relationship between the on-farm yield and the two models simulated values for maize yield with R^2<0.2 (Figure 4).

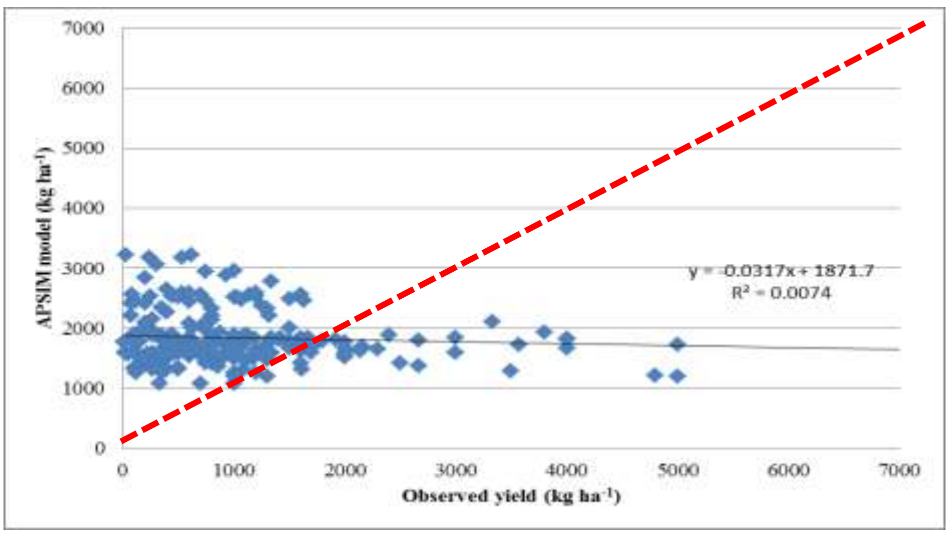


Figure 3: Relationship between APSIM simulated yields and yields reported in on-farm survey in Uganda (Red dotted line is 1)

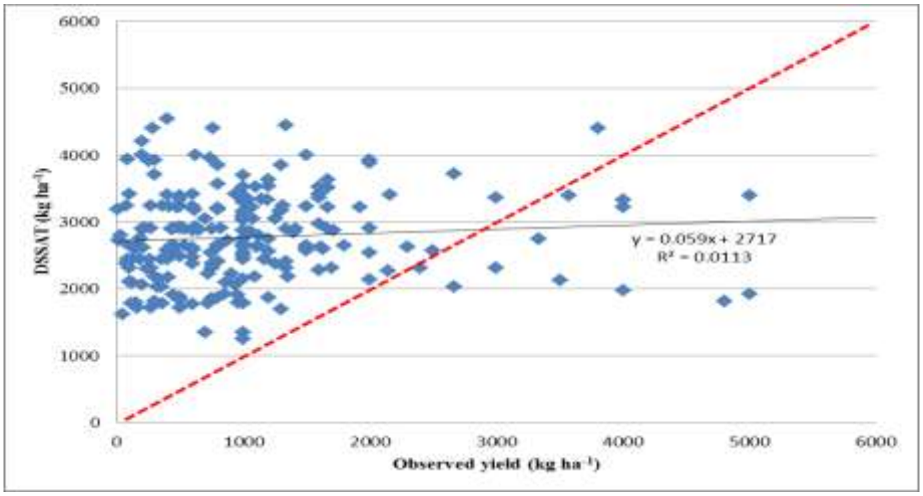


Figure 4: Relationship between DSSAT simulated yields and yields reported in on-farm survey in Uganda (Red dotted line is 1)

(d) Comparing relative yield changes using five GCMs simulated with DSSAT & APSIM models

Generally, the two models demonstrated different simulation capacities in projecting climate change impact on grain yield by Mid Century (2040-70). Both the DSSAT and APSIM models projected maize yield increase on adopting adaptation practices. A combination of practices, that is, improved cultivar (*Longe* 9), application of fertilizers (50 kg N ha^{-1}), late planting (by 15th March -short season and 15th September - long season) resulted in promising yield gains by Mid Century (Table 10).

