

Evaluation of climate change impacts on rain-fed crop production
in the Wami-Ruvu basin of Tanzania

by

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Declaration

I Philbert Modest Luhunga declare that the thesis, which I hereby submit for the degree PhD (Meteorology) at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution .

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Date: 15/12/2016.....

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Glossary of important abbreviations

CEI	Climate Emergency Institute
CERES	Crop–Environment–Resource–Synthesis
CORDEX	Coordinated Regional Climate Downscaling Experiment program
CRU	Climate Research Unit
CVV	Convective Vorticity Vector
DSSAT	Decision Support System for Agro-technological Transfer
GCMs	General Circulation Models
GDP	Gross Domestic Product
GFS	Global Forecast System
GHGs	Greenhouse Gases
GPCC	Global Precipitation Climatology Centre
GPCP	Global Precipitation Climatology Project
IDWA	Inverse Distance Weighted Average
IPCC	Intergovernmental Panel on Climate Change
IPCC	Intergovernmental Panel on Climate Change
ISS	Institute for Security Studies
ITCZ	Inter-Tropical-Convergence-Zone
JAXA	Japan Aerospace Exploration Agency
MPV	Moist Potential Vorticity
MPVV	Moist Potential Vorticity Vector
NARCCAP	North American Regional Climate Change Assessment Program
NASA	National Aeronautics and Space Administration

NCEP	National Centre for Environmental Prediction
RCMs	Regional Climate Models
RCPs	Representative Concentration Pathways
RLDP	Rural Livelihoods Development Programme
SAGCOT	Southern Agriculture Corridor of Tanzania
SSTs)	Sea Surface Temperatures
TMA	Tanzania Meteorological Agency
TRMM	Tropical Rainfall Measuring Mission
UNFCCC	United Nations Framework Convention on Climate Change
URT	United Republic of Tanzania
WMO	World Meteorological Organization
WRF	Weather Research and Forecasting

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Abstract

Agriculture is the primary source of development for most countries in Africa, including Tanzania, where the sector contributes to about 50% of the Gross Domestic Product (GDP). The sector also employs about 80% of the labour force, contributes to about 30% of export earnings and 65% of raw materials for domestic industries. However, due to climate change the sector has performed very poorly in recent years, such that its contribution to the national economy and food security in Tanzania has not been realized. The main aim of this thesis was to evaluate the impacts of climate change on rainfed maize production in the Wami-Ruvu basin of Tanzania. Four research objectives have been analysed. The first evaluated the performance of the Coordinated Regional Downscaling Experiment Regional climate models (CORDEX RCMs) in simulating present climate condition of Tanzania, the second objective assessed the impact of climate change on rainfed maize production in the Wami-Ruvu basin of Tanzania using a process-based crop model the Decision Support System for Agro-technological Transfer (DSSAT). This model was driven by high-resolution climate change simulations for current climate condition (1971-2000) as well as future climate projections (2010-2039), (2040-2069) and (2070-2099) for two Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5. These data were obtained from three CORDEX RCMs driven by three different General Circulation Models (GCMs). The third objective assessed the performance of moist potential vorticity (MPV) and moist potential vorticity vector (MPVV) in describing long term annual cycles of rainfall in Tanzania, and the fourth objective evaluated the possibility of using moist potential vorticity vector (MPVV) for diagnosis of heavy rainfall events in Tanzania.

The findings of the first objective are that CORDEX RCMs capture the annual cycle of minimum temperature (TN), maximum temperature (TX) and rainfall well, however, underestimate and overestimate the amount of rainfall in March–April–May (MAM) and October–November–December (OND) seasons respectively. CORDEX RCMs reproduce interannual variations of TN, TX, and rainfall. The source of uncertainties can be analysed when the same RCM is driven by different GCMs and different RCMs are driven by same GCM simulate TN, TX, and rainfall differently. It is found that the biases and errors from the RCMs and driving GCMs contribute roughly equally.

Overall, the evaluation finds reasonable (although variable) model skill in representing mean climate, interannual variability, and temperature trends, suggesting the potential use of CORDEX RCMs in simulating TN, TX and rainfall over Tanzania.

The findings of the second objective showed that due to climate change future maize yields over Wami-Ruvu basin will slightly increase relative to the baseline during current century for RCP 4.5 and RCP 8.5. Meanwhile, maize yields will decline in the mid and end centuries. The spatial distribution shows that decline in maize yields are projected over lower altitude regions due to projected increase in temperatures and decreased rainfall in those areas. The eastern part of the basin will feature more decrease in maize yields while central parts of the basin and western side of the basin will experience increased maize yields. The main reason for decreased and increased maize yield to many areas is associated with increased temperatures that reduce the length of growing season and hence cause the decrease in maize yields. However, the high altitude areas increase in temperature provides optimal temperature for maize production. It is therefore recommended that appropriate and adequate adaptation strategies need to be designed to help the communities adapt to the projected decrease in maize production particularly over lower altitude areas.

The findings of the third objective show that the patterns of MPVV compared better with rainfall than the MPV. The statistical relationship between MPVV and MPV against observed rainfall data from 22 weather stations using Pearson correlation coefficient indicated that MPVV bears strong and statistically significant correlation coefficient to rainfall than MPV suggesting its potential use as the predictor of rainfall events in Tanzania. The findings of the fourth objective are that MPVV provide accurate tracking of location received heavy rainfall, suggesting its potential use as a dynamic tracer for heavy rainfall events in Tanzania. Finally it is found that the first and second components of MPVV contribute almost equally in tracing locations received heavy rainfall events. The magnitude of MPVV provides better tracking of the locations received heavy rainfall compared to its components.

Chapter 1: Introduction

1.1 Background of the study

The IPCC define climate change as ‘change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer’. It is mainly driven by anthropogenic activities (IPCC, 2007). Human activities such as burning of fossil fuel and deforestation emit Greenhouse Gases (GHGS) into the atmosphere that cause global warming and climate change. The dominant and long lived greenhouse gases responsible for global warming and climate change include methane, carbon dioxide and nitrous oxide. The atmospheric concentrations of these gases have increased dramatically in the era of industrialization, driven by population growth and economic development. These gases enhance the trapping and re-radiation of the infrared radiation back to the earth’s surface affecting different components of the climate system and the climate pattern.

The IPCC (2007) assessment report confirmed that, ‘climate change is unequivocal’. It is coming to us faster with larger impacts and bigger risks than even most climate scientists expected as recently as a few years ago’ (CEI, 2011). One particular worry is the disastrous consequence to agriculture and food security sectors in many parts of the world, particularly in developing countries (IPCC, 2007 and Sarker, 2012). It is projected that between 75 and 250 million of people in Africa will face increased water stress in 2020 (IPCC, 2007). In some African countries, yields from rainfed agriculture could decline up to 50% in 2020. Agriculture production and access to food in many countries will be severely impacted. This could affect all dimensions of food security and exacerbate malnutrition.

In East African countries climate change has already affected weather patterns and hydrological cycles. Several studies over East African region (Case, 2006; Liwenga et al., 2014 and Mubaya et al., 2014) reported that temperatures have increased; rainfall has decreased in many areas affecting water availability, food security, and human health. In Tanzania local studies (Kijazi and Reason, 2009; Shemsanga et al., 2010; Kandji et. al., 2006 and Tumbo et al., 2010) have reported increased frequency of

extreme weather events: droughts and floods that have affected food production in many areas.

Climate change is projected to affect the performance of agriculture sector in Tanzania. Several studies (Mwandosya et al., 1998; Strzpeck and McCluskey, 2006; Ehrhart and Twena, 2006; de Wit and Stankiewicz, 2006; Munishi, et al., 2010; Jack, 2010; Arndt et al., 2011 and Rowhani et al., 2011) predict decline in crops yields due to changes in climate. Mwandosya et al (1998) used climate change projections from the General Circulation Models (GCMs) to drive a crop model. They found that maize will decline by 33% at the end century. Agrawala et al (2003) used climate change projections from 11 GCMs to force the Crop–Environment–Resource–Synthesis (CERES) maize model. They showed that maize yields will decline due to increased temperature and decreased rainfall. The simulation further showed that maize yields in central regions (Dodoma and Tabora), northern highlands, Lake Victoria basin, and southern highlands will decrease by 84%, 22%, 17%, and 10-15% respectively.

Arndt et al (2011) used climate data from 4 GCMs to drive a crop model to simulate maize yields over 110 districts in Tanzania during mid-century (2014-2050). They found that maize yields are expected to decline over most districts. The high decrease of -19 to -13% was predicted over northern highlands. In the Wami-Ruvu basin maize yields are predicted to decline by -12 to -3%. Several other studies (de Wit and Stankiewicz, 2006; Strzpeck and McCluskey, 2006; Ahmed et al., 2011) have evaluated the impacts of climate change on crop production in Tanzania using climate data from the GCMs.

Unfortunately, the findings from previous studies contain several uncertainties. The major source of uncertainty is that, climate change projections used to drive the crop model were derived directly from the GCMs which have too coarse spatial resolutions to reproduce the regional and local climate patterns (Jones, et al., 2004, Villegas and Jarvis, 2010, Daniels et al, 2012, Hassan et al., 2013). Maliondo et al (2012) suggested that, ‘studies on climate change impact on food security in Tanzania require higher resolution climate change information due to its regional heterogeneity’. Therefore, there is a need to evaluate the impacts of climate change on agriculture sectors in Tanzania using high-resolution climate change projections.

The GCMs output needs to be downscaled in order to be applied for impact assessment at regional or local scales. Downscaling is a process of making a link between the state of some atmospheric variable representing a large space (henceforth referred to as the ‘large scale’) and the state of some atmospheric variable representing a smaller space (henceforth referred to as the ‘small scale’) (Benestad et al., 2007). For example, the large-scale atmospheric variable may represent atmospheric circulation patterns over a large region, the small scale atmospheric variable may represent a local temperature measured at one given the point (station measurement). The main assumption used in all downscaling techniques is that GCMs simulate large scale atmospheric variables accurately.

There are two broad categories of downscaling techniques (Hewitson and Crane, 1996). The first category is the statistical or empirical-statistical downscaling (ESD) technique. This is a fully developed and widely used technique for exploring the regional, and local scale response to climate change as simulated by comparatively low-resolution GCMs (Tumbo et al., 2010). There are several statistical downscaling methods (Wilby et al., 2004 and Hewitson et al., 2014). Their general techniques are based on developing statistical relationships between simulated large scales atmospheric variables (known as ‘predictors’) and observed local climate variables (known as ‘predictand’). The developed statistical relationships are assumed to remain valid under future climate conditions and also that, the structure, variability and trends of the large atmospheric variables (predictors) are well characterized by the GCMs.

The statistical downscaling techniques require the selection of realistic predictors that are relevant to the predictands. Several researchers (Chen et al., 2010; Muchuru et al., 2014; Zorita and Von storch, 1999; Vigaud et al., 2013; Villegas and Jarvis, 2010 and Hassan et al., 2013) have used predictors such as, sea level pressure, Sea Surface Temperature (SST), geo-potential height, wind fields, relative humidity, or temperature variables from the GCMs to develop predictors-predictands transfer functions.

However, some of the predictors that are used for statistical downscaling are debated in literatures. For instance, Benestad, et al (2007) argued that, the sea surface temperature (SST), which partly depends on the ocean dynamics, is not represented well in ocean models. The spatial resolution of these models tends to be too coarse to describe the ocean currents which are important influences on the SST. Fung et al (2011) argued

that, circulation predictors alone are unlikely to capture precipitation mechanisms linked to thermodynamics and vapour contents. Wilby and Wigley (2000) suggest that atmospheric moisture must be considered as predictors as well as atmospheric circulations. Charles et al (1999) suggest that, inclusion of moisture variables as predictors can lead to convergence between statistical and dynamical downscaling approaches. Thus, there are no consensus in literature about the most appropriate predictor to be used in statistical downscaling (Fung et al. 2011). IPCC guidance, Wilby et al. (2004) provided criteria for predictor selection as follows: predictor must (1) clearly captures the local thermodynamic state of the atmosphere (2) the predictors must be related to a GCMs scale of skill (3) capture the range of frequency responses from inter-annual variability to at least daily synoptic time scales (4) is conservative under non-stationarity. Therefore there is a need to find a single appropriate predictor that can describe the dynamics and thermodynamics condition of the atmosphere to be used in statistical downscaling.

The second category of downscaling technique is dynamical downscaling and its basic approach is to nest a high resolution regional climate model (RCM) within GCM and drive it using boundary condition from the GCM (Danis et al., 2002). The main hypothesis behind the use of high resolution RCM is that, they can simulate local conditions in greater details over a limited region (Danis et al., 2002). Dynamical downscaling approach provides better representation of orographic effect on climate variables. Furthermore parameterization schemes within the high resolution RCM gridpoints produces realistic mesoscale circulation patterns (Bhuvandas et al., 2014).

Dynamical downscaling can be categorized into four types (Castro et al., 2005). The first type is when the Regional climate model (RCM) (Limited Area Model-LAM) is driven by lateral boundary conditions from a GCM or global reanalysis data at regular time interval (classically 6 or 12 hours), and bottom boundary condition (terrain, sea surface temperature) and specified initial conditions. The initial global atmospheric condition in the GCMs that provides lateral boundary conditions are not yet forgotten. This type of dynamical downscaling is used for provision of day to day weather forecast (Chen, and Kuo, 1992).

The second types is when the initial boundary condition from global atmosphere is forgotten by the GCM or reanalysis data while the RCM still run using lateral boundary

condition from the GCMs or global reanalysis data and bottom boundary condition. This type of downscaling is used for seasonal weather simulations. The third type is when the lateral boundary conditions are provided by the GCM forced by specific surface boundary conditions (e.g. observed SSTs) (Castro et al., 2005). This type of downscaling is also used for provision of seasonal weather prediction.

The fourth type is when the lateral boundary conditions are from a completely coupled GCM in which the component of the climate system; the atmosphere-biosphere-cryosphere-ocean are coupled and interactive. This type is used to generate climate simulation for multiyear periods. Generally all types of dynamical downscaling are computationally expensive. At present many collaboration projects are generating climate simulation from dynamical downscaling for model inter-comparisons and impact assessments. These projects include the Coordinated Regional Climate Downscaling Experiment (CORDEX) that produce dynamical downscaled climate simulation for all continents, the North American Regional Climate Change Assessment Program (NARCCAP) that provide high resolution climate change simulation for United states, northern Mexico and Canada (Glotter et al, 2014). These projects have made available large number of high resolution climate simulations that can be used for impact assessments.

1.2 Problem

Climate change is ‘unequivocal’ (IPCC, 2007). Adaptation is on the agenda of many countries around the world and there is a growing consensus that the impacts of climate change will hit developing countries the hardest. Tanzania is one of such countries and will need to seriously consider its adaptation strategies, especially to the agriculture sector. However, in order to start determining adaptation strategies for the agriculture sector, it is essential to evaluate the impacts of climate change on crop production to have scientific evidence that would guide the formulation of adaptation policy.

In Tanzania several research studies have evaluated the impacts of climate on crop production (Mwandosya et al., 1998; Agrawala et al., 2003; Ernhart and Twena, 2006; IPCC, 2007; Enfors and Gordon, 2008; Thornton et al., 2009; 2010; Arndt et al., 2011; Ahmed et al., 2011; Müller et al., 2011; and Rowhani et al., 2011). These studies, however, have used climate change projections derived directly from General

Circulation Models (GCMs) to drive the crop models. GCMs classically run at 300 km or more spatial resolutions and are designed to simulate global climate characteristics like global temperature. The coarse spatial resolution of the GCMs limits the direct application of their outputs in regional and sub-regional decision making (Masson and Knutti, 2011; Ramirez-Villegas and Challinor, 2012). This limitation is particularly problematic for countries like Tanzania which have high regional heterogeneity. Van wart et al (2013) underscored that GCMs climate change projections provide the poor simulation of crop yields.

The poor performance of GCMs in estimating crop yields calls into questions of the many prior evaluations of climate change impacts on crop production in Tanzania. Furthermore, adaptation and mitigation policies that were developed based on GCMs simulation are not realistic and might pose significant challenges for anticipatory adaptation in the country. Therefore, credible evaluation of climate change impacts on rainfed crop production using high-resolution climate change simulations in Tanzania is required.

1.3 Research aim and objectives

1.3.1 Aim

1.3.1.1 To evaluate the impacts of climate change on rain fed Maize production in Wami-Ruvu basin of Tanzania using high resolution climate change projections from the Coordinated Regional Climate Downscaling Experiment program Regional Climate Models (CORDEX RCMs).

1.3.2 Objectives

1.3.2.1 To evaluate the performance of the CORDEX RCMs in simulating present climate conditions of Tanzania

1.3.2.2 To assess the impacts of climate change on maize production in the Wami Ruvu basin of Tanzania using high resolution climate change projections from CORDEX RCMs

1.3.2.3 To compute and evaluate performance of the moist potential vorticity and, moist potential vorticity vector in describing long term annual cycles of rainfall

events in Tanzania and their use as predictors for statistical downscaling of climate change projections

1.3.2.4 To compute moist potential vorticity vector and evaluate its performance in diagnosis of heavy rainfall events in Tanzania

1.4 Research Hypothesis and Questions

This study is guided by the main hypothesis that, dynamical downscaled General Circulation Models (GCMs) outputs can generate reliable, actionable and applicable high resolution climate change projections that can be used in climate change impact studies. In addition to the above hypothesis the following four research questions are set to be answered,

What is the performance of the Coordinated Regional Climate Downscaling Experiment program regional climate models (CORDEX RCMs) in simulating present climate of Tanzania?

What is the impact of climate change on rainfed maize production in the Wami-Ruvu basin of Tanzania at present, mid and end centuries?

What the performance of moist potential vorticity (MPV) and moist potential vorticity vector (MPVV) in describing annual cycles of rainfall over different regions of Tanzania?

What is the performance of moist potential vorticity vector in describing heavy rainfall events in Tanzania?

1.5 Motivation and significance of the study

This study is fundamental for addressing existing uncertainties of climate change impacts on rainfed maize production in the Wami-Ruvu basin of Tanzania. This is particularly important to the existing enormous number of agricultural projects in the Wami-Ruvu basin. The agriculture projects that operates in the basin includes, the FEED the FUTURE with an investment cost of USD 300 million, the Tanzania Bread Basket Transformation project, with an investment cost of USD 173 Million, the Southern Agriculture Corridor of Tanzania (SAGCOT) with an investment cost of USD 3.4 billion and the Rural Livelihoods Development Programme (RLDP) with an

investment cost of USD 21 million (URT, 2012). For these projects to be successful, a comprehensive analysis of climate change impacts on rainfed agriculture using high-resolution climate change projections is required.

This research provides the reliable evaluation of the performance of CORDEX RCMs in simulating present climate conditions of Tanzania. The study also provides a reliable evaluation of the climate change impacts on rainfed maize production in the Wami-Ruvu basin of Tanzania.

Since there is no consensus on which is an appropriate predictor that can be used for statistical downscaling, in this study an attempt is made to test whether moist potential vorticity and moist potential vorticity vector can be used as a predictor for downscaling climate change projection, particularly for rainfall events. Moreover, the evaluation of the performance of the moist potential vorticity vector in the diagnosis of heavy rainfall events is analyzed.

1.6 Conceptual frame work of the study

According to the IPCC, (2007), Greenhouse Gases (GHGs) from anthropogenic sources are responsible for climate change. Climate change manifest itself through increased temperatures, changing rainfall patterns and amounts, and a higher frequency and intensity of extreme climatic events such as cyclone, floods, droughts, and heat wave (Sarker, 2012). The increase in temperature and change in rainfall patterns affect directly rainfed crop production.

The evaluation of climate change impact on crop production relies on future projections of climate change. GCMs are the main tools used to provide future climate change projections. However, GCMs have coarse spatial resolutions such that cannot simulate climate variations associated with landscape variability/heterogeneities. Therefore, GCMs climate projections cannot be used directly as inputs in crop models for impact assessments.

The conceptual framework of the study is presented in the Fig.3 bellow, where, TX, TN denotes maximum and minimum temperature, respectively.

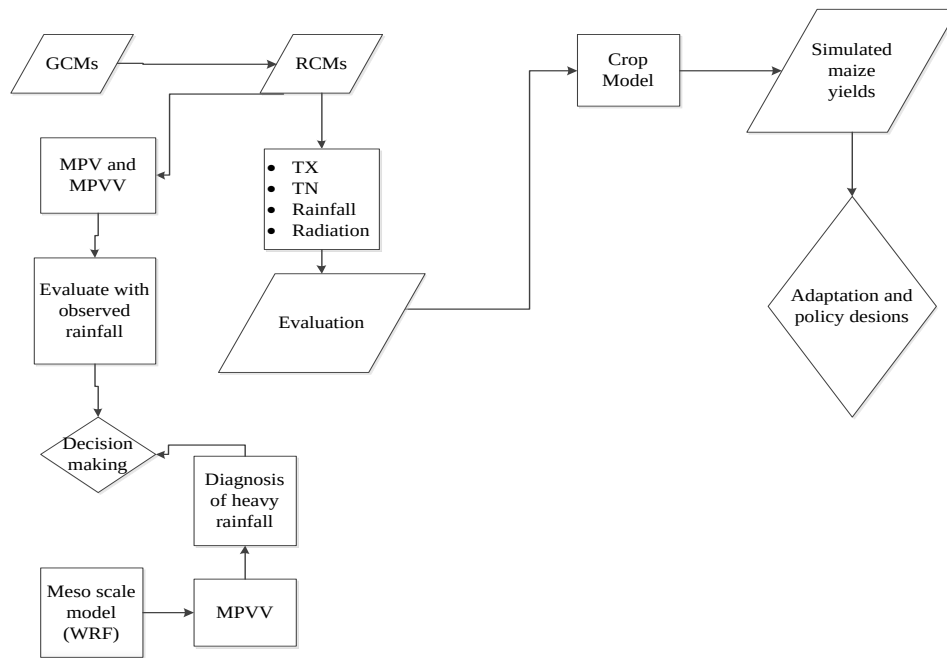


Figure 1: Conceptual framework of the study

1.7 The outline of the thesis

This thesis consists of six chapters in form of journal paper, either already published or in various stages of review processes by the journals. Chapter 1 provide the general background of the study. This chapter also describes the problem statement, aim and objectives, conceptual framework, motivation and significance of the study. Chapter 2 presents the evaluation of the performance of CORDEX RCMs in simulating present climate conditions of Tanzania. Chapter3 assesses the impacts of climate change on rainfed maize production in the Wami-Ruvu basin of Tanzania using high resolution climate simulation data from CORDEX RCMs. Chapter4 assesses the performance of moist potential vorticity and moist potential vorticity vector in describing long term (1976-2001) annual cycles of rainfall over different regions in Tanzania. Chapter5 evaluates the performance of moist potential vorticity vector in describing heavy rainfall events in Tanzania. Chapter6 presents summary of the main finding of this thesis together with recommendations for further studies.

All figures and tables are presented according to the requirements of a specific journal. Moreover, each chapter (Chapter2-6) is followed by the list of reference specific to that paper and journal requirements. The reference list of chapter1 is provided at the end of that chapter.

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Chapter 2: Evaluation of the performance of CORDEX Regional Climate Models in simulating present climate conditions of Tanzania

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Abstract

Regional Climate Models (RCMs) are widely used in regional assessment of climate change impacts. However, the reliability of individual models needs to be assessed before using their output for impact assessment. In this study, we evaluate the performance of RCMs from the Coordinated Regional Climate Downscaling Experiment program (CORDEX) to simulate minimum air temperature (TN), maximum air temperature (TX) and rainfall over Tanzania. Output from four RCMs driven by boundary conditions from three General Circulation Models (GCMs) and ERA-Interim data are evaluated against observed data from 22 weather stations. The evaluation is based on determining how well the RCMs reproduce climatological trends, interannual, and annual cycles of TN, TX and rainfall. Statistical measures of model performance that include the bias, root mean square error, correlation and trend analysis are used. It is found that RCMs captured well the annual cycle of TN, TX and rainfall, however underestimate and overestimate the amount of rainfall in March-April-May (MAM) and October-November-December (OND) seasons respectively. Most RCMs reproduce interannual variations of TN, TX and rainfall. The source of uncertainties can be analysed when the same RCM is driven by different GCMs and different RCMs driven by same GCM simulate TN, TX and rainfall differently. It is found that the biases and errors from the RCMs and driving GCMs contribute roughly equally. Overall, the evaluation here finds reasonable (although variable) model skill in representing mean climate, interannual variability and temperature trends, suggesting the potential use of CORDEX RCMs in simulating TN, TX and rainfall over Tanzania.

2.1 Introduction

The most advanced tools currently available for simulating the response of the global climate system to increased atmospheric greenhouse gas concentrations are Global Climate Models (GCMs) (IPCC, 2013). They describe the relevant physical processes in the atmosphere, oceans, land and ice surfaces that make up the climate system. However, GCMs have relatively coarse space resolution and cannot represent the fine-scale detail that characterizes the climate in many regions of the world, especially in regions with complex orography or heterogeneous land surface cover or coastlines. This can make their climate simulations of limited use in impact studies of climate change on biodiversity, ecosystem services, agricultural systems, species distributions and other landscape and environment related matters (Villegas and Jarvis, 2010; Hassan et al., 2013; Xiaoduo et al., 2012). These types of impact and adaptation studies require data with much finer spatial resolution (Daniels et al., 2012).

One widely applicable method for obtaining high resolution climate information that takes into account regional patterns and valuable local knowledge is to use regional climate models (RCMs) (Danis et al., 2002). These are atmospheric models run on a limited geographical area using boundary conditions from GCMs (Min et al., 2013). Their finer spatial resolution allows simulation of local climate conditions in greater detail by incorporation of impacts of orography (mountains, coastlines, water bodies, vegetation) and land-use, and small scale dynamical and boundary layer processes.

In recent years, RCMs have been used extensively to provide climate simulations with high resolution (Xiaoduo et al., 2012; Roux, 2009; Wilby and Fowler, 2011). These simulations, however, are subject to a number of uncertainties that come from boundary conditions, size of the integration domain, natural variability within the RCMs and RCM formulation (Min et al., 2013). Meier et al. (2011) assessed the impact of boundary conditions from three global climate models (HadCM3, ECHAM4 and ECHAM5) on the Rossby Centre Atmosphere model version 3 (RCA3) RCM in simulating surface meteorological variables over the Baltic Sea. They found that RCA3 simulated annual mean precipitation and the mean seasonal cycle of precipitation much better when driven by ECHAM5 than ECHAM4. Further, they found that ECHAM4 and ECHAM5 driven simulations both overestimated the mean sea level pressure and sea level pressure gradient, while with HadCM3 driven simulations underestimated

both of these features. Køltzow et al. (2011) examined the importance of surface forcing and the size of the integration domain for dynamical downscaling with the HIRHAM RCM in simulating the Norwegian climate for the period of 1961–1990 and found that the RCM climate simulations were sensitive to surface forcing as well as the size of the integration domain. Endris et al (2014) evaluated the performance of CORDEX RCMs in simulating East African rainfall during the period of 1990–2008. They found the RCMs simulated rainfall well in one region but less successfully in another region over the same time period. More recently Shongwe et al (2015) evaluated the performance of CORDEX regional climate model in simulating precipitation over southern Africa. They also found that the performance of the RCMs in simulating precipitation differed over different regions.

A prerequisite before using climate simulation data from the RCMs is evaluation through comparisons of model results with observations. This helps to assess the ability of the RCMs to simulate climate conditions at particular locations. This is important for assessment and the quantification of uncertainties in climate models simulations for use in climate change impact studies and policy decisions at different locations.

A large number of previous studies (e.g. Engelbrecht et al., 2009; Endris et al., 2014), have provided detailed evaluations of the performance of RCMs in simulating southern, eastern and the horn of Africa rainfall and temperature climatology. In these studies, however, the RCMs simulations were evaluated against interpolated gridded data derived from meteorological station measurements. Another recent study is that of Endris et al. (2014), which evaluated the performance of RCMs from CORDEX in simulating East Africa rainfall, where the model outputs were compared with gauge-based gridded observational datasets at 0.5° by 0.5° spatial resolution obtained from Global Precipitation Climatology Centre (GPCC), Climate Research Unit (CRU), and Global Precipitation Climatology Project (GPCP).

Although gridded data have shown to be useful for evaluation of RCMs performance, they have a number of potential inaccuracies and errors (Hofstra et al., 2009). These data use interpolation across space and time to combine weather station data into a balanced panel of observations on a fixed spatial scale or grid (Auffhammer et al., 2013). Their quality depends on the number of weather stations used in interpolation processes and the interpolation formula as different schemes produces different

estimates, particularly for precipitation (Dell et al., 2014). In developing countries with few weather stations, the quality of gridded data is questionable. For instance, Tanzania has very few weather stations (28-synoptic weather stations) which are sparsely distributed over complex topographical terrain. The use of gridded data to evaluate the performance of RCMs in simulating Tanzania climate may not provide realistic results. Christensen (2001) and Osborn and Hulme (1997) suggested the use of point measurements from weather stations to evaluate grid measurements of the climate model, especially in areas with sparse station networks and complex terrain.

The aim of this study is to evaluate the performance of RCMs from CORDEX in simulating present climate conditions over Tanzania, where actual station observations are used to evaluate the RCMs. This study is a crucial step in choosing reliable models that can be used in climate change impact studies at a particular location. The output from such models will be used in a future study as input into crop models for evaluation of climate change impacts on rain-fed crop production in both current and future climate in Tanzania. This is important since the economy of the country heavily depends on the agriculture sector, which contributes about half of gross production, 30% of export earnings, 65% of raw materials for domestic industries and employs about 80% of the labour force while facing challenges of climate change and variability. Previous studies in Tanzania (Mwandosya et al., 1998; Agrawala et al., 2003; Ernhart and Twena, 2006; IPCC, 2007; Enfors and Gordon, 2008; Thornton et al., 2009; 2010; Arndt et al., 2011; Ahmed et al., 2011; Müller et al., 2011) have evaluated the impact of climate change on rain-fed crop production using climate simulation derived directly from GCMs which are insufficient to detect the huge variations in agricultural output in different regions.

2.2 Data and Methodology

2.2.1 Study area

The study area is Tanzania (Figure1), which is located in East Africa between longitudes 29°E to 41°E and latitudes 1°S and 12°S. The country has an area of 945,000 km² of which 884,000 km² is land mass and 61,000 km² is lakes, rivers and seashore. Tanzania has complex topography that is very heterogeneous. The height of the topography ranges from sea level in the East to 1600 m in the West. In the

northeastern highlands is the highest mountain in Africa: Mt Kilimanjaro with an altitude of 5895 m, while in the north is the largest lake in Africa: Lake Victoria. In the south are Lake Nyasa and the Ruvuma River, and in the west is the deepest lake in Africa: Lake Tanganyika. Much of the country lies above 1000 m altitude with many areas over central and northern regions above 1500 m.

