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Review

Climate change impact on maize (*Zea mays* L.) yield using crop simulation and statistical downscaling models: A review

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Review of literature related to the impact of climate change on maize (*Zea mays* L.) yield using Global Climate Models (GCMs), statistical downscaling, and crop simulation (APSIM-maize-and-CERES-maize models) models are discussed. GCMs can simulate the current and future climatic scenarios. Crop yield projections using crop models require climate inputs at higher spatial resolution than that provided by GCMs. The computationally inexpensive statistical downscaling technique is widely used for this translation. Studies on regional climate modeling have mostly focused on Southern Africa and West Africa, with very few studies in Zambia. Additionally, the integrated use of climate and crop models have received relatively less attention in Africa compared to other parts of the world. Conversely, the AgMIP protocols have been implemented in Sub-Saharan Africa (SSA) (Ethiopia, Kenya, Tanzania, Uganda and South Africa) and South Asia (SA) (Sri Lanka). In Zambia, however, the protocols have not been applied at either regional or local scale. Applying crop and statistical downscaling models requires calibration and validation, and these are crucial for correct climate and crop simulation. The review shows that although uncertainties exist in the design of models, and parameters, soil, climate and management options, the climate would adversely affect maize yield production in SSA. The potential effect of climate change on maize production can be studied using crop models such as agricultural production simulator (APSIM) and decision support system for agrotechnology (DSSAT) models. There is need to use integrated assessment modeling to study future climate impact on maize yield. The assessment is essential for long-term planning in food security and in developing adaptation and mitigation strategies in the face of climate variability and change.

Key words: Review, AgMIP, climate scenario, climate change, variability, crop simulation model, bias correction, dynamical downscaling, Global Climate Model (GCM), statistical downscaling.

INTRODUCTION

Energy, water, transportation, wildlife, health, and agriculture sectors are being affected by climate change. Climate change poses challenges for sustainable development of the human society, and agriculture is the most sensitive sector facing climate change and variability (IPCC, 2007a; Ahmed et al., 2013; Wenjiao et al., 2013). Global climate models (GCMs) with very coarse spatial resolutions (50 to 400 km) are tools used for simulating the current and future climate change under increasing greenhouse gas (GHG [carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O)]) concentrations. Dynamical and statistical downscaling techniques are used to bridge the gap between the predictors (large-scale GCM output) and predictands (local-scale variables).

According to Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report (AR5), global (land and ocean) average temperature has shown a 0.85°C (0.65 to 1.06°C) increase over the period of 1800 to 2012 (IPCC, 2013a), and a 0.74 ± 0.18°C increase during the last hundred years (1906 to 2005) (IPCC, 2007b). Prediction of temperature from GCMs in Southern Africa suggests an increase of 0.6 to 1.4°C by 2030 while the mean annual temperature increase in Zambia had been 1.3°C since 1960. Conversely, annual rainfall has declined across the country by 2.3% per decade from 1960 to 1990. Before the century ends, there would be a warming between 2.4 and 4.3°C relative to 1961 to 1990, and this is likely in Zambia. Crop growth and yield are influenced by climate change and variability in the world. Frequent precipitation variability and droughts have reduced maize yields in Zambia.

Assessing climate change impact on agricultural production are mostly undertaken at large spatial scales, missing out on local scale impacts and adaptation potential under which farmers operate (Zinyengere et al., 2014). Existing studies on regional climate modeling have mostly focused on southern Africa and West Africa (Hewitson and Crane, 2006; Stockdale et al., 2010; Paeth et al., 2011) with very few studies in Zambia. The literature review indicated insufficient research on modeling local-scale climate change and variability impacts using crop and statistical downscaling models. A holistic use of GCMs, statistical downscaling, and crop simulation models are vital in assessing the site-specific climate change impact on crop growth and yield. In Zambia, maize production is dependent on climatic conditions and any changes in the climate can affect its output negatively or positively. However, documents reviewed indicated that insufficient studies had been undertaken at local-scale that combined the use of statistical downscaling techniques and crop simulation models. Very little has been documented as to the extent maize yield would change under future climate during 2010 to 2039 (the 2020s) and 2040 to 2069 (2055s). Statistical downscaling techniques such as Long Ashton Research Station Weather Generator (LARS-WG), delta-based approaches using Agricultural Model Intercomparison and Improvement Project (AgMIP) protocols and Statistical DownScaling Model (SDSM) have not been parameterized and tested locally in generating current and future climate scenarios from GCMs to drive crop simulation models like agricultural production simulator (APSIM) and decision support system for agrotechnology (DSSAT). A climate scenario is a description of the possible future climate based on radiative force and can be visualized using GCMs and regional climate models (Kang et al., 2009).

The combined use of GCMs, crop simulation models and statistical downscaling techniques are the primary tools available to assess climate change impact on maize growth and yield. Statistical downscaling techniques are computationally inexpensive tools used to generate site-specific daily climate scenarios of meteorological parameters for impact assessment of climate change under different emissions scenarios and GCM pairings. Reliable prediction of climate change scenarios and their effect on crop yield are important for identifying appropriate mitigation and adaptation strategies (Jones et al., 2014). The traditional agronomic experimentation is time-consuming, costly and labor-intensive. Crop simulation modeling offers an opportunity for exploring cultivar potential for new areas before establishing expensive and time-consuming field experiments (Bationo et al., 2012a). Therefore, system analysis and simulations provide critical roles in developing this understanding of options. A proper understanding of climate change and its impact on crop yield would assist scientists, planners and policy makers to sensitize and guide farmers to make informed discussions as it relates to aspects of proper select of crops, and cultivar, dates of planting, application of irrigation water and scheduling to reduce the risks (Rauff and Bello, 2015).

The application of GCMs, crop simulation-and-statistical downscaling models to understand climate change impact on crop growth and yield offers a direct link between climate models, crop models, economic models, agrometeorology and concerns of society (Rauff and Bello, 2015). Additionally, integrated use of GCMs, statistical downscaling techniques, and crop simulation models provide an approach that applied scientific vigor in assessing the impact of climate change on agricultural production and world food security compared to other surveys. APSIM-maize-and-CERES-maize models are employed to evaluate the effects of climate change on maize growth and yield. Reliable projections of meteorological parameters such as precipitation, the wind, solar radiation and temperature from GCMs are required for evaluating the future impact of climate change on the main sectors.

This paper reviews the use of GCMs, statistical downscaling techniques, and crop simulation models and provides a basic framework for generating information to farmers, policy makers and planners on the anticipated climate change impact on maize yield using an integrated approach.

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GLOBAL CLIMATE MODELS

The tools currently available to simulate the global climate system due to greenhouse gases (GHGs) are the GCMs (IPCC-TGCIA, 2007). The IPCC defines a GCM as a quantitative illustration of the climate system (atmosphere, ocean, land and sea ice) based on the chemical, biological and physical properties, their interactions and feedback processes (Flato et al., 2013; Charron, 2014). GCMs depict the climate using a three-dimensional grid over the globe, and these typically have 10 to 20 vertical layers in the atmosphere, a horizontal resolution of 250 and 600 km and close to 30 layers in the oceans (IPCC-TGCIA, 2007) as presented in Figure 3.

The baseline climatological data can be obtained from four sources namely: National Meteorological Agencies, GCMs and Regional Climate Models (RCMs), weather generators, global climate center, and archives and National Centres for Environmental Prediction (NCEP), and these datasets can be applied in impact assessments (IPCC-TGCIA, 2007). The GCMs focus mostly on changes in temperature and precipitation (Yin et al., 2013) and are divided into three categories, namely: (i) Atmospheric Global Circulation Models (AGCMs); (ii) Oceanic Global Circulation Models (OGCMs); and (iii) Atmospheric Oceanic Global Circulation Models (AOGCMs).

i) Atmospheric Global Circulation Models (AGCMs) represent only the atmosphere, and in these models, sea surface temperatures are imposed. The AGCM dynamically simulates the atmospheric circulation processes that regulate energy transfer and exchange in the atmospheric flow. Fundamental equations are used to represent the atmospheric flows that link the mass distribution and the wind field. Practically, AGCMs are used for meteorological forecasts and includes United Kingdom Meteorological Office (UKMO), UK High Resolution (*UKHI*), Canadian Centre for Climate (Modelling and Analysis) (Canada) (CCC), Geophysical Fluid Dynamics Laboratory (GFDL), and Goddard Institute for Space Studies (GISS) (Santoso et al., 2008). AGCMs tend to simulate the intensity of extreme precipitation analogous to observed estimates (Flato et al., 2013). Furthermore, the stand-alone AGCMs run at higher resolution compared to AOGCMs, and they provide complimentary regional-scale climate data;

ii) Oceanic Global Circulation Models (OGCMs) describe physical and thermodynamical processes in oceans, and they include all the main influences on the general oceanic circulation. Santoso et al. (2008) noted that some AOGCMs (HadCM3, ECHAM4, and CSIRO-Mk2) could simulate important aspects of El Niño-Southern Oscillation (ENSO). Aerosols included in AOGCMs may affect climate directly by scattering and absorbing solar radiation and this, in turn, cools the surface temperature and indirectly alters the properties and lifetime of the clouds (Santoso et al., 2008); and

iii) Atmospheric Oceanic Global Circulation Models (AOGCMs) are used in modelling atmospheric and oceanic processes and their interactions. These models are composed of seven basic mathematical equations with seven basic variables that describe the instantaneous state of the atmosphere over time. Additionally, it includes a three-dimensional representation of the ocean and atmosphere making it possible to determine temperatures, humidity, salinity, and the wind and ocean currents.[1] In Atmospheric Oceanic Global Circulation Models (AOGCM) such as United Kingdom Transient climate experiment (UKTR), European Centre-Hamburg model version 1 (ECHAM1), and Global Sea Ice and Sea Surface Temperature (GISSTR), ocean currents and heat transport are represented with simple land-surface parameterization schemes, and these are the models used by climatologists (Santoso et al., 2008). The quantitative estimates of future climate change using AOGCMs have gained confidence, and the ability to simulate extreme events such as El Niño-Southern Oscillation (ENSO) has improved (Santoso et al., 2008). The AOGCMs were assessed in the AR4, and they are used to understand the dynamics of the physical components of the climate system and in projecting future GHG and aerosol forcing (Flato et al., 2013).

