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The KENYA INSTITUTE for PUBLIC POLICY RESEARCH and ANALYSIS

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E. Mukhala
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THE KENYA INSTITUTE FOR PUBLIC POLICY RESEARCH AND ANALYSIS (KIPPRA)

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World Meteorological Organization Regional Office for Eastern and Southern Africa

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Bishops Garden Towers, Bishops Road
PO Box 56445-00200 Nairobi, Kenya
tel: +254 20 2719933/4; fax: +254 20 2719951
email: admin@kippra.or.ke
website: http://www.kippra.org

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Foreword

Climate change and climate change variability is a threat to food production patterns, thus exacerbating food and nutrition insecurity across Africa. Therefore, tackling poverty, hunger and food security is a priority for the Africa Union Agenda 2063 which underscores the right of Africans to live healthy and productive lifes. Further, the African Union has set a target to eliminate hunger and food insecurity by 2025 towards achieving the Sustainable Development Goal (SDG) 2 on ending hunger, achieving food security and improving nutrition. Unfortunately, Africa is not on track in meeting these targets mainly because the region is not producing enough food due to climate change and low adoption of technology. However, climate change has variable impacts on food production, with both production losses and gains across the region. As a result, regional trade is critical for facilitating the distribution of agricultural products to enhance food security in the region.

The East Africa Community (EAC) region is particularly vulnerable to climate change. The region is already experiencing increased climate change impacts, including extreme weather conditions, persistent drought, floods, and landslides and rising sea level which threaten food security and efforts to eradicate poverty. Despite the huge potential to produce enough food, the agricultural production system in the region is mainly rainfed, which consequently leads to high food and nutrition insecurity.

Finding solutions to perennial food security challenges in the EAC is crucial and urgent as climate change impacts intensify in frequency and severity. Looking beyond just agricultural production systems is thus critical in tackling this peril. Thus, there is need to apply other approaches such as the nexus approach which allows for evaluating integrative systems where, for instance, trade facilitates food security in a changing climate environment. Although agriculture production is vulnerable to climate change, food security is not necessary a result of low production but a combination of other factors such as poor food distribution caused by perverse subsidies and other trade barriers. The EAC has been able to attain a common market status, which could facilitate trade in the region and thus mitigate food shortages.

Despite the various measures and programmes adopted in EAC, some parts of the region continue to face food deficits due to restrictive trade policies and barriers to trade. Opportunities exist for adopting existing policy frameworks by member countries to address food security needs.

Preface

The project on Regional Assessment of Climate Change, Agricultural Production, Trade in Agricultural Production and Food Security in East African Community (EAC) was carried with support from the ACPC-CLIMDEV Work Programme. The ClimDev-Africa Programme is an initiative of the African Union Commission (AUC), the United Nations Economic Commission for Africa (UNECA) and the African Development Bank (AfDB). It is mandated at the highest level by African leaders (AU Summit of Heads of State and Government). The Programme was established to create a solid foundation for Africa's response to climate change and works closely with other African and non-African institutions and partners specialized in climate and development.

Over the last few years, our understanding and certainty about how climate is changing and the possible impacts this could have has grown immensely. This notwithstanding, agricultural production systems in the EAC region are highly vulnerable to climate change, consequently affecting food and nutrition security. The region is the most developed regional economic community (REC) in Africa, and cross border trade plays a critical role in facilitating food security. In response, the United Nations Economic Commission for Africa–African Climate Policy Centre (ACPC) is increasing its efforts to improve the capacity of EAC member states for mainstreaming climate change impacts in development policies, frameworks and plans.

The three-year project was launched in May 2014 covering Burundi, Kenya, Rwanda, Tanzania and Uganda. The activities carried in this study were linked to the ClimDev-Africa Programme work stream II, which focuses on solid policy analysis for decision support, and was spearheaded by the Kenya Institute for Public Policy Research Analysis (KIPPRA). The overall objective of the project was to assess whether or not agricultural production systems and trade policies in EAC can be adjusted to alleviate the impact of climate change on food security, and promote sustainable development. The project outputs include pre-project report, country scoping studies, indepth EAC studies on climate change, crop production model, economic policy and trade and finally a comprehensive regional report.

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The study was conducted as a part of the activities of the Climate Change and Development in Africa (ClimDev-Africa) Programme supported by the UK Department for International Development (DfID), European Union Commission, Norway, Sweden, France, Nordic Development Fund, and the United States Agency for International Development (USAID).

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The Economic Commission for Africa and KIPPRA would like to express their appreciation to all the government Ministries, State Departments and Agencies in Burundi, Kenya, Rwanda, Tanzania and Uganda for their active participation and providing the data and information used in preparing the report.

Executive Summary

Climate change has large influences on agriculture and thus food security, which remains heavily dependent on rainfall over Eastern Africa Community (EAC). This study sought to explore the spatial effects of climate change on agricultural production in five countries in EAC, namely Kenya, Tanzania, Uganda, Burundi and Rwanda. The climate change and crop modelling data used included observed climate, climate model output, soil profile, key informant database and maize cultivar specific parameters. This study used dynamical downscaling techniques whereby downscaled climate change models take data from GCMs and interpret them in relation to local climate dynamics. The period considered included both historical/past (1971 to 2000) and future (2016 to 2045 as mid-century and 2071 to 2100 as end century). The future projections used Representative Concentration Pathways (RCPs) scenario 4.5wm^2 and 8.5wm^2. Error analysis techniques included Normalized root mean square error (NRMSE), Modified Nash-Sutcliffe Efficiency (mNSE) and Mean Absolute Error (MAE) techniques. The study selected short, medium and long term maturity cultivars to evaluate the impacts of climate change in different agricultural zones. The calibrated model was run against the data from 1971 to 2000 and the model performance was evaluated based on farmer's estimates. Trend analysis was used to determine the spatial and temporal variability of past and future climate over EAC.

Observed rainfall and temperature climatology over EAC is well represented by ensemble CORDEX models. Besides, multimodel ensemble mean outperforms the results of individual models and thus simulates rainfall adequately over EAC and is thus useful in the assessment of future climate projections. Precipitation remained highly variable both in space and time, whereas the maximum and minimum temperatures indicated increasing trends over EAC. CORDEX model-based projections of climate change for the region clearly suggest that this warming will continue and, in most scenarios as noted in both RCP 4.5 and RCP 8.5 scenarios. Validation of crop model was based on modification of two phenology parameters (thermal time from emergence to end of juvenile and thermal time from flowering to maturity) and the results (yield estimates and APSIM simulated yields) were comparable. The baseline crop production in each country based on FAOSTAT showed that the annual percentage change in production, area harvested and yield under maize were all positive in EAC countries, indicating increasing trends in production. In EAC, baseline maize yields ranged between 0.51 t/ha to 3.29 t/ha in Kenya, 0.85 t/ha and 1.66 t/ha in Tanzania, 0.81 t/ha and 2.95 t/ha in Uganda, 1.28 t/ha and 1.54 t/ha in Burundi and 0.17 t/ha and 1.45 t/ha in Rwanda. Projected maize yields under RCP45 scenario ranged between 0 t/ha and 4.7 t/ha in Kenya, 1.1 t/ha and 3.3 t/ha in Tanzania, 0.5 t/ha and 2.9 t/ha in Uganda, 1.6 t/ha and 4.0 t/ha in Burundi and 2.2 t/ha and 4.0 t/ha in Rwanda. Projected maize yields under RCP85 scenario ranged between 0.1 t/ha and 4.6 t/ha in Kenya, 1.1 t/ha and 2.7 t/ha in Tanzania, 0.8 t/ha and 3.2 t/ha in Uganda, 1.8 t/ha and 2.1 t/ha in Burundi and 0.22 t/ha and 1.42 t/ha in Rwanda. Maize yield variability in most regions was either positive or showed no change. Under baseline climate scenario, maize yield showed variability of 10-50% in Kenya, 0-110% in Tanzania, 20-90% in Uganda, and 0-20% in Rwanda and Burundi. Under RCP45 scenario,

maize yield showed variability of 10-120% in Kenya, 10-30% in Tanzania, 30-170% in Uganda, 10-50% in Burundi and 10% in Rwanda. Under RCP85 scenario, maize yield showed variability of 10-140% in Kenya, 0-70% in Tanzania, 10-60% in Uganda, 0-60% in Burundi and 0-10% in Rwanda. Under baseline climate, computed percentage change in the trend of maize yield ranged between -1 and 2% in Kenya, -1 to 7% in Tanzania, -4 to 2% in Uganda, -1 to 1% in Burundi and -1% to 0%in Rwanda. Under RCP45 scenario, computed percentage change in the trend of maize yield ranged between -8 and 1% in Kenya, -1 to 1% in Tanzania, -6 to 0% in Uganda, -1 to 1% in Burundi and -1% to 0% in Rwanda. Under RCP85 scenario, computed percentage change in the trend of maize yield ranged between -8 and 1% in Kenya, -2 to 1% in Tanzania, -3 to -1% in Uganda, 0 to 3% in Burundi and 0 to 1% in Rwanda.

The study notes that adaptation to climate change will be required in the future. Among other alternatives, adaptation to current climate variability will form the basis for longer-term adaptations. Assessing the impacts of climate change on complex systems such as agriculture requires a trans-disciplinary effort that links state-of-the-art climate scenarios to process-based crop models with results aggregated as inputs to regional and global economic models to determine regional vulnerabilities and potential adaptation strategies to climate change in the agricultural sector.

Abbreviations and Acronyms

ACMV	African Cassava Mosaic Virus
AEZ	Agro-ecological Zones
APSIM	Agricultural Production Systems sIMulator
CIA	Central Investigation Agency
CMIP	Coupled Model Inter-Comparison Project
CORDEX	Coordinated Regional Downscaling Experiment
DfID	Department for International Development
EAC	East Africa Community
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Nino Southern Oscillation
FAO	Food and Agriculture Organization
GCMs	General Circulation Model
IPCC	Inter-governmental Panel on Climate Change
IRI	International Research Institute
RCMs	Regional Circulation Models
SMHI	Sveriges Meteorologiska och Hydrologiska Institut
SRES	Special Report on Emission Scenarios
UNFCCC	United Nations Framework Convention on Climate Change

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1. Introduction

1.1 Background Information and Justification

Agriculture is vulnerable to climate change especially in Africa where several studies have shown likely negative impacts. According to IPCC fifth assessment report, climate change is impacting regional climates and ecosystems (IPCC, 2014). Climate change has continued to alter conditions for agricultural production in Africa and thus food security. These observed changes are affecting precipitation, water availability, length of growing seasons, flood risks, incidences of extreme weather events, prevalence and distribution of human diseases.

Previous studies on climate change and agricultural production, such as Lotsch, (2007) and Barrios et al. (2008) indicate negative effects on livestock management and crop yields by up to 50 per cent in 2020. However, other global studies project increase in cereal production even under climate change (Parry et al., 2004; Fischer et al., 2005; Ludi et al., 2007). Countries in the East African Community continue to experience increasing climate variability, declining food production and hunger. This would further adversely affect food security and exacerbate malnutrition. However, crop models could be used to understand the effects of climate change on agricultural production and thus crop yield variability (Rosenzweig and Iglesias, 1994). This will enable countries to adapt their production techniques and productions to the new conditions. Further, being able to balance growing differences between food demand and production in different regions of Africa due to climate change will mean paying greater attention to develop policies and regulations supporting agricultural production and trade, and putting in place the necessary infrastructure and institutions.