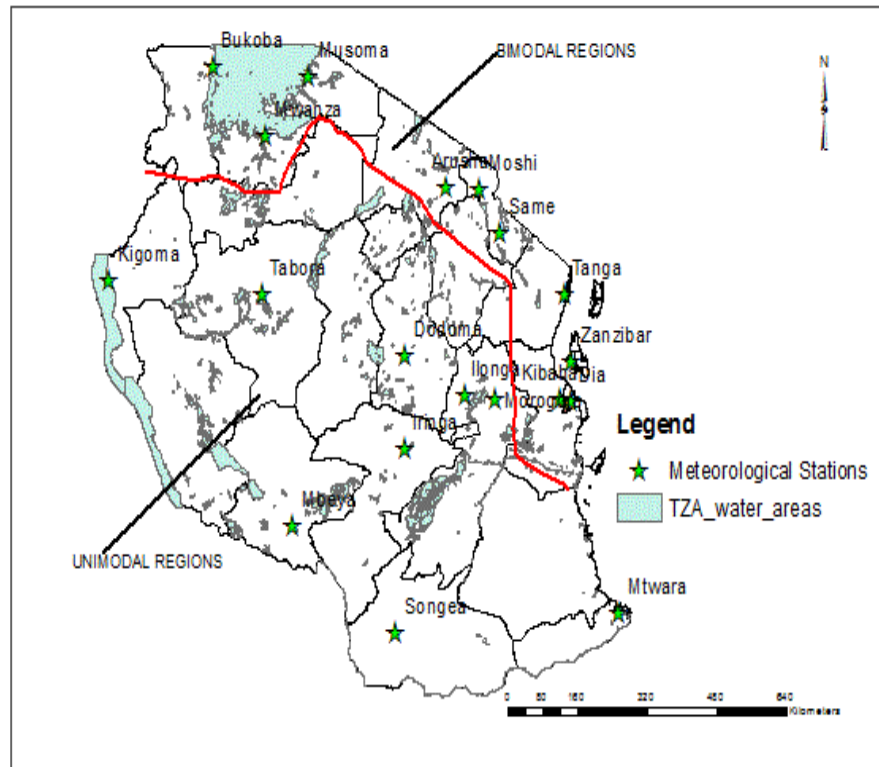


Figure 1: Map of Tanzania showing the location of meteorological stations in Unimodal and Bimodal regions separated by the red line.

The climate over Tanzania is mainly controlled by the movement of the Inter-Tropical-Convergence-Zone (ITCZ). However, seasonal interactions within the ITCZ, perturbations in global climate circulation and changes in local circulation systems which are influenced by complex topographical features all contribute to high local climate variability. The seasonal rainfall is modulated by changes in the global sea surface temperatures (SSTs) especially over the equatorial Pacific and Indian Oceans (Black et al., 2003; Black, 2005; Anyah and Semazzi 2007).

Tanzania is characterized by two rainfall seasons, namely March-April-May (MAM) and October-November-December (OND). These seasons are mainly driven by the migration of the ITCZ, which lags behind the overhead sun by 3-4 weeks over the

region (Owiti and Zhu, 2012). The ITCZ migrates towards southern regions of Tanzania in October-December, reaching southern parts of the country in January-February and reverses northwards in March, April and May (Timiza, 2011). Due to this movement, some areas experience single and double passages of the ITCZ (Owiti and Zhu, 2012). Regions with a single passage are known as unimodal areas (see Figure 1) and include the southern, southwestern, central and western parts of the country which receive rainfall from October through to April or May (Timiza, 2011). Areas that experience a double passage are known as bimodal areas, and include north, northern coast, northeastern highlands, the Lake Victoria basin and the islands of Zanzibar (Unguja and Pemba). These regions receive two distinct rainfall seasons; the long rain season (known as *Masika* in Swahili) which starts in March and continues through May (MAM) and the short rainfall season (*Vuli* in Swahili) which starts in October and continues through December (OND) (Agrawala et al., 2003).

As reported in Zorita and Tillya (2002) and Camberlin et al (2009), the amount of seasonal rainfall varies significantly in space and time, with higher variation observed during the *Vuli* season than in *Masika*. The rainfall falling in these seasons usually ranges from 50-200 mm per month but varies greatly between regions and can be as much as 300 mm per month in wettest regions and seasons (McSweeney et al., 2010). Higher amounts of seasonal rainfall are recorded over the southwestern and northeastern highlands, while central Tanzania is semi-arid, receiving seasonal rainfall of less than 50 mm per month. Annual average rainfall over Tanzania ranges from 534 mm to 1837 mm.

The annual average temperature over different stations in Tanzania ranges from 14.4°C-26.4°C. Regions with the highest temperatures are along the coast and western parts of the country. The season with high temperatures starts from October, continuing through February or March, whilst the cold season is from May to August. The annual minimum air temperature (TN) and maximum air temperature (TX) across the stations in Tanzania ranges from 9.6-22°C and 19.1-30.7°C respectively.

2.2.2 Data

2.2.2.1 Model Data

The CORDEX program archives outputs from a set of RCM simulations over different regions in the world. The CORDEX domains for model integrations are found at http://wcrp-cordex.ipsl.jussieu.fr/images/pdf/cordex_regions.pdf. In this study data sets from CORDEX-Africa were accessed from <http://cordexesg.dmi.dk/esgf-web-fe/>. These data sets are quality controlled and may be used according to the terms of use (<http://wcrp-cordex.ipsl.jussieu.fr/>). The spatial grid resolutions of all CORDEX-Africa-RCMs were set to longitude 0.44° and latitude 0.44° using a rotated pole system coordinate. These models operate over an equatorial domain with a quasi-uniform resolution of approximately 50 km by 50 km. For detailed description of CORDEX RCMs and their dynamics and physical parameterization a reader may consult Nikulin et al (2012). Table 1 lists the details of CORDEX-RCMs and the driving GCMs: CNRM-CERFACS-CNRM-CM5 (CNRM), ICHEC-EC-EARTH (ICHEC) and MPI-M-MPI-ESM-LR (MPI).

Output from CORDEX-RCMs driven by boundary conditions from the GCMs for the period 1971-2005 are used to assess the ability of the RCMs to simulate annual cycles and trends in TN and TX and rainfall. The ERA-Interim driven simulations which are available at <http://cordexesg.dmi.dk/esgf-web-fe/> for the period 1989-2008 are used to assess the ability of CORDEX-RCMs to simulate interannual variability in TN, TX and rainfall.

2.2.2.2 Observed data

Monthly mean TN, TX and rainfall for the period 1971-2005 from 22 weather stations are obtained from the Tanzania Meteorological Agency (TMA). Table 2 indicates the geographical information of weather stations managed by TMA with their long term annual statistical moments of observed TN, TX and rainfall.

Table 1: Details of CORDEX-RCMs and the driving GCMs

No.	RCM	Model Centre	Short name of RCM	GCM
1	CLMcom COSMO-CLM (CCLM4)	Climate Limited -Area Modelling (CLM) Community	CCLM4	MPI ICHEC CNRM
2	DMI HIRHAM5	Danmarks Meteorologiske Institut(DMI), Danmark	HIRHAM5	ICHEC
3	SMHI Rossby Center Regional Atmospheric Model (RCA4)	Sveriges Meteorologiska och Hydrologiska Institut (SMHI), Sweden	RCA4	MPI ICHEC CNRM
4	KNMI Regional Atmospheric Climate Model, version 2.2 (RACMO2.2T)	Koninklijk Nederlands Meteorologisch, Instituut (KNMI), Netherlands	RACMO22T	ICHEC

Table 2. Geographic information of weather stations managed by TMA with the long term (1971-2000) annual statistical moments of observed TN, TX and rainfall and their interannual standard deviations (SDV).

ID	Station Name	Latitude (°S)	Longitude (°E)	Alt (m)	TN	SDV(°C)	TX (°C)	SDV(°C)	Rainfall(mm)	SDV(mm)
1	Songea	10.41	35.35	1067	15.7	0.4	26.9	0.4	1098.7	203.1
2	Mtwara	10.21	40.11	113	20.9	0.4	30.1	0.3	1089.8	208.5
3	Bukoba	1.2	31.49	1144	16.7	0.7	25.8	0.3	1836.8	447.7
4	Musoma	1.3	33.48	1147	17.5	0.6	28.5	0.5	867.5	176.7
5	Mwanza	2.28	32.55	1140	17.4	0.9	28.1	0.5	1051.1	215.8
6	Arusha	3.2	36.37	1387	14.2	0.4	25.8	0.5	810.1	271.2
7	Moshi	3.21	37.2	813	17.8	0.4	29.4	0.4	893.8	250.3
8	Kilimanjaro	3.25	37.04	896	17.2	0.5	29.8	0.5	534.1	199.4
9	Kigoma	4.53	29.4	820	18.7	0.4	28.5	0.6	991.9	138.6
10	Same	0.5	37.43	860	17.6	0.6	29.0	0.4	561.5	200.2
11	Tabora	5.05	32.5	1182	16.9	0.5	29.6	0.8	949.2	170.4
12	Tanga	5.05	39.04	49	22.0	0.5	30.7	0.3	1325.4	325.4
13	Dodoma	6.1	35.46	1120	16.8	0.3	28.9	0.4	577.6	116.0
14	Ilonga	6.46	37.02	503	19.3	0.7	30.4	0.4	1053.3	197.0
15	Morogoro	6.5	37.39	526	18.9	0.5	30.2	0.4	847.9	166.9
16	Kibaha	6.5	38.38	167	20.7	0.8	30.3	0.4	983.1	218.8
17	Zanzibar	6.13	39.13	18	22.0	0.7	30.5	0.3	1713.4	392.7
18	Dar es Salaam	6.53	39.12	53	20.9	0.5	30.7	0.4	1146.8	228.3
19	Iringa	7.4	35.45	1428	14.5	0.5	26.4	0.4	598.1	88.1
20	Mbeya	8.56	33.28	1758	10.8	0.8	23.8	0.4	925.6	150.4
21	Mlingano	8.09	38.54	183	20.4	1.2	30.6	0.6	1145.1	295.7
22	Igeri	9.4	34.4	2250	9.6	0.6	19.1	0.5	1337.6	202.7

2.2.3 Analysis method

2.2.3.1 Interpolation of gridded climate data from the RCMs

The RCMs simulate different climate variables such as TN, TX and rainfall at each grid point. The quality of their output can be evaluated against actual measurements from weather stations using several techniques. One of the methods is to interpolate gridded climate variables to the location of weather stations and compare the results with observed station data. There are different interpolation methods (Ly et al., 2013); the simplest is to calculate the arithmetic mean of climate variables from the nearest four gridpoints around the station. This method assigns equal weights from four grids in estimating climate variable at the station, and may not give realistic estimates of climate variables such as rainfall which have strong spatial variability (Ly et al., 2013).

Another interpolation method is the nearest neighbour method, which assumes that climate simulation at a given weather station is equal to that at the closest gridpoint. This method considers discrete values and does not consider spatial variation of climate variable between four grids surrounding the station (Hartkamp et al., 1999). Therefore, the use of nearest neighbour to interpolate climate variables with strong spatial variation such as rainfall could lead to erroneous results.

The Inverse Distance Weighted Average interpolation method (IDWA) is the estimation method whereby a climate variable at a weather station is estimated by a linear combination of the simulated climate variable at the surrounding gridpoints (Hartkamp et al., 1999; Ly et al., 2013). This method is defined mathematically as:

$$\bar{V}_f = \frac{\sum_{i=1}^n \frac{1}{d_i^2} V_i}{\sum_{i=1}^n \frac{1}{d_i^2}}, \quad (1)$$

where, $\bar{V}_f$ is the interpolated value at the required station, V_i is data at grid point i , d_i is the distance from gridpoint i to the station, n is the total number of gridpoints surrounding the station (which is always 4) and $\frac{1}{d_i^2}$ is the weight of the distance from the gridpoint to station. The weighting of the grids is strictly a function of the distance from the station. This method was tested by Hartkamp et al. (1999) and yielded best results for interpolation of precipitation in comparison to other techniques.

In this study, IDWA is used to interpolate model gridded climate simulations to the location of weather stations. The distance from the gridpoint to the station is computed using the Haversine formula (Ingole and Nichat, 2013). This formula has been widely applied (e.g. Essayad, 2011; Chopde and Nichat, 2013) to compute the shortest distance between two points on the earth's surface. The Haversine formula is defined as:

$$d = 2r \sin^{-1} \left(\sqrt{\sin^2 \left(\frac{\phi_2 - \phi_1}{2} \right) + \cos \phi_1 \cos \phi_2 \sin^2 \left(\frac{\psi_2 - \psi_1}{2} \right)} \right), \quad (2)$$

where d is the distance between two points on the earth's surface, r is the earth's radius, ψ is the longitude and ϕ is latitude.

2.2.3.2 Criteria for evaluating the performance of Regional Climate Models (RCMs)

The ability of RCMs to simulate climate conditions at a particular location can be evaluated using a variety of techniques (Flato et al, 2013). However, no individual evaluation technique or performance measure is considered superior; rather, it is combination of many techniques and measures that provides a comprehensive overview of model performance (Flato et al, 2013). In this study, outputs from RCMs are evaluated against observations using some of the statistical measures recommended by the World Meteorological Organization (WMO) as reported in Gordon and Shaykewich (2000). These statistics include bias, root mean square error and Pearson correlation coefficient given in Eqns (3), (4) and (5).

$$\text{Bias} = \frac{1}{N} \sum_{i=1}^N (F_i - O_i), \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (F_i - O_i)^2}, \quad (4)$$

$$r_{(F,O)} = \frac{\sum_{i=1}^N (F_i - \bar{F})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^N (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^N (F_i - \bar{F})^2}}, \quad (5)$$

where F and O are the simulated and observed values respectively, while i refers to the simulated and observed pairs and N is the total number of such pairs. For rainfall

analysis and for simple interpretation, normalized versions of Eqn 3 and 4, that is normalised bias (hereafter NBias) and normalized root mean square error (NRMSE) given in Eqn 6 and 7 respectively are also used.

$$NBias = \frac{Bias}{MEAN_{Obs}} \times 100, \quad (6)$$

$$NRMSE = \frac{RMSE}{MEAN_{Obs}} \times 100. \quad (7)$$

The NBias is a percentage measure of whether RCMs overall under-estimate or over-estimate a particular climate variable. Positive NBias values indicate overestimation while negative values indicate underestimation by the climate model. On the other hand, the NRMSE is a measure of the absolute error of climate model in simulating certain climate variable. The smaller the NRMSE implies the better the model and vice versa. The Pearson correlation coefficient is a measure of strength of relationship between model simulations and observations and has the limits of 1 and -1. A Pearson correlation coefficient of 1 indicates a perfect positive correlation between model and observed data, while -1 indicates a perfect negative correlation between the two. In this study the Pearson correlation coefficient is calculated using Eqn. 5 where observed average annual cycles over the full period (1971-2005) from different stations are compared with the output from the RCMs (i.e. annual cycles of the 35 year averaged months).

The long term (1971-2005) annual cycle of TN and TX for Tanzania, calculated as the arithmetic mean of all 22 weather stations, is compared with the outputs from the RCMs to determine how well the RCMs driven by GCMs capture the TN and TX seasonality. Moreover, the annual cycles of rainfall in bimodal and unimodal regions, calculated as the arithmetic mean of all 14 stations in the bimodal and 8 stations in the unimodal regions, are evaluated against output from RCMs driven by ERA-Interim data, which are available for the period 1989-2008 to assess how well the RCMs capture rainfall interannual variability in two distinct regions of Tanzania.

Mann-Kendall (MK) and Theil-SEN slope estimator methods are used to test the ability of the RCMs data to simulate trends and the magnitude of the trends in interannual series of TN, TX and rainfall. All trends are computed at station level for the period

1971-2005. Mann-Kendall (MK) and Theil-SEN slope estimators are widely used for trends tests as well as estimation of magnitude of the trends in climatological time series. For detailed descriptions of mathematical formula and the applications of Mann-Kendall (MK) and Theil-SEN's slope estimator statistics the reader may consult Ahmad et al (2015).

2.3 Results

2.3.1 Spatial distribution of Biases and Root Mean Square Error

The biases and root mean square error calculated using Eqns 3 and 4 are used to assess how well the RCMs can simulate long term (1971-2005) TN and TX over different stations, while the normalized bias (NBias) and root mean square error (NRMSE) calculated using Eqs 6 and 7 are used to assess how well the RCMs can simulate long term (1971-2005) rainfall over different stations. Figure 2 presents the biases in TN at different stations. From this figure RACMO22T driven by ICHEC underestimates TN by -2°C to zero over central, parts of the northeastern highlands, northern, northern coast and western regions. It simulates TN with biases in the range of -4 to -2°C over Same, Morogoro, Tabora, Iringa, and Songea. This model simulates TN with coldest biases in the range of -5 to -4°C over Moshi and Ulanga (Ilonga) regions. Warm biases of zero to 2°C are simulated over coastal regions and over southwestern highlands. HIRHAM5 driven by ICHEC overestimates TN by zero to 2°C over central, parts of northeastern highlands, Morogoro, Iringa, Tabora and over northern coast regions and by 2 to 4°C , over western, southern, southwestern highlands, coastal and northern regions. It simulates TN with cold biases in the range of -2°C to zero over Moshi and Ulanga (Ilonga) regions.

Figure 2 allows the characterization of RCM uncertainty arising from their formulations and driving GCMs. The uncertainty due to RCM formulations is noticeable in Figure 2, where RACMO22T and HIRHAM5, both driven by ICHEC GCM, simulate TN with different level of performance over all stations. The former underestimates TN over most stations while the later overestimates TN over most stations. However, both RACMO22T and HIRHAM5 simulate TN over Moshi and Ulanga (Ilonga) regions with cold biases in the range of -5 to -4°C and -2°C to zero

respectively. Moreover, both RACMO22T and HIRHAM5 simulate TN over Mbeya region with warm biases in the range of zero to 2°C and 2 to 4°C respectively.

The uncertainties of RCMs in simulating TN that arises from the driving GCM can also be characterized from Figure 2. This figure shows that CCLM4 driven by three GCMs (MPI, ICHEC and CNRM), simulate TN differently. CCLM4 simulate TN over northern, western, southwestern highlands, and coastal regions with warm biases in the range of zero to 2°C and 2 to 4°C when is driven by CNRM, and MPI. TN over Moshi and Ulanga (Ilonga) regions is underestimated in the range of -4 to -2°C by CNRM, ICHEC and MPI driven simulations. The TN over Mbeya region is overestimated in the range of zero to 2°C, and 2 to 4°C when CCLM4 driven by ICHEC and CNRM or MPI respectively. These biases seem to be insensitive to the choice of the GCM. Generally, CCLM4 driven by all three GCMs simulate TN over most stations better compared to RACMO22T and HIRHAM5.

RCA4 shows small sensitivity to the driving GCM (Figure 2). RCA4 driven by three GCMs (ICHEC, MPI and CNRM) underestimate TN over most regions. This model driven by all GCMs overestimates TN in the range of zero to 2°C over southwestern highlands and coastal regions. RCA4 driven by all three GCMs (CNRM, ICHEC and MPI) simulate TN over western, northern, parts of northeastern highlands, central and southern regions with biases in the range of -2°C to zero. In general RCA4 driven by three GCMs simulate TN over most stations better compared to other RCMs, particularly over the coastal region suggesting its potential use in simulating TN over most regions.

Analysis of the performance of RCMs in simulating TX at different stations is presented in Figure 3. All RCMs underestimate TX over most regions. RACMO22T driven by ICHEC simulates TX over southwestern and parts of northeastern highlands with the biases in the range of -1 to 1°C. This model simulates TX over western, southern and eastern parts of Lake Victoria and Ilonga region with biases in the range -7 to -5°C.

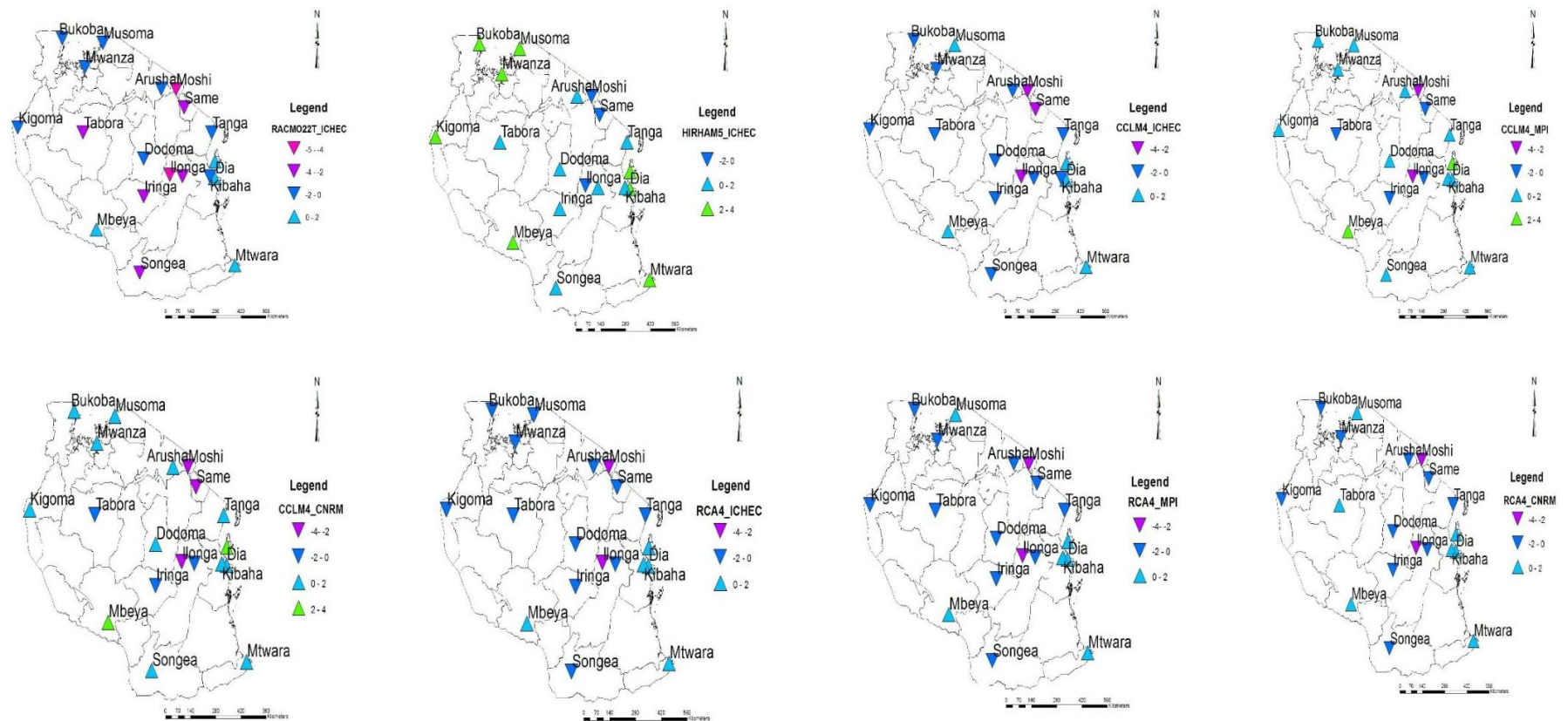


Figure 2. Bias of the RCMs (°C) in simulating minimum temperature at different stations in Tanzania

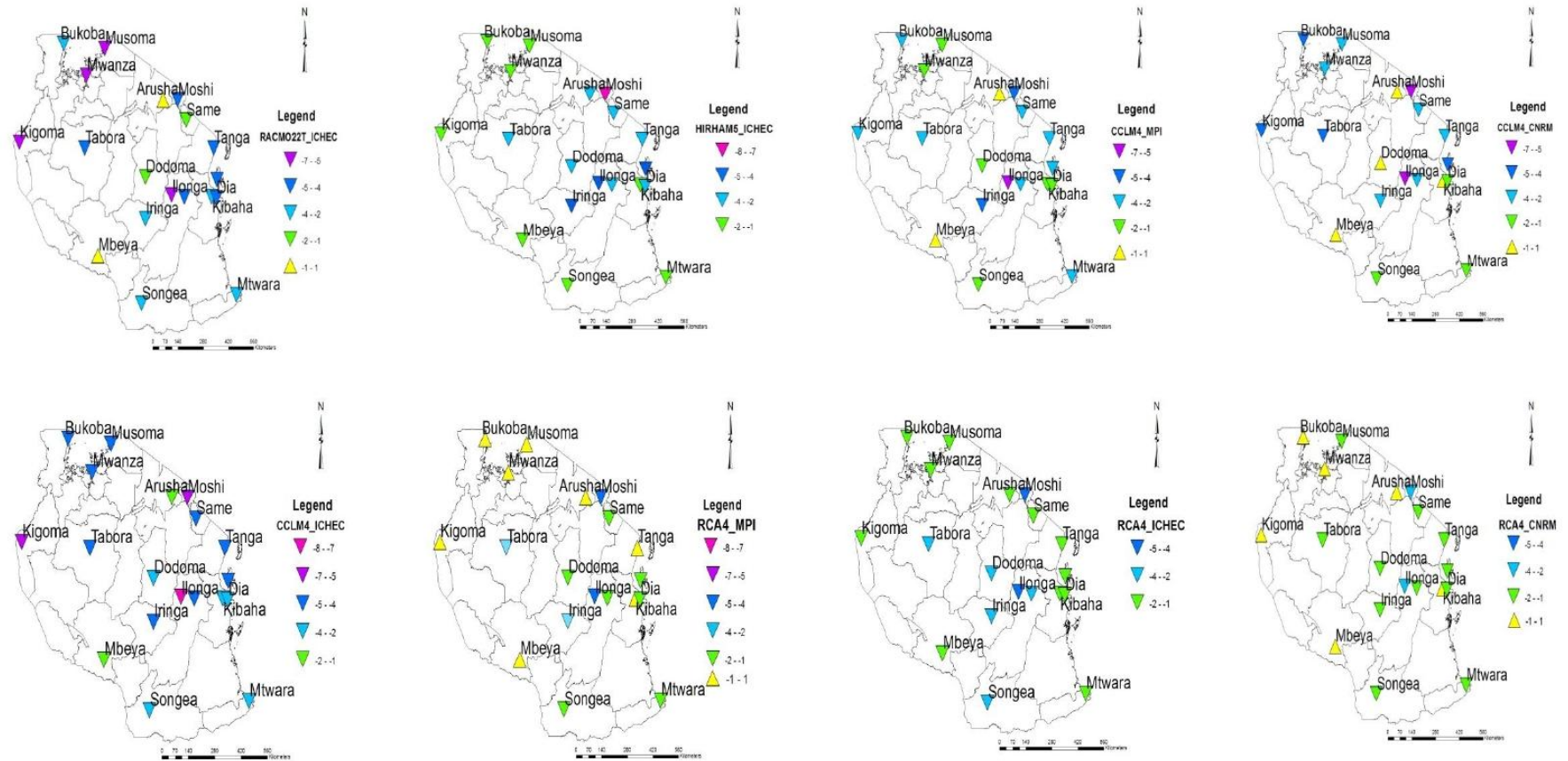


Figure 3 Bias of the RCMs (°C) in simulating maximum temperature at different stations in Tanzania

RACMO22T and HIRHAM5 both driven by ICHEC simulate TX differently over most stations. TX over central and parts of northeastern highland is underestimated in the range of -2 to -1°C, and -4 to -2°C by RACMO22T and HIRHAM5 respectively. The impact of driving GCMs on RCM to simulate TX can be characterised from Figure 3. This figure shows that CCLM4 driven by three GCMs (MPI, ICHEC and CNRM) simulate TX differently over most stations. CCLM4 simulate TX over Mbeya and Arusha with biases in the range of -2 to -1°C and -1 to 1°C when driven by ICHEC and CNRM or MPI respectively. TX over the eastern side of Lake Victoria is underestimated in the range of -5 to -4°C, -4 to -2°C, and -2 to -1°C when CCLM4 is driven by ICHEC, CNRM and IMP respectively. These biases seems to be insensitive to the choice of the GCM, thus CCLM4 driven by any of the three GCMs can be used to simulate TX over Mbeya and Arusha regions.

RCA4 driven by three GCMs (MPI, ICHEC and CNRM) simulates TX over most stations better than other models. RCA4 driven by CNRM simulates TX over southwestern highland, western, parts of northern, northeastern highlands and coastal regions with biases in the range of -1 to 1°C. Generally the biases from all GCMs are not large suggesting that RCA4 driven by all three GCMs can be used to simulate TX over most regions in Tanzania. In general, the biases that arise from the RCMs and driving GCMs in simulating TN and TX are roughly equal in most stations. The RCMs simulate TN better than TX in most stations. TX is underestimated almost in all stations.

The performance of RCMs in simulating rainfall over different stations is presented in Figure 4. This figure shows that RACMO22T and HIRHAM5 both driven by ICHEC simulate rainfall differently over northeastern highlands, parts of Lake Victoria basin, southern coast and western regions. RCA4 perform poor in simulating rainfall over southwestern and northeastern highlands, while CCLM4 perform better in simulating rainfall over the highlands. In general RCMs simulate rainfall over coastal regions with biases ranging from -6% to zero and from 1 to 11%. CCLM4 driven by MPI simulate rainfall over most stations with lower biases compared to the other RCMs (Fig.4).

The RMSE of RCMs in simulating TN over different stations is presented in Figure 5. This figure shows that RACMO22T driven by ICHEC simulates TN over Arusha, Mbeya, coastal and Musoma regions with an error in the range of 0 to 1°C. The model

simulates TN over Moshi and Ilonga regions with relatively large error in the range of 4 to 5°C. It simulates TN over western, central, southern and western parts of Lake Victoria with an error in the range of 1 to 2°C. HIRHAM5 driven by ICHEC simulate TN over central, parts of the southwestern highlands, Morogoro and Same regions with an error in the range of zero to 1°C. This model simulates TN over Musoma and parts of southwestern highlands with a relatively large error in the range of 4 to 5°C. In general RACMO22T and HIRHAM5 simulate TN with different level of performance. The former simulates TN with small error over the coastal regions and southwestern highlands, while the later simulates TN with small error over central regions. RACMO22T simulates TN with small error in the range of zero to 1°C over Musoma and southwestern highlands, while HIRHAM5 TN over the same regions with relatively large error in the range of 4 to 5°C.

CCLM4 simulates TN over most stations with an error in the range of zero to 1°C when it is driven by three GCMs (MPI, CNRM and ICHEC). Generally the model simulates TN in an almost similar way when driven by all three GCMs. This indicates that the error from the driving GCMs in simulating TN over different regions are almost equal and therefore any of the three driving GCM can be used to simulate TN over different regions in Tanzania. However, the model simulates TN over Moshi and Ilonga regions with relatively large error in the range of 3 to 4°C. Like CCLM4, RCA4 driven by MPI, CNRM and ICHEC simulate TN over most stations with an error in the range of zero to 1°C. Generally RCA4 simulate TN over most stations better compared to other models irrespective to the driving GCMs. Although RCA4 is slightly better, all models show reasonably comparable errors. In general all models are acceptable to be used to simulate TN over most stations in Tanzania.