Bias correction

Global Climate Models (GCMs) have biases in their outputs although they are used in projecting future climate. This means GCMs cannot be used directly at local-or-regional-scale for impact studies, especially in the tropics where there is spatial and temporal variation in the orographic and climatic conditions (Navarro-Racines and Tarapues-Montenegro, 2015). These biases are the deviation of GCM output from the observed time series data (Wang, 2015). It has been reported by researchers such as Ramirez-Villegas et al. (2013), that biases in GCM simulations outputs relative to observed baseline time series data are huge. Bias correction is the changing of simulated values to reflect the baseline time series distribution and statistics (Trzaska and Schnarr, 2014). It is performed in two ways; by correcting the bias in GCM outputs and bias in the predictands such as precipitation and temperature downscaled from the GCM output (Wang, 2015). Typically, regional biases of seasonal surface temperature and precipitation are usually within the range of 2°C and 50 to 60% of observed time series data, respectively (Mearns et al., 2003). Hempel et al. (2013) noted that statistical bias correction is applied to the simulated climate to correct

[1] Source: IPCC 2007 WG1, ESCRIME

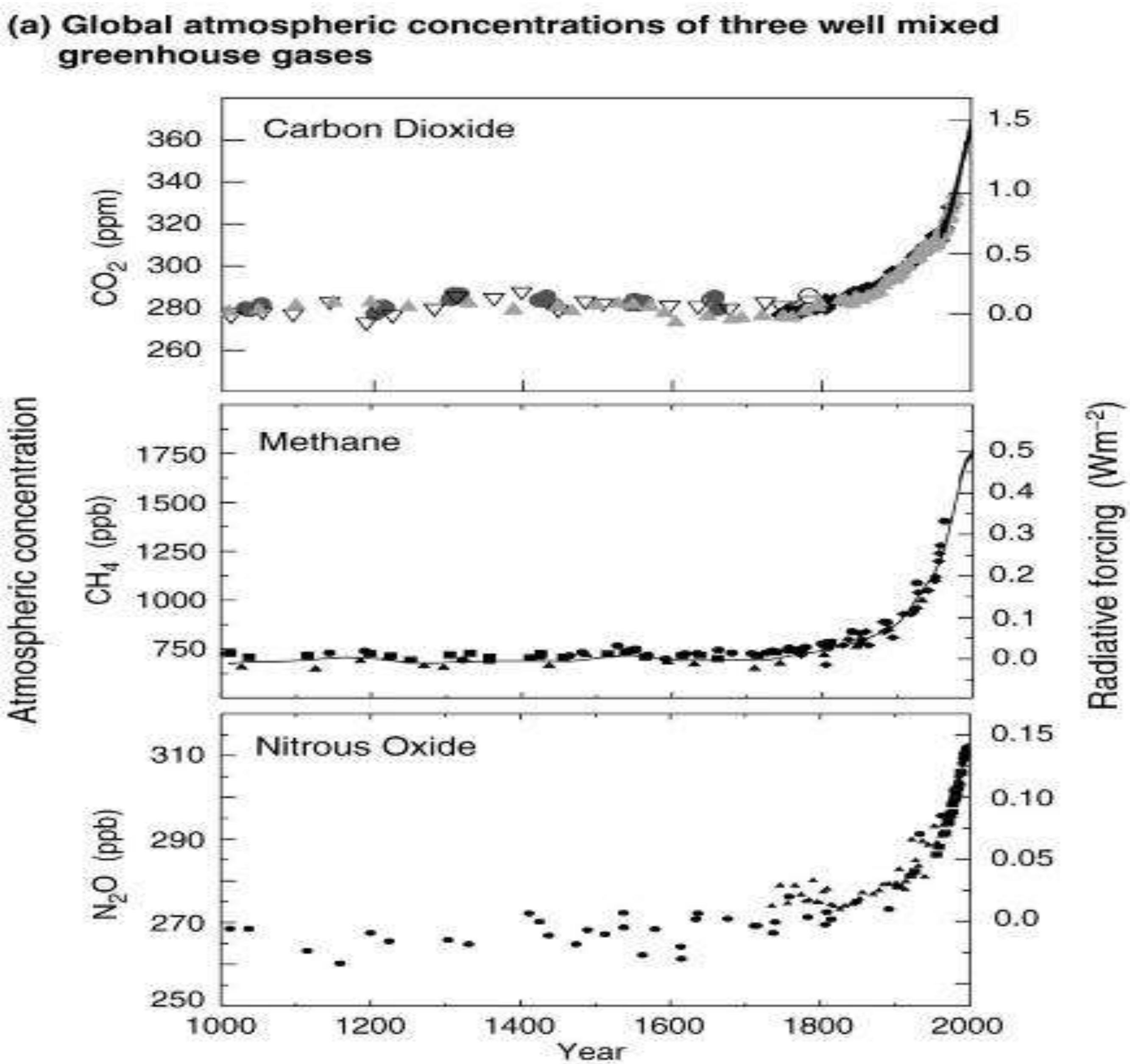

Figure 1. Atmospheric concentration of GHGs.
Source: IPCC (2007e).

for the systematic deviations from observed time series data. Many statistical bias correction approaches have been developed and are being utilized to remove systematic model errors. (Switanek et al., 2016).

In correcting for biases statistically, the probability density function (PDF) of the modelled data is mapped onto the observed time series (Haerter et al., 2011). These statistical bias correction techniques are used to link the data provided by the climate modeling community and the climate data necessary for quantitative climate data generation (Hempel et al., 2013). Moreover, Navarro-Racines and Tarapues-Montenegro (2015) showed that there is a need to correct for biases in raw climate model outputs at the downscaling stage to generate climate projections that can be used in impact studies such as agricultural and hydrological modeling. The error correction techniques are based on statistical methods such as transfer functions which can map the distribution of the simulated baseline data to the observed time series.

Statistical bias correction (BC) is performed to better match the GCM outputs to the observed daily time series data (Trzaska and Schnarr, 2014). In BC approach, the projected raw daily GCM output is corrected using the differences in the means and variances between GCM outputs and observed data in a baseline period (Navarro-Racines and Tarapues-Montenegro, 2015). Correcting and accounting for biases in climate model output is vital in producing reliable climate model simulations. Any method for correcting biases in the GCM outputs requires a baseline or reference data sets, and the bias adjustment quality is thus restricted by the quality and availability of the observed time series or reanalysis data. Three calibration methods are used to produce consistent time series data for future periods under the CGIAR Research Programme on Climate Change, Agriculture and Food Security (CCAFS) - Climate portal interface (www.ccafs-climate.org/data_bias_corrected/) and these are: (a) 'nudging' (bias correction) [Equation 1] (Hawkins et al., 2013c), (b) change factor (CF) [Equation 2] (Ramirez-Villegas and Jarvis, 2010; Hawkins et al., 2013c; Navarro-Racines and Tarapues-Montenegro, 2015); and (c) Quantile Mapping (QM) [Equation 3] (Gudmundsson et al., 2012; Gudmundsson, 2016).

The BC technique can be applied to correct both the historical and future time periods using the GCM output (Ho et al., 2012; Hawkins et al., 2013b; Chisanga et al., 2017) as presented in Equation 1.

$$T_{BC} = \bar{O}_{Baseline} + \frac{\sigma_{O,Baseline}}{\sigma_{T,Baseline}}\left(T_{RAW}(t) - \bar{T}_{Baseline}\right) \quad (1)$$

Where $\sigma_{T,Baseline}$ and $\sigma_{O,Baseline}$ is the standard deviation (σ) during the baseline of the daily GCM output and observed time series, respectively.

The CF assumes the daily variance correction is to the same degree during the future and baseline and the corrected daily time series data is computed by the equation below which considers changes in variance as reported by Ho et al. (2012) and Chisanga et al. (2017).

$$T_{CF} = \bar{T}_{RAW} + \frac{\sigma_{T,RAW}}{\sigma_{T,Baseline}}\left(O_{Baseline}(t) - \bar{T}_{Baseline}\right) \quad (2)$$

Where $\sigma_{T,RAW}$ and $\sigma_{T,Baseline}$ denote the standard deviation (σ) in the future time segment of the GCM output and observed time series, respectively.