The challenges climate change poses for development are considerable (Thornton et al., 2006). The impact and adaptation to climate change with regard to agricultural production is widely assessed using crop simulation. Assessment of the effects of climate change on potential food production makes use of physically-based, plot-specific crop models such as APSIM. Therefore, the study sought to explore the spatial effects of climate change on agricultural production in the East Africa Community (EAC) region.

1.2 Objective of the Study

The overall objectiveis to explore the spatial effects of climate change on agricultural production and food security in the East African Community region. The specific objective are:

1. To validate the performance of APSIM crop model in simulating maize yield in EAC.
2. To determine the effects of climate change on maize production in the EAC.

1.3 Scope of the Study

The study focuses on five countries in the East African Community, namely Kenya, Tanzania, Uganda, Burundi and Rwanda.

Kenya lies between latitudes 5° N and 5° S and between longitudes 34° E and 42° E. The country has climate and environmental extremes with altitude varying from sea level to over 5000m. Mean annual rainfall ranges from 250mm in the arid and semi-arid areas to 2000mm in the highlands. Kenya has a total area of 580,367 square kilometres. Further, only 12 per cent has a high potential for agriculture. A further 5.5 per cent, which is classified as medium potential, mainly supports livestock, especially sheep and goats. Only 60 per cent of this high and medium potential land is devoted to crops (maize, coffee, tea, horticultural crops) and the rest is used for grazing and forests. Most of the high potential land is found within the highland areas of the Rift Valley, Central, Eastern Nyanza and Western provinces.

Uganda lies between latitudes 4°N to 1°S and longitude 29°E to 36°E. Although temperature variations may be significant, especially over high ground areas in western, eastern, southwestern, and parts of northern Uganda, rainfall, like in many tropical areas, largely determines the climatic sub-regions (agro-climatic zones) of the country. It also determines the spatial patterns of natural resources and land use activities. The spatial climate homogeneity with regard to spatial and temporal rainfall patterns have been identified and highlighted. The homogeneous delineations benefit spatial and temporal zonal evaluations of soil moisture availability for crop production. The climate of Uganda is regarded as its most valuable natural resource and a major determinant of other natural resources such as water, forests and wildlife, as well as human activities based on these resources, such as agriculture and eco-tourism (Republic of Uganda, MWE 2007). Together these resources provide the means of livelihood for many Ugandans and enhance economic growth, which is predominantly agriculture-based.

Tanzania lies between latitudes 1° 00' S and 11° 48' S and longitudes 29° 30' E and 39°45'. The climate of Tanzania is influenced by its location close to the equator, the Indian Ocean and the physiography (Mkonda and He, 2016). As a result, Tanzania experiences highly variable climatic conditions.

Rwanda (26,300 km^2) is a small land-locked central African country lying between latitudes 1–3°S and longitudes 29–31° E. It borders the Democratic Republic of Congo (DRC), Uganda, Tanzania and Burundi. Although the country is just below the equator, its high altitude (1,000–3,000 m above sea level) moderates the climate. The average annual temperature (17–20°C) varies within the altitude ranges with small variations between the rainy and the dry season. The country enjoys high rainfall (October–June) followed by a short dry period (July–September). The average monthly rainfall of 85 mm supports a broad range of crops and vegetation. Mountain ranges and highland plateaus dominate the relief of the country.

Burundi is a small landlocked country. Topography significantly influences climate. Burundi has two main growing seasons which comprise the rainy season

(September to May) and dry season (June to August). Mean temperatures vary between 15°C and 20°C. The annual mean rainfall is between 700 mm and 1600 mm. However, the country is being affected by climate change, with an extended period of the dry season starting from mid-May and ends in October.

2. Literature Review

2.1 Impact of Climate Change on Agriculture

Climate changes as a result of increased greenhouse gases (GHG) will have significant impacts on food production (Lobell et al. 2008; Burke et al. 2009). More frequent disruption of supply in major producing regions around the world will reduce the opportunities for imports to Kenya and increase prices. The Sahel has experienced prolonged drought since the 1960s (Battisti and Naylor, 2009) and Kenya has had significant droughts in 1971-73, 1983-84, 1991-2 and most recently 2004-6, affecting food availability for 2.5 million people, and 2008-10, affecting 10 million people (Rarieya and Fortun, 2009).

Similarly, a prolonged hot summer in Ukraine and southwest Russia in 1972, with temperature anomalies of 2-4°C over the long-term mean, caused a 13 per cent decline in wheat production in this usually highly producing region (Battisti and Naylor, 2009). Such regional events invariably have global impact because of the effect upon world trade.

The El Niño Southern Oscillation (ENSO) is linked to variations in climate in many parts of Africa (Conway, 2009) and occurs every 3-7 years. In El Niño years, eastern Africa experiences wetter conditions in December to February while La Niña events result in drier periods at this time of the year. El Niño events are defined as >0.4°C anomalies for sea surface temperature in the Niño region existing for five consecutive months (Trenberth, 1997); strong events are defined as >1.5°C above the mean for five months.

Strong El Niño events were recorded in 1965, 1972, 1982, 1991 and 2009 (Null, 2010), which show a remarkable correspondence to drought events in Kenya. Global mean temperatures are seen to increase around six months after an El Niño event, and in severe occurrences, for example, 1997-98, a temperature rise of 0.2°C was observed (Trenberth et al., 2002). Such temperature effects will have significant impact on crop yield and increase uncertainty. Studies (Amissah-Arthur et al., 2002) report inconclusive impacts upon maize yields in Kenya following El Niño linked rainfall during the short rains season (October-December). Also, damage to maize crops following intense rainfall leads to reduced yields despite the beneficial increases from increased precipitation.

Other drivers of climate processes in Africa include the changes in the direction of the monsoon winds, which affect eastern Africa (Conway, 2009). Studies of the warming of the Indian Ocean (Funk et al., 2008) indicate a reduction in continental rainfall on the eastern coast of Africa. Similar vulnerabilities to changes to the monsoon predictability in India are reported in Challinor et al., 2006b. The findings of Funk et al. (2008) disagree with other predictions of possible increased rainfall in eastern Africa (IPCC, 2007) and the implication of the El Niño effect. This highlights the levels of uncertainty that exist in such climate forecasting. It may mean, however, that local differences in climate will be seen, for instance, in drier coastal regions in Kenya compared to the central and highland areas. This may have a differential impact on those crops grown in these regions, and this study could affect tea in Lamu District.

The IPCC 4th Report (IPCC, 2007) concludes that, at a local farm level, moderate warming may improve crop yields in temperate regions but decrease them in semi-arid and tropical regions. Studies included in the IPCC 4th Report indicate that for temperate regions, mean temperature increases in the range 1-3°C, coupled with increased fertilizer effects from enhanced atmospheric CO_2, and in the presence of adequate water, could produce beneficial changes in crop yields. This mechanism is also described in Challinor and Wheeler (2007). However, in tropical regions, adverse effects are reported (IPCC, 2007) for moderate mean temperature increases of 1-2°C. The overall global impact of climate change is suggested (Rosenzweig and Parry, 1994) to lead to a modest decrease in global crop production but with low latitude countries experiencing a decline in production, in agreement with the IPCC, balanced by increases in mid-latitude areas. Their model assumed physiological benefits from direct CO_2 effects with sufficient water and technological adaptation. They concluded that overall increases could only be achieved through wide-scale irrigation, putting further pressure on limited water resources (Vörösmarty et al., 2000). Unlike later studies (Challinor et al., 2005b, Semenov and Porter, 1995) their study did not take account of the possibility of extreme events. Thus, mean temperature is an important parameter for crop yields. The increased occurrence of extreme climatic events, however, such as non-linear temperature effects are likely to overshadow changes in mean temperatures in their impact upon yield (Schlenker and Roberts, 2009) and, furthermore, the likelihood of extreme events is increasing (Easterling et al., 2000).

Many studies (Conway, 2009; Dinar et al., 2008; Nkomo et al., 2006; Kurukulasuriya, 2006) have shown the vulnerability of Africa to climate change. Challinor et al. (2007) indicate the sensitivity of crop systems to variability in climate, and the adaptive capacity of farmers. Vörösmarty et al. (2000) discuss the vulnerability to water scarcity caused both by climate change and the impact of an increasing population's demand for water, both for surface and groundwater. Other authors indicate that African farmers are poorly equipped to adapt to new technological practices because of, for example, limited cash for optimal fertilizer use (Schlenker and Lobell, 2010) and lack of knowledge of adaptation possibilities (Dinar et al., 2008).

The impact of weather and environmental effects on plant growth is complex. Plant development, growth and ultimately yield is dependent upon temperature, solar radiation, precipitation, transpiration, the frequency of extreme precipitation and temperature events, increased CO_2 concentrations, soil fertility, species type as well as pests, disease and weed prevalence (IPCC, 2007). Few studies can model all of these variables; many focus on a subset of parameters that are seen to have a major effect. Temperature, light and water are acknowledged as the primary drivers of crop growth, and consequently impact from climate change that results in changes in precipitation, radiation and temperature will affect crop yields (Porter and Semenov, 2005). Soil fertility is another important factor, but the lack of precise data on soil fertility in Kenya means that this parameter is rarely included in studies. Increasingly, fertilisation effects of raised CO_2 levels are also considered as significant (Lobell and Burke, 2008, Porter and Semenov, 2005, Challinor et al., 2005a). However, Collier et al. (2008) report that whereas some crops respond positively to enhanced CO_2 levels, for example wheat, rice, and soybean, not all crops are responsive.

Wheeler et al. (2000) showed the importance to crop yields of temperature variability, extremes of high and low temperature, irrespective of changes to mean seasonal temperatures. Many crops already grow close to their tolerance limits (Conway, 2009) and a few days of extreme temperature can seriously affect yields (Challinor et al., 2006a; Wheeler et al., 2008). High temperatures cause sterility in male flowers of sorghum. Jain et al. (2007 report 27 per cent loss in the setting of seeds from spores subject to high-temperature stress. Although increased growth is reported (Collier et al., 2008) and sorghum yields are observed to increase by 26 per cent under a temperature range of 22-32°C, yields are still shown to drop significantly at higher temperatures (Prasad et al., 2006). They report a 10 per cent decrease in yield at 26-36°C in spite of the added effect of increased CO_2. In field trials for wheat (Ferris et al., 1998), grain yield decreased with maximum temperature with a peak reduction if extreme temperature occurred at the midpoint of anthesis when the flower is fully open. A 40 per cent yield reduction was observed after a 10°C rise as well as a negative correlation with time exposure over 31°C. Such controlled and field experiments are also confirmed in simulation experiments and for different crops. Challinor et al., 2005b demonstrate that high-temperature episodes around flowering time reduce crop yield in groundnut and wheat by impacting upon grain or fruit set. High-temperature thresholds, defined as the temperature at which growth and development cease, for selected crops are shown in Table 2.1. Groundnut (Arachis hypogaea L.) can tolerate temperatures above 40°C during growth (Prasad et al., 2000), which might make it a useful alternative crop under future climate scenarios.

Drought stress is a major factor in reducing yield, but the timing and the severity of the stress are critical. A study on sorghum (Craufurd and Peacock, 1993) found that grain yields could be reduced by 87 per cent with water stress at the time of stem swelling and flowering, but that there was no drop in yield if similar pressure was applied only at vegetative stages. Vörösmarty et al. (2000) conclude that increasing populations and economic activity will be a more significant factor for future water stress than climate. This implies that demand for water from densely populated urban areas will reduce availability for agriculture and thus the potential for irrigation, with a negative consequence on crop yields.