The RMSE of RCMs in simulating TX over different stations are presented in Figure 6. RACMO22T and HIRHAM5 both driven by ICHEC simulate TX over most stations differently. TX over Musoma and Kigoma is simulated by RACMO22T and HIRHAM5 with an error in the range of 5 to 6°C and 2 to 3°C respectively. RACMO22T simulates TX poorly over Mwanza and Ilonga, while HIRHAM5 performs poorly over the Moshi region. Generally CCLM4 driven by all three GCMs simulate TX over north and southern regions with error in the range of 1 to 4°C. RCA4 driven by MPI and CNRM simulate TX over all stations with similar level of performance. Generally RCA4 driven by all three GCMs simulate TX over different

regions better compared with other RCMs irrespective to the driving GCMs. Although RCA4 simulates TX slightly better, all models show generally comparable error in simulating TX over most stations in Tanzania.

Note that lower biases alone do not necessarily indicate the best model in simulating TN, TX and rainfall. One also needs to consider the RMSE: the best model may have smaller biases but should also have smaller RMSE. This is noticeable for instance with RCA4 driven by ICHEC simulating TN over Musoma and Mwanza regions with biases in the range of -2°C to zero. This indicates that RCA4 driven by ICHEC simulates TN for Musoma and Mwanza with similar level of performance. However, results from the RMSE indicate that the model simulates TN over Musoma and Mwanza with an error in the range of zero to 1°C and 1 to 2°C respectively.

The NRMSE of RCM rainfall simulations over different stations is presented in Figure 7. RACMO22T driven by ICHEC simulate rainfall over all stations with the error in the range of 3 to 11%. RCA4 simulate rainfall over southwestern highlands with large error in the range of 20 to 36%, while CCLM4 simulate rainfall over the same regions with small error in the range of 3 to 11%. RCA4 perform better in simulating rainfall over Lake Victoria basin with error in the range of 3 to 11%.

Results from the Pearson's correlation coefficient for simulating annual cycles of TN, TX and rainfall are shown in Tables 3 and 4. From these tables, simulated TN, TX and rainfall by all RCMs compared well with observed TN, TX and rainfall over most stations. Simulated TN and TX from RACMO22T driven by ICHEC are negatively correlated with observed TN and TX over Bukoba, Musoma, Mwanza, Kigoma and Mtwara. These stations are placed close to mountains and water bodies. This may affect the performance of the models due to inability to represent complex dynamics processes from interaction of water bodies and orography, including issues such as stable boundary layer processes, given that TN from all stations close to water bodies is weakly and negatively correlated with simulated TN. In general the RCMs simulate TN better than TX over most stations. The simulated rainfall by the RCMs is positively correlated with observed rainfall. It is important to mention here that the RCMs simulate TN and TX better than rainfall in most stations. Simulated rainfall correlate better with observed rainfall in the unimodal region than in the bimodal region.

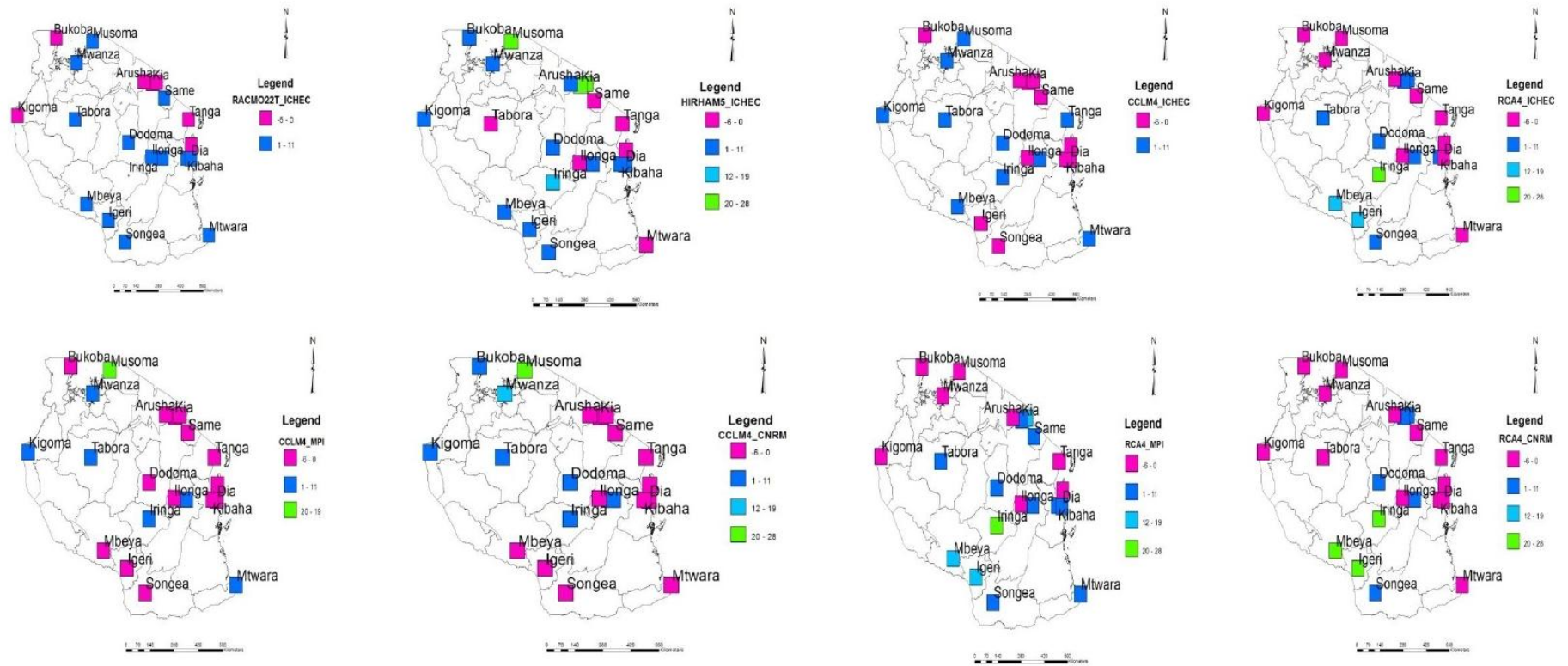


Figure 4 NBias (%) of the RCMs in simulating climatological rainfall at different stations in Tanzania

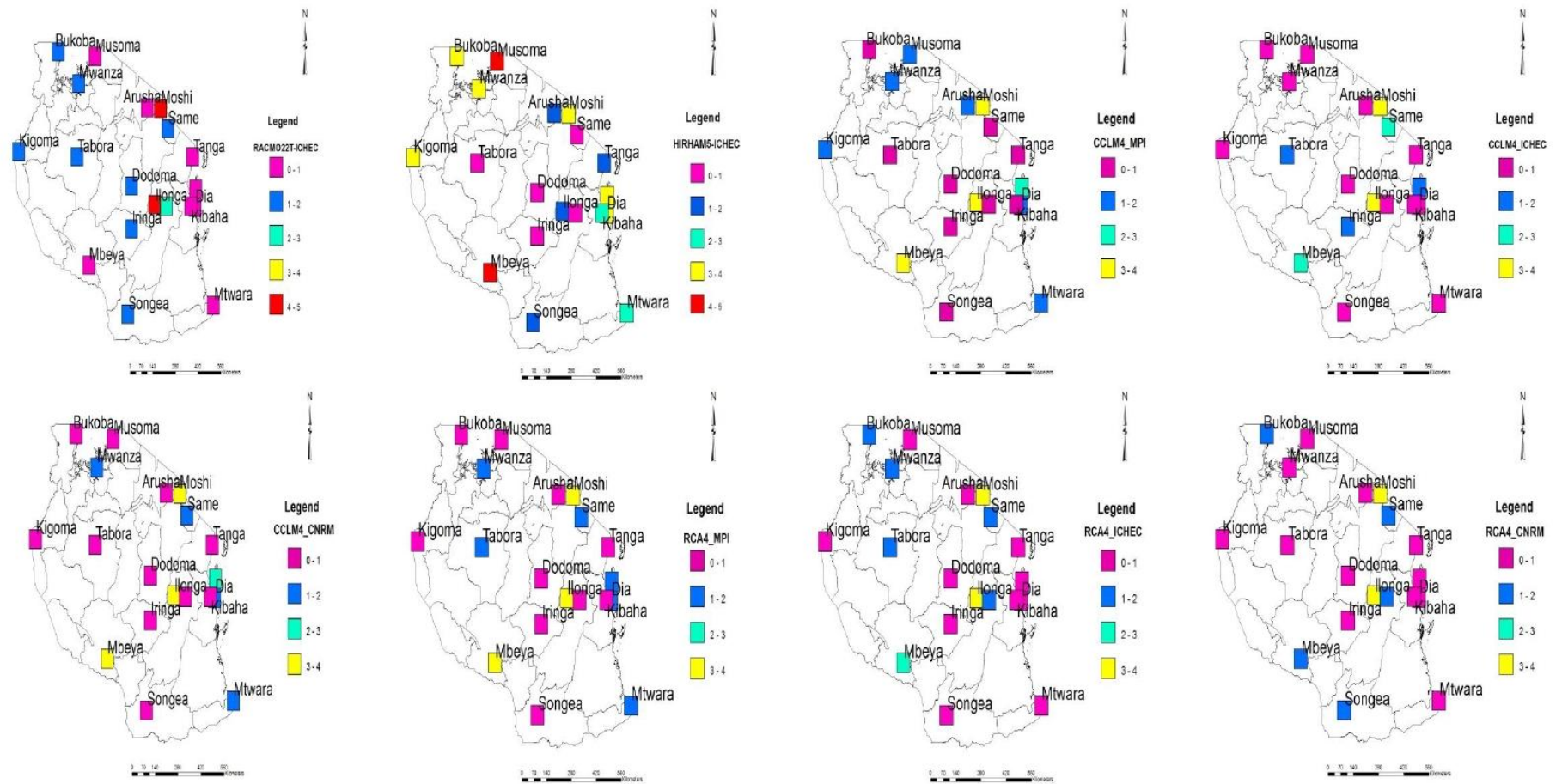


Figure 5. RMSE of RCMs ($^{\circ}\text{C}$) in simulating minimum temperature at different stations in Tanzania

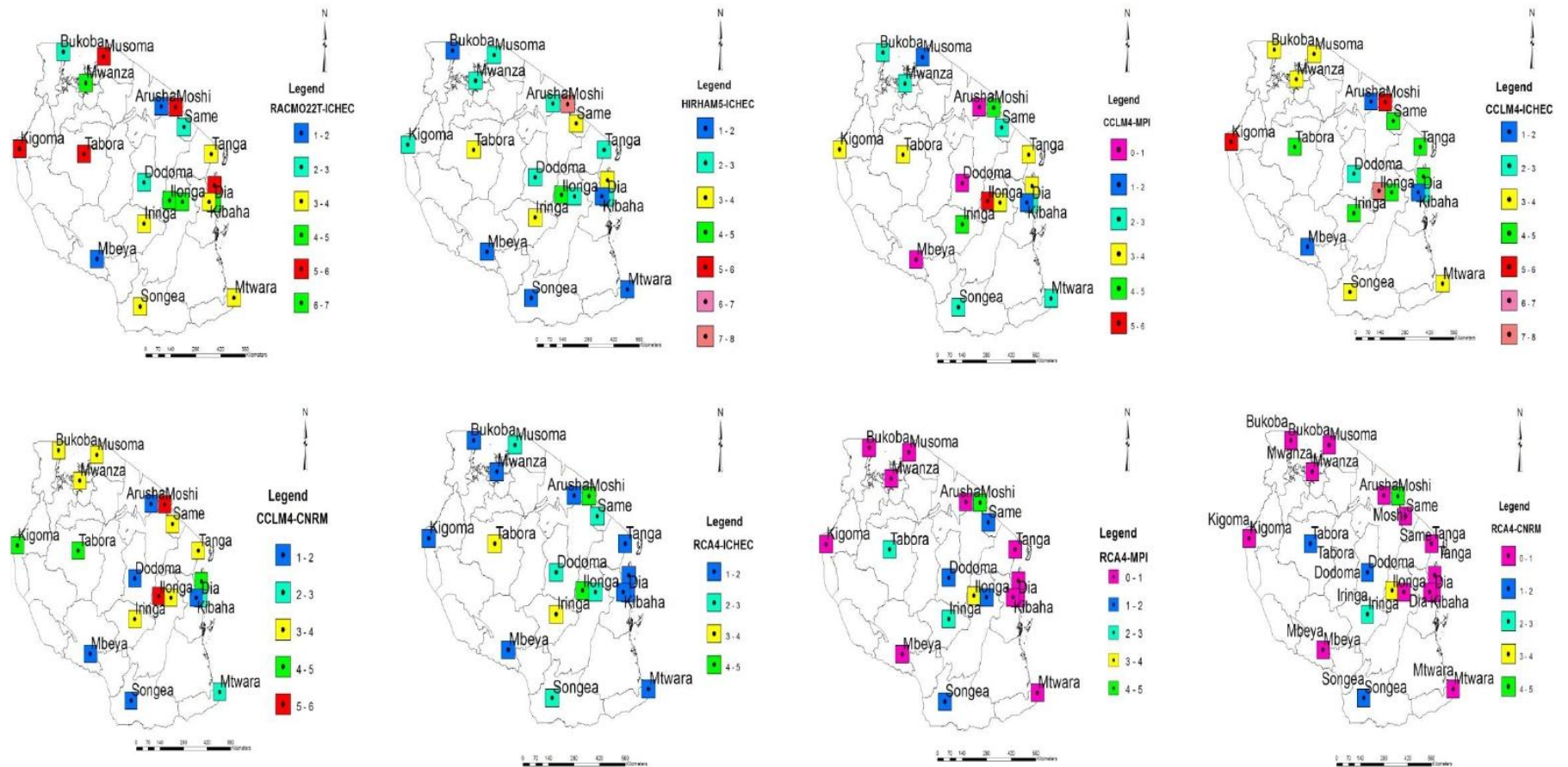


Figure 6. RMSE of RCMs (°C) in simulating maximum temperature at different stations in Tanzania

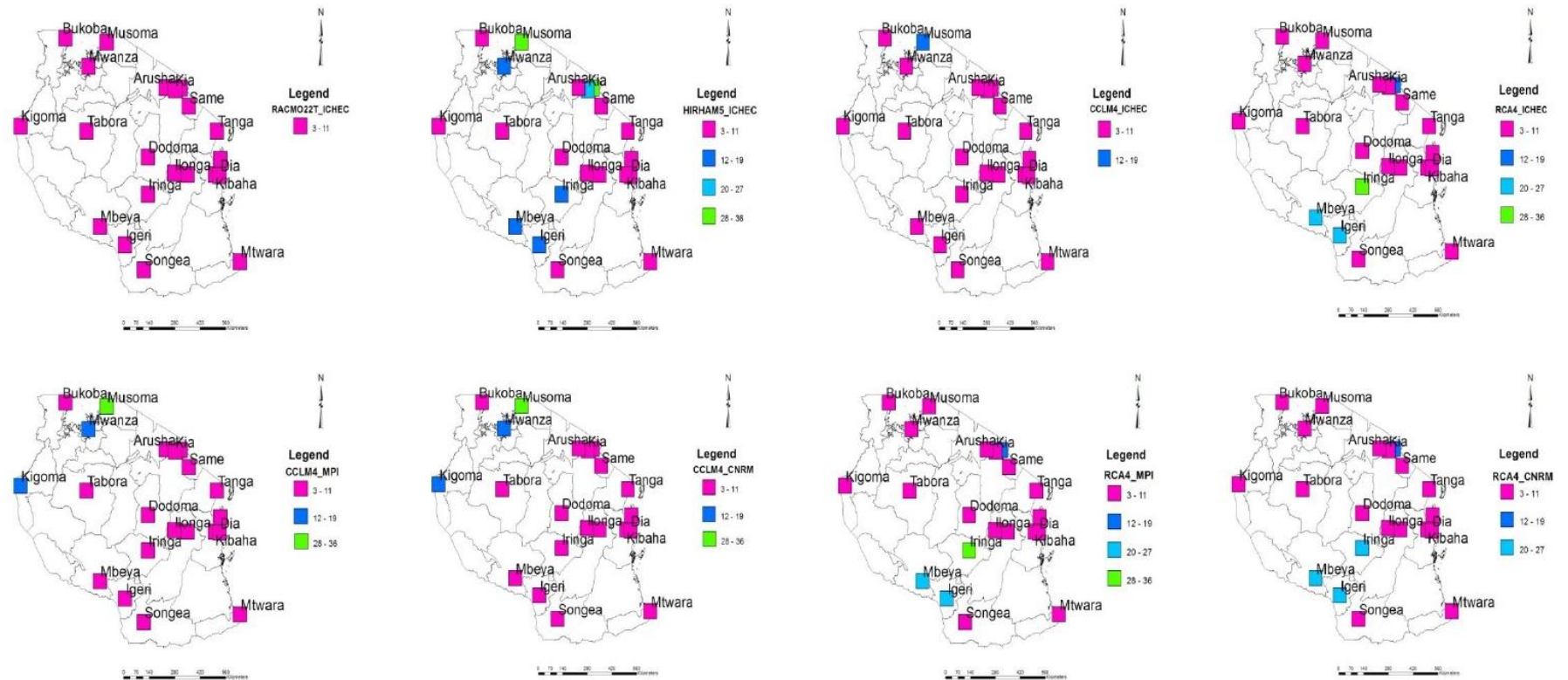


Figure 7. NRMSE (%) of RCMs in simulating rainfall at different stations in Tanzania

Table 3: Pearson correlation coefficient between observed and simulated annual cycles of minimum and maximum temperature

Station	RACMO22T-CHEC		HIRHAM5-ICHEC		CCLM-MPI		CCLM-CNRM		CCLM-ICHEC		RCA4-MPI		RCA4-ICHEC		RCA4-CNRM	
	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax
Arusha	0.7	0.4	0.7	0.9	0.7	0.9	0.9	0.8	0.8	0.9	0.8	0.8	0.8	0.6	0.8	0.8
Bukoba	-0.8	-0.5	-0.6	0.1	0.7	0.7	0.8	0.7	0.7	0.5	0.8	0.5	0.6	0.3	0.8	0.5
Dia	0.9	0.5	0.9	0.9	0.9	0.9	0.9	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8
Morogoro	0.9	0.3	0.9	0.9	0.9	0.9	0.9	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8
Musoma	-0.3	-0.1	-0.5	0.3	0.8	0.6	0.9	0.8	0.8	0.5	0.8	0.6	0.7	0.3	0.8	0.6
Tanga	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Zanzibar	0.8	0.8	0.9	0.8	0.8	0.6	0.8	0.4	0.8	0.8	0.9	0.9	0.9	0.9	0.8	0.8
Same	0.9	0.4	0.9	0.9	0.9	0.9	0.9	0.7	0.9	0.9	0.9	0.9	0.8	0.8	0.9	0.8
Mwanza	-0.5	0.6	-0.3	0.9	0.9	0.9	0.8	0.9	0.8	0.9	0.3	0.6	0.3	0.6	0.5	0.6
Moshi	0.9	0.4	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.9	0.8	0.9	0.8	0.7	0.8	0.8
Ilonga	0.9	0.4	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.8
Kibaha	0.9	0.1	0.9	0.9	0.9	0.9	0.9	0.6	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8
Dodoma	0.8	0	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.8	0.9	0.7	0.9	0.4	0.9	0.5
Iringa	0.9	0.5	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.9	0.9	0.7	0.9	0.6	0.9	0.4
Kigoma	-0.1	0.8	-0.2	0.9	0.9	-0.3	0.9	0.8	0.9	0.9	0.9	0.8	0.9	0.9	0.9	0.7
Mbeya	0.9	0.6	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.8	0.9	0.7
Mtwara	0.9	-0.2	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Songea	0.9	0.5	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.9	0.9	0.8	0.9	0.8
Tabora	0.5	0.6	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.7	0.7	0.5	0.6	0.7	0.4
Average	0.6	0.4	0.6	0.8	0.9	0.8	0.9	0.8	0.9	0.8	0.8	0.8	0.8	0.7	0.8	0.7

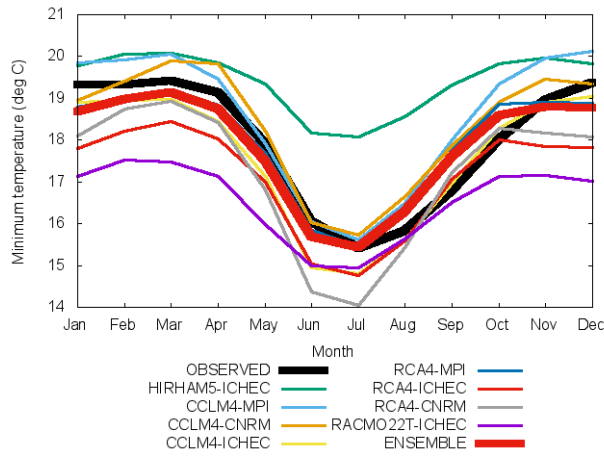
Table 4: Pearson correlation coefficient between observed and simulated annual cycles of rainfall

Station	RACMO22T-	HIRHAM5-	CCLM-	CCLM-	CCLM-	RCA4-	RCA4-	RCA4-
Arusha	0.53	0.55	0.48	0.71	0.42	0.66	0.39	0.69
Bukoba	0.59	0.84	0.42	0.63	0.49	0.66	0.66	0.57
Dia	0.87	0.80	0.74	0.41	0.85	0.80	0.88	0.43
Morogoro	0.76	0.84	0.66	0.35	0.71	0.67	0.74	0.56
Musoma	0.40	0.44	0.42	0.66	0.38	0.76	0.47	0.65
Tanga	0.82	0.55	0.69	0.36	0.65	0.68	0.65	0.42
Zanzibar	0.95	0.76	0.79	0.44	0.86	0.85	0.89	0.44
Same	0.62	0.43	0.79	0.40	0.67	0.68	0.61	0.61
Mwanza	0.42	0.87	0.64	0.72	0.68	0.70	0.51	0.67
Moshi	0.27	0.24	0.35	0.35	0.22	0.51	0.45	0.55
Ilonga	0.82	0.74	0.74	0.54	0.77	0.74	0.71	0.58
Kibaha	0.84	0.84	0.66	0.35	0.78	0.73	0.84	0.45
Kia	0.41	0.41	0.47	0.48	0.36	0.54	0.44	0.55
Mlingano	0.42	0.20	0.58	0.56	0.55	0.47	0.65	0.49
Dodoma	0.91	0.95	0.92	0.87	0.91	0.78	0.70	0.54
Iringa	0.94	0.95	0.93	0.84	0.93	0.82	0.82	0.67
Kigoma	0.87	0.87	0.83	0.96	0.83	0.92	0.87	0.84
Mbeya	0.93	0.96	0.95	0.89	0.93	0.89	0.90	0.80
Mtwara	0.93	0.96	0.75	0.55	0.93	0.71	0.68	0.65
Songea	0.96	0.96	0.97	0.95	0.95	0.88	0.91	0.82
Tabora	0.87	0.93	0.89	0.92	0.88	0.86	0.79	0.76
Igeri	0.92	0.89	0.93	0.90	0.88	0.92	0.91	0.87
Average	0.73	0.73	0.71	0.63	0.71	0.74	0.70	0.62

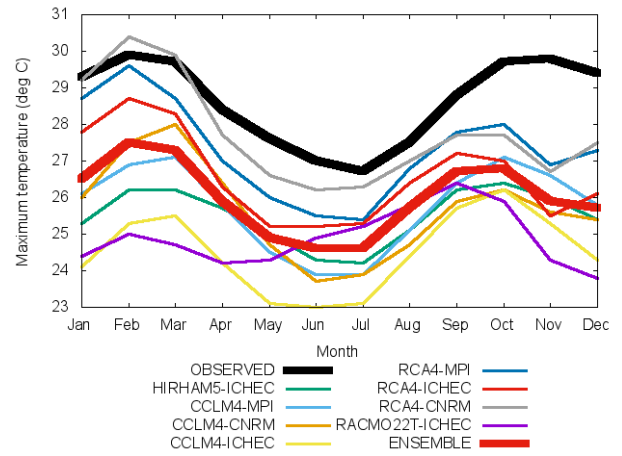
2.3.2 Annual cycle of rainfall and temperatures

The performance of RCMs in simulating the annual cycle of TN and TX for Tanzania as a whole is presented in Figure 8. Before comparison, the values of observed TN and TX from 22 stations are averaged to get a single time series of TN and TX to compare with RCMs outputs (which are calculated in the same way). It is found that overall the RCMs capture the timing of the annual cycles of TN and TX, although they do not in general reproduce the magnitude of TN and TX. HIRHAM5 driven by ICHEC and CCLM4 driven by MPI and CNRM overestimate TN throughout the annual cycle. RACMO22T driven by ICHEC, and RCA4 driven by ICHEC and CNRM underestimate TN. The RCMs, including the ensemble average, all systematically underestimate TX throughout the year. Therefore, it can be concluded that CORDEX RCMs reproduce the timing of the annual cycle in TN and TX, but underestimate TX climatology. RCA4 driven by all three GCMs reproduce the magnitude of observed TN and TX better than other models.

The performance of RCMs in simulating the annual cycle of rainfall over bimodal and unimodal regions of Tanzania is presented in Figure 9. Before comparison the values of observed rainfall from the 14 stations in the bimodal area and the 8 stations in the unimodal are averaged to get a single time series of observed rainfall to compare with the RCMs output. Over the bimodal region (see Figure 9a) the observed data exhibit two peaks of rainfall, a primary maximum is in April, a secondary one is in November and a low (minimum) in June, July and August. The RCMs systematically underestimate rainfall amount particularly in the MAM season and overestimate the rainfall amount in the OND season. In the unimodal region (see Figure 9b) the length of the rainy season extends from September to May having its peak in the month of January. Further, the models, including the ensemble average, overestimate the rainfall amount from September to January.

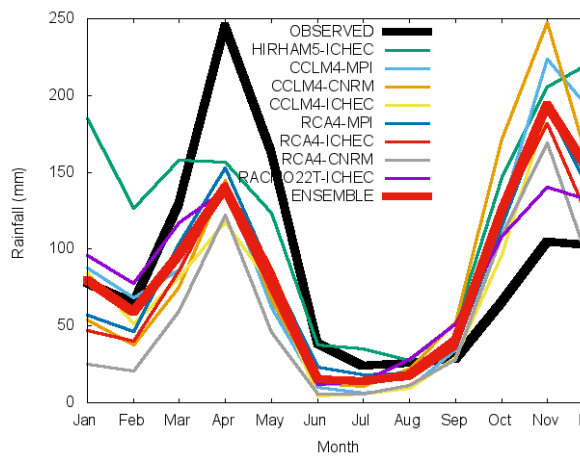


(a) TN

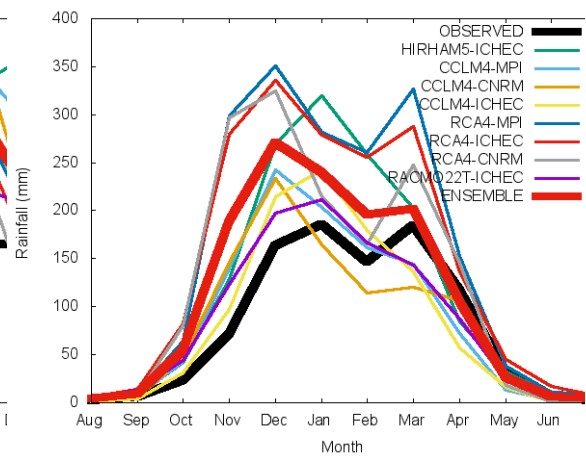


(b) TX

Figure 8. Observed and simulated monthly TN and TX over Tanzania (calculated from 1971-2005).



(a) bimodal region



(b) unimodal region

Figure 9. Observed and simulated monthly mean rainfall in bimodal and unimodal regions (calculated from 1971-2005).

2.3.3 Interannual variability of TN, TX and rainfall

Outputs from CORDEX RCMs driven by ERA-Interim data are used to assess the ability of the RCMs to simulate inter-annual variations of TN, TX and rainfall. These data are available for the period of 1989-2008. The performance of the models in simulating interannual variability in TN and TX is presented in Figure 10 (a), (b). This figure shows that all RCMs captured the pattern of interannual variability in TN and TX well. The magnitude of TN is overestimated by all RCMs. All RCMs including the ensemble average underestimate the magnitude of TX.

The performance of CORDEX RCMs in simulating interannual variability of rainfall is analyzed by comparing simulated and observed interannual variations in rainfall in bimodal and unimodal regions (see Figure 11 (a), (b)). All RCMs except HIRHAM5 reproduce the interannual variability of rainfall in unimodal regions. Furthermore, all RCMs except RCA4 reproduce the interannual variability of rainfall in bimodal regions. It can be concluded that CORDEX RCMs driven by ERA-interim data fairly capture the interannual variability of rainfall in unimodal and bimodal regions.