Observations with much higher resolution, QM attempts to bridge this scale mismatch (Chisanga et al., 2017). QM method minimizes the differences between the observed/predicted data based on empirical probability distributions (Kum et al., 2014) as presented in the following equation.

$$P(a \le x \le b) = \textstyle\sum_{a \le x_i \le b} P(x_i),$$
$$F(x) = P(X \le x) = \textstyle\sum_{X \le x} P(x_i),\ Z_i = F_{oi}^{-1}(F_{si}(\hat{Y}_i)), \quad (3)$$

Where F_{oi} is the cumulative distribution function (CDF) of the daily observation for day *i*, F_{si} is the CDF of the simulated data from historical simulations, and $\hat{Y}_i$ and Z_i are the simulated and transformed (bias-corrected) data, respectively, for day *i*. Kum et al. (2014) described that the transformed predictions have the same probability distribution with the observations, but QM has a limitation in generating distributions on a monthly basis due to insufficient data points. Other bias correction methods are: cumulative distribution function transform (CDF-t) and equidistant quantile matching (EDCDFm) (Pierce et al., 2015), gamma-gamma transformation (Sharma et al., 2007; Hawkins et al., 2013a), the non-informative Bayesian (NIB) method and the informative Bayesian (IB) method (Kim et al., 2015a), combined CF + QM method (Kum et al., 2014). These have been used to correct for errors in daily precipitation and temperature for use as inputs to impact models. Three types of information can be obtained from GCMs that describe the baseline climatology: (1) reanalysis data; (ii) outputs from GCM/RCM simulations; and (iii) stochastic weather generators (IPCC-TGCIA, 2007). The World Meteorological Organization (WMO) defined a climatological reference as a 30-year period from 1961 to 1990 (IPCC-TGCIA, 2007) and currently, 1981 to 2010. The 30-year period is used as a reference, as it has sufficient data to define a reliable climatology and corresponds to the actual highest quality of records in recent years (Wilby et al., 2004). Baseline climatological data can be obtained from four sources as earlier explained (IPCC-TGCIA, 2007). Due to potential bias within GCM models, it is recommended that impacts researchers examine downscaled results from two or more models (IPCC, 2001). The multi-model ensemble mean could be used for analyzing GCM output data as it reduces errors and reproduces a more realistic future climate situation compared with a single model (Hao et al., 2013).

Climate scenarios

Climate scenarios are defined as probable and simplified representations of future climate conditions for precipitation, temperature, the wind and other meteorological parameters constructed from climate simulations that are consistent with suppositions about future emissions of aerosols and GHGs (IPCC-TGCIA, 2007; Dos-Santos, 2011; Charron, 2014). Climate scenarios are often used as inputs into crop models to predict climate change impact as presented in Figure 4.

Three methods are used to generate climate scenarios, and these are synthetic, analogue and outputs from GCMs and RCMs. Synthetic scenarios are developed by adjusting a baseline parameter by a fixed percentage such as 10% increase in current precipitation or by a fixed amount like a 2°C increase in temperature (IPCC-TGCIA, 2007). The baseline temperature may be adjusted either by +4, +3, +2 and +1°C a nd baseline precipitation by ±20, ±15, ±10 and ±5% which may characterize different extents of future change. Analogue climate scenarios are constructed by identifying recorded climate systems which may resemble the future climate scenarios in a particular area, and these records may be obtained as historical records or spatial analogues (IPCC-TGCIA, 2007). Climate scenarios may also be constructed from GCM outputs by adjusting a baseline climate by the absolute or relative change between the current and future simulated climates (IPCC-TGCIA, 2007). Current and future climate scenarios have been constructed based on transient GCM spatial and temporal resolution outputs downscaled to the required scale (Santoso et al., 2008).

DOWNSCALING TECHNIQUES

Two downscaling techniques are used in generating climate scenarios: dynamical (10 to 50 km) and statistical techniques. Dynamical downscaling techniques uses numerical equations governing the atmosphere on a finer grid while statistical downscaling techniques try to establish empirical relationships between the predictor (large-scale climatic variables) and predictand (local scale variable) (Chen et al., 2012; Devak and Dhanya, 2014). Based on statistical relationships developed between the GCMs and observed time series data, statistical downscaling is a straightforward means of generating high-resolution local scale climate information (Bhuvandas et al., 2014). Statistical downscaling models are developed in two stages with the first, focusing on daily precipitation modelling and the second parameters such as temperature, humidity, solar radiation and wind speed conditioned based on precipitation occurrence. Statistical downscaling can be used to generate small-scale data required by impact models provided quality station data is available. Dynamical downscaling is based on the use of RCMs which are nested within the GCM and generate finer spatial resolution output. Dynamical downscaling techniques are divided into three types namely: limited-area models (LAMs), stretched-grid models, and uniformly high-resolution atmospheric AGCMs nested within a coarse resolution AOGCMs to simulate climate data that is more reliable than direct AOGCM output (Wilby et al., 2002; Irwin et al., 2012). Three statistical downscaling techniques are used: (i) synoptic weather typing; (ii) weather generation (LARS-WG); and (iii) regression methods or transfer-functions (SDSM) (Semenov and Barrow, 2002; Wilby and Dawson, 2007; CSIRO and BOM, 2015). Weather generators are computer models used to produce artificial time series of daily weather data at a single site based on the statistics of the baseline climate (IPCC-TGCIA, 2007).

Research institutions with appropriate computational capacity and technical expertise generate RCMs outputs (Trzaska and Schnarr, 2014). However, statistical downscaling methods are easy and cheaper to use in generating future climate scenarios compared to dynamical techniques (Lapp et al., 2008). They are used to downscale monthly to seasonal climate forecasts, from numerical climate models to time series datasets for use as inputs into crop simulation and hydrological models for impact studies.

IPCC SPECIAL REPORT ON EMISSION SCENARIOS AND REPRESENTATIVE CONCENTRATION PATHWAYS (RCPs)

In 1988, the United Nations Environment Programme (UNEP) and World Meteorological Organization (WMO) established the Intergovernmental Panel on Climate Change (IPCC). The establishment of IPCC was motivated by the fact that anthropogenic GHG emissions have altered the climate system. The role of the IPCC is to evaluate climate information and provide an assessment of the understanding of climate change characteristics (IPCC, 2007c). A hierarchy of GCMs is used to predict variations in the world climate systems based on human activities (IPCC, 2013b). Five assessments were undertaken by the IPCC where Special Report on Emissions Scenarios (SRES) reports have been used in negotiations under the United Nations Framework Convention on Climate Change (UNFCCC)[2]. The SRES have been utilized as inputs into the climate models for the published IPCC Third (2001), and Fourth Assessment Reports published (2007) (Nakicenovic et al., 2000; Charron, 2014). Emission scenarios are constructed based on a set of assumptions such as technological change, demographic and socio-economic development and their fundamental associations (IPCC, 2007d; Trzaska and Schnarr, 2014).

The Coupled Model Inter-comparison Project phase 3 (CMIP3) multi-model dataset consists of 112 model runs from 16 GCMs using various emissions scenarios (Trzaska and Schnarr, 2014). The A1, A2, B1, and B2 are four SRES scenario families that explore different development pathways. The SRES is useful in future climate change assessments (IPCC, 2007b). More details on the storylines are provided by Nakicenovic et al. (2000), IPCC (2007b) and IPCC-TGCIA (2007).

Climate models have improved since the AR4 (IPCC, 2013a). The Representative Concentration Pathways (RCPs) under the Coupled Model Inter-comparison Project Phase 5 (CMIP5) of the World Climate Research Programme (IPCC, 2013a) were developed based on the Integrated Assessment Models (IAMs) that incorporate climate modelling, demographic, economic and energy (Khadka and Pathak, 2016). There are four categories of RCPs (RCP2.6, RCP4.5, RCP6.0, and RCP8.5)

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[2] http://worldbank.mrooms.net/file.php/703/html/ppt/M01/index.html, Accessed: 10th April 2015

developed for the Fifth Assessment Report (AR5) and these correspond to four different levels of radiative forcing of the atmosphere by 2100 relative to preindustrial levels with 48 CMIP5 experiments (IPCC, 2014a). RCP2.6 represents radiative forcing levels of stringent mitigation scenarios (450 ppm CO_2eq), RCP4.5 and 6.0 represents intermediate scenarios 650 and 850 ppm CO_2eq, respectively. RCP8.5 is the scenario with very high GHG emissions 1370 ppm CO_2eq (IPCC, 2014a,b). The projected values of increase under RCP2.6, RCP4.5, RCP6.0 and RCP8.5 are 0.3 to 1.7°C, 1.1 to 2.6°C, 1.4 to 3.1°C and 2.6 to 4.8°C for 2081 to 2100, relative to 1986 to 2005, respectively (IPCC, 2013b, 2014a). Even with a shift to using the CMIP5, the CMIP3 models can still be used in climate studies.

AGRICULTURAL MODEL INTERCOMPARISON AND IMPROVEMENT PROJECT (AgMIP)

There is need to quantify the impacts of climate change and variability in sub-Saharan Africa (Kassie et al., 2014). This has been explored under the Agricultural Model Intercomparison and Improvement Project (AgMIP) (www.agmip.org) which aims to improve the description of climate-crop-and-economic interactions in models and to foster the application of multiple crop simulation models in climate impact assessments (Asseng et al., 2013; Kassie et al., 2014). The AgMIP launched in October, 2010 is an international research programme which focuses on climate modelling, crop modelling and economic modelling in coordinated global and regional assessments of the future impact of climate change on world food security. AgMIP (Rosenzweig et al., 2013b) goals are to advance the characterization of world food security substantially under climate change and to improve adaptive capacity in developing and developed nations. Analysing impacts of climate change and variability in the agricultural sector requires trans-disciplinary efforts to link current and future climate scenarios to crop simulation and economic models (Rosenzweig et al., 2015). Crop simulation model outputs are used as inputs into the global and regional economic models to evaluate global and regional vulnerabilities, price effects, changes in comparative advantage and potential mitigation, and adaptation strategies.

The AgMIP uses 1980 to 2010 as the baseline and three future time periods (2010 to 2039, 2040 to 2069 and 2070 to 2099). The 2010 to 2039 period is used to understand climate variability to develop effective adaptation strategies. The 2040 to 2069 and 2070 to 2099 time slices are used to assess the impact of climate change and variability (Rosenzweig et al., 2015). The AgMIP protocols define the processes and tasks required to undertake inter-comparisons and multiple-model assessments proficiently and systematically (Rosenzweig et al., 2013a, 2015). The protocols are designed to guide climate modeling, crop simulation modeling, economic modeling, and Information Technology Communication (ITC) of its projects (Valdivia et al., 2015). The protocols have been implemented in South Asia (SA) (Sri Lanka) and Sub-Saharan Africa (SSA) (Rosenzweig et al., 2013b). The AgMIP team in East Africa consists of Ethiopia, Kenya, Tanzania, Uganda and South Africa as it member states and runs projects under AgMIP umbrella in SSA. In Africa, the uses of AgMIP protocols in climate modeling have mostly been implemented in Eastern and South Africa. However, the protocols have not been applied in Zambia at either regional or local scale to evaluate impacts of climate change on agricultural productivity. This AgMIP methodology involves using of several climate scenarios, crop simulation and economic models to predict future crop growth and yield. Additionally, LARS-WG and SDSM have also not been used to produce current and future climate scenarios as inputs into crop simulation models to assess the future climate change impact on maize in Zambia.