Using the DSSAT model, only CCSM4 and GFDL-ESM2M Global Circulation Models (GCMs) resulted in decline in yield while HadGEM2-ES; MIROC5 and MPI-ESM-MR resulted in increase in yield. For APSIM model, all GCMs projected increase in yield for all the five GCMs (Figure 5 & 6).

Soil types were notably influential to simulated yields for both crop models. Low yield was associated with Petric Plinthisols while high yield was associated with Acric Ferralsols and Dystric Regosols.

Table 9. DSSAT model prediction of climate change impacts on yield and subsequent yield responses to adaptation practices (in parentheses)

Soil types	**BASELINE**	**CCSM4**	**GFDL-ESM2M**	**HadGEM2-ES**	**MIROC5**	**MPI-ESM-MR**
Acric Ferralsol	2295	2241	2331	1854	2123	1932
	(6226)	***(6332)***	***(6262)***	***(5385)***	***(6040)***	***(5945)***
Dystric regosol	2173	2190	2330	1996	2190	2056
	(6012)	***(6174)***	***(6261)***	***(5767)***	***(6089)***	***(5916)***
Petric Plinthisols	1287	1326	1448	1225	1326	1275
	(5652)	***(5758)***	***(5751)***	***(5491)***	***(5763)***	***(5641)***
Overall Averages	1919	1919	2036	1692	1880	1754
	(5963)	***(6088)***	***(6091)***	***(5547)***	***(5964)***	***(5834)***

Table 10. APSIM model prediction of climate change impacts on yield and subsequent yield responses to adaptation practices (in parentheses)

Soil types	BASELINE	CCSM4	GFDL-ESM2M	HadGEM2-ES8.5MI	MIROC58.5MID	MPI-ESM-MR8.5MID
Acric	2543	2463	2432	2395	2458	2377
	(4527)	*(4482)*	*(4972)*	*(4280)*	*(4245)*	*(3974)*
Dystric	1574	1495	1485	1447	1489	1420
	(3272)	(3214)	(3295)	(3132	(3184)	(3093)
Petric	1709	1657	1588	1702	1697	1682
	(3305)	(3304)	(3279)	(3338)	(3327)	(3342)
Overall Average	1942	1872	1835	1848	1881	1826
	(3701)	(3667)	(3849)	(3584)	(3585)	(3470)