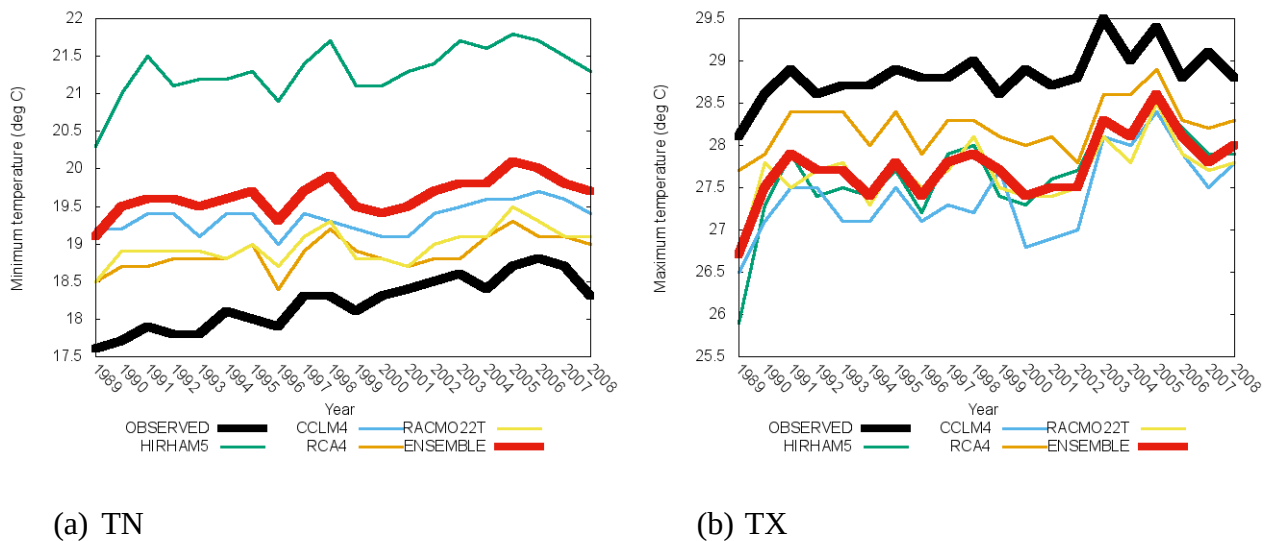


Figure 10. Annual average observed and simulated TN and TX of Tanzania

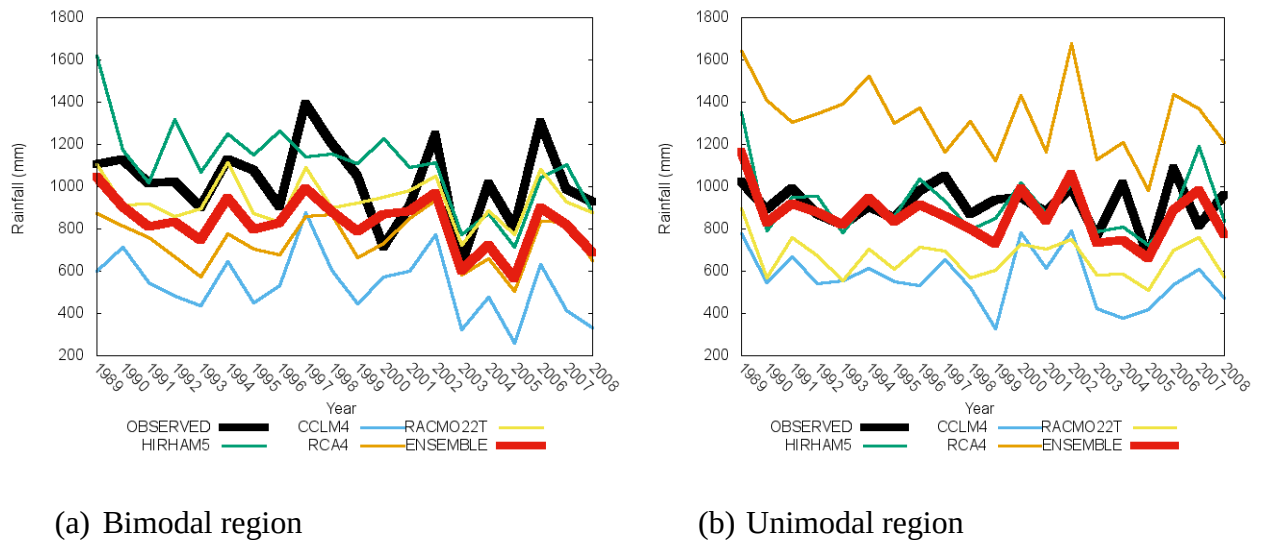


Figure 11. Annual average observed and simulated rainfall in the bimodal and unimodal regions

2.3.4 Trends in observed and simulated temperatures and rainfall

The performance of the models requires further examination, particularly in their ability to reproduce trends in TN, TX and rainfall. However, the analysis of observed rainfall trends in bimodal and unimodal regions indicated decreasing trend that is non-statistically significant (Table 5). These trends are reproduced by most of the models. For instance observed interannual rainfall in bimodal region shows non-statistically significant decreasing trends of (-2.342 mm/year). This trend is captured by the ensemble average, CCLM4 driven by CNRM, ICHEC, and RCA4 driven by MPI and ICHEC. The CCLM4 driven by CNRM, ICHEC, and RCA4 driven by MPI revealed decreasing trend in annual rainfall with gradients of (-2.559, -1.625 and -1.564 mm/year) respectively. These gradients are closer to the observed gradient of (-2.342 mm/year). The ensemble average however, shows a lowest decreasing gradient of (-0.052 mm/year). On the other hand, RACMO22T and HIRHAM5 both driven by ICHEC, and CCLM4 driven by MPI indicated increasing trend in interannual rainfall.

The trend in interannual rainfall over unimodal region indicate non-statistically significant decreasing trend of (-1.621 mm/year). This trend is captured by RCMs (CCLM4 driven by MPI, RCA4 driven ICHEC and CNRM). The CCLM4 driven MPI

shows a statistically significant decreasing trend with a gradient of (-3.735 mm/year). The ensemble average, RACMO22T and HIRHAM5 both driven by ICHEC, CCLM4 driven by CNRM, and CHEC and RCA4 driven by MPI shows an increasing trend in interannual rainfall over unimodal region.

Table 5 the Mann-Kendall trend and Sen's slope estimate in simulated and observed rainfall in bimodal and unimodal regions.

Regional Climate Model	Bimodal region	Unimodal region
	Gradient (mm/year)	Gradient (mm/year)
RACMO22T_ICHEC	0.218(.)	2.586(*)
HIRHAM5_ICHEC	1.794(.)	1.216(.)
CCLM4_MPI	1.087	-3.735(+)
CCLM4_CNRM	-2.559(.)	4.996(*)
CCLM4_ICHEC	-1.625(.)	2.078(.)
RCA4_MPI	-1.564(.)	0.151(.)
RCA4_ICHEC	-0.217(.)	-1.639(.)
RCA4_CNRM	2.349(.)	-0.060(.)
OBSERVED	-2.342(.)	-1.639(.)
ENSEMBLE	-0.052(.)	0.578(.)

(*) trend significant at $\alpha = 0.05$;(+) trend significant at $\alpha = 0.1$; and (.): trend not significant.

The ability of the RCMs to simulate trends in interannual rainfall at different stations in bimodal and unimodal regions is analysed from Table 6 and 7. In bimodal region, the trends appear predominantly negative at most stations except Dar es Salaam (Dia), Musoma, Mwanza, Kilimanjaro (Kia) and Zanzibar, where trends appears to be positive. The decreasing trends in observed rainfall are non-statistically significant at all stations except Same, where it appears to have decreasing trend at 99.95% significant level. The RCMs fairly captured the non-statistically decreasing trends in interannual rainfall at different stations; however, the gradient of the trends is not reproduced well by the models. Table 6 depict non-significant decreasing trend in interannual rainfall at different station in the unimodal region, except Dodoma and Mbeya which shows non-significant increasing trends. The models fails to reproduce the decreasing trends at most station in the unimodal region. For instance RACMO22T is indicating non-significant increasing trends. It is worth therefore to mention that the RCMs captured the non-significant trends in both unimodal and bimodal regions but fails to reproduce the magnitude of the trend in most stations.

Table 6 the Mann-Kendall trend and Sen's slope estimate (mm/year) in simulated and observed rainfall at different stations in bimodal region.

STATION S	OBSERVED	RACMO 22T-	HIRHAM 5-ICHEC	CCLM4 -MPI	CCLM4- CNRM	CCLM4 -ICHEC	RCA4- MPI	RCA4- ICHEC	RCA4- CNRM	ENSEMBLE
Arusha	-4.500 (.)	2.364(.)	3.739(.)	-2.624(.)	2.813(.)	0.493(.)	1.384(.)	1.090(.)	1.497(.)	1.595(.)
Bukoba	-5.236 (.)	3.256(**)	-5.977	0.674(.)	2.581(.)	-0.888(.)	-0.034(.)	-0.918(.)	0.327(.)	0.653(.)
Dia	0.760(.)	-2.227(.)	2.978(.)	4.565(.)	-4.273(.)	-5.151(.)	-2.582(.)	-2.471(.)	6.006(.)	-0.947(.)
Morogoro	-2.347(.)	-1.570(.)	5.635(.)	0.885(.)	-3.716(.)	-0.916(.)	-0.833(.)	-5.363(.)	1.486(.)	0.113(.)
Musoma	2.938(.)	3.586(.)	-13.302(.)	9.818(.)	-12.625(.)	-9.277(.)	-0.917(.)	0.707(.)	-0.954(.)	-2.293(.)
Tanga	-5.026(.)	-1.304(.)	-0.770(.)	1.112(.)	-1.752(.)	4.491(.)	-2.332(.)	0.023(.)	2.960(+)	0.153(.)
Zanzibar	1.705(.)	-4.239(.)	-2.098(.)	3.541(.)	-5.687(.)	-2.696(.)	-3.844(.)	-1.452(.)	4.710(+)	-0.456(.)
Same	-4.561(+)	2.549(+)	0.567(.)	0.150(.)	1.197(.)	1.525(.)	0.009(.)	0.910(.)	2.036(.)	1.537(.)
Mwanza	3.034(.)	2.186(.)	-5.910(.)	6.716(.)	2.610(.)	-7.242(.)	0.353(.)	-0.133(.)	-0.027(.)	-0.612(.)
Moshi	-4.871(.)	3.039(+)	9.215(.)	-1.592(.)	0.076(.)	2.073(.)	-2.074(.)	2.817(.)	-0.870(.)	2.689(.)
Ilonga	-6.780(.)	-1.218(.)	2.379(.)	-0.987(.)	0.477(.)	0.206(.)	1.487(.)	-0.388(.)	0.532(.)	0.284(.)
Kibaha	-3.887(.)	-1.910(.)	3.802(.)	3.611(.)	-4.758(.)	-4.964(.)	-1.126(.)	-3.859(.)	4.597(.)	-1.164(.)
Kia	0.000(.)	2.074(.)	5.883(.)	-0.683(.)	0.220(.)	1.216(.)	0.105(.)	1.640(.)	1.158(.)	1.581(.)
Mlingano	-4.488(.)	0.588(.)	2.047(.)	-0.985(.)	-1.981(.)	-0.376(.)	-3.634(.)	-3.157(.)	1.958(.)	-0.740(.)

(***) trend significant at $\alpha = 0.001$; (**) trend significant at $\alpha = 0.01$; (*) trend significant at $\alpha = 0.05$; (+) trend significant at $\alpha = 0.1$ and (.) trend not significant.

Table 7 the Mann-Kendall trend and Sen's slope estimate (mm/year) in simulated and observed rainfall at different stations in unimodal region

STATION S	OBSERVED	RACM O22T-	HIRHA M5-	CCLM4- MPI	CCLM4- CNRM	CCLM4- ICHEC	RCA4- MPI	RCA4- ICHEC	RCA4- CNRM	ENSEM BLE
Dodoma	1.890(.)	1.540(.)	1.908(.)	-3.079(.)	10.126(*)	0.548(.)	2.229(.)	1.940(.)	0.039(.)	1.461(.)
Iringa	-0.859(.)	1.650(.)	3.885(.)	-4.586(.)	11.030(*)	-1.548(.)	-0.881(.)	0.192(.)	-0.949(.)	1.311(.)
Mbeya	0.812(.)	1.720(.)	3.388(.)	-2.367(.)	8.172(*)	-0.568(.)	1.386(.)	1.188(.)	-6.173(.)	-0.195(.)
Mtwara	-5.386(.)	3.838(.)	0.244(.)	-10.81(+)	-1.797(.)	6.407(+)	0.013(.)	-8.978(*)	-0.492(.)	-1.907(.)
Kigoma	-3.727(+)	1.262(+)	-2.402(.)	3.391(.)	-4.339(.)	1.356(.)	0.403(.)	0.655(.)	-1.313(.)	-0.245(.)
Songea	-7.133(*)	2.483(.)	1.624(.)	-3.567(.)	12.008(*)	4.020(.)	0.345(.)	0.457(.)	1.751(.)	1.905(.)
Tabora	-1.484(.)	3.322(.)	-0.606(.)	-3.486(.)	-3.803(+)	-1.928(.)	3.167(+)	-0.243(.)	-2.217(.)	-0.766(.)
Igeri	-6.190(+)	3.646(+)	4.807(.)	-3.324(.)	10.318(*)	1.508(.)	-0.901(.)	-14.105(+)	7.622(.)	1.089(.)

(***) trend significant at $\alpha = 0.001$; (**) trend significant at $\alpha = 0.01$; (*) trend significant at $\alpha = 0.05$; (+) trend significant at α

= 0.1 and (.) trend not significant.

The performance of the RCMs to simulate trends in TN and TX for Tanzania is presented in Table 8. Observed data indicate increasing trends in TN and TX at 99.9% significant level. These trends are reproduced by the models. Furthermore the models reproduce fairly the gradient of TN. These results suggest the potential use of the CORDEX RCMs in simulating TN and TX over Tanzania.

Table 8: The Mann-Kendall trend and Sen's slope estimate in simulated and observed minimum temperature

Regional Climate Model	TN (°C/year)	TX (°C/year)
RACMO22T-ICHEC	0.017(***)	0.011(**)
HIRHAM-ICHEC	0.013(**)	0.009(+)
CCLM-MPI	0.019(***)	0.021(**)
CCLM-CNRM	0.017(***)	0.010(+)
CCLM-ICHEC	0.018(***)	0.016(+)
RCA-MPI	0.021(***)	0.017(**)
RCA-ICHEC	0.019(***)	0.015(**)
RCA-CNRM	0.019(***)	0.013(**)
ENSEMBLE	0.018(***)	0.016(***)
OBSERVED	0.029(***)	0.020(***)

(***) trend significant at $\alpha = 0.001$; (**) trend significant at $\alpha = 0.01$ and (+) trend significant at $\alpha = 0.1$

The ability of the RCMs to simulate trends and gradient in TN and TX at different stations in Tanzania is presented in Table 9-10. The models captured well the trends in TN and TX. However, the models fail to reproduce non-significant decreasing trend in minimum temperature over Same, Mwanza and Kigoma weather stations. This could be due to complex topographical terrain (mountains and Lakes) surrounding these stations and complex stable boundary layer dynamics associated with the orography that may not be well represented in the models. In generally, CORDEX RCMs captured the trends in temperatures at different stations.

Table 9 the Mann-Kendall trend and Sen's slope estimate (°C/year) in simulated and observed TX at different stations in Tanzania

Stations	OBSERVED	ENSEMBLE	RACMO22T - ICHEC	HIRHAM5- ICHEC	CCLM 4-MPI	CCLM4- CNRM	CCLM4 -ICHEC	RCA4- MPI	RCA4- ICHEC	RCA4- CNRM
Arusha	0.012(.)	0.014(**)	0.006(.)	0.000(.)	0.026(*)	0.014(.)	0.013(.)	0.016(*)	0.011(+)	0.013(*)
Bukoba	0.018(**)	0.016(***)	0.000(.)	0.025(**)	0.018(*)	0.018(***)	0.018(*)	0.017(*)	0.016(**)	0.019(**)
Dia	0.010	0.015(***)	0.020(***)	0.008(.)	0.014(+)	0.015(*)	0.022(*)	0.016(**)	0.014(*)	0.007(.)
Morogor	0.018(*)	0.017(***)	0.026(***)	0.004(.)	0.016(+)	0.016(.)	0.018(.)	0.016(*)	0.019(*)	0.011(.)
Musoma	0.026(***)	0.016(***)	-0.001(.)	0.016(**)	0.020(*)	0.017(*)	0.020(*)	0.016(*)	0.020(**)	0.018(**)
Tanga	0.004(.)	0.015(***)	0.021(***)	0.010(+)	0.014(*)	0.014(**)	0.016(*)	0.020(***)	0.011(+)	0.008(.)
Zanzibar	0.001(.)	0.014(***)	0.020(***)	0.011(*)	0.014(*)	0.010(**)	0.014(**)	0.018(**)	0.013(+)	0.008(.)
Same	0.011(.)	0.012(**)	0.007(.)	0.005(.)	0.018(*)	0.020(+)	0.012(.)	0.018(**)	0.009(.)	0.007(.)
Mwanza	0.036(***)	0.016(***)	0.003(.)	0.018(**)	0.022(*)	0.019(**)	0.017(.)	0.015(*)	0.018(**)	0.019(**)
Moshi	0.022(**)	0.015(**)	0.006(.)	0.004(.)	0.023(*)	0.021(*)	0.006(.)	0.018(**)	0.008(.)	0.013(*)
Ilonga	0.014(+)	0.016(**)	0.026(***)	0.004(.)	0.025(*)	0.012(.)	0.020(.)	0.015(.)	0.018(+)	0.013(.)
Kibaha	0.029(**)	0.016(***)	0.022(**)	0.008(.)	0.012(.)	0.015(+)	0.026(*)	0.020(**)	0.015(*)	0.006(.)
Dodoma	0.008(.)	0.014(**)	0.018(.)	0.006(.)	0.040(*)	-0.013(.)	0.024(.)	0.013(.)	0.016(*)	0.017(*)
Iringa	0.029(***)	0.014(**)	0.018(**)	0.003(.)	0.027(*)	-0.003(.)	0.020(+)	0.015(*)	0.016(*)	0.018(**)
Kigoma	0.043(***)	0.015(***)	0.008(+)	0.016(**)	0.008(.)	0.018(**)	0.011(.)	0.016(+)	0.020(***)	0.022(**)
Mbeva	0.026(***)	0.016(**)	0.011(*)	0.008(.)	0.027(*)	-0.001(.)	0.018(.)	0.016(*)	0.021(**)	0.019(**)
Mtwara	0.009(+)	0.015(***)	0.016(***)	0.012(*)	0.028(*)	0.010(**)	0.010(.)	0.012(+)	0.023(***)	0.010(+)
Songea	0.023(***)	0.012(*)	0.014(**)	0.004(.)	0.026(*)	-0.023(+)	0.007(.)	0.014(*)	0.019(**)	0.014(*)
Tabora	0.049(***)	0.019(**)	0.004(.)	0.017(+)	0.026(*)	0.024(*)	0.021(*)	0.017(+)	0.015(**)	0.024(**)

(***) trend significant at $\alpha = 0.001$; (**) trend significant at $\alpha = 0.01$; (*) trend significant at $\alpha = 0.05$, (+) trend significant at $\alpha = 0.1$ and (.) non-significant trend

Table 10 the Mann-Kendall trend and Sen's slope estimate (°C/year) in simulated and observed TN at different stations in Tanzania

Stations	OBSERVED	RACMO22T- ICHEC	HIRHAM5- ICHEC	CCLM4- MPI	CCLM4- CNRM	CCLM4- ICHEC	RCA4- MPI	RCA4- ICHEC	RCA4- CNRM
Arusha	0.036(***)	0.016(**)	0.009(*)	0.017(**)	0.021 (***)	0.017(***)	0.023(***)	0.015(**)	0.024(***)
Bukoba	0.010(.)	0.010(*)	0.025(***)	0.021(***)	0.018(***)	0.013(***)	0.025(***)	0.015(***)	0.022(***)
Dia	0.039(***)	0.017(***)	0.009(*)	0.016(**)	0.015(***)	0.018(***)	0.021(***)	0.020(***)	0.018(**)
Morogoro	0.034(***)	0.022(***)	0.011(*)	0.015(**)	0.015(***)	0.019(***)	0.021(***)	0.025(***)	0.018
Musoma	0.021(*)	0.009(*)	0.018(**)	0.024(***)	0.015(***)	0.014(**)	0.020(**)	0.019	0.020(***)
Tanga	0.028(***)	0.018(***)	0.015(***)	0.017(**)	0.014(**)	0.015(***)	0.022(***)	0.019(***)	0.015(**)
Zanzibar	0.046(***)	0.018(***)	0.011(**)	0.015(**)	0.013(***)	0.013(***)	0.023(***)	0.019(***)	0.017(**)
Same	-0.001(.)	0.016(***)	0.015(**)	0.014(**)	0.019(***)	0.017(***)	0.020(***)	0.015(**)	0.014(**)
Mwanza	-0.007(.)	0.008(+)	0.017(**)	0.023(**)	0.018(***)	0.016(**)	0.020(***)	0.020(**)	0.021(***)
Moshi	0.014(+)	0.018(**)	0.013(**)	0.016(**)	0.021(***)	0.016(***)	0.022(***)	0.016(***)	0.019(***)
Ilonga	0.055(***)	0.023(***)	0.010(*)	0.017(**)	0.017(***)	0.020(***)	0.020(***)	0.024(***)	0.017(***)
Kibaha	0.054(***)	0.018(***)	0.009(+)	0.016(**)	0.016(***)	0.019(***)	0.024(***)	0.022(***)	0.017(**)
Dodoma	0.019(**)	0.023(***)	0.010(+)	0.023(***)	0.010(*)	0.023(***)	0.022(**)	0.018(**)	0.020(***)
Iringa	0.000(.)	0.022(***)	0.012(**)	0.017(**)	0.014(**)	0.021(***)	0.021(***)	0.018(***)	0.019(***)
Kigoma	-0.009(.)	0.014(***)	0.017(**)	0.019(**)	0.018(***)	0.014(***)	0.025(***)	0.017(**)	0.022(***)
Mbeva	0.053(***)	0.022(***)	0.011(***)	0.020(***)	0.015(**)	0.022(***)	0.020(**)	0.023(***)	0.018(***)
Mtwara	0.025(**)	0.015(***)	0.013(**)	0.021(***)	0.015(***)	0.018(***)	0.020(***)	0.022(***)	0.018(**)
Songea	0.035(***)	0.018(***)	0.009(*)	0.023(**)	0.012(*)	0.021(***)	0.021(**)	0.025(***)	0.013(*)
Tabora	0.053(***)	0.014(**)	0.014(+)	0.023(***)	0.019(***)	0.024(***)	0.022(**)	0.016(*)	0.029(**)

(***) trend significant at $\alpha = 0.001$; (**) trend significant at $\alpha = 0.01$; (*) trend significant at $\alpha = 0.05$, (+) trend significant at $\alpha = 0.1$ and (.) non-significant trend

2.4 Conclusions

In this study, four CORDEX Regional Climate Models (RCMs) driven by three GCMs (MPI, ICHEC and CNRM) and ERA-Interim data are analysed for their ability to simulate historical climate conditions of Tanzania. The analysis is based on determining how well the RCMs reproduce climatological trends, and interannual and annual cycles of TN, TX and rainfall. Statistical measures of model performance that include the bias, root mean square error, correlation and trend analysis are used. Results showed that all RCMs captured the annual cycle of TN, TX and rainfall, however, generally fail to reproduce the magnitude of rainfall in the March-April-May (MAM) and October-November-December (OND) seasons. Furthermore, most of the RCMs reasonably reproduce interannual variations and trends in TN and TX. Although RCA4 is slightly better than other RCMs in simulating TN and TX over different stations in Tanzania, all models show reasonably comparable errors. RACMO22T driven by ICHEC simulates rainfall over most stations better than other RCMs irrespective of the driving GCM.

The sources of the uncertainties for RCMs in simulating climate variables at different stations can be compared. These uncertainties come from both RCMs and the driving GCMs. RACMO22T and HIRHAM5 both driven by ICHEC GCM simulate TN, TX and rainfall with different level of performance over all stations, suggesting this difference is mainly due to RACMO22T and HIRHAM5 formulations. The uncertainties that arise from driving GCMs are analyzed when the same RCM driven by different GCMs simulate TN, TX and rainfall differently over most stations. For example, CCLM4 driven by three GCMs (MPI, ICHEC and CNRM), simulate TN differently over most stations. In general, the biases and the RMSE arising from the RCMs and driving GCMs in simulating TN and TX are not too large in most stations. The RCMs simulate TN better than TX in most stations, with TX underestimated almost everywhere. Although simulated rainfall over unimodal compares with observed rainfall with high correlation coefficients, analysis from NBias and NRMSE indicate the models simulate rainfall better over bimodal regions than over unimodal region.

The results presented in this study are useful, first to climate modellers, since the results may help them to try to investigate why one model can well simulate one climate parameter and poorly simulate other climate parameters. The results may also be useful to studies that require weather variables at specific location, for example studies that evaluate the impact of climate change on the agriculture sector, or require specific location climate information. Therefore one can choose specific RCMs that well reproduce the climate of the location of interest.

The results of this study also reveal that the dynamical downscaling although is based on the same first principal conservation equation give quite different results depending on the parameterisation schemes used for different physical, chemical and biological processes and the boundary conditions from the GCMs. The task of choosing suitable RCM for particular region and given meteorological variable is a complex task which in many cases may be more computer and analytically demanding than the climate change task posed by the need of the country. It is recommended that statistical downscaling method to be used for predicting the climate change by using one parameter like moist potential vorticity (MPV) which takes into account the dynamical and thermodynamic variables responsible for the rain formation and incorporates all meteorological scales participating in the climate change process.

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Chapter 3: Assessment of the impacts of climate change on maize production in the Wami Ruvu basin of Tanzania

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Abstract

The IPCC assessment reports confirm that climate change will hit developing countries the hardest. Adaption is on the agenda of many countries around the world. However, before devising adaption strategies, it is crucial to assess and understand the impacts of climate change at regional and local scales. In this study, the impact of climate change on rain-fed maize (*Zea mays*) production in the Wami-Ruvu basin of Tanzania is assessed using process based crop model the Decision Support System for Agro-technological Transfer (DSSAT). The model was calibrated using detailed field and household survey information of (crop yields, soil and management data inputs). Daily minimum and maximum temperatures, rainfall and solar radiation for current climate condition (1971-2000) as well as future climate projections (2010-2039), (2040-2069) and (2070-2099) for two Representative Concentration Path ways (RCPs): RCP45 and RCP85 scenarios were used to drive the crop model. These data were obtained from three high-resolution regional climate models (RCMs), used in the Coordinated Regional Climate Downscaling Experiment program (CORDEX). Impact of climate change on maize production is assessed by analyzing the changes in simulated maize yields for the period 2010-2039, 2040-2069 and 2070-2099 relative to baseline period 1971-2000. Projection results from different models showed that due to climate change, the length of growing season and future maize yields over Wami-Ruvu basin will decrease under both RCP4.5 and RCP8.5 at the current, mid and end of the centuries. However, the projected yields estimates and the length of growing season differ from model to model highlighting the uncertainties associated with the projections. Climate data from the ensemble average of five model members was constructed to address the issue of uncertainties from individual climate models and used to drive DSSAT. Results showed that due to climate change future maize yields over Wami-Ruvu basin will slightly increase relative to the baseline during current century under RCP 4.5 and RCP 8.5. Meanwhile, maize yields will decline in the mid and end centuries. The spatial distribution shows that high decline in maize yields are projected over lower altitude regions due to projected increase in temperatures and decreased rainfall in those areas. The eastern part of the basin will feature decrease in maize yields, while central parts of the basin and the western side of the basin will experience increase in

maize yields during current, mid and end centuries under RCP 4.5 and RCP 8.5. The main reason for decrease and increase maize yields is the projected increase in temperatures that will reduce the length of growing seasons and hence affecting maize productivity. It is therefore recommended that appropriate and adequate adaptation strategies need to be designed to help the communities adapt to the projected decrease in maize production.

3.1 Introduction

Climate change studies including the latest IPCC assessment reports consistently show that many of the world's regions are already experiencing increasing frequency and severity of droughts and floods, increasing inter-annual and inter-seasonal rainfall variability, and warmer temperatures (IPCC 2007, 2013 and 2014). Developing countries, are particularly vulnerable to climate change, especially to extreme weather and climate events due to their high dependence on rain-fed agriculture and natural resources for their livelihoods (Sarker et al, 2012; Akram, 2010; IPCC, 2007, 2012 and 2013). The IPCC (2007) assessment report, projected that between 75 and 250 million of people in Africa will be exposed to increased water stress due to climate change by 2020. In some countries, yields from rainfed agriculture are projected to decline by 50%. Agricultural production, including access to food, in many African countries will be severely compromised (IPCC, 2007). This would further adversely affect food security and exacerbate malnutrition.

African countries need to prioritize on formulation of adaptation strategies and mitigation policy in order to prevent the destructive impacts of future climate change on agriculture (Rowhani et al., 2010). Tanzania as one of African countries will need to seriously consider its adaptation strategies, since agriculture is one of the largest sectors of Tanzania's economy (Ahmed et al., 2011). It is critical to ensure that there are adequate and credible adaptation strategies in this sector. However, in order to begin determining adaptation strategies for the agriculture sector, it is essential to have credible assessment of climate change impacts on crop production to have scientific evidence that would guide the formulation of adaptation policy.

Previous studies in Tanzania (Mwandosya et al., 1998; Agrawala et al., 2003; Ernhart and Twena, 2006; Enfors and Gordon, 2008; Thornton et al., 2009, 2010; Arndt et al., 2011;

Ahmed et al., 2011; and Müller et al., 2011) have assessed the impact of climate change on crop production using climate simulation derived directly from General Circulation Models (GCMs). These models classically run at spatial resolution of 300 km or more such that their climate change projections cannot reproduce climate details at local or region scales where farming practices are predominant. The coarse resolution of GCMs, severely limits the direct use of their output in regional and sub-regional decision making or in impact studies (Masson and Knutti, 2011; Daniel et al., 2012). This limitation is particularly for countries like Tanzania with high regional heterogeneity of its climate, influenced by heterogeneous topography.

The limitation of direct use of GCMs outputs for decision making at regional and sub-regional scales or in impact studies call into questions many prior assessments of climate change impact on crop productions based on GCMs. Furthermore, adaptation strategies and mitigation policy developed based on GCMs simulations are not realistic and might pose significant challenges for anticipatory adaptation in many countries.

In this study we assess the impact of climate change on maize production over Wami-Ruvu basin of Tanzania using high resolution climate data from Regional Climate models (RCMs) and the uncertainties associated with the assessment from individual RCMs and driving GCMs. The main aim is to update the results from previous studies that were based on coarse resolution climate data from the GCMs. Maize is the most important cereal crop in perspectives on financial value and food security in Tanzania (Rowhani et al., 2010; Washington and Pearce, 2012), therefore deserve special attention to be examined on how future climate will affects its production. The Wami-Ruvu basin of Tanzania is chosen due to the fact that, the basin contain many agriculture projects that aims to develop the Southern parts of Tanzania, into a major regional food producer and engine of national economic development (Milder et al., 2012). Moreover, there is no climate change impact study addressing knowledge problem in rain-fed area that have used high resolution climate information.

3.2 Data and Methodology

3.2.1 Study Area

Tanzania which is located in East Africa between latitudes 1°S and 12°S and longitudes 29°E to 41°E has nine basins (URT, 2013). The Wami-Ruvu basin which covers an area of about 66,820 km² is located in six regions: Dar es Salaam, parts of Coast, Morogoro, Dodoma, Tanga and Manyara in the eastern part of Tanzania along latitudes 5°–7°S and longitudes 36°–39°E. The topographical features of the Wami-Ruvu basin are described in detail in URT (2013), it is covered by low lying and mountains landscape (Fig.1). The dominant mountain landscape includes the Uluguru Mountains with an altitude of 400m to 2500m, Nguru Mountains with an altitude of 400 to 2000 m, Rubeho Mountains with an altitude of 500 to 1000 m, Ukaguru Mountains with an altitude of 400 to 1000 m and Nguu Mountains located in the western part of Wami River with an altitude of 400 to 2000 m above mean sea level. The low lying areas include, Mkata plains with an altitude of 400-800 m, Lower Wami with an altitude of 200-400 m, Kisi located south east of Uluguru mountain with an altitude of 140 to 200 m, Kimbiji and Mbezi located to the southern coastal area of Dar es Salaam with an altitude of 50 to 100 m above mean sea level.

The Wami-Ruvu basin is divided into three sub basins: Wami sub basin which covers an area of 43,946 km², the Ruvu sub basin with an area of 18,078 km², and Coastal sub basin with an area of 4,796 km². These sub basins are further divided into seven sub catchments: Kinyasungwe, Mkondoa, Wami, Upper Ruvu, Ngerengere, Lower Ruvu and Coast sub catchments (Fig. 2).