Table 2 1: High temperature thresholds for growth in crops

Crop	**Threshhold temperature**	**Growth stage**	**Source**
Maize	38°C 36°C	Grain filling	Thompson (1986)Lin et al. (2008)
Wheat	26°C	Post-anthesis	Ferris et al. (1998)
Groundnut	40°C		Prasad et al. (2000)
Coffee	24°C		Nunes et al. (1968)

2.2 Use and Availability of Crop Models in Assessing Agricultural Production

Agricultural system models are essential tools for understanding complex system interactions with the objective of achieving increased productivity and environmental goals. Cropping system models such as APSIM (Keating et al., 2003), DSSAT (Jones et al., 2003) and others have the potential to replicate the production systems. The underlying assumption in crop modelling applications is that the model can accurately simulate the processes occurring within the agricultural system (Thorp et al., 2005). Model calibration is needed to optimise the model input parameters, either for plots across different conditions (e.g. Cheyglinted et al., 2001; Mall and Aggarwal, 2002) or for regions which have a relatively homogeneous state. However, a lack of sufficient data to fully characterise spatial variability and scale problems of integration of field measurements and model parameters hinders the model calibration and validation for regional simulation, especially for climate change impacts. All crop models should be calibrated and validated for the environment of interest if results are to be credible (Timsina and Humphreys, 2006). Model calibration involves minimising the error between model outputs and observed data and the determination of model parameters for an intended purpose (Jones et al., 2003). Model validation assesses the ability of a calibrated model to simulate the characteristics of an independent dataset (e.g. Irmak et al., 2005; Carbone et al., 2003). Tools that use meteorological data such as DSSAT, APSIM, RIDEV, or SARRA are useful to estimate risks, which is often a significant consideration for the farmer.

Uncertainties also exist about the application of plot-specific crop models to the estimation of crop production in large areas (Hansen and Jones, 2000; Challinor et al., 2004). This arises from the scale mismatches between plot-specific crop models, global (or regional) climate model outputs and regional agricultural production. Most crop models are designed to represent the plot scale, and this makes it difficult to predict the impact of climate change at a regional level unless some major assumptions are made to upscale results (Hoogenboom, 2000; Challinor et al., 2005). The conventional approach in impact studies has been either to run a model for several sites, and then upscale the results to the regional scale (Iglesias et al., 2000), or to model regional yields using region-specific representative soil(s) types, crop varieties, and management practices (Haskett et al., 1995).

For regional impact assessment of climate change, the large geographical area and limited observed data means that calibration is usually confined to using results from yield trials from agricultural experiment stations (Alexandrov et al., 2002), or the most commonly cultivated crop varieties (e.g. Saseendran et al., 2000; Jin, 2003). Selection of calibration sites may be rather arbitrary, driven by data availability rather than a true representation of regional practices or spatial heterogeneity. There is need for a more practical and robust calibration process suitable for regional simulation, especially for climate change impact assessment. It should concentrate more on predicting the pattern or trend of agricultural production at both spatial and temporal scales by using currently available limited geographical data and models, rather than on estimating precise farm production.

Jones and Thornton (2003), in a study in Africa and Latin America, estimate that maize production may reduce by only 10 per cent by 2055 but that this hides huge variability in yields in specific areas. Conversely, Hansen and Indeje (2004) in their study of maize in Machakos District in Kenya report 28-33 per cent variance in yield predictions.

The use of crop simulation models (such as APSIM) in conjunction with climate forecast information enhances the opportunity to improve the value and usefulness of seasonal forecasts for agricultural decision-making (Hansen, 2004). The APSIM model is capable of quantifying the effects of possible management alternatives in response to a seasonal forecast (Meinke and Stone, 2005). While seasonal forecasts predict rainfall, APSIM can generate probable crop yields for different production strategies relevant to the forecast. Such projections can be made over an extended period, thereby helping farmers to select better options in various seasons. The integration of the two information sets improves the possibility of matching farmer needs to likely changes in weather. Integrating forecasts and APSIM also facilitates relevant discussions between farmers and experts. Such discussions generate information that can be used by small-scale farmers (Selvaraju et al., 2004).

2.3 Agricultural Production Systems Simulator (APSIM)

2.3.1 Overview of APSIM model

APSIM is a crop simulation model developed as a result of the need for accurate predictions of crop yields in line with environmental, climatic, and management factors (Keating et al., 2003). Predictions from a model that incorporates all factors at play in a crop production system simultaneously are more credible than those from stand-alone models. APSIM was designed to simulate various processes taking place in the soil during crop production under a range of management options in different climates (Agricultural Production system Research Unit - APSRU, undated; Probert and Dimes, 2004). According to Climate Kelpie (2010), APSIM simulates effects of environmental variables and farm management decisions on crop yield and profits. The fact that APSIM is made up of different soil modules, a range of crop modules and crop management options under different climates makes it an accurate tool for predicting crop yields if all the data input is done correctly. This also implies that it can be used everywhere in the world, including in small-scale farming systems in Africa, as long as it is validated for local conditions and crops. APSIM is also concerned about the long-term repercussions of the actions of farmers, for example on yield levels and soil nutrient status. Keating et al. (2003) noted that the main thrust of APSIM is a combination of crop yield estimation as a result of how farmers manage their farming systems, and effects of these management decisions in the long run.

APSIM operates using input data namely, soil data, crop management data and long-term daily climate data. Climate data required are daily rainfall (in mm), daily temperatures (both minimum and maximum in °C units), minimum temperature (°C) and radiation (MJ/m^2). The important soil parameters are the initial nitrogen and organic carbon. For the model to predict correctly, there is need to accurately input the data. Crop management data include crop type and variety, sowing dates, weeding dates and fertiliser management (type, amount, dates of application) (Keating et al., 2003; Climate Kelpie, 2010). In general, APSIM was mainly designed for modelling cropping system aspects at a single point level being a reliable model regarding modelling detail included in both crop and soil processes.

2.3.2 Application of APSIM

The APSIM modelling platform has been applied widely elsewhere, mostly due to two important features. First, the model has a friendly user interface that offers advanced flexibility in setting up simple and complex simulations without the need of writing additional code; that is, rotations (Keating et al., 2003) or inter-cropping systems (Carberry et al., 1996) including annual or perennial species (Snow et al., 2013). The transition between seasonal and sequential analysis is simple, and the model also offers a rich graphical interface including animated videos which are valuable teaching tools (Archontoulis et al., 2012; Miguez et al., 2012). Second, APSIM simulates various levels of production situations, including potential, attainable (water/N and/or P limited plant growth) and actual situations (including weed competition for resources) for more than 30 species including crop rotations (Robertson et al., 2002; Wang et al., 2002; Keating et al., 2003). It also simulates soil processes such as C, N, and P dynamics, gas emissions (CO_2 and N_2O), water balance using either simple (cascading approach) or comprehensive (Richard's equations) modules, and soil erosion (Probert et al., 1998; 2005; Thorburn et al., 2010; Huth et al., 2012).

Dimes and Du Toit (2009) used APSIM to simulate maize, groundnut and cowpea yields as well as their water balance in the Limpopo Province for the 2007/2008 cropping season. Field experiments were conducted at a smallholder farming village located in Tafelkop, Sekhukhune District. On-farm experimentation aimed to quantify the water use efficiency of maize, groundnut and cowpea crops. Plant biomass, grain yield and soil water balance of the crops were simulated by APSIM, and the model outputs were compared to measured data.

APSIM simulated maize yields were better than that of the two legumes for which both grain and biomass yields were slightly under-simulated. The model indicated differences in crop water distribution within the root zone when simulating the soil water content over time. When the model outputs were used to fill gaps in the field measurement, it indicated reduced water use efficiency for all three crops. The model also managed to capture the soil water distribution in the sample rooting layer for all crops. The overall performance of APSIM in simulating changes in soil water was reliable for maize, but not for cowpea and groundnut. Dimes and Du

Toit (2009) found that APSIM's good performance in simulating the crop growth and yield, as well as the associated observed changes in the soil water content of the rooting zones encouraged the use of the model as a tool to quantify water productivity of crops in the Limpopo Province.

Whitbread et al. (2010) highlighted exercises where APSIM was used to simulate soil processes in response-constrained and low yielding maize/legume systems in southern Africa. APSIM was used: (a) to add value to field experimentation and demonstration; (b) to facilitate direct engagement with farmers; (c) to explore system constraints and opportunities with researchers and agents; and (d) to help create the information or systems that can be used by policy makers, banks, insurance institutions and service providers.

APSIM was also modified for southern African conditions by Ncube et al. (2007; 2009) to add value to field experimentation and demonstration to smallholder farms. This involved the interpretation of field experiments and incorporating seasonal variability and risk assessment. The main advantages were the development of an understanding of treatment response over a range of seasons and the development of extension guidelines. Kamanga (2002) used APSIM to simulate the response of maize to low N-fertiliser application rates, the potential use of leguminous cash crops (e.g. soybean and cowpea) instead of maize and green manure legumes in rotation with maize. This aided in building an understanding of the key drivers of the system in Zimbabwe and Malawi. The outcomes showed that under low levels of soil fertility, the most efficient and lower risk decision was to plant maize using a low plant population density.

For direct engagement with farmers, replication of the Australian programme (FARMSCAPE) with smallholder farmers in southern Africa was carried out (Carberry et al., 2002). Farmer participation was encouraged to address soil fertility management issues at the smallholder level (Twomlow, 2001). This was to explore the complementarities between farmer participatory research approaches and computer-based simulation modelling for ICRISAT-Bulawayo in Zimbabwe in 2001 (Carberry et al., 2004; Whitbread et al., 2004). The above approaches were tested by six teams made-up of crop modellers and researchers trained in participatory rural research and rural tools and methods, as well as local researchers knowledgeable about African farming systems (Whitbread et al., 2010). The participatory tools were used to build realistic farming scenarios for the computer simulations by engaging farmers to obtain their reactions and suggestions for improvements in farm practice.

APSIM was also used to explore system constraints while creating opportunities for researchers and agents of smallholder farmers in highly constrained resource situations (Whitbread et al., 2010). The approach was to develop farm scale models that considered resource situations and the impacts on productivity to determine optimal management strategies that could maximise efficiency. An alternative approach was developed in an attempt to capture the key interactions and constraints that determine productivity within a farm system. In these systems, APSIM was used to develop an understanding of the key drivers of the maize crop and how it would most efficiently respond to nitrogen fertiliser. Results showed that the efficient fertiliser response of maize depended on weeding at the time of nitrogen application. APSIM's outputs were used in the generation of information for policy makers, banking and insurance institutions, and service providers (Carberry, 2005; Dimes and Twomlow, 2007). The study demonstrated how APSIM could be applied in exploring risk to financing cropping loans. Simulation of alternative management scenarios and the subsequent analysis using the probability of non-exceedance graphs were useful to financial institutions (MacLeod et al., 2008).

APSIM model was used by Shamudzarira and Robertson (2002) to simulate the response of maize to nitrogen from 1991-1998 at the Makoholi Research Station in Zimbabwe. The model was used as an analytical tool to explore the combination of nitrogen (N) fertiliser and management strategies to minimize risk. Statistically, the simulated results indicated a negative response of nitrogen in 15 per cent of years within the long-term record, whereas no negative response to nitrogen was recorded in the field trials. Results for both measured and simulated yields revealed a median response of 20-30 kg maize grain kg-1 N applied. Results also suggested that reasonable rates of N application (30 kg N ha-1) would give better responses per unit N applied than smaller N applications such as 15 kg N ha-1. No evidence was found that fertiliser strategies, conditionally based on rainfall, would present significant profit over fixed application strategies. However, proper agronomic practices (soil tillage, cultivar selection, planting date, fertiliser application rate, and weed control) do assist in the realisation of nitrogen input returns.