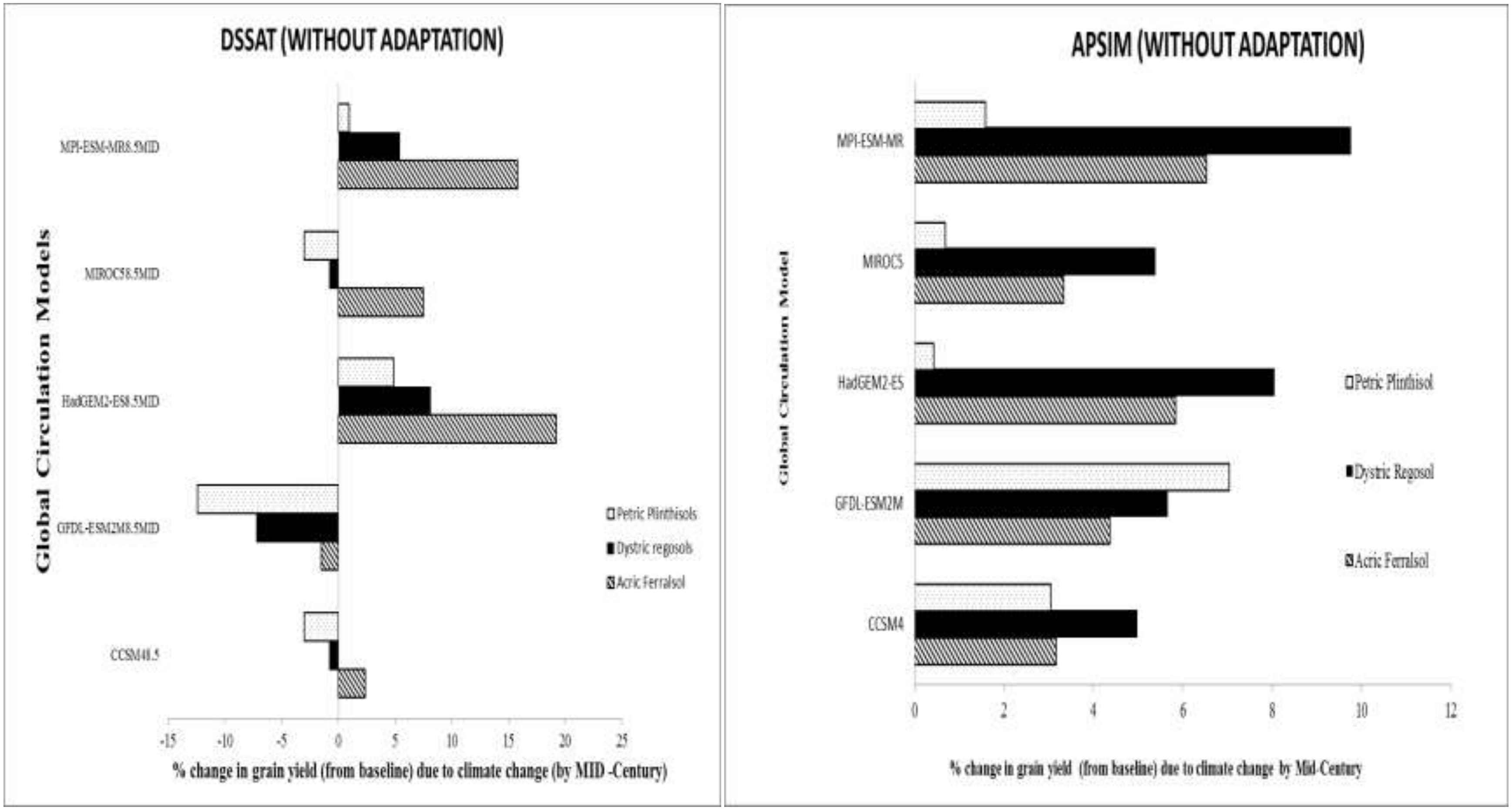


Figure 5. Average yield changes from the baseline by Mid Century based on DSSAT and APSIM models simulations of impact of climate change using five GCMs