The climate over Wami-Ruvu basin is mainly controlled by the movement of the Inter Tropical Convergence Zone (ITCZ), where some areas within the basin receive unimodal type of rainfall (due to single passage of the ITCZ), while others receive bimodal rainfall (due to double passages of the ITCZ). The former is experienced in the Wami sub basin (Kinyasungwe sub catchment), while the latter is experienced in Wami sub basin (Mkondoa and Wami sub catchments), Ruvu (Upper and lower Ruvu), Ngerengere and Coast sub catchments.

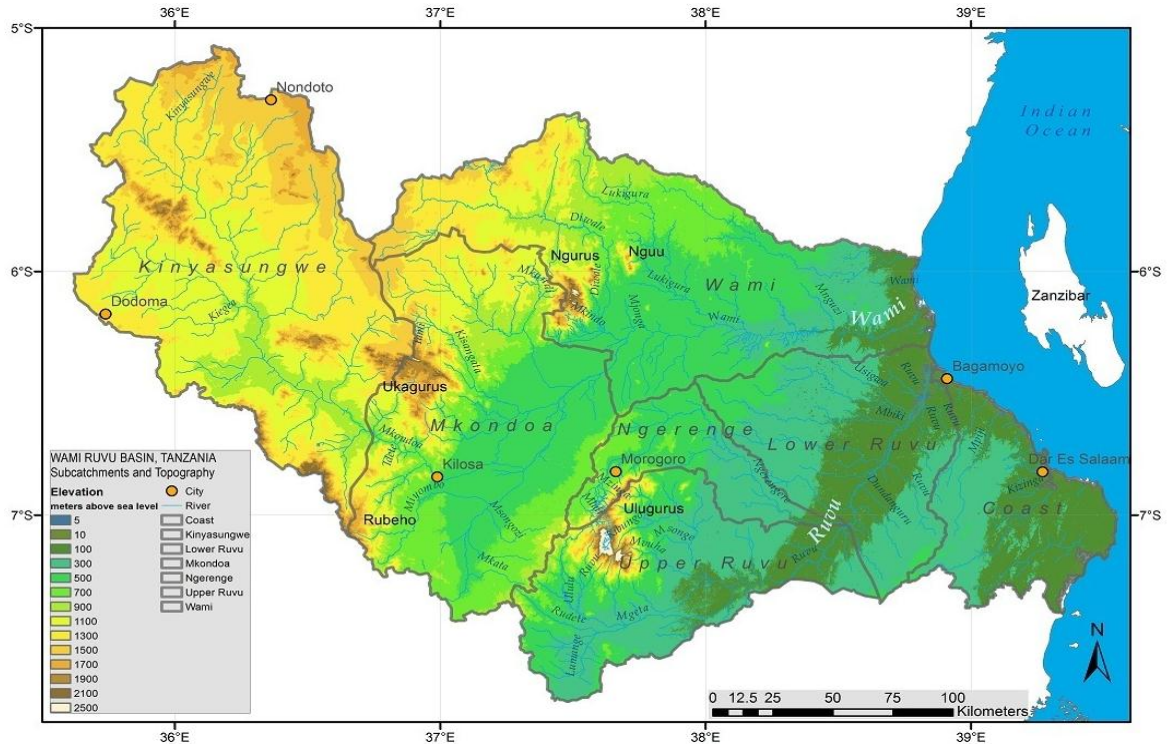


Figure 1. Topographical map of the Wami-Ruvu basin, (adopted from Global Water for Sustainability Program), available at:

[http://dpanther.fiu.edu/dpService/glowProjectServices/project/iWASH%20\(Tanzania\)#](http://dpanther.fiu.edu/dpService/glowProjectServices/project/iWASH%20(Tanzania)#)

Although ITCZ is the dominant driver of rainfall within the basin, but its distribution is possibly influenced by orographic features. For example, in the plains annual rainfall ranges from 800 mm to 1000 mm near the Coast and 500-600 mm inland towards Dodoma and North of Wami sub-basin (Kashaigili, 2011). Over the high grounds, in the Uluguru Mountains, the annual rainfall exceeds 1500 mm (Mwandosya et al., 1998). The eastern slopes of Uluguru Mountain, receive highest annual rainfall of 2500 – 4000 mm while the western slopes receive an annual rainfall of 1200-3100 mm (Mbwaga, 2005). The Nguru-Rubeho Mountains receive rainfall between 800-1200mm, and the Ukaguru Mountains receive rainfall between 1000-1800mm annually (Kashaigili, 2011).

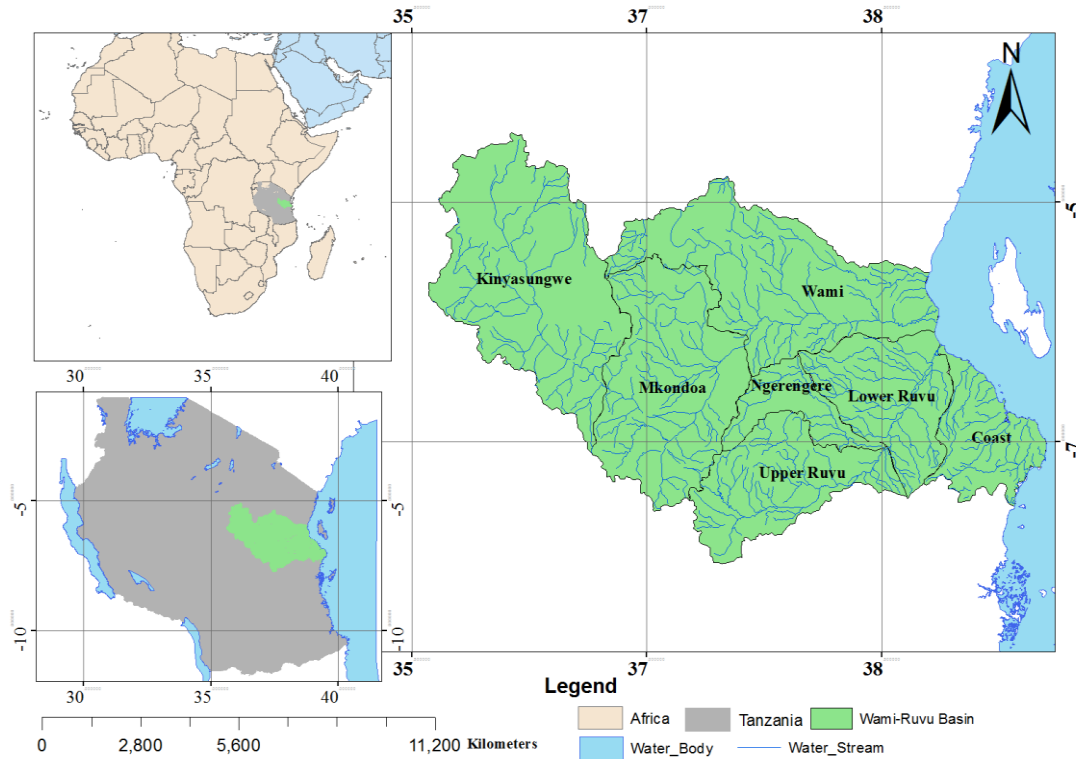


Figure 2 Map of Africa, and Tanzania showing the location of the study area the Wami-Ruvu basin and its seven sub catchment.

The Wami-Ruvu basin is characterized by twelve soils types: Cambisols, Ferralsols, Acrisols, Fluvisols, Luvisols, Lixisols, Arenosols, Leptosols, Nitisols, Vertisols, Planosols and Haplic Phaeozems (Fig.3) (URT, 2013). The dominant soils are Cambisols which cover parts of Bagamoyo, Kisarawe, Mkuranga, Morogoro Rural, Dodoma Urban, Bahi and Chamwino. These types of soils make good agricultural land and are intensively used for agriculture production.



Farming activities in Wami-Ruvu basin are shaped by two agro-ecologies: semi-arid and sub-humid agro-ecologies. The earlier covers parts of Dodoma region and the latter covers parts of Morogoro, Tanga and Coast regions. Crop production in the basin is mainly subsistence. However in recent years the basin has witnessed many agriculture projects, which are outlined in URT, (2012), includes the FEED the FUTURE with an investment cost of USD 300 million, Tanzania Bread-Basket Transformation Project with an investment cost of USD 173 Million, Southern Agriculture Corridor of Tanzania (SAGCOT) with an investment cost of USD 3.4 billion and Rural Livelihoods Development Programme (RLDP) with an investment cost of USD 21 million.

3.2.2 Data

3.2.2.1 Data from RCMs simulations

This study makes use of high resolution climate simulation from the Coordinated Regional Climate Downscaling Experiment program regional climate models (CORDEX_RCMs). CORDEX program is archiving outputs from a set of RCMs simulations over different regions in the world. Fig.4 indicates the CORDEX domain for model integrations. Data sets from CORDEX Africa are accessed from <http://cordexesg.dmi.dk/esgf-web-fe/> website. These data sets are quality controlled and may be used according to the terms of use (<http://wcrp-cordex.ipsl.jussieu.fr/>). The spatial grid resolutions of all CORDEX_RCMs are set to longitude 0.44° and latitude 0.44° using a rotated pole system coordinate where the model operates over an equatorial domain with a quasi-uniform resolution of approximately 50 km by 50 km. For detailed description of CORDEX RCMs and their dynamics and physical parameterization a reader may consult Nikulin et al (2012). The CORDEX_RCMs and their driving GCMs used here are listed in Table 2.

Daily values of minimum, maximum temperatures, rainfall and solar radiation from CORDEX_RCMs for two Representative Concentration Pathways (RCP4.5) and (RCP 8.5) scenarios for the period 1971-2000, 2010-2039, 2040-2069 and 2070-2099 are used. Since climate model simulate climate variables at grids, interpolation technique of inverse square distance weighting average is used to transfer model grid climate simulation to the location where farming is carried out. This enables to use site specific climate information to simulate maize yields. For detailed description about the inverse square weighting average interpolation technique the reader may consult Hartkamp et al (1999) and Ly et al (2013). Interpolated daily minimum, maximum temperatures, rainfall and solar radiations from individual CORDEX_RCMs are used by crop model to simulate maize growth, development and yields.

3.2.2.2 Data for Soils profiles and Management practices

A total of 20 soil profiles data are used in this study, 8 were excavated within the study region and 12 were obtained from Africa soil profiles database (Leenaars, 2013). The

hydrological characteristics of layers for each soil profile are estimated using soil water properties calculator (Saxton and Rawls 2009). Where input parameters are soil type (sand, silt or clay) and organic matter, whereas the output parameters are drained lower limit (SLLL; mm mm⁻¹), drained upper limit (SLDUL; mm mm⁻¹), saturation (SLSAT), and water content for each soil layer (Table 1).

Table 1 Soil physical and chemical characteristics at Mvomero research station, Morogoro, Tanzania

Soil depth	Lower limit	Upper limit	SAT	BD	pH	NO3	NH4	ORG
cm	<i>cm³/cm³</i>	<i>cm³/cm³</i>	<i>cm³/cm³</i>	<i>g/cm³</i>		<i>ugN/g</i>	<i>ugN/g</i>	%
0-5	0.116	0.253	0.432	1.1	5.4	0.45	0.15	0.24
5-15	0.116	0.253	0.432	1.1	5.4	0.45	0.15	0.24
15-30	0.116	0.31	0.452	1.1	5.2	0.45	0.15	0.24
30-45	0.116	0.31	0.452	1.1	5.2	0.45	0.15	0.24
45-67	0.131	0.31	0.468	1.2	6	0.45	0.15	0.11
67-90	0.131	0.31	0.468	1.2	6	0.45	0.15	0.11

Management practices and actual and previous yield information, types of fertilizers were obtained from a comprehensive household panel survey database (National Bureau of Statistics 2012) (Table 2). Information about planting and harvesting dates, planting density and the type of maize cultivars used per farm were obtained from interview conducted across the study region. This information was used to create crop model input data files.

Table 2. Detailed information about the farms used to create crop model data input files

Location name	No.	Planting.	Planting.	Planting density	Planting	Nitrogen	Maize yields	By-product	Planting window
DODOMA	15	1-30	12-1	3	75	50	683	3	12/01-12/15
KONGWA	13	1-30	12-1	3	100	40	603	3	12/01-12/15
MLALI	16	2-28	2-3	4	75	0	571	7	02/02-02/16
MOROGORO	9	2-31	3-3	3	75	40	736	7	03/02-03/16
MLALI-VILLAGE	11	3-29	12-1	2	100	40	1229	2	12/03-12/17
UKAGURU	15	2-28	2-3	3	75	50	871	7	02/02-02/16
NONDOTO	11	2-30	12-1	2	75	0	979	3	12/02-12/16
CHIBWANGULA	10	3-26	12-1	3	75	0	609	3	12/03-12/17
IDIFU	8	2-30	12-1	3	100	0	222	3	12/02-12/16
KIBERASHI	11	1-23	2-3	3	75	0	800	6	02/01-02/15
WAMI-TULIANI	16	1-23	3-3	3	77	30	996	7	03/01-03/15
KILOSA	11	5-31	3-3	3	75	10	1224	5	03/05-03/19
ULAYA	11	7-25	12-1	3	80	10	960	3	12/07-12/21
MBWEWE	8	1-28	2-3	3	75	40	1287	6	02/01-02/15
KIBAKWE	3	15-9	12-1	4	100	40	2167	7	12/15-12/29
GRAND TOTAL	168						861	5	

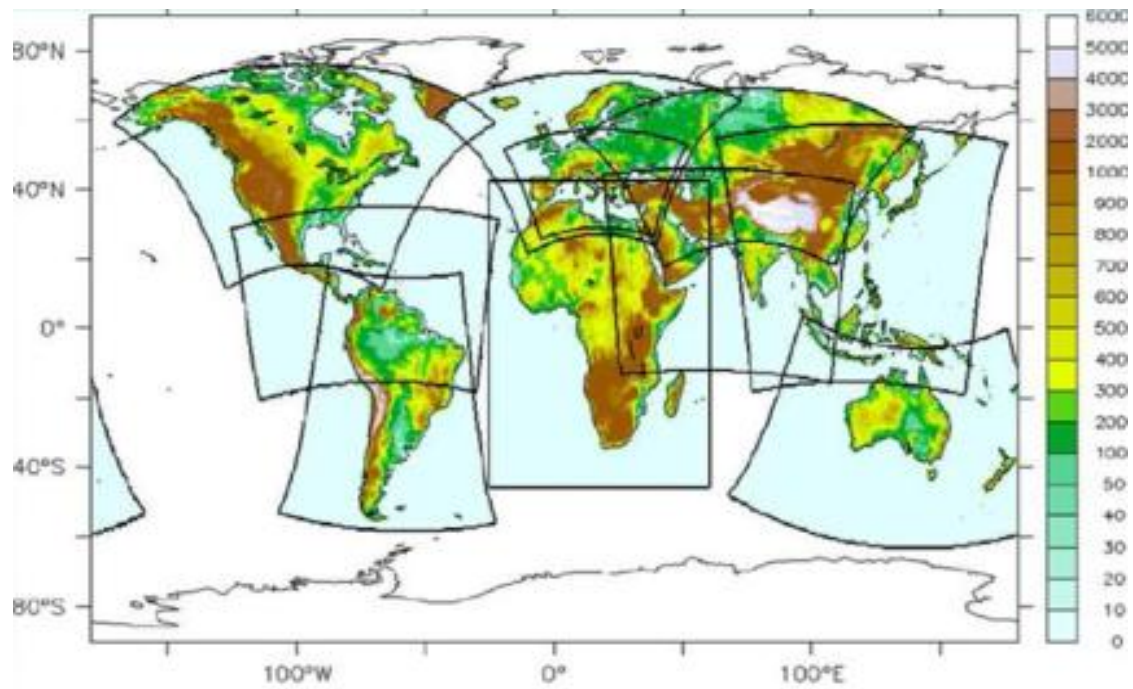


Figure 4 CORDEX regional domain (adopted from Pechlivanidis, 2013)

Table 3. Details of CORDEX-RCMs and the driving GCMs

No	Regional Climate Model	Model Centre	Short name of RCM	Short name General Circulation Model
1	DMI HIRHAM5	Danmarks Meteorologiske Institut(DMI), Danmark	HIRHAM5	ICHEC-EC-EARTH
2	SMHI Rossby Center Regional Atmospheric Model (RCA4)	Sveriges Meteorologiska och Hydrologiska Institut (SMHI), Sweden	RCA4	MPI-M-MPI-ESM-LR ICHEC-EC-EARTH CNRM-CERFACS -CNRM-CM5
3	KNMI Regional Atmospheric Climate Model, version 2.2 (RACMO2.2T)	Koninklijk Nederlands Meteorologisch Instituut (KNMI), Netherlands	RACMO22T	ICHEC-EC-EARTH

3.2.3 Crop model

Crop models simulate crop growth by numerical integration of constituent processes with the aid of computers (Graves et al., 2002). They are used to study crop growth and calculate growth responses to environmental changes. There are different types of crop models that can be classified as descriptive and explanatory. The descriptive model simulates the behaviour of the system (plant organs and processes) in a simple way (Miglietta and Bindi, 1993), where experimental data are used to develop one or more mathematical equations to describe the system. These types of models are suitable only when a quick look is required to describe the behaviour of a crop under field condition where conditions remain relatively stable. Explanatory crop models describe quantitatively the mechanisms and processes that cause the behaviour of the system. To develop explanatory crop model a system is analysed where its processes and mechanisms are quantified separately. An example of explanatory crop model is the Decision Support System for Agro-technological Transfer (DSSAT). This model has been widely used worldwide over the last two decades because it is reasonably accurate, process-oriented, simple to use and requires minimum data sets. The model requires daily solar radiations, minimum and maximum temperatures and rainfall. The other input parameter of the model includes soil properties, crop characteristics and management practices such as planting and harvesting dates, row spacing, plant population, irrigation amount, fertilizer rate and date of application. In this study, we use DSSAT version 4.5 to simulate maize yields over Wami-Ruvu basin of Tanzania. This version has 28 different crop models and new tools to facilitate creation and management of experimental, soil, and weather data files. DSSAT version 4.5 has new application programs for analyzing crop rotation to assess economic risks and environmental impacts. For instance impacts from irrigation, fertilizer and nutrient management, climate variability, climate change, soil carbon sequestration, and precision management.

3.2.4 Model input files

A new protocol of the Agricultural Model inter-comparison and Improvement Project (AgMIP) was used. This protocol has new computing tools for crop modeling and has capacity to handle data from multiple sites through different software such as Data overlay

for Mult-model Export (DOME), that contain data for field overlay, AgMIP Crop Experiment (ACE) database that contains site based crop experiment or from farm survey data. The data are translated into format ready for crop model using QuadUI desktop utility. For detailed information about AgMIP protocol the reader may visit www.agmip.org.

The data preparation was done by creating three excel files: (1) the first file is the FIELD ALL, it contain all information from each farm/field, the file contain information about the planting dates, soil profiles, type and amount of fertilizer used per farm, plant population, plant row spacing and weather stations used (2) the second file the FIELD OVERLAY, it contain information about soil organic carbon, soil water and nitrogen contents, types of cultivars, where in this study SITUKA maize was used due to its drought tolerance and is grown by many farmers in the study area (3) the third file is SEASONAL STRATEGIES contain information about the span of the year from which simulation is carried, the concentration of atmospheric carbon dioxide, automatic planting date and windows. In this study planting date was set to start automatic within planting window only if cumulative rainfall reaches 25mm in three consecutive days. These excel files are translated by QuadUI desktop utility to DSSAT folder. From this folder simulation was initiated by running DSSAT45.BAT file

3.2.5 Model calibration and validation

The Crop–Environment–Resource–Synthesis (CERES)-Maize model is incorporated within DSSAT 4.5 to simulate maize yields as influenced by several factors. The calibration and validation of CERES-Maize model to obtain reasonable estimates of model genetic coefficient was performed by comparing simulated and observed maize yields data at 168 farms (Table 2). The calibration was robust since there was good agreement between simulated and observed yields with coefficient of determination (R^2) of .91. For detailed description on how the model was calibrated and validated a reader may consult Mourice et al (2014).

3.2.6 Simulation of maize yield

Using the calibrated CERES maize model, maize yields simulation was carried out with historical climate data from individual RCMs for the baseline period 1971-2000 and future projections: 2010-2039, 2040-2069 and 2070-2099 for RCP4.5 and RCP 8.5 scenarios. In order to address properly the uncertainties introduced by the climate models in simulating maize yields, an ensemble average of three CORDEX_RCMs driven by three different GCMs was constructed for RCP 4.5 and RCP 8.5 and used to force CERES maize model to simulate maize yields for baseline period (1971-2000), near future (2010-2039) mid (2040-2069) and end centuries (2070-2099).

3.2.7 Spatial interpolation of climate variables, length of growing seasons and maize yields

The spatial distribution of length of growing season, maize yields, seasonal minimum (TN), and maximum (TX) temperatures, rainfall and solar radiation was estimated using the Inverse Distance Weighting (IDW) interpolation technique. This is the deterministic interpolation method. This technique produce interpolated value in the range of input values. The interpolated value is not greater than the highest or lower than the lowest values of input data. The influence of an input point data on interpolated value is isotropic since the influence on the input data point is distance related (Philip and Watson, 1982). The results from this method may not represent the desired surface when the sampling input points are sparse or uneven (Watson and Philip, 1985). This method work in such a way that the characteristics of interpolated surface can be controlled by limiting the input data points used in the calculation of each output data. This can be done using variable or fixed search method. Under variable search method, interpolated value is calculated even if there is no enough points within the maximum distance search radius to meet number of points criteria, then the point within maximum distance are used. If the minimum point required for estimation of unsampled data point the search radius is increased until the required number of points is satisfied. The search radius is increased until the required minimum number of point fall within the radius. The interpolated points used in this study were from 15 farms distributed in the basin almost evenly.

3.3 Results

The impact of climate change on maize production in the Wami-Ruvu basin of Tanzania is assessed using a dynamic crop growth model CERES-maize embedded within DSSAT version 4.5. The model was run under fixed atmospheric carbon dioxide concentration (of 360ppm). This was to limit simulation of other crop processes such as photosynthesis that can affect yields. The change in maize yields simulated here are due to change in climate variables which are derived from the climate models during the present, mid and end centuries under RCP 4.5 and RCP 8.5 scenarios. The climate projections from the RCMs driven by GCMs are used to drive CERES maize model. It is important to note that all presented results are for the main growing season in the study area, that starts from December and ends early June (Table 2).

3.3.1 Temporal averaged maize yields for the baseline period (1971 - 2000).

The temporal averaged maize yields over Wami-Ruvu basin simulated by CERES forced by climate data from different RCM-GCM combinations for the baseline period (1971-2000) are presented in Table 4-8. These tables show that average maize yields over Wami-Ruvu basin for the baseline period (1971-2000) differs when CERES is forced with different RCM-GCM sets. Highest maize yields of 1303 Kg/ha is simulated by CERES forced with RACMO22T-ICHEC and lowest maize yields of 951 Kg/ha is simulated by CERES forced with RCA4-CNRM. CERES simulates maize yields over Wami-Ruvu basin differently even when forced with RACMO22T and HIRHAM5 both driven by same GCM. Mean maize yields of 1303 Kg/ha and 1158 Kg/ha are simulated by CERES forced with RACMO22T and HIRHAM5 respectively. This variation is mainly due to differences in RACMO22T and HIRHAM5 formulation.

CERES simulates maize yields differently even when forced by same RCM driven by different GCMs. It simulates maize yields of 1126 Kg/ha, 1212 Kg/ha, and 951 Kg/ha when forced with RCA4 driven by ICHEC, MPI and CNRM respectively. These variations are mainly coming from differences in formulation of the driving GCMs. Therefore

simulation of maize yields using climate data from individual RCM-GCM sets have large uncertainties that come from both RCM and driving GCM.

To account for uncertainties that arise from RCM and driving GCM, the ensemble average of 5 climate model members was constructed and used to force CERES. Table 9 shows maize yields simulated by CERES forced with ensemble average. This maize yields differ greatly from that of individual models. This is an indication of large uncertainties involved in climate change impact studies particularly for the agriculture sector. However, results from ensemble average that take into account the uncertainties from individual RCMs and driving GCMs are the best estimate of future climate change in the basin. Therefore CERES driven by ensemble average provide reliable estimate of future maize yields in the Wami-Ruvu basin.

3.3.2 The impact of climate change on maize yields over Wami-Ruvu basin.

The percentage change in maize yields relative to the baseline over Wami-Ruvu basin for present (2010-2039), mid (2040-2069) and end (2070-2099) centuries under RCP 4.5 and RCP 8.5 are presented in Table 4-9. It is clear that the impacts of climate change on future maize yields are not considerably big in comparison with the simulated baseline yields. Table 4 presents maize yields when CERES is driven by RACMO22T-ICHEC. From this table, decrease in maize yields by 2.2%, 2.8% and 2.2% are projected in 2010-2039, 2040-2069, and 2070-2099 respectively under RCP 4.5. Slightly higher decrease in maize yields is projected under RCP 8.5 where maximum decrease in maize yields of 4.8% is projected during the end century. This projected change in maize yields are mainly attributed to increased maximum and minimum temperatures. Hampton et al (2012) indicated the increase in temperatures reduces pollen viability, reduces seed yields and reduces seed germination. Moore et al (2012) suggests that increase in temperatures reduce the length of growing season that can either decrease yields (if currently warm) or increase yields (if currently cool).

Table 4 and 5 allows the analysis of the performance of RCMs in simulating future maize yield over Wami-Ruvu basin whereas CERES forced with RACMO22T and HIRHAM5

both driven by ICHEC GCM simulate future maize yields differently under RCP4.5 and 8.5. For instance decrease in maize yields by 2.2%, 3.4% and 3.0% are projected in 2010-2039, 2040-2069, and 2070-2099 respectively, when CERES was forced with HIRHAM5 under RCP4.5. This change in maize yields slightly differs with what was observed when CERES was forced with RACMO22T under the same scenario during mid and end centuries. Table 5 shows that maximum decrease in maize yields is projected during the end century under RCP8.5 with a decrease of 6.7% whereas the minimum decrease in maize yield is projected during the present century (2010-2039) with a decrease of 0.5% under the same scenario RCP 8.5.

The impact of driving GCMs on simulated maize yield can be characterized in Table 6-8, where CERES forced with RCA4 driven by three different GCMs simulates maize yields differently. The variations in simulated maize yields are mainly due to differences in GCMs formulations.

In general, CERES forced with different RCM-GCM sets simulate maximum decrease in maize yield during the end century under RCP 8.5. Furthermore, projected maize yields over Wami-Ruvu basin showed a consistent decline in present, mid and end centuries, except a slight increase of maize yields is simulated by CERES forced with RCA4-CNRM during present century under RCP 8.5.

Table 9 shows simulated maize yields when CERES is forced by ensemble average. From the table it is clear that increased maize yield is projected during the current century under RCP4.5 and RCP 8.5 and decrease in maize yields is projected during the mid and end centuries under RCP 4.5 and RCP 8.5. Minimum decrease in maize yields of 0.7% is projected during mid century under RCP 4.5 and maximum decrease of 4% is projected during mid century under RCP 8.5. The increase in maize yields during current century and decrease in maize yields in mid and end centuries is due to slightly increased temperatures and rainfall in current century and higher increased temperatures during the mid and end centuries that shortened the length of growing season by triggering maturity stages faster.

Table 4 Maize yields and seasonal climatic variable as simulated by crop model fed with climate data from RACMO-RCM for (.)RCP4.5 and (..)RCP8.5

	1971-2000	2010-2039		2040-2069		2070-2099	
	Mean	Mean	% change	Mean	% change	Mean	% change
Maize-yield(kg/h)	1303	1274(.)	-2.2(.)	1266(.)	-2.8(.)	1275(.)	-2.2(.)
		1273(..)	-2.3(..)	1259(..)	-3.4(..)	1240(..)	-4.8(..)
Length of growing season (days)	130	121(.)	-6.9(.)	114(.)	-12.3(.)	111(.)	-14.6(.)
		121(..)	-6.9(..)	110(..)	-15.4(..)	101(..)	-22.3(..)
Seasonal maximum temp (°C)	24	25(.)	4.2(.)	25(.)	4.2(.)	26(.)	8.3(.)
		25(..)	4.2(..)	26(..)	8.3(..)	27(..)	12.5(..)
Seasonal minimum temp (°C)	15	16(.)	6.7(.)	17(.)	13.3(.)	17(.)	13.3(.)
		16(..)	6.7(..)	17(..)	13.3(..)	19(..)	26.7(..)
Seasonal solar radiation (MJ/m ² /day)	19	19(.)	0(.)	19(.)	0(.)	19(.)	0(.)
		19(..)	0(..)	18(..)	-5.3(..)	18(..)	5.3(..)
Total rainfall (mm)	425	406(.)	-4.5(.)	403(.)	-5.2(.)	404(.)	-4.9(.)
		418(..)	-1.7(..)	407(..)	-4.2(..)	392(..)	-7.8(..)
Total evapotranspiration (mm)	366	354(.)	-3.3(.)	355(.)	-3(.)	355(.)	-3(.)
		358(..)	-2.2(..)	357(..)	-2.5(..)	343(..)	-6.3(..)

Table 5 Maize yields and seasonal climatic variable as simulated by crop model fed with climate data from HIRHAM5-RCM for (.)RCP4.5 and (..)RCP8.5

	1971-2005	2010-2039		2040-2069		2070-2099	
	Mean	Mean	% Change	Mean	% change	Mean	% change
Maize-yield(kg/h)	1158	1132(.)	-2.2(.)	1119(.)	-3.4(.)	1123(.)	-3.0 (.)
		1152(..)	-0.5(..)	1111(..)	-4.1(..)	1080(..)	-6.7 (..)
Length of growing season (days)	110	104(.)	-5.5(.)	100(.)	-9.1(.)	98(.)	-10.9(.)
		104(..)	-5.5(..)	97(..)	-11.8(..)	90(..)	-18.2(..)
Seasonal maximum temp (°C)	25	26(.)	4.0(.)	27(.)	8.0(.)	27(.)	8.0(.)
		26(..)	4.0(..)	28(..)	12.0(..)	29(..)	16.0 (..)
Seasonal minimum temp (°C)	18	19(.)	5.6(.)	20(.)	11.1(.)	20(.)	11.1 (.)
		19(..)	5.6(..)	20(..)	11.1(..)	22(..)	22.2(..)
Seasonal solar radiation (MJ/m ² /day)	16	17(.)	6.3(.)	17(.)	6.3(.)	17(.)	6.3(.)
		16(..)	0.0(..)	17(..)	6.3(..)	17(..)	6.3(..)
Total rainfall (mm)	356	345(.)	-3.1(.)	373(.)	4.8(.)	373(.)	4.8(.)
		340(..)	-4.5(..)	358(..)	0.6(..)	396(..)	11.2(..)
Total evapotranspiration (mm)	259	255(.)	-1.5(.)	257(.)	-0.8(.)	260(.)	0.4(.)
		255(..)	-1.5(..)	257(..)	-0.8(..)	258(..)	-0.4(..)