Under AgMIP methodologies, future scenarios have been produced using the change factor, and this allows comparison with many published studies. Stochastic weather generators and quantile-based distributional shifts are used to generate climate scenarios that change interannual and intraseasonal climate variability based on RCM and GCM projections (Rosenzweig et al., 2015). Rosenzweig et al. (2013a) stated that AgMIP also coordinates inter-comparison studies on global biophysical and economic modelling and this brings together key international modeling groups to test the observational and future impact of climate change under the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP). Agricultural assessment models operate at both global and regional scales and global level biophysical models can be simulated on a gridded basis or a point basis and then aggregate the data (Valdivia et al., 2015).

For each site of interest, changes corresponding to monthly precipitation, maximum, and minimum temperature are calculated by comparing 30-year future climate periods. Under AgMIP, 20 CMIP5 GCMs for the best-calibrated site have been implemented. It has been reported by Rosenzweig et al. (2014) that climate scenarios should be generated based on 20 GCMs at the best-calibrated site at the region of interest. Moreover, farm survey sites can only use a subset of 5 GCMs (Community Climate System Model 4 [CCSM4 (E)], Geophysical Fluid Dynamics Laboratory-Earth System Model 2M [GFDL-ESM2M (I)], Hadley Centre Global Environmental Model 2 - Earth System [HadGEM2-ES (K)], Model for Interdisciplinary Research On Climate version 5 [MIROC5 (O)] and Max Planck Institute – Earth System Model - Medium Resolution [MPI-ESM-MR (R)]) to generate climate scenarios for crop simulation that focuses on the primary climate change impact questions. According to Ruiter (2012), the five GCMs are accessible in the Cartesian latitude-longitude grid while the grid-size and reference system for each model is different. The CCSM4, GFDL-ESM2M and MIROC5 models have a 365-day calendar without leap-days. The MPI-ESM-LR model uses a Gregorian based calendar which includes leap days. The HadGEM2-ES GCM, on the other hand, uses a 360-day calendar. The 5 GCMs are necessary for generating current and future climate scenarios. This GCM subset has been used in South-east Asia, Europe, and Africa due to their long history of development, assessment, higher spatial resolution, established performance and suitability (McSweeney et al., 2012; Msongaleli et al., 2015). The AgMERRA weather data have been used as alternatives in regions where quality observational time series data are unavailable (Zare et al., 2016).

IMPACT OF CLIMATE CHANGE ON AGRICULTURE

Agricultural production is dependent on weather and as a result is affected by climate variability and change (Nelson et al., 2014). Agriculture contributes to climate change through anthropogenic emissions of GHGs and the conversion of non-agricultural land such as forests into agricultural land. The GHG concentration in the atmosphere has been increasing since 1750 due to anthropogenic activity (IPCC, 2013a). Additionally, an increase is expected in crop yield for most crops by approximately 13% due to elevated levels of CO_2 in the atmosphere. Unfortunately, crop yields for C4 crops will remain unchanged. Climate change will lead to the reduction in water utilization by all crops, but this effect will be nearly canceled out by the effect of the increased temperature on evapotranspiration rates. In many places, the temperature increase would provide prospects in plant breeding to enhance crop performance. Results based on the GCM predictions show that the African climate was warmer 100 years ago compared to the current condition. The finding suggested that the continent was warming up and this would continue to accelerate over Africa in most future climate scenarios (Herrero et al., 2010). It is projected that African countries will be compromised severely due to climate change and variability (IPCC, 2013b). The suitable agricultural areas, growing season length and the potential crop yield within the arid and semi-arid areas would decrease. Additionally, crop yields in some African countries would reduce under rain-fed conditions by 50% in 2020. Studies have revealed that the most vulnerable continents in the world to climate change and variability is Africa due to numerous stresses and low capacity for adaptation (IPCC, 2013b).

Southern Africa will experience temperature and precipitation changes by 2 to 4°C and 10 to 15% (Makadho, 1996), respectively. Temperature prediction using 20 GCMs from 2020 to 2040 over Southern Africa would increase from 0.6 to 1.4°C relative to the baseline (1980 to 2000) (Arslan et al., 2015b). Variability in precipitation affects agriculture more significantly, and maize yields in southern Africa have been projected to reduce by 30% without adaptation strategies in place (Lobell et al., 2008). It has been noted by IPCC (2014a) that under RCP8.5 temperatures over large areas of Africa would range from 3 to 6°C from the mid to the end of the century. As a consequence, land temperature over Africa would increase faster compared to the average global land temperature, especially in arid regions. The minimum temperature would increase at a faster rate compared to the maximum temperature.

Eighty percent of the global cropped land area is under rain-fed agriculture (Turral et al., 2011). Globally, 60% of the food output is susceptible to climate change impact especially in the semi-arid and arid regions (Turral et al., 2011). The agricultural production system is dominated by rain-fed agriculture which accounts for 97% of the cropped land and. The rain-fed agricultural production suffers from the risks of seasonal precipitation variability (Tumbo et al., 2012). The African agriculture is dominated by small-scale farms, mainly rain-fed with low and unpredictable rainfalls over the whole continent (Turral et al., 2011) and crop growth is limited by water availability (Turral et al., 2011; Sebastian, 2014). Agricultural production is affected by changes in precipitation during the growing season, and this leads to variability in yields. The other reason is that 85% of Africa's water is used for agriculture and the farming techniques are less mechanized, and the greater part of the continent is already hot and dry. The sub-Saharan Africa agriculture sector contributes 30% to Gross Domestic Product (GDP) and sustains 70 to 80% of employment (Tumbo et al., 2012). Future climate change poses challenges to agricultural production in Africa as it is the most susceptible sector to climate change and variability due to extensive poverty and this limits its adaptive capacity (Tumbo et al., 2012).

IMPACT OF CLIMATE CHANGE ON MAIZE YIELD USING CROP MODELS

Crop simulation models

Crop simulation models (CSM) or crop models are computerized representations of crop growth, development, and yield, simulated through mathematical equations as a function of soil conditions, weather, and management options (Hoogenboom et al., 2004; Salvacion, 2011; Basso et al., 2013). Crop models have been developed to simulate risks associated with crop management options in the face of climatic change and variability. They simulate plant growth, development, and yield in response to water, temperature, solar radiation and nutrient inputs. They describe crop growth, development and yield at field scale on a daily time stamp and require site-specific, spatially homogeneous weather data as input (Zare et al., 2016). Crop models assist in understanding the relationship between weather, climate and crop yield (Vučetić, 2006). They are used in impact and climate change and variability studies, as they account for plant eco-physiological processes, environmental and management options for different cultivars and locations (Bassu et al., 2014).

Yield forecasting can be carried out using crop models to give the yield of a precise and scientific crop as early as possible during the crops' growing season by considering the effect of the weather and climate (Basso et al., 2013). Crop models can be used to evaluate the site-specific impact of climate change, agro-technologies and to accurately predict crop yield with prior knowledge of the soil properties and crop management practices or options (Figure 4). Crop models have been applied in approximating yield potential in crop ideotypes designed for simulated future climate scenarios (Rötter et al., 2015). Crop simulation models have been used to describe systems and processes at genotype level, crop, farming system, region, and global environment. However, the extent to which crop models in developing countries have benefited the poor is limited (Uthes et al., 2011). Crop models offer opportunities for exploring cultivar potential in areas not explored before, establishing expensive and laborious field trials (Bationo et al., 2012b,c). Lengthy and costly agronomic and modelling field trials with a high number of treatments, could be pre-evaluated by conducting, in minutes, experiments on a desktop computer or laptop (Steduto et al., 2009). Crop simulation modeling can be used to decide on the optimum plant densities and dates of planting for maize crop (Soler et al., 2005; Chisanga et al., 2015).

Crop simulation models such as APSIM (Keating et al., 2003) and DSSAT (Jones et al., 2003) can be used to analyze different scenarios to combat the impact of climate change on agricultural production. The literature review showed that 5 crop simulation models: APSIM-Wheat, CERES-Wheat, two SALUS wheat models and APES-Wheat have been used to analyze the baseline, in sensitivity tests, and future climate predictions by the AgMIP team (Rosenzweig et al., 2015). Simulation models are widely used to address "what if" type questions (Mohanty et al., 2012). The Crop Environmental Resource Synthesis (CERES) maize model in DSSAT (Jones et al., 1986; Kiniry et al., 1997; Yang et al., 2004; Liu et al., 2012) is a process-oriented, management-level model that simulates crop growth, development and yield, soil water and nitrogen balance on homogeneous units from field to regional scales. It is the most widely used maize model and is a recognized reference for comparing new developments in maize growth, development and yield simulation (Lizaso et al., 2011). It has been evaluated under a wide range of experimental practices and environmental conditions (Jones et al., 2003, 2010). The model is able to accurately predict yield variability, nitrogen uptake and maize growth response to nitrogen (Pang et al., 1997). It can also be used to explore the potential of new cultivars for new areas before establishing costly field experiments (Bationo et al., 2012b) and to determine the optimum planting dates (Soler et al., 2005; Chisanga et al., 2015). The APSIM, on the other hand, is a modular modeling framework that runs at a daily time-step and mimics crop growth and development, yield, soil water and nitrogen dynamics either for single crop or crop rotations in response to climatic and management scenarios (He et al., 2015).