2.4 Limitations of Climate and Crop Modelling

The APSIM model is an excellent tool for quantifying risks due to climate variability and simulation of various processes that take place in the cropping systems. However, its use in small-scale systems is restricted due to a shortage of capable modellers as well as a lack of reliable input data, especially in semi-arid Africa (Struif-Bontkes and Wopereis, 2003). The model does not include the effects of pests and diseases in its framework, hence the simulation results are most likely to be higher than the actual observed yields (Holzworth et al., 2006). APSIM is also very complex and needs expert support and skills to aid simulation building, for example soil scientists and agronomists. While this support is usually available to modellers, the same cannot be said about small-scale farmers (Holzworth et al., 2006).

3. Data and Methodology

3.1 Data

Data collected for crop modelling purpose included: soil profile data, soil characteristics, climate data (rainfall, temperature, and solar radiation) and crop management data.

3.1.1 Climate data

(i) Observed

Daily observed data were used in the study. These included precipitation, maximum temperature and minimum temperature. Model results were compared to observed datasets obtained from the national meteorological and dydrological services of Burundi, Kenya, Tanzania Rwanda and Uganda. Representative agro-climatic zones were selected evaluate the performance of APSIM model as shown in Table 3.1.

Solar radiation was estimated using the Hargreaves and Samani (1982; 1985) equation for each township centre, using interpolated daily maximum and minimum temperature measurements. This equation estimates solar radiation as a function of the difference between the daily maximum and minimum temperatures with an adjustment coefficient of 0.16. Additionally, it uses Julian day, latitude and elevation to estimate the suns position relative to the point of interest on the earth's surface. The equation is given by:

$$R_s = K_t * R_a * (T_{max} - T_{min})^{0.5}$$

Where R_s is the estimated solar radiation in (MJ $m^{-2}day^{-1}$), T_{max} is the daily maximum air temperature (°C), T_{min} is the daily minimum air temperature (°C), K_t is the adjustment coefficient approximated to 0.16 and R_a is the extraterrestrial radiation (MJ $m^{-2}day^{-1}$).

$$R_a = \frac{1440}{\pi} Gsc * drf(nws * \sin(lat) * \sin(ndec) + \cos(lat) * \cos(ndec) * \sin(nws))$$

where:

$Gsc = 0.082$

$$dfr = 1 + 0.33 * \cos(2 * \pi * \frac{Jday}{Ndays})$$

$$nws = arcos(-\tan(lat)\tan(ndec))$$

$$ndec = 0.409 \sin\left(\frac{2\pi Jday}{365} - 1.39\right)$$

Where *elev* is station elevation [m], *Jday* is Julian day, *Ndays* is Number of days in a year (366 in a leap year), *Gsc* is solar constant [MJ $m^{-2}day^{-1}$], *dfr* is inverse relative distance, *ndec* is solar declination angle, *nws* is sunset hour angle, *lat* is station latitude in radian, T is mean daily temperature at 1.5 to 2.5 m height from the ground [^{o}C] and P is mean atmospheric pressure at station elevation [m].

Table 3.1: List of synoptic stations used in the study

Uganda	**Rwanda**	**Tanzania**	**Kenya**	**Burundi**
Arua	Byumba	Tanga	Eldoret	Bujumbura
Iganga	Gabiro	Dodoma	Kakamega	Gisozi
Kabale	Gikongoro	Shinyanga	Kisumu	Musasa
Kapchorwa	Gisenyi	Mbeya4	Machakos	Muyinga
Lira	Kamembe	Mbeya5	Makindu	Nyanza_Lac
Masaka	Kigali	Kilimanjaro	Mombasa	
Mbarara	Ruhuha	Morogoro		
Soroti	Save			

(ii) Regional Climate Model (RCM) data

In this study, we used simulated daily rainfall, maximum and minimum temperature and sunshine duration data from 8 CORDEX RCMs described in Table 3.2. The RCMs were forced by lateral and surface boundary conditions from the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Re-Analysis (ERA-Interim), and downscaled data are available for the period 1980-2010 and 8 GCMs over the Africa domain for both RCP4.5 and 8.5 and running in transient mode for the period 1951-2100. All simulations were performed at 50km (0.448) resolution over the EAC domain. Nikulin et al. (2012) provides detailed information on the a full list of the RCMs used (with full expansions) with the details of their dynamics and their physical parameterizations.

Table 3.2: List of CMIP5 GCMs used in the study

Institute name	GCM name	Calendar
CCCma (Canada)	CanESM2	365 days
CNRM-CERFACS (France)	CNRM-CM5	standard
MOHC (UK)	HadGEM2-ES	360 days
NCC (Norway)	NorESMI-M	365 days
ICHEC (Europe)	Ec-EARTH	Standard
MIROC (Japan)	MIROC5	365 days
NOAA-GFDL (USA)	GFDL-ESM2M	365 days
MPI-M (Germany)	MPI-ESM-LR	standard

3.1.2 Soil profile data

Soil information is often a key input to the models, yet it is difficult to obtain extensive, quantitative, and geo-referenced soil property data for the areas (or regions) of interest. Global soil databases exist (e.g., Harmonized World Soil Database (HWSD) by IIASA/FAO/ISSCAS/ISRIC/JRC, 2009) but they do not provide all the required information for the models at specific site. In addition, existing global soil profile databases (e.g., WISE by ISRIC, 2002) do not extensively cover large areas in developing world.

To overcome the limitation of location-specific soil profile data for crop modeling applications, we generated a set of generic soil profiles based on three criteria that crop models are most responding to: texture, rooting depth, and organic carbon content. By classifying three levels for each category and setting their boundary conditions (Table 3.3), 27 soil profiles, HC27, were generated in formats compatible with DSSAT and APSIM. The boundary conditions were defined based on soil profiles recorded in Sub-Saharan Africa, thus are subject to further adjustments in other regions where extensive soil profiles are available.

Table 3.3: Classes and boundary conditions that define the 27 generic soil profiles

Class	Conditions
Texture	Clay, Loam and Sand
Fertility (soil organic carbon content)	Low: less than 0.7%
Medium: between 0.7 and 1.2%	
High: greater than 1.2%	
Rooting depth	Shallow: less than 90cm; Medium: between 90 and 150cm; Deep: deeper than 150 cm

3.1.3 Key informant database

A relevant set of yield estimates for maize crop and management conditions were obtained by surveying project agronomists with local experience of experimental and farmer-based yields. Key informants included agronomists from the partner states in the East African Community–EAC. Surveyed information included varietal selection (cultivar, days to flowering and maturity), management (sowing windows, sowing date, plant row spacing and population), and estimated grain yield of the maize crop. Overall, short term and long term maize cultivars were selected in each country to assess the effects of climate change on maize production. Observed data on crop production was also sourced from the FAOSTATS (http://faostat3.fao.org/download/Q/QC/E).

3.1.4 Maize cultivar specific parameters

Available maize cultivar-specific values in APSIM model for short, medium and long maturity maize varieties were used in the study. In APSIM version 7.7, maize varieties available include Katumani composite (Kenya), Makueni composite (Kenya), Dekalb XL82 (tropical hybrid with photoperiod sensitivity), USA 18 leaf (generic 18 leaf hybrid with no photoperiod sensitivity), Hycorn 424, Pioneer 3237, Pioneer 3527, Pioneer 3153, Hybred 511 (Kenyan hybrid -medium maturing) and Hybred 614 (Kenyan hybrid -late maturing). Other include Zimbabwe and Malawi maize varieties that comprise of:

- Early maturing (NSCM_41, sc401 and r201)
- Early-medium maturing (sc501, sr52, r215, MH18, CG4141)
- Medium-late maturing (sc601, sc625, sc623)
- Malawi local (MH12, MH16, MH17, MH19)
- Late maturing (sc709).

3.1.5 Data limitations

The EAC region lacks high-quality observation data sets at suitable temporal and spatial resolution necessary for evaluating RCM simulations. Therefore, the study relied on post-processed data available at CORDEX data portal. Data on soil profile, soil characteristics, crop management, and crop genetic coefficients were not easily accessible. Therefore, estimates published in reports and peer-reviewed papers were used. It should be noted that there exists inaccuracy of one-crop modelling as a proxy to crop production in the region, since other crops may respond in different ways (Thornton et al., 2008).

3.2 Methodology

3.2.1 APSIM model calibration and validation

The Agricultural Production System Simulator (APSIM, version 7.7) (Keating et al., 2003; Wang et al., 2002; 2004) was used to simulate the phenology and yield of maize. For an efficient model calibration and evaluation, reliable and comprehensive datasets are needed. Ideally, the data have to cover several aspects of the soil–plant–atmosphere continuum, but in reality such data are rare and modellers have set priorities or minimum data requirements for model calibration and evaluation (Hunt and Boote, 1998). In general, the use of a large dataset in which numerous variables have been measured (e.g., soil water, plant growth) improves the robustness of model calibration while, on the other hand, the complexity of the calibration process increases. It should also be noted that APSIM model comes bundled and distributed with databases of previously tested crops and soil parameters to minimize the laborious process of parameterization/calibration (Daniel, et al., 2006).

The interval from flowering to maturity is determined by a single thermal time value that was calculated from measurements (Table 3.4). In contrast, the interval from emergence to flowering is computationally more laborious than the previous phase and requires some assumptions to be made regarding the internal sub-phases and hybrid photoperiodic sensitivity in case of no available information. The time from emergence to flowering is determined by the following parameters: (i) thermal time from emergence to end of juvenile (around 250°C-d for Iowa hybrids; Hammer et al., 2009); (ii) two leaf appearance rates and the leaf number at which the change in leaf appearance rate occurs; (iii) a leaf initiation rate and the number of leaf primordia in maize seeds (APSIM default values were used); (iv) a photoperiod adjusted thermal time value for the phase from the end of juvenile to tassel initiation phase (assumed zero in this study); (v) thermal time from flag leaf to silking, which was set to 1°C-d as this phase is negligible.

The APSIM model was calibrated using the provided data on climate, soil, and management and modification of selected cultivar-specific phenological parameters for maize. The study then followed an iterative approach in which the crop phenology of the systems was evaluated. The iterative process of calibrating the APSIM model was initialized by developing phenological parameters for the maize cultivar as shown in Table 3.4. The study selected short, medium and long term maturity cultivars to evaluate the impacts of climate change in different agricultural zones. According to Archontoulis et al. (2014), the phenology module drives many plant processes that have a strong impact on soil water and N balances. For model evaluation, the study used the end-of-season grain yield data provided by country agronomists.

In this study, two phenology parameters are used. They comprise thermal time from emergence to end of juvenile stage (tt_emerg_to_endjuv, oCd) and thermal time from flowering to maturity (tt_flower_to_maturity, ◦Cd). These were adjusted to achieve a good match between observed and simulated emergence, flowering and maturity date using days after sowing (DAS). It should be noted that the APSIM parameters given in thermal time are related directly to DAS with an assumption that the longer the period of a particular stage in days the longer is the thermal time. Thereafter, the calibrated model was run against the data from 1971 to 2000 and the model performance was evaluated based on farmers estimates. Simulating trial-and-error method was used for model calibration. The study used graphical analysis to assess the performance of simulated maize yield in EAC.