Table 6 Maize yields and seasonal climatic variable as simulated by crop model fed with climate data from RCA4-ICHEC-RCM for (.)RCP4.5 and (..)RCP8.5

	1971-2005	2010-2039		2040-2069		2070-2099	
	Mean	Mean	% change	Mean	% change	Mean	% change
Maize-yield(kg/h)	1126	1120(.)	-0.5(.)	1109(.)	-1.5(.)	1118(.)	-0.7 (.)
		1118(..)	-0.7(..)	1087(..)	-3.5(..)	1061(..)	-5.8(..)
Length of growing season (days)	112	106(.)	-5.4(.)	101(.)	-9.8(.)	99(.)	-11.6(.)
		105(..)	-6.3(..)	98(..)	-12.5(..)	91(..)	-18.8(..)
Seasonal maximum temp (°C)	27	27(.)	0.0(.)	28(.)	3.7(.)	28(.)	3.7(.)
		27(..)	0.0(..)	28(..)	3.7(..)	30(..)	11.1(..)
Seasonal minimum temp (°C)	16	17(.)	6.3(.)	18(.)	12.5(.)	19(.)	18.8(.)
		18(..)	12.5(..)	19(..)	18.8(..)	21(..)	31.3(..)
Seasonal solar radiation (MJ/m ² /day)	21	21(.)	0.0(.)	21(.)	0.0(.)	20(.)	-4.8(.)
		21(..)	0.0(..)	21(..)	0.0(..)	20 (..)	-4.8(..)
Total rainfall (mm)	349	372 (.)	6.6(.)	372(.)	6.6(.)	382(.)	9.5(.)
		377(..)	8.0(..)	386(..)	10.6(..)	418(..)	19.8(..)
Total evapotranspiration (mm)	280	288(.)	2.9(.)	284(.)	1.4(.)	290(.)	3.6(.)
		284(..)	1.4(..)	286(..)	2.1 (..)	292(..)	4.3(..)

Table 7 Maize yields and seasonal climatic variable as simulated by crop model fed with climate data from RCA4-MPI-RCM for (.)RCP4.5 and (..)RCP8.5

	1971-2005	2010-2039		2040-2069		2070-2099	
	Mean	Mean	% change	Mean	% change	Mean	% change
Maize-yield(kg/h)	1212	1150(.)	-5.1(.)	1117(.)	-7.8(.)	1083(.)	-10.6 (.)
		1122(..)	-7.4(..)	1087(..)	-10.3(..)	1032(..)	-14.9(..)
Length of growing season (days)	108	102(.)	-5.6(.)	97(.)	-10.2 (.)	95(.)	-12.0 (.)
		100(..)	-7.4(..)	93(..)	-13.9(..)	86(..)	-20.4(..)
Seasonal maximum temp (°C)	27	28(.)	3.7(.)	29(.)	7.4(.)	29(.)	7.4(.)
		28(..)	3.7(..)	29(..)	7.4(..)	31(..)	14.8(..)
Seasonal minimum temp (°C)	17	18(.)	5.9(.)	19 (.)	11.8(.)	20(.)	17.6(.)
		19(..)	11.8(..)	20(..)	17.6(..)	22(..)	29.4(..)
Seasonal solar radiation (MJ/m ² /day)	21	20(.)	-4.8(.)	21(.)	0.0(.)	21(.)	0.0(.)
		21(..)	0.0(..)	20(..)	-4.8(..)	20(..)	-4.8(..)
Total rainfall (mm)	415	473(.)	14.0(.)	434(.)	4.6(.)	430(.)	3.6 (.)
		425(..)	2.4(..)	439(..)	5.8(..)	443(..)	6.7(..)
Total evapotranspiration (mm)	314	318(.)	1.3(.)	304(.)	-3.2(.)	307(.)	-2.2(.)
		307(..)	-2.2(..)	307(..)	-2.2(..)	302(..)	-3.8(..)

Table 8 Maize yields and seasonal climatic variable as simulated by crop model fed with climate data from RCA4-CNRM for (.)RCP4.5 and (..)RCP8.5

	1971-2005	2010-2039		2040-2069		2070-2099	
	Mean	Mean	% change	Mean	% change	Mean	% change
Maize-yield(kg/h)	951	947(.)	-0.4 (.)	915(.)	-3.8(.)	909(.)	-4.4(.)
		962(..)	1.2 (..)	893(..)	-6.1(..)	849(..)	-10.7(..)
Length of growing season (days)	105	99(.)	-5.7 (.)	95(.)	-9.5(.)	91(.)	-13.3(.)
		99(..)	-5.7 (..)	92(..)	-12.4(..)	85(..)	-19.0(..)
Seasonal maximum temp (°C)	28	29(.)	3.6 (.)	30(.)	7.1(.)	31(.)	10.7(.)
		29 (..)	3.6 (..)	31(..)	10.7(..)	32(..)	14.3(..)
Seasonal minimum temp (°C)	17	18(.)	5.9 (.)	18(.)	5.9(.)	19(.)	11.8(.)
		18(..)	5.9 (..)	19(..)	11.8(..)	20(..)	17.6(..)
Seasonal solar radiation (MJ/m ² /day)	23	23(.)	0.0(.)	23(.)	0.0(.)	23(.)	0.0(.)
		23(..)	0.0(..)	23(..)	0.0(..)	23(..)	0.0(..)
Total rainfall (mm)	256	274(.)	7.0(.)	263(.)	2.7(.)	269(.)	5.1(.)
		292(..)	14.1(..)	264(..)	3.1(..)	267(..)	4.3 (..)
Total evapotranspiration (mm)	230	233(.)	1.3(.)	233(.)	1.3(.)	235(.)	2.2 (.)
		246(..)	7.0(..)	232(..)	0.9(..)	234(..)	1.7 (..)

Table 9 Maize yields and seasonal climatic variable as simulated by crop model fed with climate data from ENSEMBLE-RCM for (.)RCP4.5 and (..)RCP8.5

	1971-2005	2010-2039		2040-2069		2070-2099	
	Mean	Mean	%	Mean	%	Mean	%
			change		change		change
Maize-yield(kg/h)	1238	1241(.)	0.2(.)	1229(.)	-0.7(.)	1220(.)	-1.5(.)
		1257(..)	1.5(..)	1188(..)	-4.0(..)	1198(..)	-3.2(..)
Length of growing season (days)	112	106(.)	-5.4(.)	101(.)	-9.8(.)	99(.)	-11.6(.)
		105(..)	-6.3(..)	98(..)	-12.5(..)	90(..)	-19.6(..)
Seasonal maximum temp (°C)	26	27(.)	3.8(.)	28(.)	7.7(.)	28(.)	7.7(.)
		27(..)	3.8(..)	28(..)	7.7(..)	30(..)	15.4(..)
Seasonal minimum temp (°C)	17	18(.)	5.9(.)	18(.)	5.9(.)	19(.)	11.8(.)
		18(..)	5.9(..)	19(..)	11.8(..)	21(..)	23.5(..)
Seasonal solar radiation (MJ/m ² /day)	20	20(.)	0.0(.)	20(.)	0.0(.)	20(.)	0.0(.)
		20(..)	0.0(..)	20(..)	0.0(..)	20(..)	0.0(..)
Total rainfall (mm)	349	357(.)	2.3(.)	360(.)	3.2 (.)	357(.)	2.3(.)
		357(..)	2.3(..)	355(..)	1.7(..)	369(..)	5.7(..)
Total evapotranspiration (mm)	375	376(.)	0.3(.)	371(.)	-1.1(.)	375(.)	0.0(.)
		375(..)	0.0(..)	372(..)	-0.8(..)	371(..)	-1.1(..)

3.3.3 Spatial distribution of climate variables, length of growing seasons and maize yields

The spatial distribution of minimum temperature (TN), maximum temperature (TX), rainfall, length of growing season and maize yields during the base line period (1971-2000) are presented in Figure 5. This figure shows high temperatures greater than 26 °C for TX and 17°C for TN are observed in the lower altitude areas, particularly in the eastern part of the basin. Temperatures are particularly higher over eastern part of Wami sub-catchment. Lower temperatures are found in high altitude areas in the western side of the basin. Particularly over western part of Wami sub catchment, North and eastern parts of Kinyasungwe sub catchment.

Seasonal rainfall is higher in high altitude than low altitude areas, particularly over Kinyasungwe sub catchment, eastern parts of Mkondoa, western parts of Wami and over upper Ruvu sub catchments. Meanwhile lower rainfall are found over low altitude than high areas, particularly over Coast, eastern part of Wami, lower Ruvu, and Ngerengere sub catchments. The length of growing season is higher over high altitude than in low altitude areas, which have lower temperatures and higher rainfall. Meanwhile lower lengths of growing season are found in low altitude areas, which have higher temperatures and lower rainfall. Simulated maize yields are highest in areas with highest rainfall, particularly over southeastern parts of Kinyasungwe and northwestern parts of Mkondoa sub catchments.

Figure 6 shows the distribution of changes in temperatures, rainfall, maize yields and length of growing season during the present century under RCP 4.5. Highest change in temperatures of 1.8°C for TX and 1.2°C for TN are found over southeastern parts of Mkondoa and over upper Ruvu sub catchments. Meanwhile lower change in temperatures of 0.5°C for TX and 0.7°C for TN are found over Kinyasungwe sub catchment. Decrease in rainfall of 5mm is found over large part of Mkondoa, eastern part of Ngerengere and southern part of Wami sub catchments. Highest decrease in the length of growing season is found over northern and southeastern parts of Mkondoa, western parts of Wami and over upper Ruvu sub catchments. This is due to increased TX and TN over these areas. Maize yields are projected to decrease by 1 to 5% over parts of northwestern and southeastern of

Mkondoa, western parts of upper and lower Ruvu, western and northern parts of Wami sub catchments. Meanwhile, maize yields over large parts of Mkondoa, Kinyasungwe and Wami sub catchments are projected to increase by 3 to 9%. Maize yields over coast and western parts of upper and lower Ruvu are projected to increase by 1 to 3%.

Figure 7 shows the distribution of change in temperatures, rainfall, maize yields and the length of growing season during mid-century under RCP 4.5. High change in temperatures of 1.8°C to 2.7°C for TX and 1.9°C to 2.2°C for TN are found over upper and lower Ruvu, Mkondoa, Ngerengere, coast and western parts of Wami sub catchments. Lower change in temperatures of 0.9°C for TX and 1.5°C for TN are found over Kinyasungwe, southwestern parts of Mkondoa and some eastern parts of Wami sub catchments. Rainfall is projected to increase by 14 to 49 mm high over coast, southern parts of upper Ruvu, southeastern parts of Mkondoa, lower Ruvu, large parts of Kinyasungwe and Wami sub catchments. Meanwhile decrease in rainfall of 3 mm is projected over Ngerengere, southern parts of Wami, large parts of Mkondoa and southeastern parts of Kinyasungwe sub catchments. Highest decrease in length of growing season is found over upper Ruvu, western parts of Wami and large parts of Mkondoa sub catchments. Maize yields are projected to decrease from zero to 8% over upper and lower Ruvu, eastern and northern parts of Wami, Ngerengere, southeastern parts of Mkondoa and western parts of coast sub catchments. Meanwhile maize yields over large parts of Mkondoa, Kinyasungwe, southern parts of Wami and eastern parts of coast sub catchments are projected to increase by 2 to 10%. This increase is mainly due to increased rainfall and small decrease in the length of growing seasons or small increase in TX and TN over those areas. Generally eastern part of the basin is projected to have decreased maize yield. This is due to the high increase in TX and TN that reduced the length of growing season. It is important to note that in some areas such as north of Mkondoa will benefit from projected increase in temperatures, since the observed increased TX and TN that reduced the length of growing season and the projected decrease in rainfall, maize yields continue to increase. Meanwhile other areas such as upper Ruvu, Ngerengere, lower Ruvu, northern and western parts of Wami sub catchments are projected to have decreased maize yields in present, mid and end centuries, due to increased TX and TN.

Figure 8 shows the distribution of temperatures, maize yields, rainfall and the length of growing season during the end century. High change in temperatures in the range of 2.3⁰C to 3.2⁰C for TX and 2.3⁰C to 2.7⁰C for TN are found over upper and lower Ruvu, large part of Mkondoa, Ngerengere, coast and western parts of Wami sub catchments. Lower change in temperatures of 1.5⁰C for TX and 1.9⁰C for TN are found over Kinyasungwe, southwestern parts of Mkondoa and eastern parts of Wami sub catchments. Rainfall is projected to increase by 4 to 30 mm almost over the entire basin except eastern parts of Ngerengere, southwestern parts Mkondoa and southeastern parts of Kinyasungwe sub catchments where is projected to decrease by 9%. Highest decrease in length of growing season is found over upper Ruvu, western parts of Wami and large parts of Mkondoa sub catchments. Maize yields are projected to decrease from 1 to 10% over upper and lower Ruvu, eastern and northern parts of Wami, Ngerengere, southeastern parts of Mkondoa and western parts of coast sub catchments. Meanwhile maize yields over large parts of Mkondoa, Kinyasungwe, southern parts of Wami and eastern parts of coast sub catchments are projected to increase by 2 to 11%.

The distribution of TX, TN, rainfall, and the length of growing season during present, mid and end centuries under RCP 8.5 are presented in Figure 9-11. Temperatures are projected to increase more over central and south eastern parts of the basin. This will reduce maize yields particularly during mid and end centuries. Generally rainfall is projected to increase in many areas of the basin but maize is projected to decrease. This is due to fact that the entire basin is projected to warm in present, mid and end centuries. This warming will reduce the length of growing seasons which in turn reduce maize yields. This is observed under both RCP4.5 and RCP 8.5. Thus regardless of projected increased rainfall that seems to benefits agriculture production, need arises to undertake more studies that address on how to adapt the future increase in TX and TN.

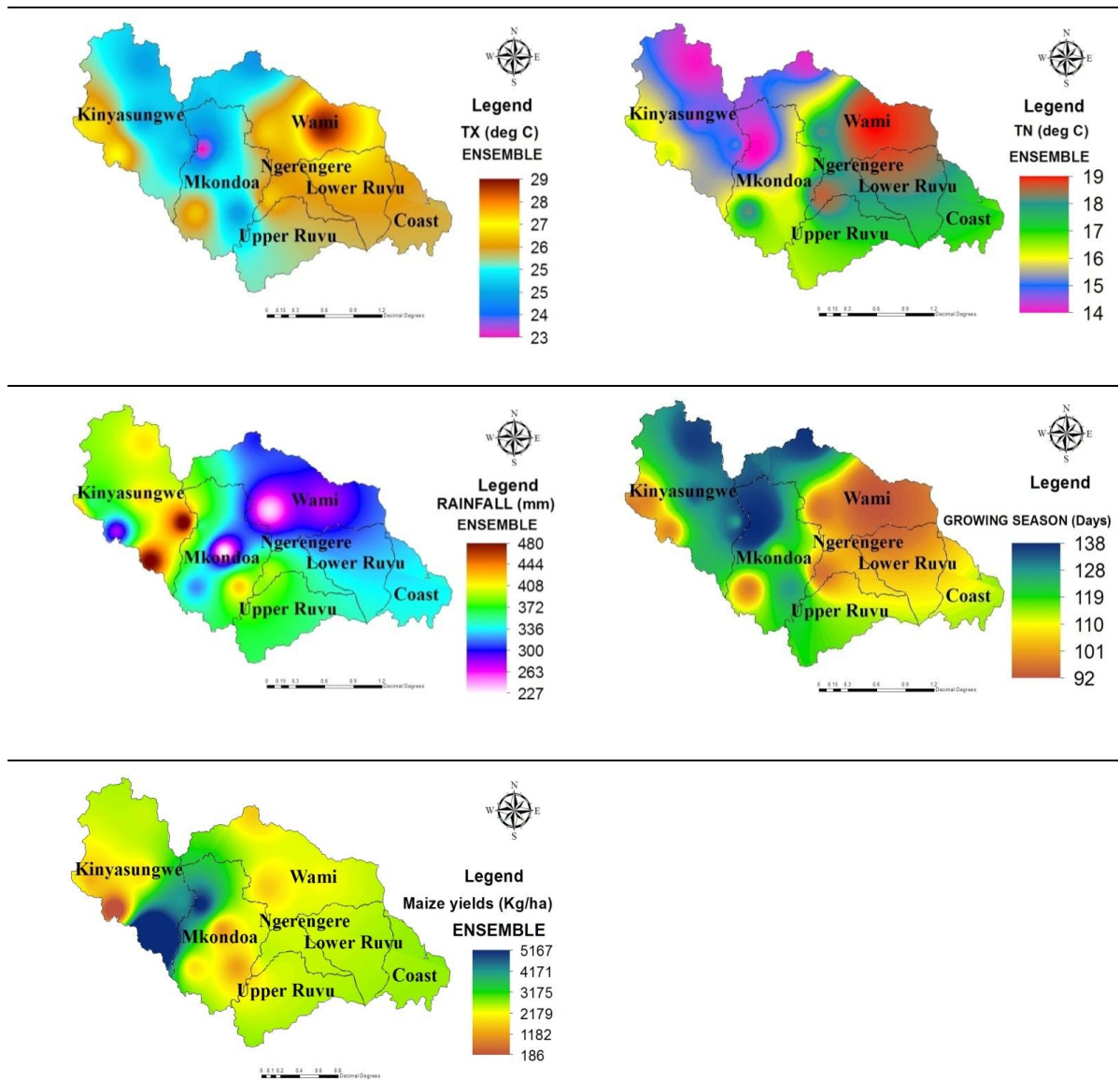


Figure 5. The spatial distribution minimum (TN) and maximum (TX) temperatures, rainfall, length of growing season and maize yields over Wami-Ruvu basin during the baseline period (1971-2000) under RCP 45

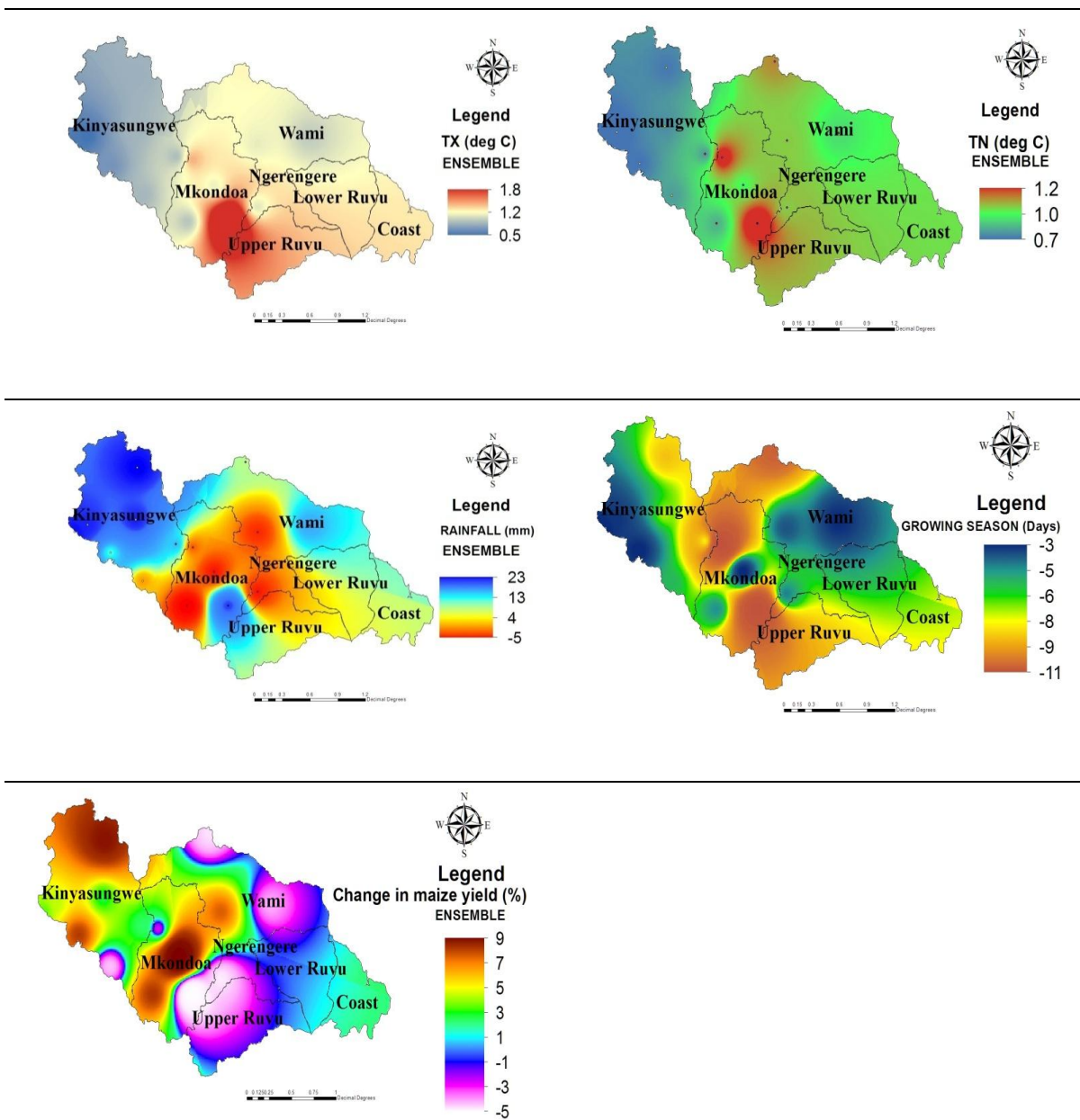


Figure 6. Change in spatial distribution of minimum (TN) and maximum (TX) temperatures, rainfall, length of growing season and maize yields over Wami-Ruvu basin during present century (2010-2039) under RCP 45

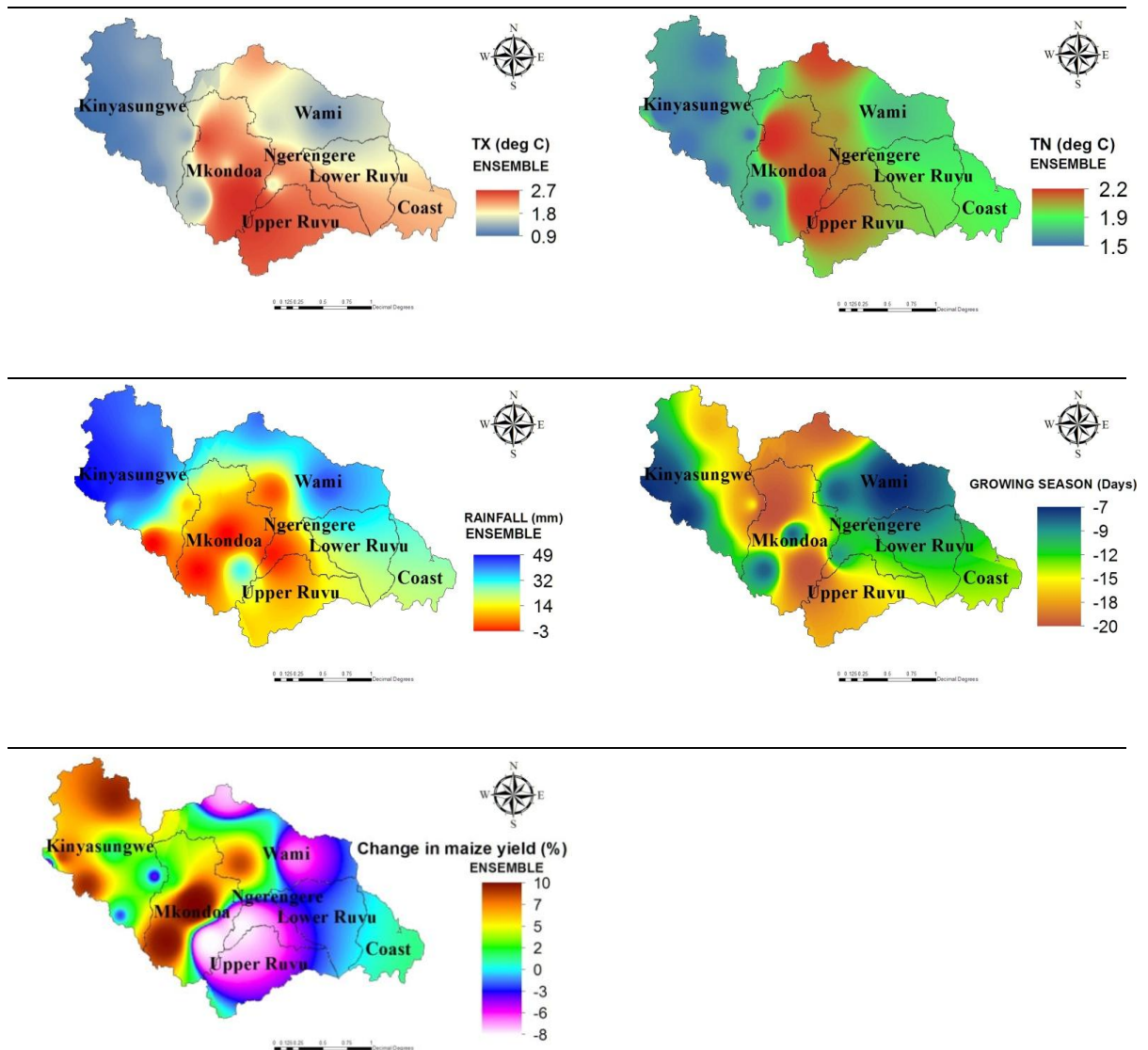


Figure 7. Change in spatial distribution of minimum (TN) and maximum (TX) temperatures, rainfall, length of growing season and maize yields over Wami-Ruvu basin during mid century (2040-2069) under RCP 45

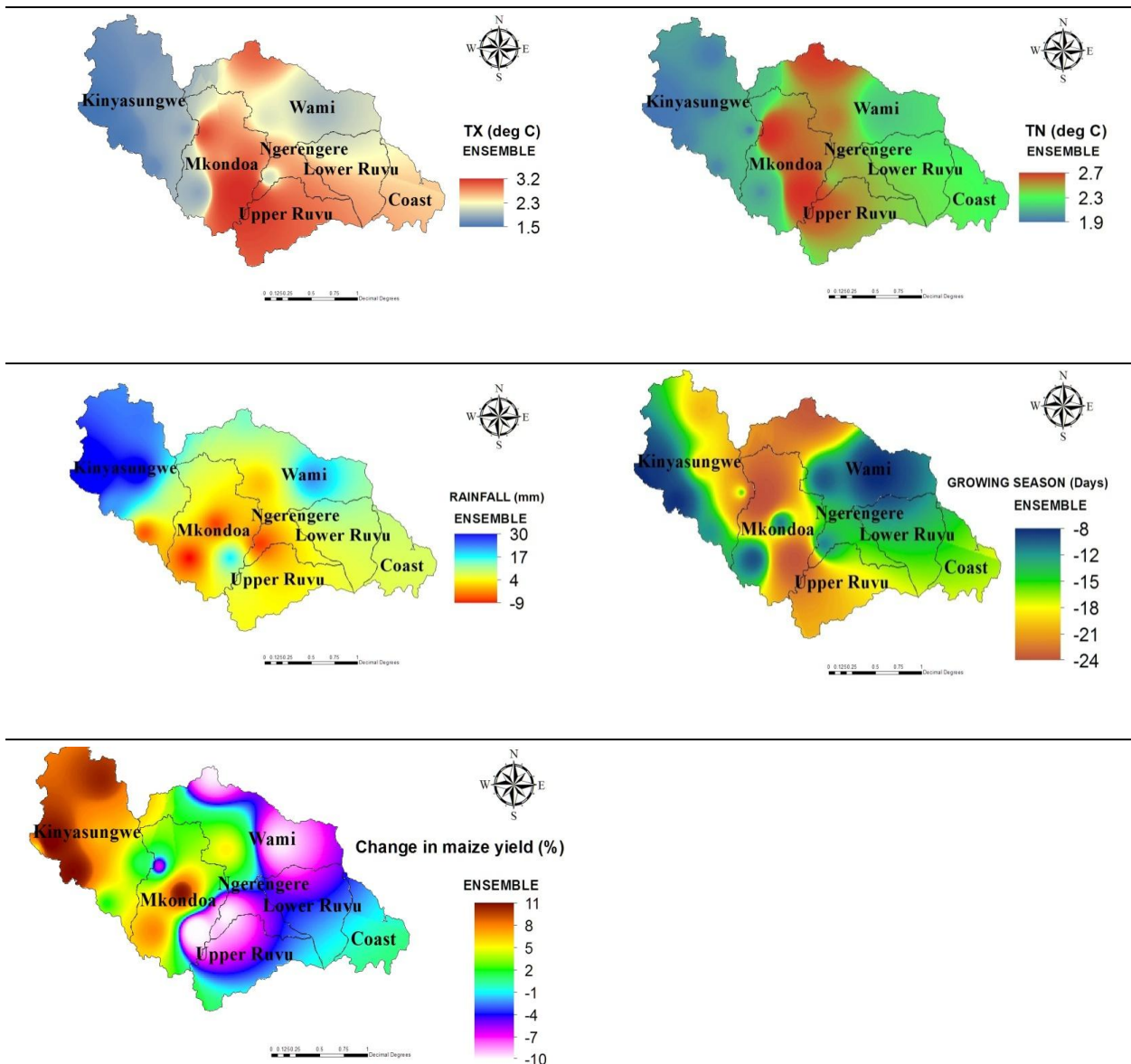


Figure 8. Change in spatial distribution of minimum (TN) and maximum (TX) temperatures, rainfall, length of growing season and maize yields over Wami-Ruvu basin during mid century (2070-2099) under RCP 45