The CERES-Maize, SWAP (soil-water-atmosphere-plant), CERES-Wheat and APSIM models have been used extensively to evaluate crop production due to the effects of climate variability and change and in analyzing crop yield-climate sensitivity under different climate scenarios (Kang et al., 2009). The required data as input into CSMs include: weather data (rainfall, maximum, and minimum temperature, solar radiation), location (weather station latitude and longitude), soil physical and chemical properties, crop management practices (cultivar, irrigation, fertilizer type and amounts, row spacing, planting date, planting depth, plant population, tillage operations and dates, weed control, leaf area index [LAI]) and cultivar genetic coefficients.

Understanding the impact of climate change based on carbon dioxide fertilization, temperature changes and rainfall on plant growth, development and yield can be evaluated using crop models. The APSIM-and-CERES-Maize models have been used effectively to simulate maize growth, development, and yield (Rauff and Bello, 2015). The performance of APSIM-and-CERES-maize models is limited by the quality of input data such as daily weather data, soil profile characterization data, surface residues, crop management, initial soil condition and plant growth analysis. In cropping systems, it is very common to have sufficient data collected on aboveground biomass but inadequate data on soil characterization and root growth (Motha, 2011). Most crop simulation models necessitate that meteorological data such as precipitation, temperature, and solar radiation be reliable, complete and of good quality.

Crop model requires reliable and complete meteorological parameters. Agromet stations may not have complete daily time series data at a specific location, and in some cases, data may be available only for temperature and precipitation or rainfall only, solar radiation may be missing or unavailable which is required by crop models in the estimation of photosynthesis and biomass accumulation. Gaps in incomplete data records are filled using stochastic weather generators (Motha, 2011). As explained by Motha (2011), a stochastic weather generator produces synthetic data based on statistical characteristics of observed data of unlimited length. The WGEN, SIMMETEO, CropSyst (ClimGen) and LARS-WG stochastic weather generators have been used widely in crop simulation studies to determine the potential impact of future climate scenarios on crop growth, development, and yield (Wang, 2015). Wang (2015) stated that the weather generators simulate temperature and solar radiation accurately, nonetheless, they have difficulties in reproducing precipitation values and their performance differs from location to location. Modelling of daily precipitation using statistical downscaling models are useful in characterizing precipitation and temperature in conjunction with climate, agricultural, hydrological and economic modelling.

Impact of climate change on maize yield using crop simulation models

Crop productivity as affected by climate change can be projected by evaluating the outputs from crop models when running with baseline and future climate scenarios generated from GCM (Ruiz-Ramos and Mínguez, 2010). Crop models simulate daily interactions with climate, soils, and management that determine growth, development, and yield of individual crops (Ruiz-Ramos and Mínguez, 2010). Climate models, and in particular RCMs and weather generators provide the necessary driving climatic variables of solar radiation, temperature, rainfall, pressure water vapor and the wind at several geographic scales (Mearns and Hulme, 2001; Mearns et al., 2003). The currently available crop models being utilized in evaluating climate change include options for simulating the effects of increased CO_2 on crop yield and water use (Rosenzweig and Iglesias, 1998). All widely used crop models include consideration of nitrogen and water balance, and the impact of crop water deficit.

The crop models due to rising global temperature predict minor changes in world agricultural production as a result of the negative impact of climate change in the tropics and most developing countries, and these are offset by gains in temperate in industrial countries (The World Bank, 2007). Moderate warming of 1 and 2°C for wheat, maize, and rice in tropical countries would lead to the reduction of crop yields significantly (The World Bank, 2007). Temperature increases have multiple effects on crop growth, development and yield depending on the crop growth stage. Higher temperatures usually accelerate rates of crop development and this results in a shortened growing period, and typically but not always in lower crop yields (Rötter and Höhn, 2015; Rötter et al., 2015). For example, temperature thresholds of 32 to 36°C for a few hours around flowering may strongly affect floret mortality/spikelet fertility, resulting in reduced yield that is dependent on the frequency and intensity of the stress - as has been reported for wheat, groundnut, sunflower, maize and rice (Rötter and Höhn, 2015).

Crop yields are most sensitive to heat stress at flowering and grain filling stages (The World Bank, 2007). Furthermore, a small temperature increase occurring at flowering and grain filling stages affect the crop, and this is not included in crop simulation model (The World Bank, 2007).

There is need to appreciate the observed historical time series data. GCMs are calibrated to reproduce historical time series data while weather generators and crop models are calibrated and validated using historical time series data. The scenarios generated from GCMs are indispensable for evaluating potential crop yield, but they do not represent the actual environment that would occur (Iglesias, 2006; Donatelli et al., 2012). Crop modeling shows positive trends of climate change impact on the main crop yields in 2050 (Reidsma et al., 2015). Moreover, Reidsma et al. (2015) noted that crop models could be exploited in assessing the impacts of climate change, but these models are intended to assess the potential or water-limited yields rather than actual yield. Therefore, the influence of management is widely neglected. Seasonal crop yield forecasts can be produced by utilizing downscaled current and future climate scenarios to effectively and efficiently plan for the allocation of agricultural resources to reduce risk and uncertainties due to seasonal climate variability (Jintrawet, 2015). The integrated use of GCMs, crop models, and statistical downscaling models has received relatively less attention in Africa in comparison to another part of the world. Crop model can be used in assessing the impact of climate change on grain yield, yield variability, and spatial distribution. They can use climate scenarios generated from downscaling of GCM outputs as inputs to quantify the impact of climate change on crop growth, development and yield of maize.

Impact of climate change on maize yield using DSSAT CERES-maize model

Soler et al. (2007) evaluated the effect of planting dates (PDs) four maize cultivars grown under irrigated and rain-fed conditions off-season in a subtropical region in Brazil. The CERES-maize model was used to simulate the impact of variable conditions on maize production. Results revealed that the CERES-Maize was capable of simulating phenology and grain yield accurately, with normalized root-mean-square error (RMSE) being <15%. Analysis showed that a delay in sowing from February 1 to April 15 caused a 55 and 21% decrease in grain yield under rainfed and irrigated conditions, respectively. The SIMMETEO weather generator programme in DSSAT version 3.5 was used to generate future climate scenarios based on weather data from 9 consecutive years in Kharagpur, West Bengal, India (Sarkar and Kar, 2006). Sarkar and Kar (2006) noted that the generated weather scenarios were used as inputs into DSSAT to conduct the seasonal analysis. The study showed that the generated future climate scenarios used by the DSSAT were reliable and could be used to predict the future crop yields under different management options to select the best. The prediction of maize yield using the generated future climate scenarios for 2050 in the states of Indiana and Ohio was simulated using the CERES-Maize model by Johnston (2013). Results indicated that predicted evapotranspiration in maize grown under irrigated and rain-fed increased. However, evapotranspiration predicted under rain-fed condition declined. Maize yields in Indiana and Ohio were predicted to increase under rainfed and irrigation conditions relative to 1997 to 2007. Under rain-fed conditions, declines in maize yield predictions were observed in Illinois, Indiana, and Ohio. Predicted maize yield was observed under irrigated conditions in South Dakota. The study envisaged that maize yield would improve under future climate change scenarios and shifts in maize production should be made to the western locations to maximize maize yield in 2050.

The CERES-maize model was used to assess the date of planting and cultivar variations in China for mitigating the risks of climate change. The results showed that the duration of reproductive phases in maize from emergence to flowering and physiological maturity would be shortened under future climate change, and yield would reduce by 11 to 46% from 2011 to 2099 relative to 1981 to 2010 (Lin et al., 2015). Additionally, maize production would not benefit significantly from increased CO_2 fertilization. A sequential model simulation of the long-term maize yield from 1959 to 2008, 0 to 30 cm soil, nitrogen (N) content, and soil nitrate loss from 1998 to 2000 was compared to measured values using DSSAT CERES-maize v4.5 model at Woodslee, Ontario, Canada by Liu et al. (2011). Study results revealed that the CERES-Maize model did not provide accurate annual maize yield and the overall agreement was as good as those obtained by other researchers.

In Eastern India, historical weather data at Kharagpur (1977 to 2007), Dumdum (1974 to 2003), and Purulia (1986 to 2000) was used as an input into the CERES-Maize model in DSSAT v4.0 to simulate maize yield under climate variability scenarios. The study results revealed that temperature would increase by 3°C above the current and it would have substantial negative impact on maize yield; while the positive effect on maize grain yield was observed at 700 ppm of CO_2.[3] The CERES-Maize model in DSSAT version 3.0 was used to simulate the current and future management practices in Greece. The GISS, GFDL, and UKMO GCMs were used to generate CO_2 doubling climate scenarios while the GISS GCM was used to derive a transient scenario as input into the CERES-maize model (Kapetanaki and Rosenzweig, 1997).

The results showed increases in temperature and solar radiation while precipitation showed variability. Under present management practices, maize yield decreased due to reduced duration of the growing period at all study sites. Early sowing and the use of new maize varieties were the proposed mitigation measures (Kapetanaki and Rosenzweig, 1997). The impact of climate change was assessed in semi-arid and sub-humid regions of Ethiopia using a calibrated and validated CERES-maize model and major maize varieties by Araya et al. (2015a). It was observed that the median maize yield increased slightly and decreased in the sub-humid and semi-arid regions of Ethiopia, respectively. The study concluded that future maize yield would not decrease significantly relative to the baseline (Araya et al., 2015a, b).