3.2.2 Effects of climate change on the crop production in EAC

The calibrated APSIM model was used to estimate the trend in the yield of crops under current and projected climate. The change between the projected and baseline yield were determined using the percentage difference technique. The presence of a monotonic increasing or decreasing trend was tested with the non-parametric Mann-Kendall (Mann K) test while the slope of a linear trend was estimated with the non-parametric Sen's method (Gilbert, 1987). Furthermore, the true slope of the existing trend (as change per year) was estimated using the Sen's non-parametric method.

Mann-Kendall test is a test that evaluates whether y values tend to increase or decrease over time through what is essentially a non-parametric form of monotonic trend regression analysis. The Mann-Kendall test analyzes the sign of the difference between later-measured data and earlier-measured data. Each later-measured value is compared to all values measured earlier, resulting in a total of n(n-1)/2 possible pairs of data, where n is the total number of observations. Missing values are allowed and the data do not need to conform to any particular distribution. The Mann-Kendall test assumes that a value can always be declared less than, greater than, or equal to another value; that data are independent; and that the distribution of data remain constant in either the original units or transformed units (Helsel and Hirsch, 1992). Because the Mann-Kendall test statistics are invariant to transformations such as logs (i.e., the test statistics will be the same value for both raw and log-transformed data), the Mann-Kendall test is applicable in many situations. To perform a Mann-Kendall test, compute the difference between the later-measured value and all earlier-measured values (yj-yi), where j>i and assign the integer value of 1, 0, or –1 to positive differences, no differences, and negative differences, respectively. The test statistic, S, is then computed as the sum of the integers:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(y_j - y_i)$$

Where sign (yj - yi), is equal to +1, 0, or -1 as indicated above. When S is a large positive number, later-measured values tend to be larger than earlier values and an upward trend is indicated. When S is a large negative number, later values tend to be smaller than earlier values and a downward trend is indicated. When the absolute value of S is small, no trend is indicated. The test statistic τ can be computed as:

$$\tau = \frac{S}{n(n-1)/2}$$

which has a range of –1 to +1 and is analogous to the correlation coefficient in regression analysis. The null hypothesis of no trend is rejected when S and τ are significantly different from zero. If a significant trend is found, the rate of change can be calculated using the Sen slope estimator (Helsel and Hirsch 1992) given as:

$$\beta_1 = median\left(\frac{y_j - y_i}{x_j - x_i}\right)$$

for all i < j and i = 1, 2, ..., n-1 and j = 2, 3,..., n; in other words, computing the slope for all pairs of data that were used to compute S. The median of those slopes is the Sen slope estimator. The tested significance levels α are 0.001, 0.01, 0.05 and 0.1. A two-tailed test is used for four different significance levels α : 0.1, 0.05, 0.01 and 0.001. The significance level 0.001 means that there is a 0.1 per cent probability that the values xi are from a random distribution and with that probability we make a mistake when rejecting H0 of no trend. Thus, the significance level 0.001 means that the existence of a monotonic trend is very probable. Respectively, the significance level 0.1 means that there is a 10 per cent probability that we make a mistake when rejecting *H0*.

For the four tested significance levels, the symbols are used include *** if trend at $\alpha = 0.001$ level of significance, ** if trend at $\alpha = 0.01$ level of significance, * if trend at $\alpha = 0.05$ level of significance and + if trend at $\alpha = 0.1$ level of significance. If the cell is blank, the significance level is greater than 0.1. The true slope of an existing trend (as change per year) was estimated using the Sen's non-parametric method. The Sen slope was then expressed as a percent of the mean quantity per unit time (Salmi et al., 2002; Slack et al., 2003). That is:

$$\% \, trend = \frac{[Sen \ Slope \ Estimator \ Q]}{mean \ f(year)}$$

4. Results and Discussion

4.1 Calibration and Validation of APSIM Model in Simulating Maize Productivity

Calibration and validation of APSIM model in simulating maize yield was based on modification of two phenology parameters are presented in Table 4.1.

In Kenya, tt_emerg_to_endjuv values ranged from 150°Cd in the lowlands and coastal region to 450°Cd in the highlands with similar pattern for tt_flower_to_maturity with values ranging from 225°Cd to 535°Cd. In Tanzania, tt_emerg_to_endjuv ranged between 100°Cd to 300°Cd while the tt_flower_to_maturity values varied between 315°Cd to 1000°Cd. In Uganda, tt_emerg_to_endjuv ranged between 150°Cd to 300°Cd while the tt_flower_to_maturity values varied between 400°Cd to 990°Cd. In Burundi, tt_emerg_to_endjuv ranged between 200°Cd to 350°Cd while the tt_flower_to_maturity values varied between 450°Cd to 800°Cd. In Rwanda, tt_emerg_to_endjuv ranged between 100°Cd to 350°Cd while the tt_flower_to_maturity values varied between 550°Cd to 850°Cd. The study notes that increasing the tt_emerg_to_endjuv reduces the expected yields. However, increasing the tt_flower_to_maturity increased the expected yields. It should also be noted that it was possible to match the observed maize yield by adjusting the two phenology parameters selected for the study. It should be noted that the combination of parameters presented in Table 4.1 predicted the maize crop phenology (flowering and maturity) very well for the calibration dataset (Loecke et al., 2004a). Figure 4.1 shows that adjusting the phenology parameters for maize cultivars resulted to comparability of actual observed (farmers estimate) and APSIM simulated yields.

Table 4.1: Calibration and validation of APSIM model maize simulation based on farmers estimates

Zone	Location (Station)	tt_emerg to endjuv (oCd)	tt_flower to maturity (oCd)	Actual Yield (YA)	Simulated Yield (YM)
	Kenya				
1	Eldoret	450	520	3.28	3.29
2	Kakamega	350	535	2.21	2.27
3	Kisumu	300	325	0.96	0.96
4	Machakos	150	225	0.90	0.94
5	Makindu	150	225	0.50	0.51
6	Mombasa	300	360	0.97	0.99
	Tanzania				
1	Tanga	100	1000	1.00	0.97
2	Dodoma	300	350	1.13	1.13
3	Shinyanga	180	700	0.83	0.85
4	Mbeya4	300	315	1.20	1.23

5	Mbeya5	180	420	1.70	1.66
6	Kilimanjaro	N/A	N/A	NA	NA
7	Morogoro	300	370	1.20	1.16
	Uganda				
1	Arua	250	800	1.75	1.75
2	Iganga	200	990	3.00	2.95
3	Kabale	300	500	1.12	1.10
4	Kapchorwa	300	570	1.50	1.52
5	Lira	300	570	0.80	0.81
6	Masaka	150	950	2.00	2.02
7	Mbarara	200	550	2.30	2.29
8	Soroti	300	400	1.56	1.63
	Burundi				
1	Bujumbura	300	600	1.30	1.28
2	Gisozi	350	450	1.20	1.24
3	Musasa	250	700	1.28	1.33
4	Muyinga	200	800	1.39	1.44
5	Nyanza_Lac	N/A	N/A	N/A	N/A
	Rwanda				
1	Byumba	150	770	1.20	1.26
2	Gabiro	100	850	0.24	0.17
3	Gikongoro	300	620	1.52	1.45
4	Gisenyi	350	650	1.43	1.35
5	Kamembe	200	680	1.26	1.33
6	kigali	320	550	1.37	1.42
7	Ruhuha	NA	NA	0.90	NA
8	Save	NA	NA	0.80	NA

4.2 Effects of Baseline Climate Change on Maize Production

4.2.1 Crop production analysis based on FAOSTAT in EAC

Crop production in each country was based on FAOSTAT. Table 4.2 and Table 4.3 present statistics for the annual percentage change in crop production (computed based on least squares method) and long-term mean annual crop production, respectively, for the period 1961 to 2012a.

Figure 4.1: Comparison of observed (actual) and simulated yields in EAC

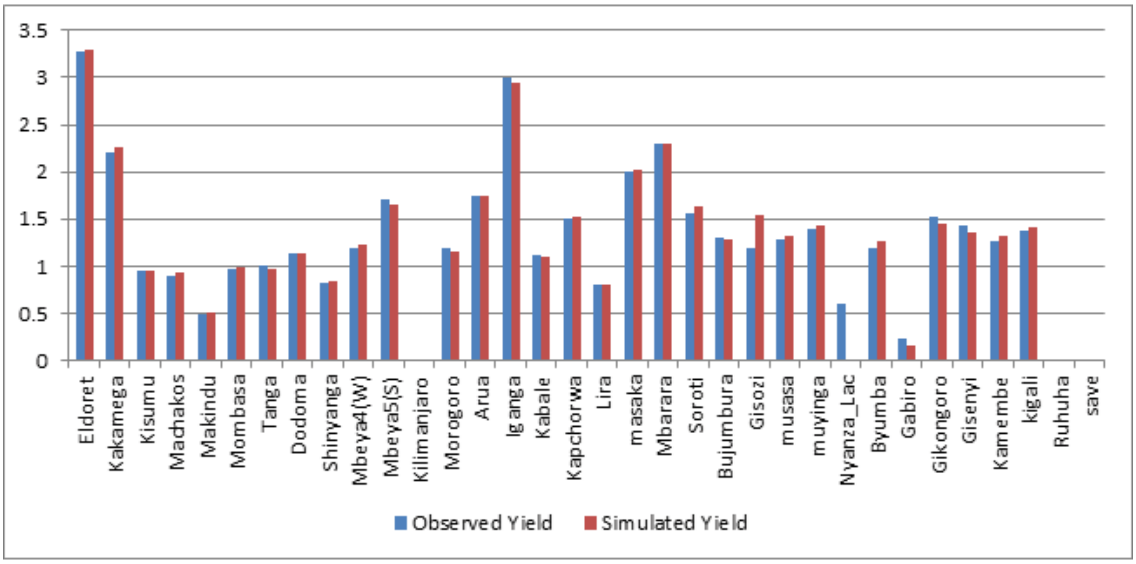

Table 4.2: Annual percentage change in crop production in EAC (1961-2012)

Country	Variable	Annual Change (%)					
		Maize	**Wheat**	**Millet**	**Sorghum**	**Beans**	**Rice**
Burundi	Area (ha)	0.17	0.23	0.23	2.62	0.09	6.97
	Production (MT)	0.32	0.75	0.71	3.02	-0.38	8.08
	Yield (Hg/ha)	0.14	0.52	0.47	0.39	-0.47	1.03
Kenya	Area (ha)	1.10	0.63	0.82	-0.45	4.68	3.32
	Production (MT)	1.78	2.03	-2.02	-0.43	4.45	2.78
	Yield (Hg/ha)	0.68	1.40	-2.83	-0.98	-0.21	-0.52
Rwanda	Area (ha)	3.23	7.88	0.77	0.26	1.99	-
	Production (MT)	3.55	9.05	2.15	0.15	2.03	2.66
	Yield (Hg/ha)	0.31	1.09	1.36	-0.11	0.04	9.10
Uganda	Area (ha)	2.99	3.85	-1.69	0.24	3.63	7.44
	Production (MT)	4.43	3.14	-0.63	0.57	2.83	8.85
	Yield (Hg/ha)	1.39	-0.69	1.08	0.33	-0.77	1.31
Tanzania	Area (ha)	0.17	0.23	0.23	2.62	0.09	6.97
	Production (MT)	0.32	0.75	0.71	3.02	-0.38	8.08
	Yield (Hg/ha)	0.14	0.52	0.47	0.39	-0.47	1.03

NB: Data is based on FAOSTAT

Table 4.2 shows that the annual percentage change in production, area harvested and yield under maize were all positive (increase) in Burundi (0.32%, 0.17% and 0.14%), Kenya (1.78%, 1.1% and 0.68%), Rwanda (3.55%, 3.23% and 0.31%), Uganda (4.43%, 2.99% and 1.39%) and Tanzania (0.32%, 0.17% and 0.14%). The highest percentage increase in maize yield was recorded in Uganda (1.39%) and Kenya (0.68%). For wheat, the annual percentage change in production, area harvested and yield under maize were all positive (increase) in Burundi, Kenya, Rwanda and Tanzania except Uganda which indicated a decrease of 0.69 per cent. The highest percentage increase in area harvested for wheat was recorded in Rwanda (7.88%) and Uganda (3.85%). These higher annual percentage change in area harvested translated to higher wheat production in the countries. For millet, the annual percentage change in yield were all positive in EAC except Kenya with a percentage change of -2.83 per cent. Although the percentage change in yield increased by 1.08 per cent, it should be noted that area under harvested under had decreased by 1.08 per cent. For sorghum, all countries in EAC indicated a positive change in yield except Kenya (-0.98%) and Rwanda (-0.11%). However, area in which sorghum was harvested indicated positive annual change (0.26%) implying that the observed decrease in sorghum yield could be attributed to other factors other than land availability. For beans, all countries in the EAC showed a negative annual percentage change in yield except Rwanda, which was positive with a value of 0.04 per cent. For rice, all countries except Kenya showed a positive annual percentage change in yield. Notably, in countries with positive annual percentage change, the larger positive percentage change in area harvested translated to a observed large annual percentage change in production.