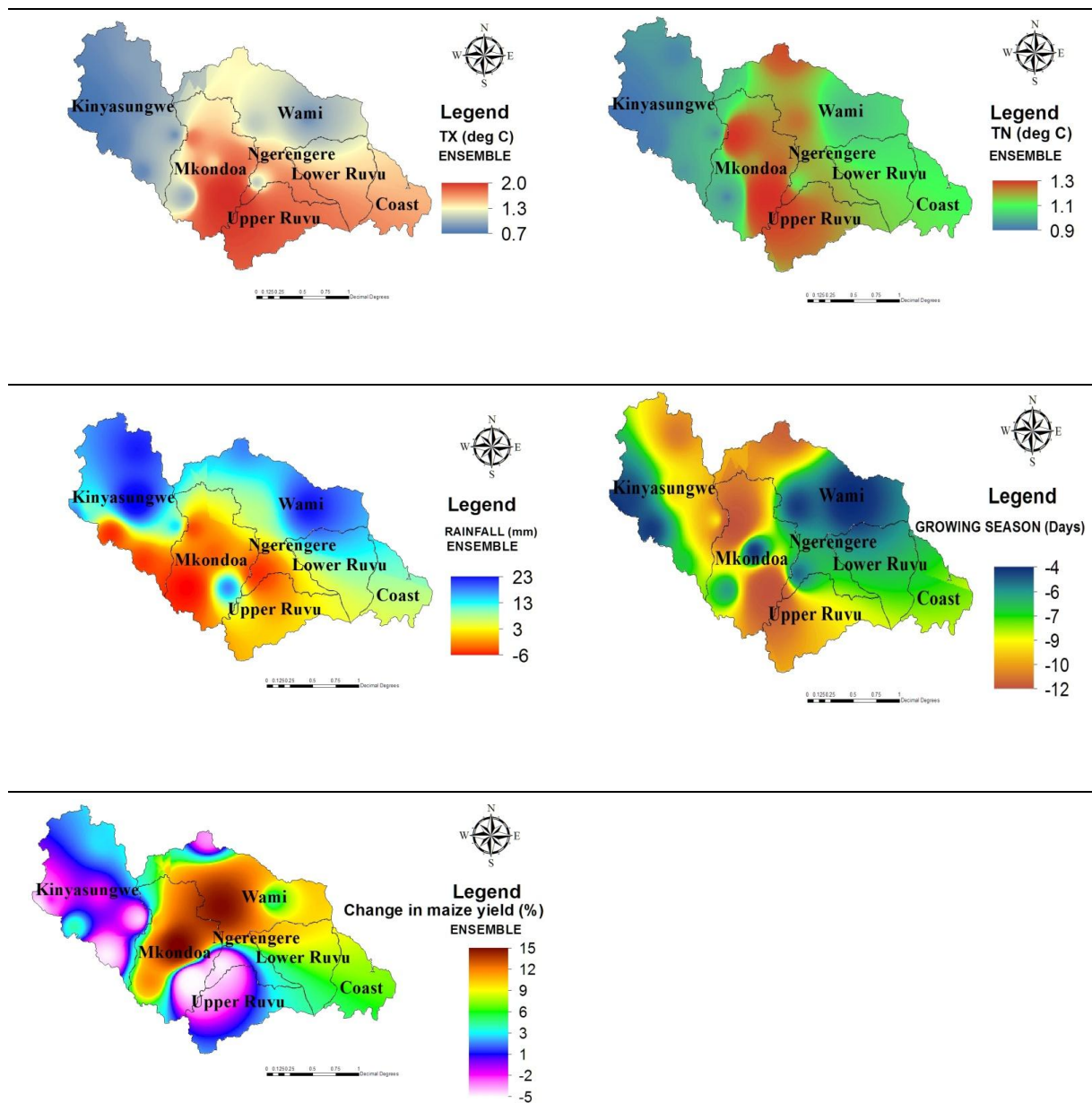


Figure 9. Change in spatial distribution of minimum (TN) and maximum (TX) temperatures, rainfall, length of growing season and maize yields over Wami-Ruvu basin during present century (2010-2039) under RCP 85

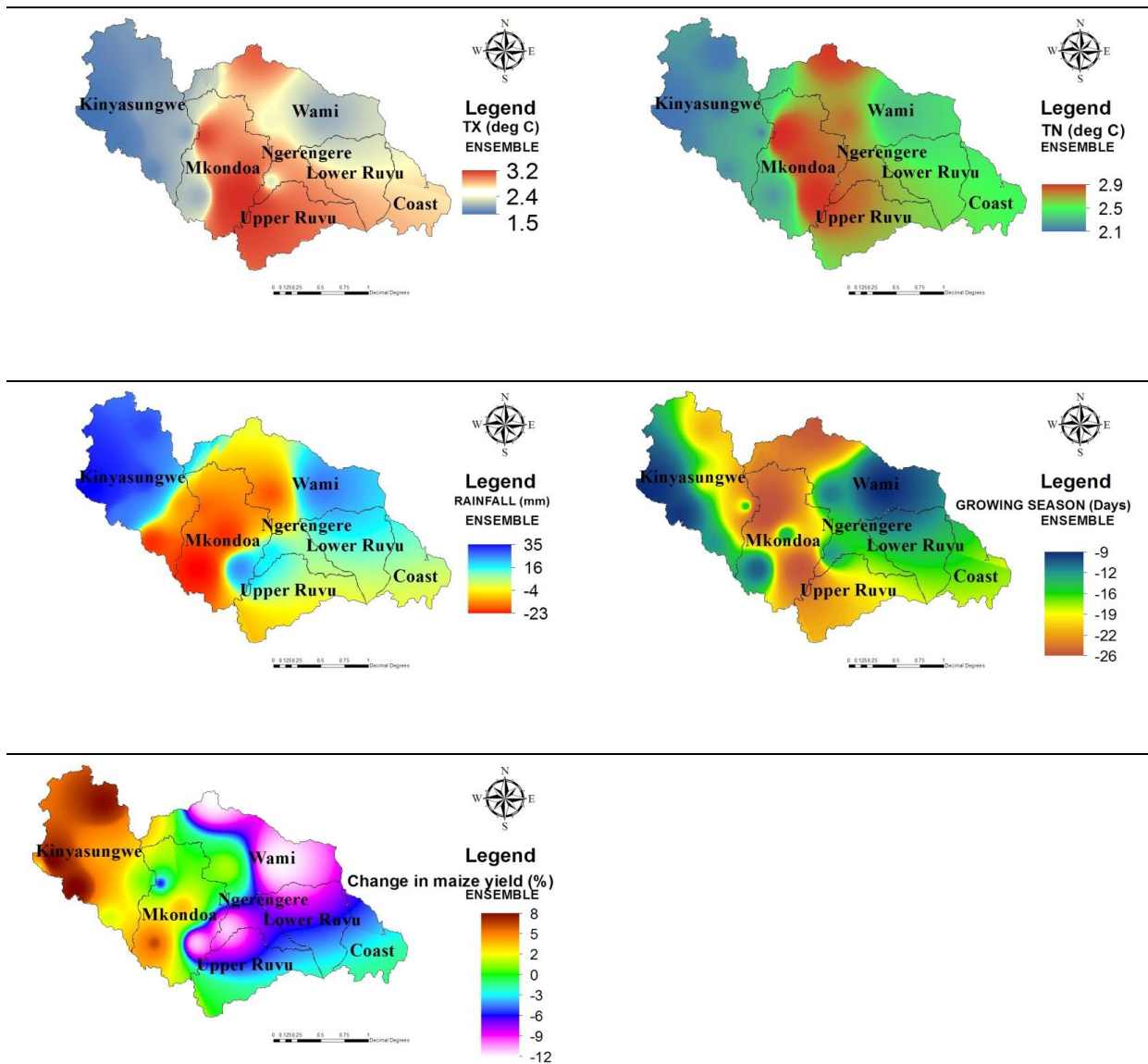


Figure 10. Change in spatial distribution of minimum (TN) and maximum (TX) temperatures, rainfall, length of growing season and maize yields over Wami-Ruvu basin during mid century (2040-2069) under RCP 85

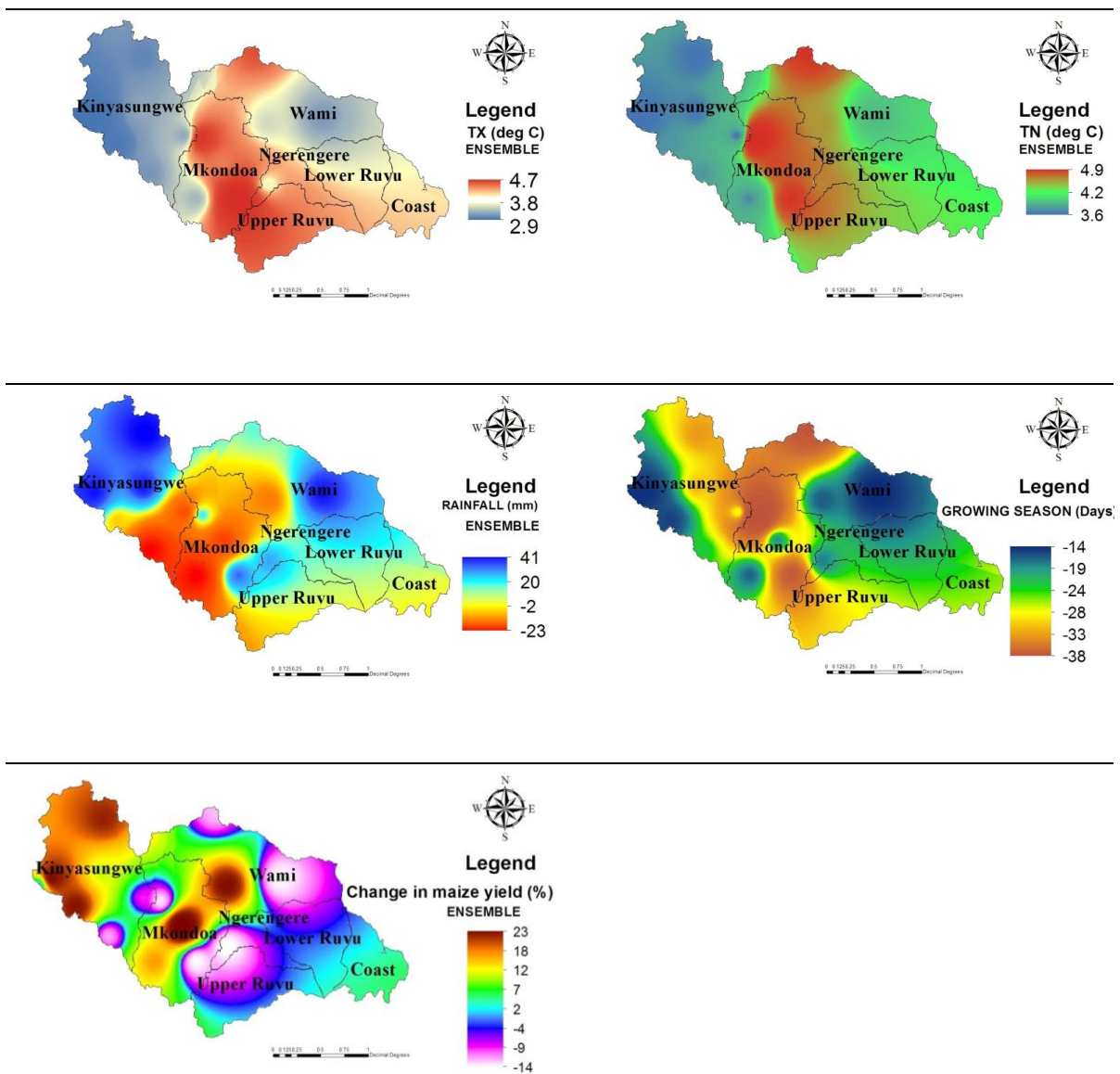


Figure 11. Change in spatial distribution of minimum (TN) and maximum (TX) temperatures, rainfall, length of growing season and maize yields over Wami-Ruvu basin during end century (2070-2099) under RCP 85

3.4 Discussion

In this paper, high resolution climate change information derived from three Regional Climate Models (RCMs) driven by three General Circulation Models (GCMs) and process based crop model CERES- maize model embedded in DSSAT version 4.5, are used to simulate maize yields over Wami-Ruvu basin during current, mid, and end centuries under RCP 4.5 and RCP 8.5. The primary aim was to examine, how climate change will affect maize yields in the basin. The analysis is limited within the growing season which starts from December and continues to June. We found that temperatures are projected to increase through the basin. Different RCM-GCM combination projects increase in temperatures differently. However, all the RCMs-GCMs combinations agree that the basin will experience high change in temperatures during the end century under RCP 8.5. Highest increase in TN of 31.3% (5°C) is projected by RCA4 driven by ICHEC under RCP 8.5 and no change in temperature is projected by the same model during current century under both RCP 4.5 and RCP 8.5. The ensemble average also suggests highest change in temperatures within the basin during the end century under RCP 4.5 and RCP 8.5. TN will increase by 23.5% (4°C) under RCP 8.5 and TX will increase by 15.4% (4.4°C) under the same scenario RCP 8.5. These increases in temperatures will reduce the length of growing seasons and reduces maize yields particularly in warmer low altitude areas (Moore et al, 2011). In general presented results in this study agree with prior study by Glows–Fiu (2014), who indicated that the temperatures within the basin will rise by 4°C in the last quarter of the century.

Our results differ greatly with prior studies (e.g. Mwandosya et al., 1998; Paavola, 2003; Matari et al., 2008; Moore et al, 2011; Glows–Fiu, 2014), which examined climate change within the basin or assessed its impacts on maize yields based on GCMs simulations. For instance, a more referenced paper Mwandosya et al. (1998) that was used for development of climate change policies in Tanzania indicated that maize yield over central Tanzania (Dodoma) region will decline by 80 to 90% towards the end of century. In this study it is found that maize yields over Dodoma will increase by 5 to 8% and 7 to 23% during the end century under RCP 4.5 and RCP 8.5 respectively. Generally Dodoma region which is located in southwestern part of Kinyasungwe sub catchment is predicted to have small

change in temperatures, length of growing season and increasing rainfall during present, mid and end centuries under RCP 4.5 and RCP 8.5. Moore et al, (2011) used data from the GCMs indicated that maize yields over Ngerengere, lower and upper Ruvu sub-catchments will increase by 20 to 30% towards the mid-century. However, we found that maize yields will decrease in those areas during mid century under both RCP 4.5 and RCP 8.5. Maize yields will decrease by 3 to 8% and 3 to 12% under RCP 4.5 and RCP 8.5 respectively during mid-century. Studies that used climate simulations from GCMs to characterize the climate over different regions in Tanzania may have considerable uncertainties since the country has heterogeneous climate over shorter distances which are unlikely to be resolved by coarse resolution GCMs. More recently Glows–Fiu (2014) used 16 GCMs to assess the vulnerability of water resources to climate/forest cover change over Wami-Ruvu basin indicated that the western parts of the basin is expected to see a higher temperatures as compared with the coast, giving reason that due to the proximity to the Indian ocean, that regulates temperatures over the coast. The report indicated further that, temperatures within the basin will increase from inland to coast. In this study we found the vice versa, temperatures are expected to increase over the lower altitudes compared to the high altitudes, the eastern part of the basin over coast, upper and lower Ruvu, Ngerengere and eastern side of the Wami sub catchments are projected to have increased temperatures in current, mid and end centuries. Recently Tumbo et al (2015) analyzed the impact of climate change on maize yields over Wami-Ruvu basin where 20GCMs were statistically downscaled using delta method. The downscaled GCMs data were used to force CERES to simulate maize yields in the present and future centuries under RCP 4.5 and RCP 8.5. They found that maize yields over the basin will decrease by 5 to 40% due to projected increase in temperature. Although statistical downscaling may improve the coarse scale of the GCMs but depends to the choices of the predictor (Wilby and Dawson, 2004) and the choice of mathematical transfer function (Wilby and Hayley, 2011). Delta method is not strictly downscaling methods (Hewitsone et al., 2014). The uncertainties of this method are detailed described by Wilby and Hayley (2011). In this study it is found that maize yields in the Wami Ruvu basin will increase during current century under RCP 4.5 and RCP 8.5 and decrease during mid and end centuries. The minimum decrease in maize yields of 0.7% and maximum decrease of maize yield of 4% is projected in the mid-century under

RCP 8.5 and RCP 4.5 respectively. The decrease in maize yields during the mid and end centuries are attributed to projected increase in temperatures that will shorten the growing season. The spatial distribution indicates that climate changes will contribute to increased maize yields over high altitude areas such as over Kinyasungwe, western side of Wami and Mkondoa sub catmints. However, the low altitude areas such as lower and upper Ruvu, coast, Ngerengere and western parts of Wami sub catchments will have decreased maize yields due to projected increase in temperatures. Furthermore western parts of the basin are projected to have increased rainfall, small change in temperatures and length of growing season. Meanwhile the eastern side of the basin is projected to have high increase in temperatures, decrease in rainfall and length of growing season.

Presented results may be used by farmers and to plan how to adapt to the projected increase in temperatures particularly over low altitude areas where the negative impact of climate on maize yields are projected. Since the Wami-Ruvu basin has many national and international projects and contains many sources of water for big cities regions like Dar es Salaam and Morogoro, it is crucial to developed adaptation strategies to the projected increase in temperatures and decrease in rainfall particularly in the eastern side of the basin. It is also recommended that further studies need to be carried out that addresses the impact of climate change on crop production in all agro ecological zones of Tanzania using high resolution climate change projections. It is important to note that one season actual crop yields data (2009/2010) was the only available data used to validate the crop model. This may be a limitation of this study, therefore more studies need to be carried that uses long time actual yields data to validate crop models to update the findings of this study.

3.5 Conclusions and recommendations

In this study the assessment of the impacts of climate change on maize (*Zea mays*) production over Wami-Ruvu region is carried out using high resolution Regional Climate models (RCMs). The RCMs used are those driven by boundary condition from General Circulation Models (GCMs). Daily minimum, maximum temperatures, rainfall and solar radiations for the period of 1971-2000, 2010-2039, 2040-2069 and 2070-2099 were fed into the Decision Support System for Agro -technological Transfer (DSSAT) to simulate maize growth and yields. In addition to climate data, detailed field and house hold survey

information (crop yield, soil and management data inputs) were used to calibrate the crop model. Maize simulations were carried out under RCP4.5 and RCP8.5 for future climate. We found that crop model (DSSAT) simulate maize yield over Wami-Ruvu basin differently when fed with climate data from RCMs GCMs combinations. In general DSSAT simulates decreased in maize yields over Wami Ruvu basin during mid and end centuries. This decrease is small relative to the baseline. Since climate data fed to crop model results into different maize yields production, climate data from ensemble average of five model members was constructed and used as input into DSSAT to simulate maize growth and yields. Results also showed that maize yield slightly decreased relative to the base line. The maximum decrease of maize yield is projected during the mid century under RCP8.5 and the minimum decrease is projected over the same time period (mid century) under RCP 4.5. On other hand there is increase in maize yields in current century (2010-2039) under RC P4.5 and RCP 8.5 respectively.

The spatial distribution of seasonal TX, TN, rainfall, length of growing season and maize yields during present, mid and end centuries have shown similar patterns. The central and the eastern parts of the basin are projected to have high increased TX, TN. It is important to mention here that in some places TX and TN are projected to increase by 4.7⁰C and 4.9⁰C during the end century under RCP 8.5. The western and north western parts are projected to feature slightly increased temperature. Rainfall is projected to increase of most areas during present, mid and end centuries under RCP 4.5 and RCP 8.5. However maize yields are projected to be impacted by increased temperature than increased rainfall. The increase in temperature shorten the length of growing season that contribute to the projected decrease in maize yields in current, mid and end centuries. However, in some cases a slight increase in maize yield is projected due to slight increase in rainfall. The assumption made during maize simulation was that all agronomical and management practices were constant. We recommend more research geared towards minimizing the impacts of climate change by designing effective and adequate adaptation strategies that will enhance and sustain crop production in the context of the projected increase in temperatures over Wami-Ruvu basin.

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Chapter 4: Evaluation of the use of moist potential vorticity and moist potential vorticity vector in describing long term annual cycles of rainfall in Tanzania

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Abstract

The economy of Tanzania heavily depends on agriculture sector which is primarily rain-fed. However, rainfall prediction over different regions in Tanzania is complicated due to several factors that contribute to its formation and distribution. In this paper, we compute the moist potential vorticity (MPV) and evaluate its usefulness as a predictor of rainfall events. We also modify the convective vorticity vector (CVV) which was defined as the cross product of absolute vorticity and the gradient of equivalent potential temperature to moist potential vorticity vector (MPVV). This vector is calculated as a cross product of absolute vorticity and the gradient of moist air entropic potential temperature. The performance of MPVV to describe rainfall events over different regions in Tanzania is analyzed. Twenty six (26) years (1976-2001) daily data of air temperature, specific humidity, zonal and meridional components of the wind at 850 and 600hPa from numerical output generated by the Rossby Center regional climate model version four (RCA4) are used for computation of MPV and MPVV at 700hPa. The patterns of MPV and MPVV are qualitatively compared with surface-reanalysis rainfall data from the National Centers for Environmental Prediction/ National Center for Atmospheric Research (NCEP/ NCAR). Results indicate that the patterns of MPVV compared better with rainfall than the MPV. The statistical relationship between MPVV and MPV against observed rainfall data from 22 synoptic meteorological stations using Pearson correlation coefficient indicate that MPVV bears stronger and statistically significant correlation coefficient to rainfall than MPV suggesting its potential use as predictor of rainfall events.

4.1 Introduction

There is an urgent need for better rainfall prediction in Tanzania (Chang'a et al., 2010, and Kijazi and Reason, 2009). However, rainfall prediction over Tanzania is difficult due to several factors that contribute to its formation and distribution. These includes, complex topographical terrain, numerous big inland water bodies, variation in vegetation types, land-ocean contrasts, planetary waves (Rossby waves), tropical waves (Madden-Julian oscillation), atmospheric-ocean interactions (El Niño-Southern Oscillation) and atmospheric-land-ocean interactions (Inter Tropical Convergence Zone) (Archanya and Bhaskara, 1981; Nicholson, 1986; Zhang, 2013; Schneider et al., 2014 and Dixon and Moore, 2015). Many physical processes that contributes to formation and distribution of rainfall associated with the aforementioned factors are not well known in such a way that they can be modeled explicitly in prediction models. As a result the contemporary weather and climate models suffer a pitfall to predict rainfall over different regions in Tanzania.

In order to improve the skills of weather and climate models to predict rainfall, it is important to understand physical processes on formation of rainfall from local to large scales atmospheric flows and parameterize them in weather and climate models. An alternative approach is to derive certain physical variable that combine the influence of large and local scales atmospheric flows on formation and distribution of rainfall. Physical variable such as moist potential vorticity (MPV) which is conserved quantity and obeys invertibility principle can be used to describe the impact of large and local scale features on the formation and distribution of rainfall. In this study we explore the use of MPV to describe rainfall events of Tanzania to see if it can be used as a predictor for downscaling climate change projections. The same task is performed using the moist potential vorticity vector (MPVV) which is a modified version of convective vorticity vector (CVV) defined by Gao et al (2004b).

4.2 Background information on potential vorticity

The concept of Potential Vorticity (PV) has long history in the study of fluid dynamics. It has been used in meteorology and oceanography for many years back (see Bjerknes, 1898, Rossby, 1939 and Ertel, 1942). This concept has many applications in meteorology,

oceanography and aerodynamics (Hoskins et al., 1985). It is mentioned in Hoskins et al (1985) that “PV can be used to understand the dynamics and thermal conditions of atmospheric flow to the lower limit to the fineness of the structures that may occur, all the way down to the length scales at which molecular diffusion acts”. Many important synoptic scale processes can be understood within the framework of PV. Recently McIntyre (2015) indicated that PV can explain the balanced flows and basic dynamical processes of large scale features such as breaking and propagation of Rossby-wave and its many consequences in the Earth’s atmosphere. PV can describe global-scale teleconnections, anti-frictional phenomena such as jet stream self-sharpening, and the genesis of cyclones, anticyclones and storm tracks, answering the child’s age-old question of where the wind comes from. PV is conservative and is subject to invertibility principle (Marquet, 2014). The conservative and inevitability properties of PV form the bases of understanding many important atmospheric flow processes.

Ertel (1942) definition of PV (see Schubert et al (2004)) is

$$PV(\theta) = \rho^{-1} \zeta_a \cdot \nabla(\theta), \quad (1)$$

where ρ is density of air, ζ_a is absolute vorticity and $\nabla(\theta)$ is the three dimensional gradient of the potential temperature. This definition emerged from fundamental concepts on circulation and vorticity that have been laid in the works of Bjerknes (1898a, b) and Rossby (1936, 1938, and 1940).

Eq. 1 is often used to study the thermodynamic properties of the atmosphere (Godoy et al., 2011 and Rocheta et al., 2014), while it is based only on dry-air potential temperature θ . In moist atmosphere, Eq.1 is not conserved when latent heat release is taken into account (Cao and Cho, 1995; Mo for and Lu, 2009). To avoid this drawback, Bennetts and Hoskins (1979) defined a moist potential vorticity (MPV) by replacing dry-air potential temperature θ with wet bulb potential temperature θ_w as;

$$MPV(\theta_w) = \rho^{-1} \zeta_a \cdot \nabla(\theta_w) \quad (2)$$

Eq.2 is conserved in moist adiabatic and frictionless processes and its generalization used in dry atmosphere lead to annihilation of solenoidal term in MPV tendency (Schubert et al., 2001).

Since the atmosphere is never completely dry or saturated, but non-uniformly saturated. Thus neither Eq.1 nor Eq.2 can be used to study non-uniform saturated atmospheric flow and fulfil the demand to verify, at the same time, a moist and dry air conservative property and the invertibility principle. To overcome this drawback Gao et al (2004a) defined a new Generalized Moist Potential Vorticity (GMPV) by replacing θ with a Generalized Potential Temperature $GMPV(\theta^*)$ (GPT) as;

$$GMPV(\theta^*) = \rho^{-1} \zeta_a \cdot \nabla(\theta^*), \quad (3)$$

where θ^* is defined as;

$$\theta^*(T, p, q) = \theta \exp \left(\frac{Lq_s}{c_p T} \left(\frac{q}{q_s} \right)^k \right), \quad (4)$$

where q and q_s are specific humidity and saturated specific humidity respectively, $\left(\frac{q}{q_s} \right)^k$ is a condensation probability function. In case of absolutely dry atmosphere where $q = 0$, Eq.4 reduces to dry potential temperature, $\theta^*(T, p, q) = \theta$ while in completely saturated atmosphere where $q = q_s$ it reduces to equivalent potential temperature $\theta^*(T, p, q) = \theta_e = \theta \exp \left(\frac{Lq_s}{c_p T} \right)$. In realistic atmosphere which is non-uniformly saturated, the introduction of condensation probability function fixes the discontinuity of latent heat term due to the impact of water phase changes in the thermodynamic equation. Therefore a smooth transition from completely dry atmosphere and saturated atmosphere is achieved through the change of specific humidity from q to q_s . Eq.4 has been used in computation of MPV (Gao et al, 2004a; Liang et al, 2010; Mofo and Lu, 2008; and Yang et al 2014), and found that the solenoidal term does not cancel out in the MPV tendency equation in moist and dry atmosphere. However, Gao et al (2004a) noted some limitations of applicability of the condensation density function in regions of no condensation or lower relative humidity conditions.

Recently Marquet (2014) defined a new MPV using the specific entropy formulation expressed in terms of moist-air entropy potential temperature (θ_s) as;

$$MPV(\theta_s) = \frac{1}{\rho} \zeta_a \cdot \nabla(\theta_s), \quad (5)$$

where θ_s is defined in Marquet (2011) as;

$$\theta_s \equiv (\theta_s)_1 \left(\frac{T}{T_r} \right)^{\gamma q_t} \left(\frac{p}{p_r} \right)^{-k \delta q_t} \left(\frac{r_r}{r_v} \right)^{\gamma q_t} \frac{(1+\eta r_v)^{k(1+\delta q_t)}}{(1+\eta r_r)^{k \delta q_t}}, \quad (6)$$

$$(\theta_s)_1 = \theta \exp(\Lambda_r q_t) \exp\left(-\frac{L_v q_l + L_s q_i}{c_{pd} T}\right), \quad (7)$$

where $\Lambda_r = \frac{(s_v^0 - s_d^0)}{c_{pd}} \approx 5.87$ is a key quantity. It is mentioned in Marquet (2011) that Λ_r depends on the standard entropies of water vapour and dry air (s_v^0 and s_d^0). It is also mentioned that $(\theta_s)_1$ is a good approximation of θ_s . For detailed derivation of θ_s the reader may consult Marquet (2011, 2014).

θ_s is valid for a general mixing of dry air, water vapour and all possible condensed water species. It is mentioned in Marquet (2014) that “ θ_s verifies the same conservative properties as the moist entropy, even for varying dry air or total water content”. The moist formulation for θ_s is valid for a general mixing of dry air, water vapour, and all possible condensed water species (Marquet, 2011). In this paper, we compute Marquet (2014)’s MPV formulation and explore its usefulness as a predictor of rainfall events over different regions of Tanzania.

We also suggest a modification of the convective vorticity vector (CVV) proposed by Gao et al (2004b) which is conservative only in moist adiabatic and frictionless processes (Schubert et al., 2001), by replacing the equivalent potential temperature θ_e with conservative moist-air entropy potential temperature (θ_s) to form moist potential vorticity vector (MPVV). This vector is also evaluated as a predictor of rainfall event over different regions in Tanzania. We argue that the results from the scalar product of absolute vorticity and gradient of temperature may not explain all atmospheric dynamics over the tropics that

contribute to formation and distribution of rainfall events. This is due to (1) the Coriolis parameter that contributes for many dynamical processes in mid and extra tropical regions is very small over the tropics and is zero over the equator. Therefore equatorial flows, especially two dimensional equatorial flows, may not be explained by any version of MPV as Gao et al (2004b) argued. (2) The vertical gradient of temperature over the tropics is small due to strong convective mixing processes. The scalar MPV derived from dot product of absolute vorticity and gradient of temperature may not be accurate enough to explain convective processes associated with rainfall events over tropics.

4.3 Data and analysis

4.3.1 Model data

Rossby center has produced and made available a very large number of climate simulation that are included in the Coordinated Regional Downscaling Experiment (CORDEX). Rossby Centre Atmospheric (RCA) model is driven by several general circulation models (GCMs) and ERA-Interim global reanalysis datasets (Strandberg et al, 2014). In this study daily data of air temperature, specific humidity, zonal and meridional components of the wind at 850 and 600 hPa from numerical output generated by the Rossby Center regional climate model version four (RCA4) forced by CCCma-CanESM2 (GCM) are used for computation of MPV and MPVV at 700hPa. RCA4 has high space resolution of 0.4° by 0.4° corresponding to 50 km by 50 km and has ten vertical levels (standard pressure levels).

The land surface characteristics used to initialize Soil-Vegetation-Atmosphere Transfer schemes (SVTs) in RCA4 come from a new global physiography data bases ECOCLIMAP for vegetation, lake depth and soil carbon density, and Gtopo30 for orography. The near surface diagnostic quantities: temperature, specific humidity and wind speed are solved using new version of Turbulence Kinetic Energy (TKE) scheme (Strandberg et al, 2014). This scheme combines TKE based on local stability measurement (using Richardson number) and the non-local parcel method (Lenderink and Holtslag, 2004). Convection scheme in RCA4 is based on Bechtold-KF (Strandberg et al, 2014). In this scheme the

triggering function forcing for convection is the large scale vertical velocity, closure assumption and cloud top is based on CAPE closure (Bechtold et al., 2001).

4.3.2 Reanalysis data

The National Centers for Environmental Prediction/ National Center for Atmospheric Research (NCEP/ NCAR) provide a comprehensive reanalysis data that are prepared using observed data from several sources including surface land synoptic meteorological stations, aircraft, and rawinsonde, ship, aircraft, and satellite data. The data assimilation for the NCEP reanalysis system is performed using a global spectral model with spatial resolution of 1.875^0 by 1.875^0 which has 28 vertical levels, for detailed descriptions on how the NCEP reanalysis rainfall data are generated a reader may consult (Kalnay et al, 1996). NCEP/NCAR reanalysis precipitation rate accessed from their Web site at <http://www.esrl.noaa.gov/psd/> are used for comparison with MPVV and MPV patterns.

4.3.3 Observation data

Monthly observation rainfall data from 22 synoptic meteorological stations over the period of 1976-2001 are obtained from the Tanzania Meteorological Agency (TMA). These data are quality controlled to remove the inhomogeneity and gaps by using the HOMER software package. For detailed descriptions of methodology used for homogeneity tests the reader may consult Luhunga et al (2014).