A study by Zinyengere et al. (2014), in Southern Africa, exploring the effect of climate change on various crops in specific locations using statistically downscaled climate scenarios from nine GCMs and the DSSAT, indicated that impacts of climate change on crop yields varied across locations and crops. The DSSAT-CERES-maize model has been extensively used and tested for different soil types and under a wide range of climatic conditions using various types of cultivars. The CERES-maize model was evaluated by Pang et al. (1998), in characterizing nitrate leaching potential in various soil types. Study results showed that the CERES-maize model could be used as a decision support system for soil specific nitrogen leaching characterization and to increase food production while using the fertilizers and water efficiently (Sarkar, 2009) in both developed and developing countries. The CERES-maize model has been evaluated in Zimbabwe, Malawi and South Africa (Tsimba, 2011; Tsimba et al., 2013) and Zambia (Chinene, 1985; Chisanga et al., 2015). It has also been extensively tested in Kenya and under tropical conditions in Hawaii, Indonesia, and the Philippines.

A study by Makadho (1996), in Zimbabwe, using GCMs and CERES-maize model to evaluate the potential effect of climate change on maize, concluded that maize productivity decreased drastically under non-irrigated and irrigated conditions

in selected agricultural production regions. The reduction in maize yield was attributed to a temperature increase which shortened crop growth period during grain-filling period. A study in Latin America and Africa carried out by Jones and Thornton (2003) using DSSAT for simulating the impacts of climate change on maize productivity revealed that there would be a 10% decrease in aggregate maize yield by 2055.

The DSSAT and APSIM were used in the West African Sub-Saharan region, and yields of maize were reasonably simulated from the household survey.[4] R and K GCMs gave the lowest simulated maize yield under

[3] http://ijc.cgpublisher.com/product/pub.185/prod.134; Accessed 5th November 2016

[4] http://www.agmip.org/wp-content/uploads/2013/12/MacCarthy-et-al_Crop-modelling.pdf; Accessed on 6th Nov 2016

future climate scenarios. The reduced maize yield was as a result of low projected precipitation. It was suggested by Kang et al. (2009a) that the projected impact of climate change on maize yield would be different in diverse areas. It is anticipated that in some regions there would be an increase or decrease in maize yields depending on the latitude and application of irrigation. Available modeling results indicate that an increase in rainfall would increase crop yield. Reduction of water availability under future climate change shows that soils with high water holding capacity would abate the impact of drought while sustaining crop yield. It has been reported that crop growth, development, and yield are more sensitive to rainfall compared to temperature (Kang et al., 2009).

Impact of climate change on maize yield using APSIM model

Araya et al. (2015b) undertook a study in Ethiopia to assess the impact of climate change on future maize yield from 2010 to 2039, 2040 to 2069 and 2070 to 2099. Future climate simulations were generated for 20 GCMs for two RCPs (4.5 and 8.5). Simulation results from APSIM and CERES-Maize models showed that anthesis, maturity, and crop yield were reasonable with CERES-maize d-index of 0.86, 0.80, and 0.77 and APSIM d-index of 0.50, 0.89 and 0.60, respectively. Project increases in yields were 1.7 to 2.9% (2010 to 2039) and 0.6 to 4.2% (2040 to 2069). Results indicated that uncertainty in grain yield would increase toward mid-and-end of the century relative to the baseline.

The response of maize yield potential (Yp) to climate change scenario using APSIM model over the Southwestern United States (SWUS) region was investigated by Kim et al. (2015b). Results showed that maximum and minimum temperature greatly contributed to the variation in maize yields over the SWUS at inter-annual time scale (Kim et al., 2015a). The planting date of maize was sensitive to climate change and variability. The effect of planting date on maize yields under various temperature regimes in the SWUS was studied by Myoung et al. (2015). The study findings showed that maize planted earlier would give higher yield due to the length of the growing season in cold mountainous regions. In mountainous regions, there are warmer than normal conditions during the planting period, and this tended to advance the planting date which resulted in increased maize yield (Myoung et al., 2015). Furthermore, in warmer low laying altitudes, yields were less correlated with dates of planting. The growing season length and higher temperatures enhanced the fast growth of the crop. In warmer regions, maize yield was sensitive to temperature variations during the early and late planting due to the adverse effects of extremely high-temperature events on maize development. The study concluded that appropriate adaptations in planting date could improve maize yield considerably.

A study undertaken by Dimes et al. (2008), using APSIM showed that increasing CO_2 concentrations would lead to a 6 to 8% upsurge in crop yield while the reduction in rainfall amount had an adverse impact on grain yield. Wheat growth, development, yield and water balance processes for 117 years using the baseline, the 2050s and 2070s under climate change were simulated using the APSIM model by Wang et al. (2009). The study concluded that wheat yield reduced by a 1°C increase in temperature and a 10% decrease in the amount of rainfall. Additionally, the yield of wheat could be compensated by an increase of CO_2 to 266 ppm without any interactions between treatment effects. Increases in temperature had very little effect on the long-term average water balance, while CO_2 levels reduced evapotranspiration.

A study by Fosu-mensah (2013), to simulate the effects of climate change on maize yield using different rates of nitrogen (N) and phosphorus (P) under rainfed conditions was carried out in 2008, Ejura, Ghana. The A1B and B1 (2030 to 2050) scenarios obtained from the regional mesoscale model MM5 were used as inputs into APSIM to assess the impact of climate change on the onset of the rainy season (ORS). The simulated results suggested a six-week probable shift on the onset of the rainy season from week three of March to week two of May. A six-week delay in planting caused a significant reduction in maize yield and increased maize yield variability under A1B and B1 scenarios. Another study by Tachie-Obeng et al. (2013) in Ghana using the statistically downscaled climate scenarios for 9 GCMs as inputs into the APSIM and farmer practices were used to develop adaptation options shortly (2046 to 2065) based on IPCC A2 emission scenario at the local scale in Wa and Wenchi. The findings from the single-maize cropping season at Wa savannah zone showed a six-week delay in planting from 1961 to 2000. Planting maize on the 1st May to 15th June was considered as the most appropriate period to offset the adverse effects of potential climate change resulting in maize yield increase of 8.2%. At Wenchi, a four-week delay in the major seasons sowing date from 15th March to 15th April showed no change in the minor season sowing date of 15th August which resulted in a slight maize yield increase of 3.9%.

A study in Zimbabwe using APSIM model and climate data from Bulawayo (1951 to 2001), examined the impact of climate change on the potential yield of maize, sorghum, pigeon pea and groundnut (Dimes et al., 2008). The output from APSIM showed that increasing CO_2 concentrations would increase maize yields in the order of 6 to 8%. Reduction in rainfall amount would reduce grain yield (Dimes et al., 2008). On the other hand, increasing temperature had the most dramatic impact on maize grain yields; 16, 31 and 3% reduction in two bowls of cereals, groundnut, and pigeon pea, respectively.

Maize simulation efforts have focused on both rainfed and irrigated conditions under climate change and variability, and this has a lead of drought-prone rainfed environments based on eco-physiological being understood properly. Many agronomists, climatologist, soil scientists and crop modellers do not fully understand the concept of statistical downscaling and crop simulation models and systems-based research, hence capacity building in this area is inevitable. Comprehensive calibration and validation are needed for both statistical downscaling and crop simulation models to be used efficiently and more in conducting research that would conserve resources and significantly contribute to developing mitigation and adaptation strategies that meet the world's needs for food.

Limitation of statistical downscaling and crop simulation models

According to Chen et al. (2010), stochastic weather generators and transfer functions are good at preserving the precipitation quantities but tend to underestimate low-frequency variations and inter-annual variability. Inter-annual variability is a year-to-year change in the mean state of the climate (Trzaska and Schnarr, 2014). An example of the inter-annual variability is the El Niño-Southern Oscillation (ENSO) that causes a periodic variation in the atmospheric and oceanic circulation patterns in the Pacific Ocean. It is a quasi-periodic change of atmospheric and oceanic circulation patterns in the Tropical Pacific region. Weather generators are conditioned using local climate relationships and may not be automatically applied in other climatic conditions (Hassan et al., 2014). Wilby and Wigley (1997) argued that non-stationarity of predictor-predictand relationships has long been recognized as a limitation of all downscaling techniques. Weather generators do not take into account the spatial structure of weather and climate for any given region.

All crop simulation models require adequate calibration, testing and validation against measured field data to ensure that the simulation results are reasonable (Thorp et al., 2009; Chisanga, 2014). All crop models require adequate calibration and validation to account for cultivars parameters, soil water and nitrogen balance, crop growth, development, and yield and environmental conditions for the study site in question (Sinclair and Seligman, 1995). The models need data and technical expertise, and they do not provide an answer and a solution to all the problems and requirements, therefore, stakeholder interaction is essential. Some simulation models such as DSSAT CERES-maize, APSIM, and GROWIT have been used in simulating land use, land cover changes, soil and landscape evaluation (Bhatt et al., 2014). However, interpreting and visualizing the crop simulation model output is laborious and time-consuming. Consequently, comparing the simulated and measured values usually requires the use of statistical software packages (Yang et al., 2000). Conversely, crop models have limitations in simulating the impact of extreme events such as precipitation including pests and diseases (Reidsma et al., 2015).