Table 4.3: Long-term mean annual crop production (1961-2012)

Country	Statistic	Crop Production					
		Wheat	Maize	Millet	Sorghum	Beans	Rice
Burundi	STDEV	1,773.8	21,602.7	1,975.3	23,451.7	42,906.7	27,183.4
	Mean (MT)	7,203.6	134,590.6	10,462.7	49,436.4	260,863.2	31,256.8
	CoV	0.2	0.2	0.2	0.5	0.2	0.9
Kenya	STDEV	90,429.9	660,922.6	39,271.4	56,245.6	155,950.5	25,166.3
	Mean (MT)	244,873.5	2,236,216.0	82,446.5	146,639.3	275,410.8	44,256.4
	CoV	0.4	0.3	0.5	0.4	0.6	0.6
Rwanda	STDEV	23,182.2	133,374.8	2,141.0	34,569.2	86,456.7	27,773.8
	Mean (MT)	13,732.6	115,666.0	2,815.5	152,933.0	196,546.8	19,682.9
	CoV	1.7	1.2	0.8	0.2	0.4	1.4
Uganda	STDEV	5,195.0	689,476.1	139,082.5	61,745.0	128,775.6	586,669.9

	Mean (MT)	11,286.0	826,780.9	533,512.8	353,290.2	309,336.9	657,631.6
	CoV	0.5	0.8	0.3	0.2	0.4	0.9
Tanzania	STDEV	25,359.6	1,350,002.2	92,015.2	243,931.8	263,134.2	68,695.6
	Mean (MT)	70,259.2	2,200,403.1	233,707.3	483,726.4	366,408.0	66,449.6
	CoV	0.4	0.6	0.4	0.5	0.7	1.0

NB: Data is based on FAOSTAT

Table 4.3 shows that in Burundi, the mean annual crop production was ranked high for sorghum, rice, beans, maize, millet and wheat in order of magnitude with rice production indicating highest variability compared to other crops. In Kenya, maize production was ranked highest and followed by beans, wheat, sorghum, millet and rice. Worth noting, production of rice and beans indicated highest variability compared to other crops under consideration. In Rwanda, beans ranked highest followed by sorghum, wheat, maize, rice and millet. The variability for wheat production was highest with CoV value of 1.7 compared to sorghum whose variability was lowest with CoV value of 0.2. In Uganda, maize was ranked the highest followed by rice, millet, sorghum, beans and then wheat. Rice production indicated highest variability with sorghum production undergoing lowest variation. In Tanzania, maize production was ranked highest and followed by sorghum, beans, millet and wheat. The CoV was highest for rice with a value of 1.0 while wheat and millet had lowest variability of 0.4. In general, maize production was ranked highest in Kenya followed by Tanzania, Uganda, Burundi and then Rwanda. For wheat production, the highest production was recorded in Kenya followed by Rwanda, Uganda, Tanzania and then Burundi. For millet, highest production was recorded in Uganda followed by Tanzania, Burundi, Kenya and then Rwanda. For sorghum, highest production was recorded in Tanzania followed by Uganda, Rwanda Kenya and then Burundi. For beans, highest production was recorded in Tanzania followed by Uganda, Kenya, Burundi and then Rwanda. For rice, highest production was recorded in Tanzania, Uganda, Kenya, Burundi and Rwanda.

4.2.2 Maize productivity in EAC

Analysis of actual yield (YA) and simulated yield (YM), coefficient of variation (CoV) of simulated yields, magnitude of slope (sen slope) and percentage change in slope for the baseline period (1971-2000) are presented in Table 4.4.

Table 4.4 shows that in Kenya, the yield varied from 0.51 t/ha to 3.29 t/ha while maize yield in Tanzania varied between 0.85 t/ha and 1.66 t/ha. In Uganda, the maize yield varied between 0.81 t/ha and 2.95 t/ha while in Burundi it varied between 1.28 t/ha and 1.54 t/ha. In Rwanda, the maize yield varied between 0.17 t/ha and 1.45 t/ha. The CoV indicated that the variability in maize yield were all positive, with values between 0 and 1.1. However, the magnitude of the slopes were noted to be highly variable (both positive and negative) with significant positive trend (change) at significant level (α=<0.1). In Tanzania, trend in maize yield were all noted to be significant at α level greater than 0.1. The study also noted that in Uganda and Burundi, the trend were significant and negative at significant α level less than 0.1. In Rwanda, all the selected stations with available data showing a decrease with α levels less than 0.12. The study notes that cereal yields in EAC have fluctuated below 2 t/ha since the 1960s. Country reports and data provide further evidence of declining or stagnating productivity, not just for cereals, but also for other crops. For example, UBOS (2010) indicates that between 2004 and 2009, Uganda experienced a decline in the yields of beans, cassava, plantain bananas, Irish potatoes and maize. Bekunda (1999) indicates that banana production in Uganda has been declining since the 1990s. Similarly, statistics from Kenya's Ministry of Agriculture and Livestock indicate that maize yields are declining in Kenya.

Table 4.4: Analysis of actual yield and simulated yield and related trend statistics for historical period (1971-2000)

Location	Yield (t/ha)	Trend Statistics for Baseline (1971-2000)				
Zone		Simulated (YM)	CoV	Sen slope	Sen slope (%)	Pvalue
	Kenya					
1	Eldoret	3.29	0.5	65.1	2.0	0.0
2	Kakamega	2.27	0.5	54.8	2.4	0.0
3	Kisumu	0.96	0.3	-9.0	-0.9	0.1
4	Machakos	0.94	0.0	-1.6	-0.2	0.3
5	Makindu	0.51	0.1	-0.4	-0.1	0.3
6	Mombasa	0.99	0.1	0.4	0.0	0.9
	Tanzania					
1	Tanga	0.97	0.6	64.5	6.7	0.3
2	Dodoma	1.13	0.3	0.6	0.1	1.0
3	Shinyanga	0.85	1.1	-4.4	-0.5	0.6
4	Mbeya4(W)	1.23	0.0	0.2	0.0	0.9
5	Mbeya5 (S)	1.66	0.0	-1.5	-0.1	0.2
6	Kilimanjaro	NA	NA	NA	NA	NaN
7	Morogoro	1.16	0.0	0.11	0.01	0.45
	Uganda					
1	Arua	1.75	0.5	-49.76	-2.84	0.00
2	Iganga	2.95	0.4	-120.38	-4.07	0.00
3	Kabale	1.10	0.4	-19.01	-1.73	0.00
4	Kapchorwa	1.52	0.4	-54.90	-3.62	0.00
5	Lira	0.81	0.9	10.68	1.32	0.38
6	Masaka	2.02	0.5	32.76	1.62	0.18

7	Mbarara	2.29	0.2	-28.38	-1.24	0.01
8	Soroti	1.63	0.3	-37.26	-2.29	0.01
	Burundi					
1	Bujumbura	1.28	0.2	-9.82	-0.29	0.02
2	Gisozi	1.54	0.0	2.00	0.04	0.64
3	Musasa	1.33	0.0	-5.80	-0.15	0.09
4	Muyinga	1.44	0.0	-1.78	-0.04	0.62
5	Nyanza_Lac	NA	NA	NA	NA	NaN
	Rwanda					
1	Byumba	1.26	0.1	-32.39	-0.86	0.00
2	Gabiro	0.17		NA	NA	NaN
3	Gikongoro	1.45	0.0	-5.01	-0.12	0.01
4	Gisenyi	1.35	0.1	-33.23	-0.82	0.00
5	Kamembe	1.33	0.2	-3.42	-0.09	0.12
6	Kigali	1.42	0.0	-12.99	-0.30	0.00
7	Ruhuha	NA	NA	NA	NA	NaN
8	Save	NA	NA	NA	NA	NaN

4.3 Effects of Projected Climate Change on Maize Production

The projected effects of climate change in maize yield are simulated using the calibrated APSIM model for both RCP 4.5 wm^{-2} and RCP 8.5 wm^{-2} for the period 2016 to 2045. The results are presented in Table 4.5 and 4.6.

Table 4.5 shows that in Kenya, projected maize yield for RCP 45 scenario ranged between 0 t/ha and 4.7 t/ha. Compared to the baseline yield, it was noted that the selected zones indicated a negative percentage change in maize yield except Eldoret located within the Kenyan highlands. The CoV values were also noted to vary between 0.1 and 1.2 indicating highest variability in the highlands and surrounding zones. The magnitude of the slope was noted to either increase or decrease, with Kakammega location showing highest magnitude in absolute values. The corresponding percentage change in slope ranged from -8.4 to 1.0, with all the selected locations indicating significant trend at α level less than 0.1 except in Makindu.

Table 4.5 shows that in Tanzania, projected maize yield for RCP 45 scenario ranged between 1.1 t/ha and 3.3 t/ha. Compared to the baseline yield, it was noted that Tanga, Dodoma and Shinyanga showed positive change unlike Mbeya and Morogoro region. Further, the projected yields were noted to have a smaller CoV, which ranged between 0.1 and 0.3. Notably, all locations indicated a negative change except Tanga and Dodoma. The study also noted that Morogoro and the south-western highlands of Mbeya region had a significant trend at α level less than 0.1.

Table 4.5 shows that in Uganda, projected maize yield for RCP 45 scenario ranged between 0.5 t/ha and 2.9 t/ha. Compared to the baseline yield, it was noted that most locations indicated negative change in yield except Arua, Kapchorwa, Lira and Masaka. Although the CoV values were also noted to be smaller, computed sen slope showed that all the locations had a negative change in projected with corresponding percentage change in trend ranging between 0.2 per cent and 5.5 per cent. Further, the trend in annual yield were noted to be significant at α level less than 0.1 except Lira, Masaka, Mbarara and Soroti.