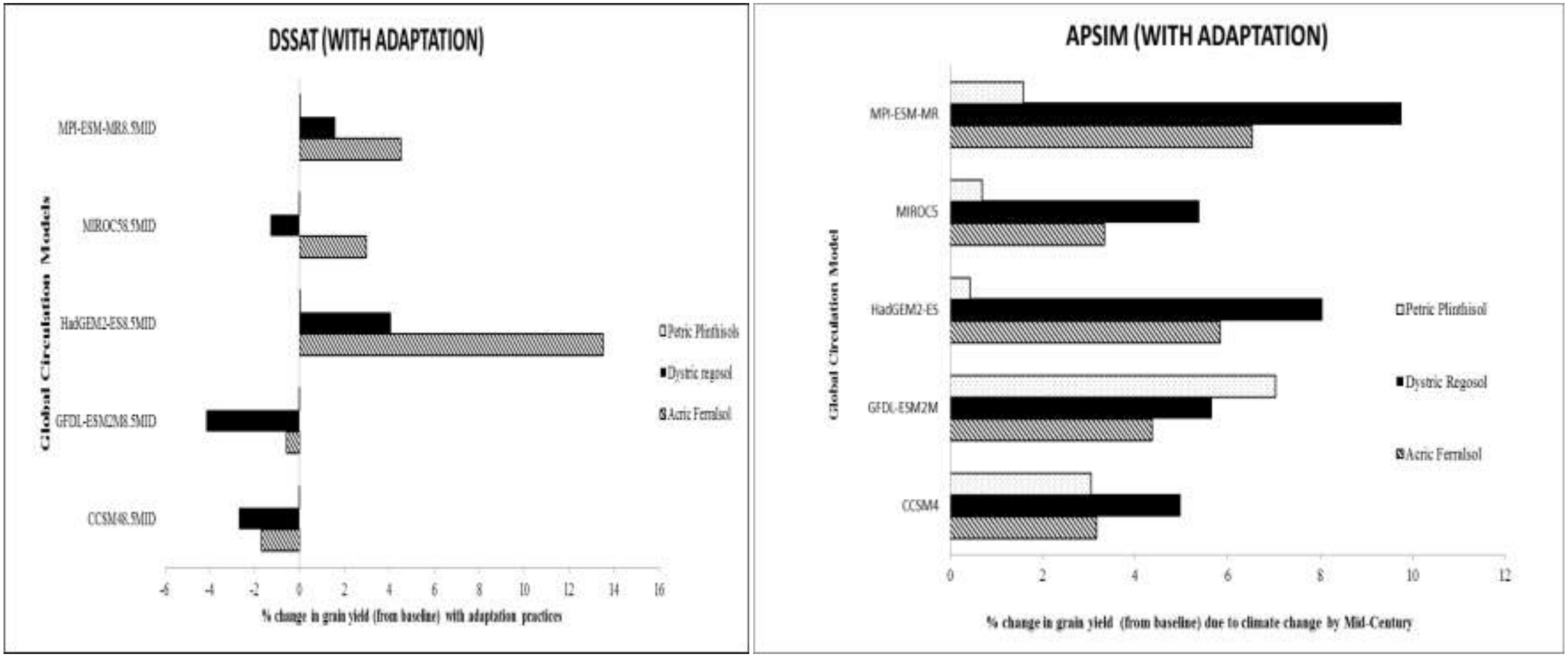


Figure 6. Average yield changes from the baseline by Mid Century using DSSAT and APSIM models with five GCMs, all responding to adaptation practices

Discussion

From the calibration and validation datasets, DSSAT and APSIM models simulated yield compared positively with the observed. However, APSIM as compared with DSSAT model under simulated yield compared to the observed. These observations suggest that both DSSAT and APSIM models have different model structures developed for predicting yields. It also justifies the need for studies to compare models mechanistically. This would improve their predictive capacities for better agricultural planning for the present and future generation.

The two crop models predicted climate change and simulated adaptation strategy differently, again suggesting differences in the model development and techniques. Several studies have cited high level of uncertainty to predict yields using crop models and this became apparent with the DSSAT and APSIM. From our findings, the models seemingly pointed to gains from climate change especially the APSIM model. This predicted yield increase despite climate change that has been projected to cause negative effects on agricultural productivity. IPPC recent reports have also associated climate change to negative yield gains, but model simulations seem to suggest the contrary with positive effects likely to outweigh the negative effect. This implies that potential threats such as food insecurity and hunger may not merit since high yield would be expected. However, with the rapid human population growth, and rapid societal dynamics, it can be difficult to preclude potential threats of food insecurity that may arise from yield limiting factors.

With projected population increase, it is critical that factors that would drive Uganda into a positive development trajectory are not ignored. All efforts should be geared towards high crop productivity mindful of changes from other factors such as policies, infrastructure, prices, land size, production costs, family size, trade, and investment opportunities that are expected to change by Mid Century. Inclusion of such socio-economic settings, presently described as Representative Agricultural Pathway (RAPS) need to assessed to have comprehensive prediction for the future and for a food secure nation (Antle, 2011)

Howevr, the impacts of climate change in East Africa remain uncertain since the DSSAT model was able simulate yield decline. This again applied to only 5 GCMS providing a basis for further studies with other GCMs compared in the predictions. Lobell et al. (2011) projected that climate change of about 1°C can result in significant yield losses of about 65%. This was evidently not possible with DSSAT and APSIM model projections. The findings suggest that adapting improved varieties (L*onge* 9), using fertilizers and changing planting dates can form a good adaptation package for high yield by Mid Century. With projected food insecurity concerns globally due to the rapidly growing human population, it is critical that efforts are aimed at increasing food supply using available technologies. Investments in plant breeding and efficient fertilizer packages, and adoption of sound agronomic practices need to be considered. If not, a daunting task in adapting to climate change is a major threat due to inherent physical vulnerabilities and socio-economic constraints that engulf developing countries.

Conclusion

Crop model simulations clearly showed the importance of improving certainty in predicting climate change impacts on yield. Both the DSSAT an APSIM model simulated differently the impact of climate change on maize productivity and adaptation strategies. Use of improved varieties, application of fertilizer and adopting sound agronomic practices such as late planting proved to be a promising package for increasing maize yield.

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