Integrated assessment models (IAMs)

Scientists and researchers have developed integrated assessment models (IAMs), and these combine climate models (GCMs), crop models (APSIM, DSSAT, AquaCrop, CropSyst) and economic models (Tradeoff Analysis Model for Multi-Dimensional Impact Assessment [TOA-MD]). IAMs describe the causes and effects of climate change and integrates knowledge from different academic disciplines to assess the natural and economic impacts due to the accumulation of GHGs in the atmosphere (De Salvo et al., 2013). IAM, for agriculture under climate change either at the farm, regional or supranational level requires that many biophysical output variables be considered simultaneously. In evaluating effects of climate change and management options besides crop yields, crop models need to provide information based on the effects of the production process on environmental indicators such as nitrogen leaching, GHG emissions and water use (Rötter and Höhn, 2015). Nelson et al. (2014) argued that simplified representation of future climate change impacts on agriculture requires combined use of climate models, crop simulation models and economic models. A unique opportunity for analyzing multi-model ensembles of current and future climate scenarios across different sectors in a consistent, holistic framework is provided for by the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP, www.isi-mip.org) and this should be adopted (Piontek et al., 2014). The multi-model ensemble approach that uses many different climate models, emissions scenarios, downscaling techniques, crop models and economic models would enable a move towards a complete assessment of uncertainty in future crop (maize) yield forecasting and predictions (Surampalli et al., 2012; UNFCCC, 2012).

Situational analysis of climate change in Zambia

Temperature and precipitation

Zambia is characterized by classic dry and wet climate (Sichingabula, 1998; Palijah, 2015). The annual rainfall is strongly influenced by the shifting of the Pacific Ocean's El Nino Southern Oscillation (ENSO), the Inter-Tropical Convergence Zone (ITCZ) and the Congo Air Boundary. The mean annual temperature has increased since 1960 by 1.3°C, an average of 0.29°C per decade (MTENR,

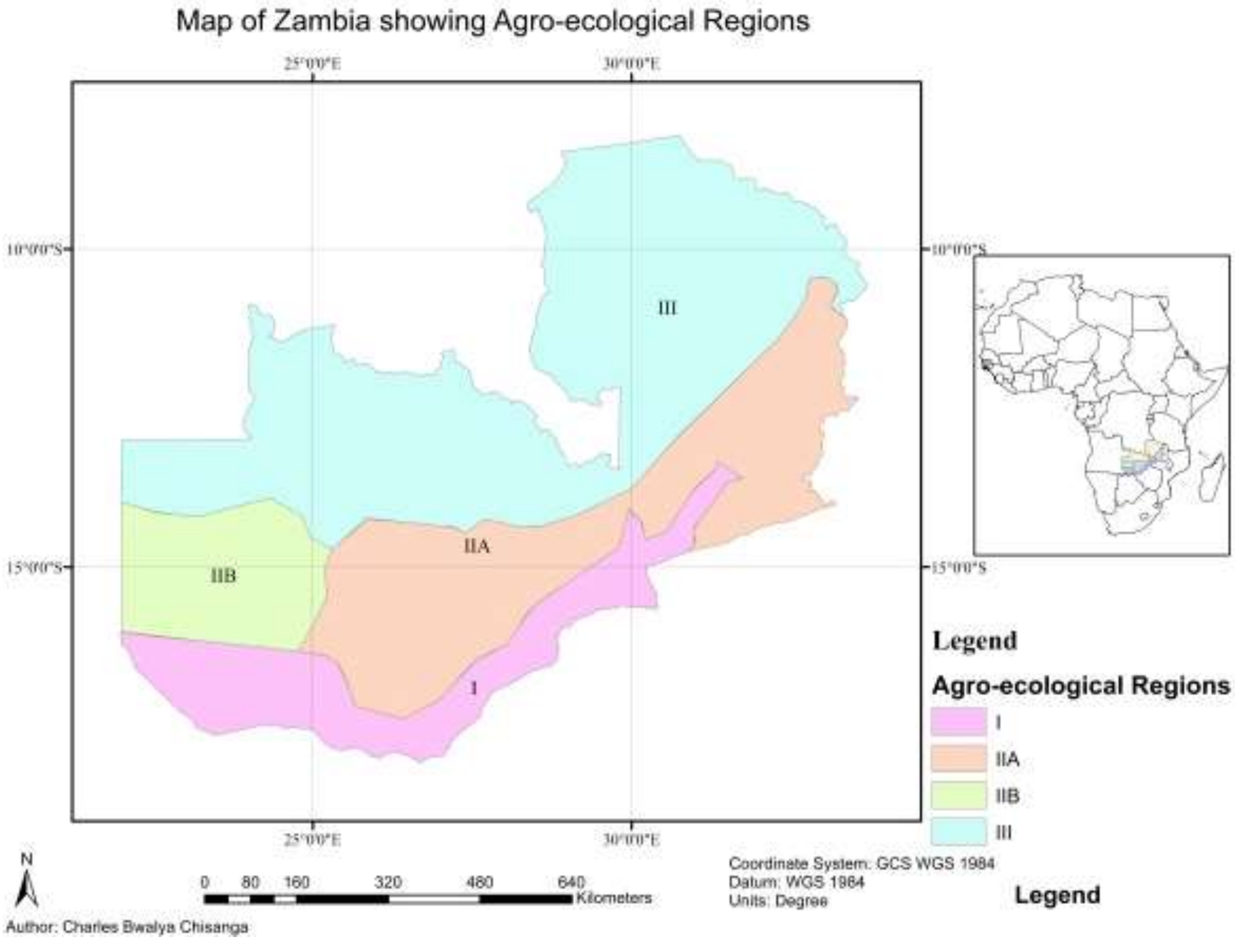

Figure 2. Agro-ecological regions of Zambia.

2010; Muchanga, 2012; UN, 2012). A slight increase in temperature was observed from 1970 to 2000 across the country. Warming rates per decade of 0.48, 0.34 and 0.26°C for Agricultural Ecological Regions (AERs) I, II, and III (Figure 2) have been observed from 1970 to 2000. The AERs differ based on the amount of precipitation: Region I is a low rainfall (<800 mm/year) area which covers the country's major valleys; Region II, the medium rainfall (800 to 1000 mm/year) area, covers Sandveld plateau of Central, Eastern, Lusaka and Southern provinces; and Region III has the highest rainfall (1000 to 1500 mm/year). There has been a decrease in annual rainfall of 1.9 mm per month (2.3% per decade) since 1960 particularly in December, January and February (MTENR, 2010; UN, 2012). Baseline data (1961 to 1990) showed that AERI has the lowest rainfall followed by AERs II and III (Fumpa-Makano, 2011). Temperature projections from GCMs suggest an increase in temperature by the end of the century ranging from 2.4 to 4.3°C relative to 1961 to 1990 is likely (GIZ, 2014). GCMs predictions over Zambia indicated that rainfall in AER I, IIa and IIb has decreased with significant warming detected in AER I while rainfall in AER III has increased (Arslan et al., 2015b). The estimated maize yield decline in Zambia is concentrated in Southern and Eastern provinces, highlighting the importance of how climate change impacts on crop yields.

In Zambia, the threat of climate change is characterized by floods and droughts (Fumpa-Makano, 2011). In the last 20 years, maize yield has reduced by 40% in AERs I and II as a result of shortening rain season and persistent dry spell (UNDP, 2010). The worst of these was the 1991 to 92 droughts and 2006 to 07 floods (Fumpa-Makano, 2011). Zambia has experienced droughts (1916/17, 1924/25, 1949/50, 1983/84, 1987/88, 1991/92, 1994/95 and 1997/98) and high intensity of floods (2007/08, 2009/2010) (Sichingabula, 1998). There has been a tendency for late-onset and early withdrawal of rains in Zambia since the end of the 1980s (Fumpa-Makano, 2011). The strong dependence on maize as the staple food in Zambia is a serious concern and requires much effective adaptation options to reduce negative impacts of climate change since much of the maize is grown by small-scale farmers and is rain-fed. The ability of the