Table 4.5 shows that in Burundi, projected maize yield for RCP 45 scenario ranged between 1.6 t/ha and 4.0 t/ha. Compared to the baseline yield, it was noted that the change were all positive and ranged between 11 per cent and 201 per cent. It was worth noting that the CoV values were all below 0.5, an indication that the variations were small. Further, computed slope showed that it was negative in all selected stations, except the zone represented by Muyinga. However, the computed percentage change in computed slope were all under 0.3 per cent in absolute values. Further, the trend in Gisozi and Musasa locations were noted o be significant at α level less than 0.1.

Table 4.5 shows that in Rwanda, projected maize yield for RCP 45 scenario ranged between 2.2 t/ha and 4.0 t/ha. Compared to the baseline yield, it was noted that the projected yield underwent a positive change in all locations with the corresponding percentage change ranging between 75 per cent and 182 per cent. Notably, the CoV values were all less than 0.1 and thus less variability. The sen slope indicated that the projected yield was decreasing in all stations with corresponding decrease in percentage change in trend of less than 0.1. However, the observed trends were noted to be significant at α levels greater than 0.1.

Table 4.6 shows that in Kenya, projected maize yield for RCP 85 ranged between 0.1 t/ha and 4.6 t/ha. Compared to the baseline yield, all selected locations indicated negative percentage change in yield except Eldoret. The CoV values showed that the projected maize yield varied between 0.1 and 1.4. The computed slope were all decreasing except Eldoret, with the corresponding slopes ranging between -7.7 per cent and 1.2 per cent. Consequently, only Eldoret and Kakamega were noted to display a significant change at α level less than 0.1.

Table 4.6 shows that in Tanzania, projected maize yield for RCP 85 ranged between 1.1 t/ha and 2.7 t/ha. Compared to the baseline yield, Tanga, Dodoma and Shinyanga indicated a positive change in yield of between 24 per cent and 178 per cent. The central plateau and southern and western highlands of Mbeya showed decline in maize yield of between -2 per cent and -10 per cent. However, the CoV values showed low variability in yield in Tanzania with values ranging from 0 to 0.7. Further, computed sen estimator indicated a negative slope in most locations except Dodoma and Morogoro. The corresponding percentage change in trend of the slope ranged between -1.6 per cent and 0.1 per cent. The p value showed that only Dodoma and Highlands zones in Mbeya were significant at α level less than 0.1.

Table 4.6 shows that in Uganda, projected maize yield for RCP 85 ranged between 0.8 t/ha and 3.2 t/ha. Compared to the baseline yield, all selected locations indicated positive change of between 3 per cent and 85 per cent except Kabale and Mbarara locations. The CoV values showed low variability attributed to COV values ranging between 0.1 and 0.6. Computed sen slope indicated negative change in all locations except Lira. The corresponding change in slope were all negative and ranged between -1.1 and 2.6 except in Lira, which had a positive value of 3.6. It should be noted that in all locations, the computed slope were significant at α level less than 0.1.

Table 4.6 shows that in Burundi, projected maize yield for RCP 85 ranged between 1.8 t/ha and 2.1 t/ha. Compared to the baseline yield, all selected locations indicated an increase in yield with corresponding percentage change of between 25% and 64%. Notably, the CoV values were all low and less than 0.6 thus indicating low variability. Further, computed slope indicated negative change in projected yield for all the locations except Muyinga. Worth noting, locations in which the computed sen slope were decreasing showed a significant trend at α level less than 0.1.

The Table 4-6 shows that in Rwanda, projected maize yield for RCP 85 ranged between 0.22 t/ha and 1.42 t/ha. Compared to the baseline yield, the change in yield were all positive. The CoV values were all below 0.1 and thus an indication of low variability. Further, the trend of the computed slope were all positive except Gikongoro. However, the percentage change in trend were all positive except in Gikongoro and Kigali which showed no trend. Consequently, only Byumba location indicated presence of significant trend at α level less than 0.1.

Table 4.5: Analysis of simulated baseline and RCP 45 and related trend statistics for RCP 45 period (2016-2045)

Location		**Yield (t/ha)**			**Trend Statistics for RCP45 (2016-2045)**			
Zone		**Baseline**	**RCP45**	**Δ%**	**CoV**	**Sen slope**	**Sen slope (%)**	**P value**
	Kenya							
1	Eldoret	3.29	4.7	43	0.2	9.4	0.2	0.0
2	Kakamega	2.27	0.5	-78	1.2	-16.9	-3.7	0.1
3	Kisumu	0.96	N/A	N/A	NaN	N/A	N/A	NaN
4	Machakos	0.94	0.9	-4	0.1	-2.7	-0.3	0.0
5	Makindu	0.51	0.0	-100	0.7	-3.9	-8.4	0.3
6	Mombasa	0.99	0.9	-9	0.1	9.3	1.0	0.1
	Tanzania							
1	Tanga	0.97	1.6	65	0.3	2.7	0.2	0.9
2	Dodoma	1.13	1.3	15	0.1	0.1	0.0	0.8
3	Shinyanga	0.85	3.3	288	0.1	-6.6	-0.2	0.2

4	Mbeya4 (P)	1.23	1.1	-11	0.1	-2.5	-0.2	0.3
5	Mbeya5 (H)	1.66	1.3	-22	0.1	-9.2	-0.7	0.0
6	Kilimanjaro	NA	NA	N/A	NaN	NA	NA	NaN
7	Morogoro	1.16	1.1	-5	0.1	-3.7	-0.3	0.1
	Uganda							
1	Arua	1.75	2.0	14	0.4	-50.6	-2.5	0.0
2	Iganga	2.95	2.9	-2	0.3	-55.0	-1.9	0.0
3	Kabale	1.10	0.9	-18	0.3	-19.3	-2.0	0.0
4	Kapchorwa	1.52	1.8	18	0.3	-35.2	-1.9	0.0
5	Lira	0.81	1.3	60	0.5	-9.8	-0.7	0.6
6	Masaka	2.02	2.1	4	0.5	-4.3	-0.2	0.8
7	Mbarara	2.29	1.9	-17	0.3	-9.1	-0.5	0.3
8	Soroti	1.63	0.5	-69	1.7	-26.6	-5.5	1.0
	Burundi							
1	Bujumbura	1.28	3.6	181	0.1	-10.4	-0.3	0.2
2	Gisozi	1.54	3.8	147	0.1	-6.5	-0.2	0.0
3	Musasa	1.33	4.0	201	0.0	-7.1	-0.2	0.1
4	Muyinga	1.44	1.6	11	0.5	1.1	0.1	1.0
5	Nyanza_Lac	NA	NA	N/A	NaN	NA	NA	NaN
	Rwanda							
1	Byumba	1.26	2.2	75	0.1	-1.9	-0.1	0.7
2	Gabiro	0.17	NA	N/A	NaN	NA	NA	NaN
3	Gikongoro	1.45	3.7	155	0.1	-3.7	-0.1	0.6
4	Gisenyi	1.35	NA	N/A	NaN	NA	NA	NaN
5	Kamembe	1.33	NA	N/A	NaN	NA	NA	NaN
6	Kigali	1.42	4.0	182	0.1	-3.5	-0.1	0.4
7	Ruhuha	NA	NA	N/A	NaN	NA	NA	NaN
8	Save	NA	NA	N/A	NaN	NA	NA	NaN

Table 4.6: Analysis of simulated baseline and RCP 85 and related trend statistics for RCP 85 period (2016-2045)

Location		**Yield (t/ha)**			**Trend Statistics for RCP 85 (2016-2045)**			
Zone		**Baseline**	**RCP 85**	**Δ%**	**CoV**	**Sen slope**	**Sen slope (%)**	**P value**
	Kenya							
1	Eldoret	3.29	4.6	40	0.2	55.7	1.2	0.0
2	Kakamega	2.27	0.5	-78	1.1	-12.9	-2.5	0.1
3	Kisumu	0.96	NA	NA	NA	NA	NA	NA

4	Machakos	0.94	0.9	-4	0.1	-0.1	0.0	0.9
5	Makindu	0.51	0.1	-80	1.4	-7.1	-7.7	1.0
6	Mombasa	0.99	0.9	-9	0.1	-1.0	-0.1	0.9
	Tanzania							
1	Tanga	0.97	2.7	178	0.4	-29.7	-1.1	1.0
2	Dodoma	1.13	1.4	24	0.0	0.8	0.1	0.1
3	Shinyanga	0.85	1.7	100	0.7	-28.2	-1.6	0.3
4	Mbeya4 (P)	1.23	1.2	-2	0.0	-1.9	-0.2	0.2
5	Mbeya5 (H)	1.66	1.5	-10	0.0	-3.6	-0.2	0.0
6	Kilimanjaro	NA	NaN	NA	NaN	NA	NA	NaN
7	Morogoro	1.16	1.1	-5	0.0	0.1	0.0	0.4
	Uganda							
1	Arua	1.75	1.8	3	0.4	-45.6	-2.5	0.0
2	Iganga	2.95	3.2	8	0.4	-82.3	-2.6	0.0
3	Kabale	1.10	0.8	-27	0.3	-15.5	-1.9	0.0
4	Kapchorwa	1.52	1.8	18	0.3	-38.0	-2.2	0.0
5	Lira	0.81	1.5	85	0.6	50.1	3.4	0.0
6	masaka	2.02	2.7	34	0.4	-42.5	-1.6	0.1
7	Mbarara	2.29	2.1	-8	0.1	-23.6	-1.1	0.0
8	Soroti	1.63	1.7	4	0.2	-40.0	-2.0	0.1
	Burundi							
1	Bujumbura	1.28	2.1	64	0.0	-4.1	-0.1	0.0
2	Gisozi	1.54	2.1	36	0.0	-4.1	-0.1	0.0
3	musasa	1.33	2.1	58	0.0	-7.2	-0.2	0.0
4	muyinga	1.44	1.8	25	0.6	8.0	1.0	0.7
5	Nyanza_Lac	NA	NaN	NaN	NaN	NA	NA	NaN
	Rwanda							
1	Byumba	1.26	2.01	60	0.1	8.2	0.3	0.0
2	Gabiro	0.17	0.22	29	0.1	5.9	3.2	1.0
3	Gikongoro	1.45	1.52	5	0.0	-2.0	0.0	0.2
4	Gisenyi	1.35	NaN	NaN	NaN	NA	NA	NaN
5	Kamembe	1.33	NaN	NaN	NaN	NA	NA	NaN
6	kigali	1.42	1.55	9	0.0	0.7	0.0	0.8
7	Ruhuha	NA	NaN	NA	NaN	NA	NA	NaN
8	save	NA	NaN	NA	NaN	NA	NA	NaN

5. Summary

Agriculture is highly sensitive to climatic parameters and is thus one of the sectors most vulnerable to climate change, especially over Africa where several studies have shown likely negative impacts. Therefore, there is need to explore the spatial effects of climate change on agricultural production the East African Community. Improved understanding of the influence of climate on agricultural production is needed to cope with expected changes in temperature and precipitation, and an increasing number of undernourished people in food insecure regions. Weather patterns are an important predictor of agricultural productivity trends in the EAC region and other regions in Africa. Rainfall, in particular, is one of the binding constraints to agricultural productivity in Africa. This is not surprising given the heavy reliance on rain for agricultural production. Periods of drought are associated with significant drops in levels of productivity and *vice versa*.

Data collected for crop modelling purpose included: soil profile data, soil characteristics, climate data (rainfall, temperature, and solar radiation) and crop management data. A relevant set of yield estimates for maize crop were obtained. In overall, short term and long term maize cultivars were selected in each country to assess the effects of climate change on maize production. Observed data on crop production was also sourced from FAOSTATS. The EAC region lacks high-quality observation datasets at suitable temporal and spatial resolution necessary for evaluating RCM simulations. Data on soil profile, soil characteristics, crop management, and crop genetic coefficients were not readily available. Therefore, estimates published in reports and peer-reviewed papers were used. It should be noted that there exists inaccuracy of one-crop modelling as proxy to crop production in the region, since other crops may respond in different ways.