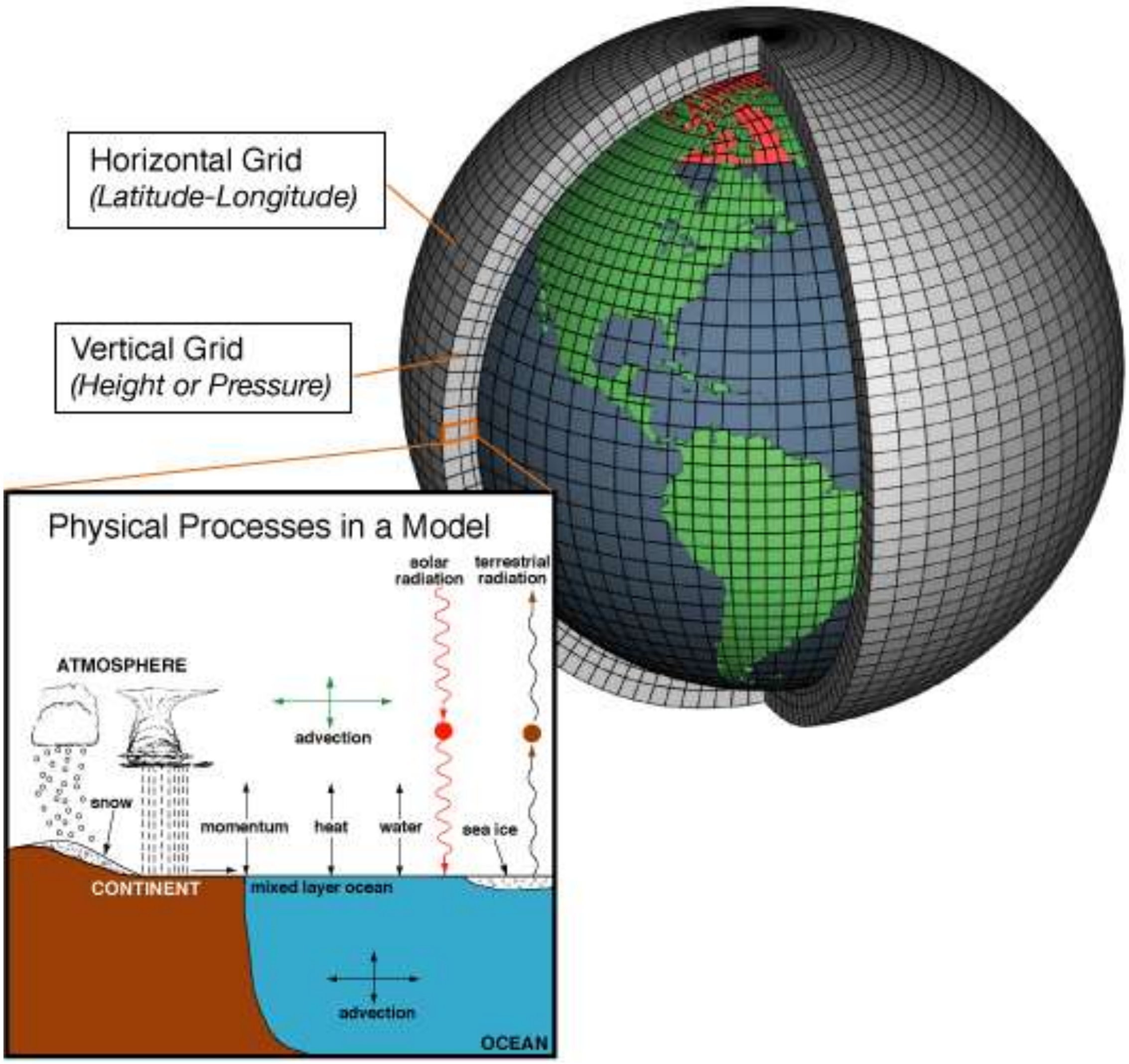

Figure 3. Climate models are based on basic laws of physics, biology, fluid motion and chemistry. Source: (https://celebrating200years.noaa.gov/breakthroughs/climate_model/welcome.html; Date accessed 18th May 2017, https://celebrating200years.noaa.gov/breakthroughs/climate_model/modeling_schematic.html; Accessed 7th August 2017).

agricultural sector in Zambia to cope with projected changes in rainfall and temperatures is limited due to low levels of investment, land degradation, limited access to agricultural inputs such as fertilizers and seed and reduced labor due to HIV/AIDS (Arslan et al., 2015a).

Impact of climate change on maize yield using APSIM and DSSAT models in Zambia

The CERES-maize model has been used in Zambia by researchers such as Chinene (1985), GRZ and UNDP (2007) and Chisanga et al. (2015) in simulating maize yield. Chinene (1985) also evaluated the effect of water and nitrogen on grain yield on a clayey, kaolinitic isohyperthermic oxic paleausalf in Zambia. He observed that nitrogen and water availability were the factors limiting grain yield. The United States Country Studies Programme (USCSP) undertook an assessment in Zambia that focused on the vulnerability of crop cultivars under a variety of climate change scenarios in the AERs of Zambia using DSSAT version 3. Assessments by MTENR et al. (2007) and UNDP (2010) using DSSAT revealed that the predicted reduction in the length of the rainy days would inhibit crop varieties such as maize attaining physiological maturity in AER I and II. Current and future climate scenarios (2 × CO_2) were generated using the CCCM and GFDL GCMs and used as inputs into DSSAT version 3 by GRZ and UNDP (2007). DSSAT models were used to simulate the length of the growing

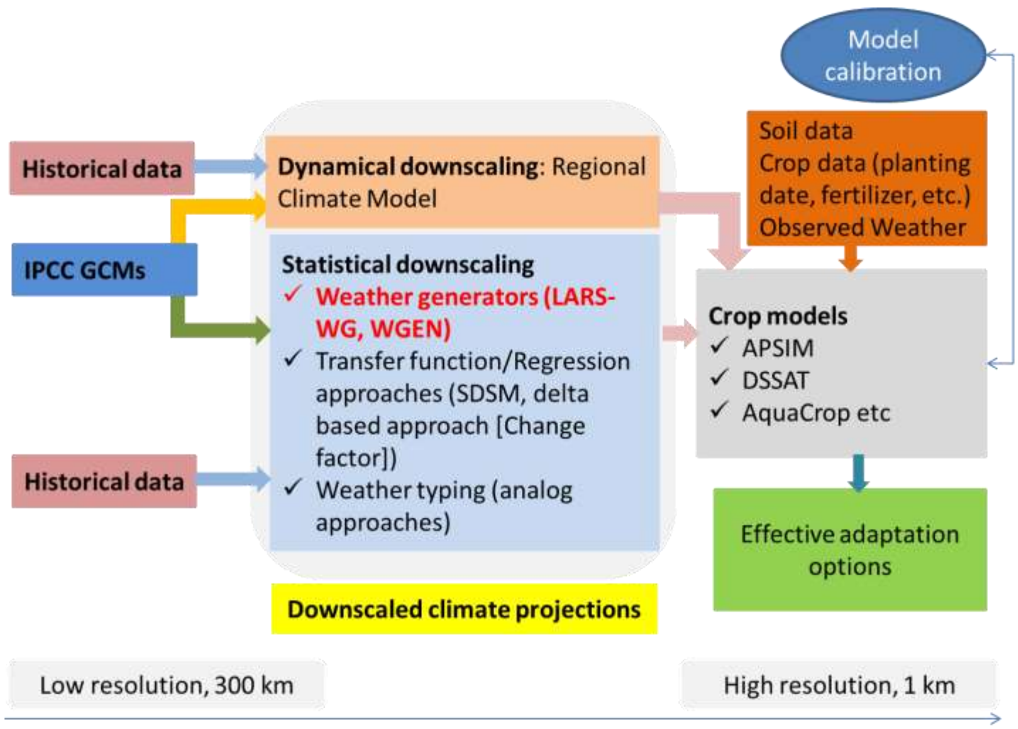

Figure 4. Scenarios of climate change scenarios for agricultural applications.
Source: Authors (2017).

season and crop yield under irrigated and rain-fed conditions. Furthermore, the nitrogen and water balance were simulated to estimate the vulnerability to climate change of the selected maize varieties (MM 752, MM603 and MM601], sorghum variety (SIMA) and groundnut varieties (Natal Common, Makulu Red, and Chalimbana). The 1997/78 simulated outputs indicated that MM752 and MM603 maize varieties would not mature due to shortening of the growing season in AERs I and II, respectively.[5] In ensuring the national and household food security, adaptation strategies were proposed by GRZ and UNDP (2007). These strategies were: diversification of the agricultural sector (that is, promoting horticulture), adopting and planting new seed such as open pollinating varieties (OPV), developing drought-tolerant and early maturing crop varieties by plant breeder, improvement of crop management through information dissemination to farmers and construction of dams for water storage in drought-prone areas of the country and maintaining all feeder roads to reduce post-harvest losses. There is also need to use a combination of climate models and crop simulation models to study the impact of future climate scenarios on maize growth, development and yield. This is essential for long-term planning in household food security and in developing mitigation and adaptation plans.

Maize growth, development and yield are projected to be affected differently by climate change in diverse locations depending on temperature and water availability. The review shows that although uncertainties exist in the model design parameters, soil, climate and management options, the climate would adversely affect maize yield production in Sub-Saharan Africa. The focus of crop modeling has been on maize for decades, and the widely known maize models are DSSAT CERES-Maize model (Jones et al., 1986) and APSIM (Keating et al., 2003) platforms. CERES-Maize-and-APSIM-Maize models have been designed to support management decisions and to develop management strategies, though their calibration parameters are quite demanding. Comprehensive data on grain number per cob and the rate of grain filling in milligrams per day, or the phyllocron interval in thermal time are required by the two crop simulation models.

CONCLUSION AND RECOMMENDATION

Reliable projections of meteorological parameters from climate models are needed to evaluate impacts of future climate change. Combining climate models and crop simulations models represent a holistic approach that synthesizes information about different system

[5] http://adaptation-undp.org/sites/default/files/downloads/zambia_snc_prodoc.pdf; Accessed on 7th November 2016

components, synthesizing of data and dissemination of the study findings to end users. The literature review suggests that many crop models such as APSIM-maize and DSSAT-CERES-maize have been employed in many applications such as precision agriculture and on-farm management and regional assessments of the impact of climate variability and change. The effects of climate change on climate-plant interaction can be evaluated quantitatively using crop models. There is significant uncertainty in future climate scenarios used in simulating crop response due to climate change.

The use of GCMs, statistical downscaling, and crop models are the primary tools available to assess the site-specific effects of climate change on maize growth, development and yield. Statistical downscaling techniques are computationally cheap to run and produce local-scale synthetic daily time series of meteorological parameters for impact assessment of climate change under different emissions scenarios and GCM pairings. Developing proactive mitigation and adaptation plans using climate data for managing inter-annual variability within the agricultural communities and the organizations that interface with them in the agricultural sector would assist in building resilience due to long-term climate changes. The multi-ensemble methodology that uses different GCMs/RCMs, and downscaling techniques and crop simulation models would facilitate a move towards a complete assessment of uncertainty in crop yield simulations.

The GCM outputs should be corrected for biases, and this depends on improvement advances achieved in both GCMs and downscaling approaches. The generated future climate scenarios should be of high-quality required by crop simulation models and must include the simulated changes in mean and variability of climate variables. It is recommended that an integrated assessment modeling framework should be adopted that generate useful information for the farmer, planners and policy makers. The framework should incorporate climate, crop simulation, and economic modeling.

CONFLICTS OF INTERESTS

The authors have not declared any conflict of interests.

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Acronyms: Atmospheric Oceanic Global Circulation Models (**AOGCM**). United Kingdom Transient climate experiment (**UKTR**). European Centre-Hamburg model version 1 (**ECHAM1**). Global Sea Ice and Sea Surface Temperature (**GISSTR**). Canadian Centre for Climate (Modelling and Analysis) (**CCC**). Intergovernmental Panel on Climate Change and Task Group on Data and Scenario Support for Impact and Climate Analysis (**IPCC-TGICA**)

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