The Agricultural Production System Simulator was used to simulate the phenology and yield of maize. The APSIM model was calibrated using the provided data on climate, soil, and management and modification of selected cultivar specific phenological parameters for maize. The study then followed an iterative approach in which the crop phenology of the systems was evaluated. The iterative process of calibrating the APSIM model was initialized by developing phenological parameters for the maize cultivar. In this study, two phenology parameters are used. They comprise of thermal time from emergence to end of juvenile stage (tt_emerg_to_endjuv, ^{o}Cd) and thermal time from flowering to maturity (tt_flower_to_maturity, ^{o}Cd) were adjusted to achieve a good match between observed and simulated emergence, flowering and maturity date using days after sowing (DAS). Thereafter, the calibrated model was run against the data from 1971 to 2000 and the model performance was evaluated based on farmers estimates. Simulating trial-and-error method was used for model calibration. The study used graphical analysis to assess the performance of simulated maize yield in the EAC. The calibrated APSIM model was used to estimate the trend in the yield of crops under current and projected climate. The change between the projected and baseline yield were determined using the percentage difference technique. The presence of a monotonic increasing or decreasing trend was tested with the non-parametric Mann-Kendall (Mann K) test, while the slope of a linear trend was

estimated with the non-parametric Sen's method (Gilbert, 1987). Furthermore, the true slope of the existing trend (as change per year) was estimated using the Sen's non-parametric method.

Calibration and validation of APSIM model in simulating maize yield was based on modification of two phenology parameters (thermal time from emergence to end of juvenile and thermal time from flowering to maturity). In Kenya, thermal time from emergence to end of juvenile ranged from 150°Cd in the lowlands and coastal region to 450°Cd in the highlands, with similar pattern for thermal time from flowering to maturity with values ranging from 225°Cd to 535°Cd. In Tanzania, thermal time from emergence to end of juvenile ranged between 100°Cd to 300°Cd while thermal time from flowering to maturity values varied between 315°Cd to 1000°Cd. In Uganda, thermal time from emergence to end of juvenile ranged between 150°Cd to 300°Cd while thermal time from flowering to maturity values varied between 400°Cd to 990°Cd. In Burundi, thermal time from emergence to end of juvenile ranged between 200°Cd to 350°Cd while thermal time from flowering to maturity values varied between 450°Cd to 800°Cd. In Rwanda, thermal time from emergence to end of juvenile ranged between 100°Cd to 350°Cd while thermal time from flowering to maturity values varied between 550°Cd to 850°Cd. The study notes that increasing the thermal time from emergence to end of juvenile reduces the expected yields. However, increasing thermal time from flowering to maturity increased the expected yields. It should also be noted that it was possible to match the observed maize yield by adjusting the two phenology parameters selected for the study. It should be noted that the combination of parameters predicted the maize crop phenology (flowering and maturity) very well for the calibration dataset. The study indicated that adjusting the phenology parameters for maize cultivars resulted to comparability of actual observed (farmers estimate) and APSIM simulated yields.

Baseline crop production in each country based on FAOSTAT showed that the annual percentage change in production, area harvested and yield under maize were all positive (increase) in Burundi (0.32%, 0.17% and 0.14%), Kenya (1.78%, 1.1% and 0.68%), Rwanda (3.55%, 3.23% and 0.31%), Uganda (4.43%, 2.99% and 1.39%) and Tanzania (0.32%, 0.17% and 0.14%). The highest percentage increase in maize yield was recorded in Uganda (1.39%) and Kenya (0.68%). For wheat, the annual percentage change in production, area harvested and yield under maize were all positive (increase) in Burundi, Kenya, Rwanda and Tanzania except Uganda which indicated a decrease of 0.69 per cent. The highest percentage increase in area harvested for wheat was recorded in Rwanda (7.88%) and Uganda (3.85%). These higher annual percentage change in area harvested translated to higher wheat production in the countries. For millet, the annual percentage change in yield were all positive in EAC except Kenya with a percentage change of -2.83 per cent. Although the percentage change in yield increased by 1.08 per cent, area under harvested had decreased by 1.08 per cent. For sorghum, all countries in EAC indicated a positive change in yield except Kenya (-0.98%) and Rwanda (-0.11%). However, area in which sorghum was harvested indicated positive annual change (0.26%), implying that the observed decrease in sorghum yield could be attributed to other factors other than land availability. For beans, all countries in the EAC showed a negative annual percentage change in yield except Rwanda which was positive with a value of 0.04 per cent. For rice, all countries except Kenya showed a positive annual percentage change in yield. Notably, in countries with positive annual percentage change, the larger positive percentage change in area harvested translated to a observed large annual percentage change in production.

Baseline maize productivity in EAC showed that in Kenya, the yield varied from 0.51 t/ha to 3.29 t/ha while maize yield in Tanzania varied between 0.85 t/ha and 1.66 t/ha. In Uganda, the maize yield varied between 0.81 t/ha and 2.95 t/ha while in Burundi it varied between 1.28 t/ha and 1.54 t/ha. In Rwanda, the maize yield varied between 0.17 t/ha and 1.45 t/ha. The CoV indicated that the variability in maize yield were all positive with values between 0 and 1.1. However, the magnitude of the slopes were noted to be highly variable (both positive and negative) with significant positive trend (change) at significant level (α=<0.1). In Tanzania, trend in maize yield were all noted to be significant at α level greater than 0.1. The study also noted that in Uganda and Burundi, the trend were significant and negative at significant α level less than 0.1. In Rwanda, all the selected stations with available data showed a decreasing trend with α levels less than 0.12.

In Kenya, projected maize yield for RCP 45 scenario ranged between 0 t/ha and 4.7 t/ha. Compared to the baseline yield, it was noted that the selected zones indicated a negative percentage change in maize yield except Eldoret located within the Kenyan highlands. The CoV values were also noted to vary between 0.1 and 1.2, indicating highest variability in the highlands and surrounding zones. The magnitude of the slope was noted to either increase or decrease, with Kakamega location showing highest magnitude in absolute values. The corresponding percentage change in slope ranged from -8.4 to 1.0, with all the selected locations indicating significant trend at α level less than 0.1 except in Makindu. However, projected maize yield for RCP 85 ranged between 0.1 t/ha and 4.6 t/ha. Compared to the baseline yield, all selected locations indicated negative percentage change in yield except Eldoret. The CoV values showed that the projected maize yield varied between 0.1 and 1.4. The computed slope were all decreasing except Eldoret with the corresponding slopes ranging between -7.7 per cent and 1.2 per cent. Consequently, only Eldoret and Kakamega were noted to display a significant change at α level less than 0.1.

In Tanzania, projected maize yield for RCP 45 scenario ranged between 1.1 t/ha and 3.3 t/ha. Compared to the baseline yield, it was noted that Tanga, Dodoma and Shinyanga showed positive change unlike Mbeya and Morogoro region. Further, the projected yields were noted to have a smaller CoV, which ranged between 0.1 and 0.3. Notably, all locations indicated a negative change except Tanga and Dodoma. The study also noted that Morogoro and the south-western highlands of Mbeya region had a significant trend at α level less than 0.1. However, projected maize yield for RCP 85 ranged between 1.1 t/ha and 2.7 t/ha. Compared to the baseline yield, Tanga, Dodoma and Shinyanga indicated a positive change in yield of between 24 per cent and 178 per cent. The central plateau and southern and western highlands of Mbeya showed decline in maize yield of between -2 per cent and -10 per cent. However, the CoV values showed low variability in yield in Tanzania with values ranging from 0 to 0.7. Further, computed sen estimator indicated a negative slope in most locations except Dodoma and Morogoro. The corresponding percentage change in trend of the slope ranged between -1.6 per cent and 0.1 per cent. The p value showed that only Dodoma and Highlands zones in Mbeya were significant at α level less than 0.1.

In Uganda, projected maize yield for RCP 45 scenario ranged between 0.5 t/ha and 2.9 t/ha. Compared to the baseline yield, it was noted that most locations indicated negative change in yield except Arua, Kapchorwa, Lira and Masaka. Although the CoV values were also noted to be smaller, computed sen slope showed that all the locations had a negative change with corresponding percentage change in trend ranging between 0.2 per cent and 5.5 per cent. Further, the trend in annual yield were noted to be significant at α level less than 0.1 except Lira, Masaka, Mbarara and Soroti. However, projected maize yield for RCP 85 ranged between 0.8 t/ha and 3.2 t/ha. Compared to the baseline yield, all selected locations indicated positive change of between 3 per cent and 85 per cent except Kabale and Mbarara locations. The CoV values showed low variability attributed to COV values ranging between 0.1 and 0.6. Computed sen slope indicated negative change in all locations except Lira. The corresponding change in slope were all negatives and ranged between -1.1 and 2.6 except in Lira which had a positive value of 3.6. It should be noted that in all locations, the computed slope were significant at α level less than 0.1.

In Burundi, projected maize yield for RCP 45 scenario ranged between 1.6 t/ha and 4.0 t/ha. Compared to the baseline yield, it was noted that the changes were all positive and ranged between 11 per cent and 201 per cent. The CoV values were all below 0.5, an indication that the variations were small. Further, computed slope showed that it was negative in all selected stations except the zone represented by Muyinga. However, the computed percentage changes in slope were all under 0.3 per cent in absolute values. Further, the trend in Gisozi and Musasa locations were noted to be significant at α level less than 0.1. However, in Burundi, projected maize yield for RCP 85 ranged between 1.8 t/ha and 2.1 t/ha. Compared to the baseline yield, all selected locations indicated an increase in yield with corresponding percentage change of between 25 per cent and 64 per cent. Notably, the CoV values were all low and less than 0.6, thus indicating low variability. Further, computed slope indicated negative change in projected yield for all the locations except Muyinga. The locations in which the computed sen slope were decreasing showed a significant trend at α level less than 0.1.

In Rwanda, projected maize yield for RCP 45 scenario ranged between 2.2 t/ha and 4.0 t/ha. Compared to the baseline yield, the projected yield underwent a positive change in all locations, with the corresponding percentage change ranging between 75 per cent and 182 per cent. Notably, the CoV values were all less than 0.1 and thus less variability. The sen slope indicated that the projected yield was decreasing in all stations, with corresponding decrease in percentage change in trend of less than 0.1. However, the observed trends were noted to be significant at α levels greater than 0.1. However, projected maize yield for RCP 85 ranged between 0.22 t/ha and 1.42 t/ha. Compared to the baseline yield, the change in yield were all positive. The CoV values were all below 0.1 and thus an indication of low variability. Further, the trend of the computed slope were all positive, except for Gikongoro. However, the percentage change in trend were all positive except in Gikongoro and Kigali which showed no trend. Consequently, only Byumba location indicated presence of significant trend at α level less than 0.1.

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Kenya Institute for Public Policy Research and Analysis
Bishops Garden Towers, Bishops Road
P.O. Box 56445-200, Nairobi, Kenya
Tel: +254 20 2719933/4, 2714714/5, 2721654, 2721110
admin@kippra.or.ke

African Climate Policy Center
UN Economic Commission for Africa
Menelik II Ave.
P.O. Box 3001, Addis Ababa, Ethiopia
Tel: +251 11 544 5000
acpc@un.org