4.3.4 Analysis

4.3.4.1 Marquet (2014)'s MPV

For simplification of the analysis Eq. 5 can be re-written into three terms under hydrostatic balance as;

$$MPV(\theta_s) = -g \left(-\frac{\partial v}{\partial p} \frac{\partial \theta_s}{\partial x} + \frac{\partial u}{\partial p} \frac{\partial \theta_s}{\partial y} + (\zeta + f) \frac{\partial \theta_s}{\partial p} \right). \quad (8)$$

$$\text{First term} = MPV_z = -g(\zeta + f) \frac{\partial \theta_s}{\partial p}. \quad (9)$$

$$\text{Second term} = MPV_x = g \frac{\partial v}{\partial p} \frac{\partial \theta_s}{\partial x}. \quad (10)$$

$$\text{Third term} = MPV_y = -g \frac{\partial u}{\partial p} \frac{\partial \theta_s}{\partial y}. \quad (11)$$

4.3.4.2 The moist potential vorticity vector (MPVV)

Gao et al (2004) defined convective vorticity vector as;

$$CVV = \frac{\zeta_a \times \nabla \theta_e}{\rho}. \quad (12)$$

We modify Eq. 12 by replacing θ_e with θ_s to form MPVV as;

$$MPVV(\theta_s) = \frac{\zeta_a \times \nabla \theta_s}{\rho}, \quad (13)$$

Eq. 13 can be re-written into component form as;

$$\begin{aligned} MPVV(\theta_s) &= \frac{1}{\rho} \begin{pmatrix} -\frac{\partial v}{\partial z} \\ \frac{\partial u}{\partial z} \\ (\zeta + f) \end{pmatrix} \times \begin{pmatrix} \frac{\partial \theta_s}{\partial x} \\ \frac{\partial \theta_s}{\partial y} \\ \frac{\partial \theta_s}{\partial z} \end{pmatrix} = \frac{1}{\rho} \begin{pmatrix} \frac{\partial u}{\partial z} \frac{\partial \theta_s}{\partial z} - (\zeta + f) \frac{\partial \theta_s}{\partial y} \\ \frac{\partial v}{\partial z} \frac{\partial \theta_s}{\partial z} + (\zeta + f) \frac{\partial \theta_s}{\partial x} \\ -\frac{\partial v}{\partial z} \frac{\partial \theta_s}{\partial y} - \frac{\partial u}{\partial z} \frac{\partial \theta_s}{\partial x} \end{pmatrix} = \\ &\begin{pmatrix} MPVV_x \\ MPVV_y \\ MPVV_z \end{pmatrix}, \end{aligned} \quad (14)$$

where ρ is density which is defined as

$$\rho = \frac{p}{\theta(\rho, p) R_d} \left(\frac{p_0}{p} \right)^k, \quad (15)$$

where p is atmospheric pressure (in Pa) at different pressure levels, p_0 is atmospheric pressure at reference level, $\theta(\rho, p)$ is potential temperature in this case θ_s is used to

account for moist air, R_d is specific gas constant for dry air and $k = \frac{R_d}{c_p}$, c_p is specific heat capacity at constant pressure.

The absolute vorticity ζ_a is defined as

$$\zeta_a = -\frac{\partial v}{\partial z}i + \frac{\partial u}{\partial z}j + (\zeta + f)k, \quad (16)$$

where ζ is the relative vorticity defined as $\zeta = \frac{\partial v}{\partial x} - \frac{\partial u}{\partial y} + \frac{u}{a}\tan(\varphi)$, where a is the radius of the earth and φ is the latitude, f is the coriolis parameter defined as $f = 2\Omega\sin(\varphi)$.

Considering the hydrostatic equilibrium $\partial/\partial z = -\rho g \partial/\partial p$, Eq.14 can be re-written as

$$\text{First component } MPVV_x = \rho g^2 \frac{\partial u}{\partial p} \frac{\partial \theta_s}{\partial p} - \frac{(\zeta+f)}{\rho} \frac{\partial \theta_s}{\partial y} \quad (17)$$

$$\text{Second component } MPVV_y = \rho g^2 \frac{\partial v}{\partial p} \frac{\partial \theta_s}{\partial p} + \frac{(\zeta+f)}{\rho} \frac{\partial \theta_s}{\partial x} \quad (18)$$

$$\text{Third component } MPVV_z = g \frac{\partial v}{\partial p} \frac{\partial \theta_s}{\partial y} + \frac{\partial u}{\partial p} \frac{\partial \theta_s}{\partial x} \quad (19)$$

The magnitude of MPVV is written as

$$|MPVV| = \sqrt{(MPVV_x)^2 + (MPVV_y)^2 + (MPVV_z)^2} \quad (20)$$

$MPVV_x, MPVV_y$ and $MPVV_z$ are the x, y and z component of $MPVV$ respectively and $|MPVV|$ is the magnitude of MPVV, u and v are zonal and meridional winds. It is important to note that the vertical component of the wind w is neglected in the computation of $MPVV$ due to fact that it is much smaller than the horizontal components of the winds, therefore $\frac{\partial w}{\partial x}$ and $\frac{\partial w}{\partial y} \approx 0$

4.3.4.3 MPV and MPVV interpolation and statistical analysis

The MPV and MPVV are calculated at each grid point. In order to be compared with rainfall data at different meteorological stations the grid values of points MPV and MPVV are interpolated to the location of meteorological stations using arithmetic mean technique. The daily values of MPV and MPVV interpolated at each station are used to calculate monthly averages of MPV and MPVV. The Pearson correlation coefficient between observed station rainfall and the MPV and between rainfall and MPVV is computed at each meteorological station using Eq. 21 and Eq. 22.

$$r_{(R,MPV)} = \frac{\sum_{i=1}^N (R_i - \bar{R})(MPV_i - \overline{MPV})}{\sqrt{\sum_{i=1}^N (R_i - \bar{R})^2} \sqrt{\sum_{i=1}^N (MPV_i - \overline{MPV})^2}}, \quad (21)$$

$$r_{(R,MPVV)} = \frac{\sum_{i=1}^N (R_i - \bar{R})(MPVV_i - \overline{MPVV})}{\sqrt{\sum_{i=1}^N (R_i - \bar{R})^2} \sqrt{\sum_{i=1}^N (MPVV_i - \overline{MPVV})^2}}, \quad (22)$$

where R , MPV and $MPVV$ are the observed rainfall, moist potential vorticity and moist potential vorticity vector respectively, while i refers to the observed rainfall and MPV or MPVV pairs and N is the total number of such pairs. The value of r ranges between -1 for the perfect negative relationship to +1 for the perfect positive relationship between two variables. The statistical analysis for significant testing of Pearson correlation coefficient used in this study is called a test of the statistical significance of a regressor which is well documented in many statistical text books (e.g. Rangaswamy, 2006).

4.4 Results

4.4.1 Case study

First we motivate, why our computation of MPV and MPVV is done at 700hPa. The reason is that over the tropics, especially over equatorial regions, moist air thermodynamics become active within the lower troposphere, thus why weather system that determine the day to day forecast are frequently diagnosed at 850hPa and 700hPa. The 850hPa level is the lower level close to the boundary layer and is usable for diagnosis of weather triggering

systems along the coastal regions where boundary layer clouds produced by large amount of moisture flux convergence may determine the formation of rainfall. Away from the coastal regions over high grounds, weather systems that are triggering the formation of rainfall are normally diagnosed at 700hPa. Generally over the tropics rainfall formation is dominated by the low level clouds and shallow convergence of moist air as large amount of moisture is found over low levels. This is different from mid and extra tropics where rainfall is determined by deep convection triggered by the movement of cold fronts and cut off lows.

A one day (1-12-1991) case study, when many countries over the tropics received rainfall is analyzed. Fig.1 shows the spatial distribution of MPV and its three terms at different countries in Africa.

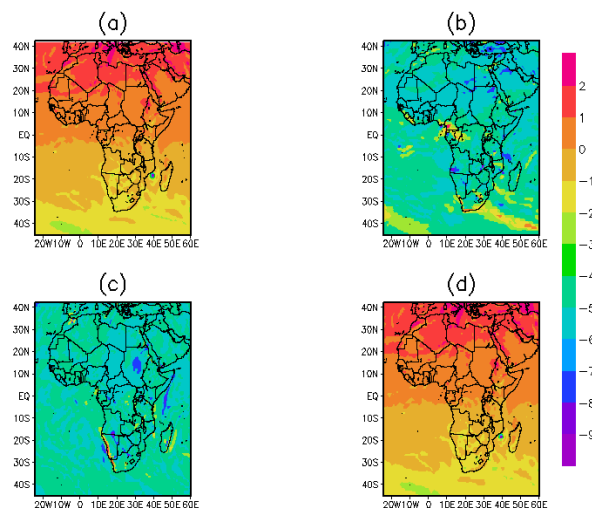


Figure1: The spatial pattern of moist potential vorticity (MPV) in (PV-units) at 700hPa calculated using data from 850 and 600hPa on 1-12-1991 (a) is the first term (b) is the second term (c) the third term and (d) is the total MPV.

The first term (vertical term) of MPV is the larger one when compared with the second and thirds terms. This confirms the experimental test performed in the mid latitude by Marquet (2014) who noted that the vertical term is larger than the horizontal terms. The MPV is mostly positive in the northern hemisphere and negative in the southern one. In comparison with the spatial distribution of rainfall events presented in Fig.3, there is no clear pattern from MPV that collaborate with the pattern of rainfall events that occurred

over different countries in Africa. The expected pattern was that areas with positive values of MPV should receive rainfall, while the areas with negative values of MPV should be dominated with condition that suppresses rainfall formation.

Fig.2 shows the spatial distribution of the magnitude of MPVV and its three components.

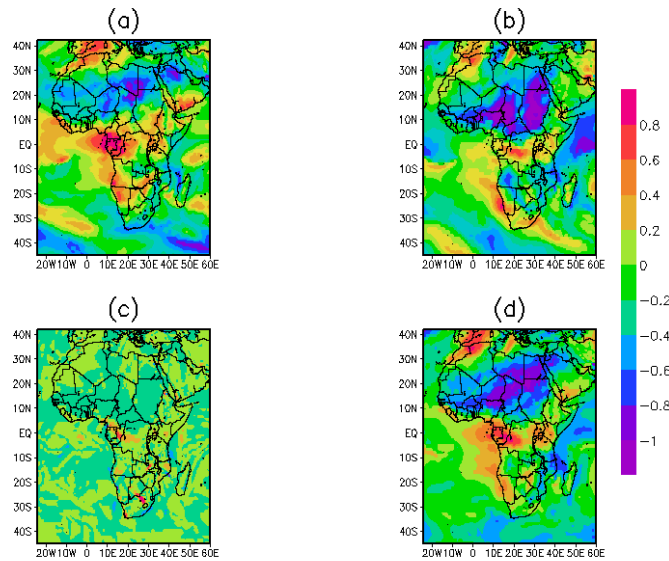


Figure 2: The spatial pattern of moist potential vorticity vector (MPVV) ($10^2 \cdot \text{PV-units}$) at 700hPa calculated using data from 850 and 600hPa on 1-12-1991 (a) first component (b) the second component (c) the third component (d) the magnitude of MPVV.

The magnitude of MPVV together with its components portrays the patterns of rainfall in Fig.3. The areas with positive values of MPVV are associated with convective vortices that influence rainfall formation. It is also seen from MPVV patterns that the areas with positive values of MPVV dominate over the southern part of Nigeria where the inter-tropical convergence zone (ITCZ) reach its maximum zonal displacement. Further it is even possible to trace the zonal and meridional displacement of the ITCZ from the MPVV see Fig.2 (a), (b) and (d) where the region with positive values of MPVV extends in zonal and meridional components from Gabon and Congo Brazzaville indicating the regions of strong convective process as also described by the ITCZ. The regions with no rainfall are well described by MPVV. For instance in some North Africa regions where the value of MPVV were negative have received no rainfall (Fig.3).

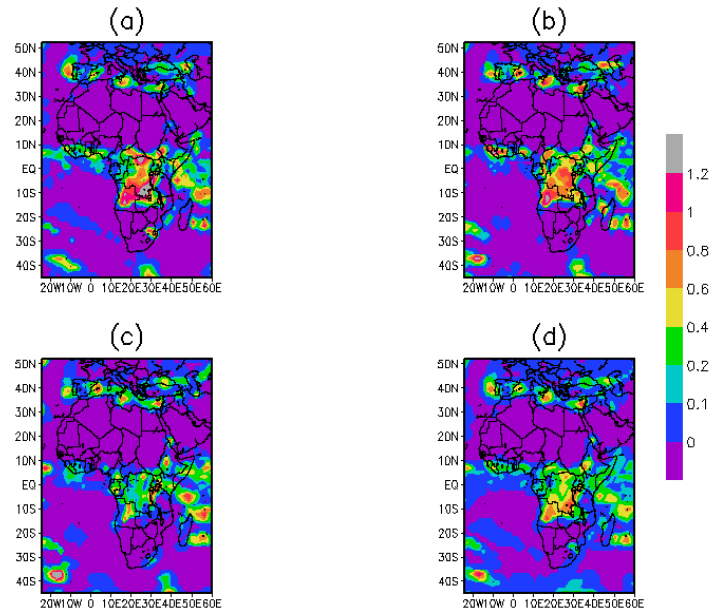


Figure 3: Spatial distribution of rainfall intensity (mm/hour) in Africa on 1-12-1991 (a) at 06 (b) 12 (c) at 18 and (d) average from 00 to 18 hrs

In east African regions, Fig.4 demonstrates the spatial patterns of MPV.

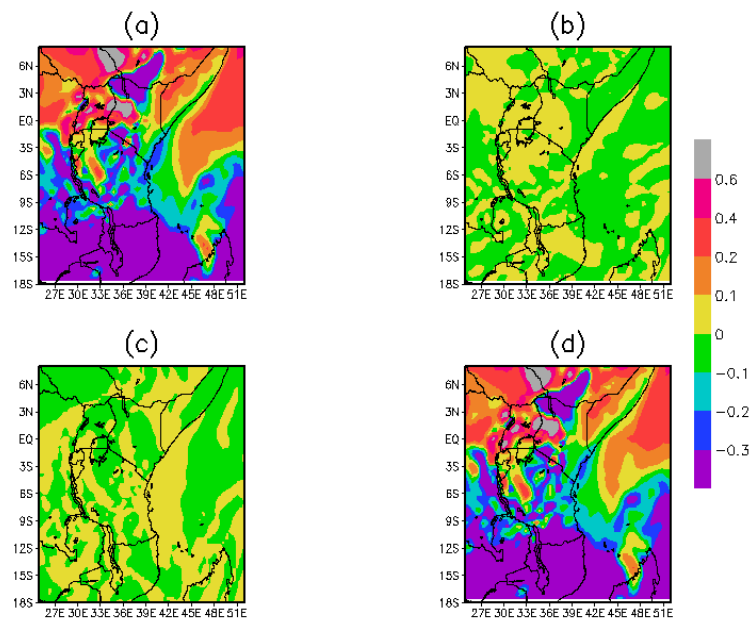


Figure 4. MPV on 1.12.1991, (a) first term (b) second term (c) third term and (d) total MPV at 700hPa

This figure correlates little with rainfall pattern in Fig.6. The region with positive values of MPV do not necessarily received high rainfall rate. On the other hand Fig.5 demonstrates the spatial structure of MPVV indicating regions with positive values MPVV collaborate with the pattern of rainfall in Fig.6. The positive MPVV dominated over northern region (Lake Victoria regions) and over western regions (western of Lake Tanganyika). These areas received high rainfall rate (see Fig.6).

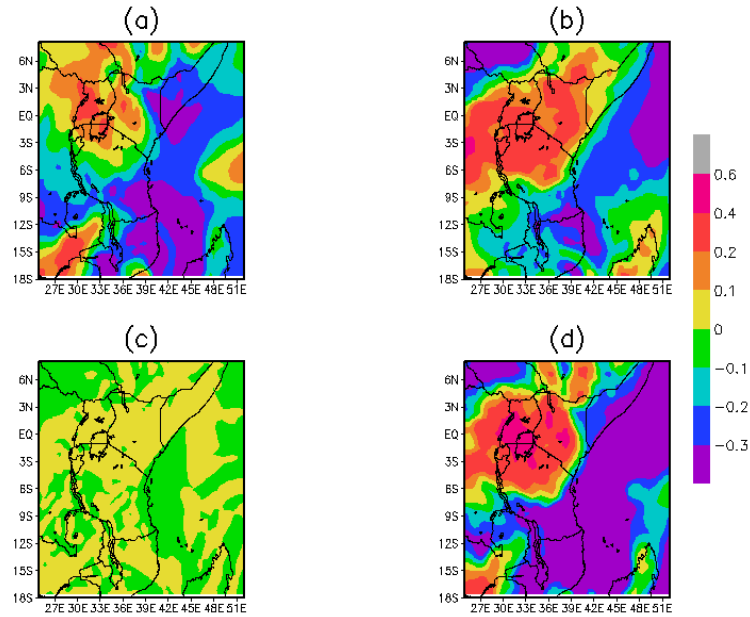


Figure 5: MPVV on 1.12.1991, (a) first component (b) second component (c) third component MPVV at 700hPa

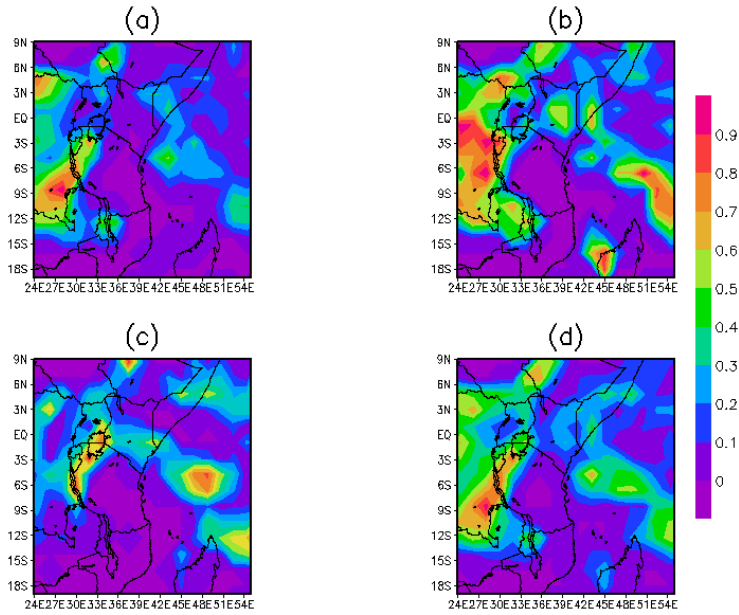


Figure 6 Rain rate (mm/hour) data source NCEP reanalysis data, on 1-12-1991 (a) at 06 (b) at 12 (c) at 18 (d) average from 00 to 18

4.4.2 Statistical analyses

The Pearson correlation coefficient is the measure of relationship between two variables. It is performed to measure the strength of relationship between MPV and rainfall and between MPVV and rainfall. The Pearson correlation coefficient above 0.4 is considered relatively strong and correlation between 0.2-0.4 is considered moderate and those below 0.2 are considered weak (Mayor et al., 2015). Further statistical test is carried computing the statistical significance level (p) and the coefficient of variation (R^2). The significant test is referred to know how reliable the results are. The statistical test here is employed where p should be less than or equal to 0.05, for the results to be statistically significant.

Table 1, indicates the Pearson correlation coefficient between annual cycles of first term of MPV against rainfall computed as monthly average from 1971-2001. It is clear that MPV indicate relatively strong correlation with observed rainfall at 4 meteorological stations, moderate correlated with rainfall at 6 meteorological stations and weakly correlated with rainfall at 12 meteorological stations. The highest correlation coefficient between the first term of MPV and rainfall is observed at Igeri ($r=0.62$, $p=0.032$). On the other hand, Table 2

indicates the Pearson correlation coefficient between annual cycles of the first component of MPVV against rainfall computed as monthly average from 1971-2001. The first component of MPVV has relative strong correlation with rainfall at 12 meteorological stations and moderately correlated with rainfall at 6 meteorological stations and weakly correlated with rainfall at 4 meteorological stations. As shown in Table 2, Kibaha and Morogoro have the highest correlation coefficients of ($r=0.8$, $p=0.002$) and ($r=0.79$, $p=0.002$) respectively.

The second term of MPV has shown correlation coefficient of greater than or equal to 0.4 at 6 meteorological stations (Table 1), while the second component of MPVV has high correlation coefficient of greater or equal to 0.4 at 8 stations (Table 2). The third term of MPV has correlated with rainfall with correlation coefficient of greater or equal to 0.4 at 7 stations (Table 1), while the third component of MPVV has correlation coefficient of greater or equal to 0.4 at 11 meteorological stations (Table 2). The total MPV has relatively strong correlated with rainfall at 4 meteorological stations (Table 1). On the other hand the magnitude of MPVV has relatively strongly correlated with rainfall at 14 meteorological stations (Table 2). Overall, the findings implied that the MPVV and its components correlate better with rainfall than the MPV. Also the first component and the magnitude of MPVV correlated better with rainfall than the other components.

The bivariate regression analysis to examine the predictive power between annual cycle rainfall as independent variable and the total MPV and its terms are also presented in (Table 1). This table indicates that Term1 explains better the variation of rainfall over Mbeya ($R^2=0.336$, $p=0.048$), while term2 explain better the variation of rainfall over Igeri ($R^2 =0.550$, $p=0.006$). Term 3 explain better the variation of rainfall over Dodoma ($R^2 =0.542$, $p=0.006$), Iringa ($R^2 =0.478$, $p=0.013$), Tabora ($R^2 =0.537$, $p=0.007$), and Mwanza ($R^2 =0.348$, $p=0.044$). The total MPV explain better the variation in rainfall only over Mtwara ($R^2 =0.479$, $p=0.013$).

On the other hand, the bivariate regression analysis is conducted to examine the predictive power between annual cycle rainfall as independent variable and the magnitude and its components of MPVV are presented in Table 2. Results showed that over Dar es Salaam (DIA), the first component of MPVV explains the variation of rainfall with ($R^2=0.547$,

$p=0.006$), followed by the magnitude of MPVV with ($R^2=0.546$, $p=0.006$). The first component of MPVV explain better the variation of rainfall over Morogoro with ($R^2=0.618$, $p=0.002$), Ilonga with ($R^2=0.530$, $p=0.007$), and over Mlingano with ($R^2=0.401$, $p=0.027$).

The magnitude of MPVV explain better the variation in rainfall over Dodoma ($R^2=0.627$, $p=0.002$), Iringa ($R^2=0.637$, $p=0.002$), Tabora ($R^2=0.682$, $p=0.001$), Kibaha ($R^2=0.682$, $p=0.001$), Kigoma ($R^2=0.558$, $p=0.005$), Mwanza ($R^2=0.478$, $p=0.013$) and Zanzibar ($R^2=0.426$, $p=0.021$). Term3 better explain the variation of rainfall at Igeri ($R^2=0.354$, $p=0.041$).

The variations of annual cycles in rainfall and first component of MPVV over unimodal and bimodal regions represented by Tabora and Kibaha stations respectively are presented in Fig.7 and Fig.8. It is clear that the first component of MPVV catches the annual cycles of rainfall.

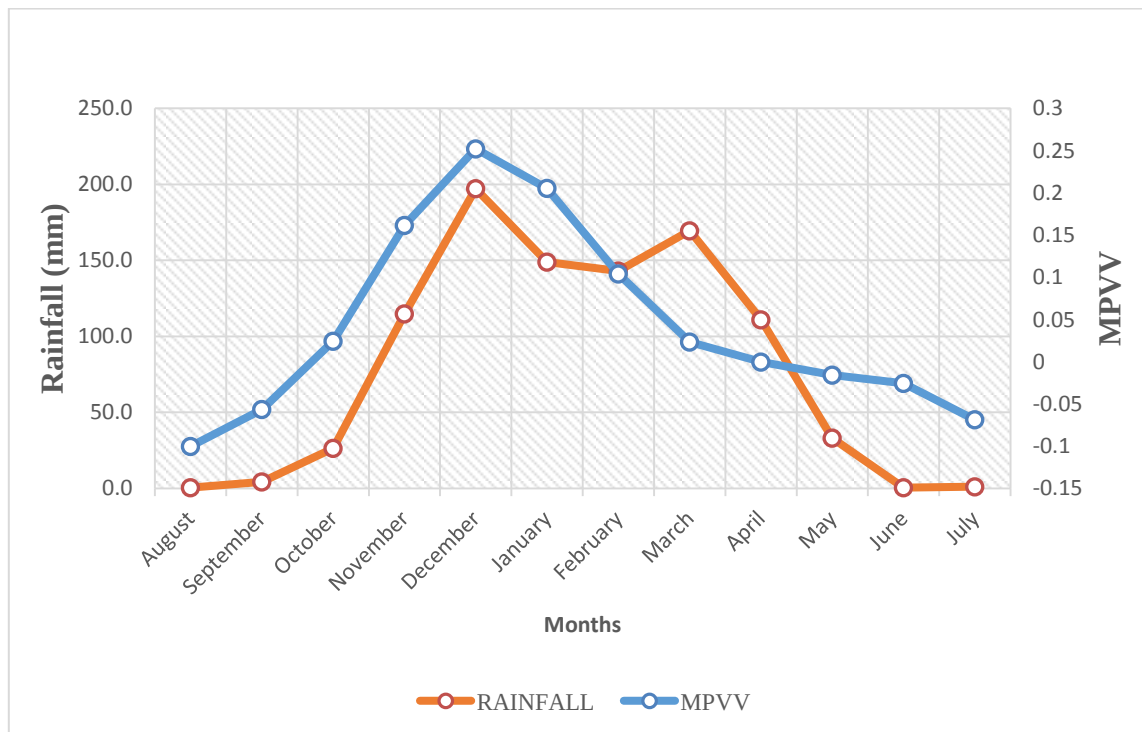


Figure 7. Annual cycle of rainfall and magnitude of MPVV at 700hPa calculated from 1976-2001 at Tabora meteorological station

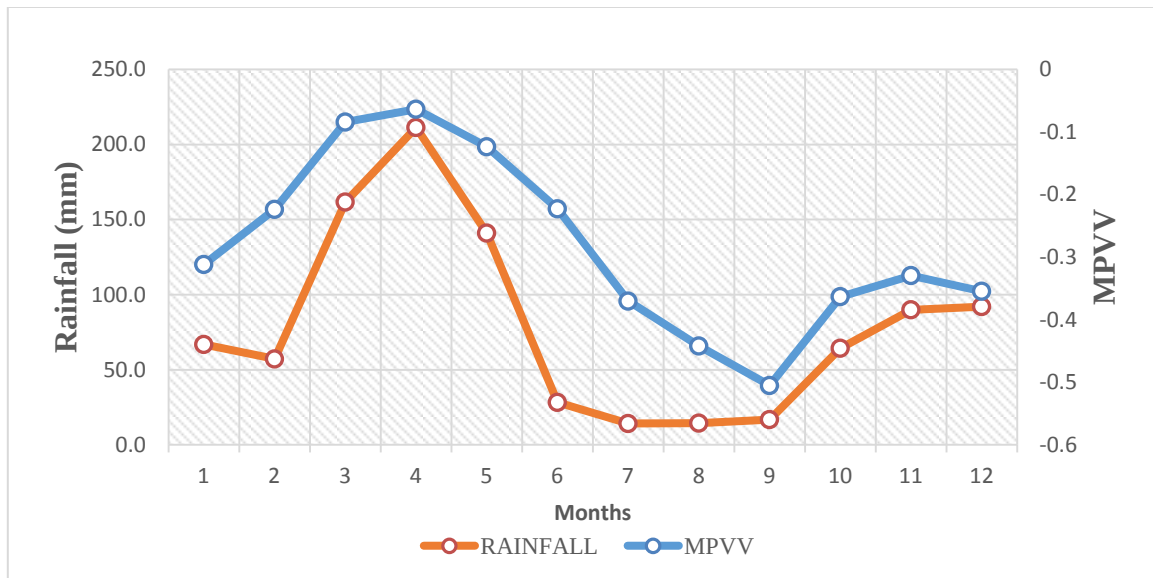


Figure 8. Annual cycle of rainfall and first component of MPVV at 700hPa calculated from 1976-2001 at Kibaha meteorological station

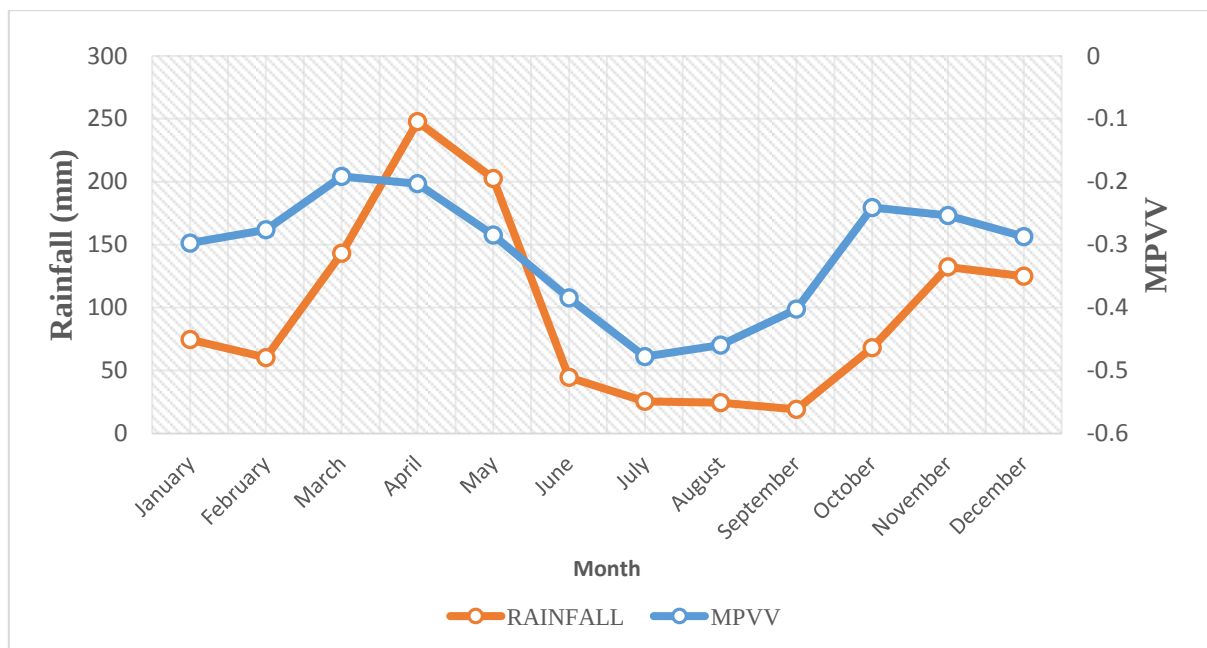


Figure 9. Annual cycle of rainfall and first component of MPVV at 700hPa calculated from 1976-2001 at Dar es Salaam meteorological station

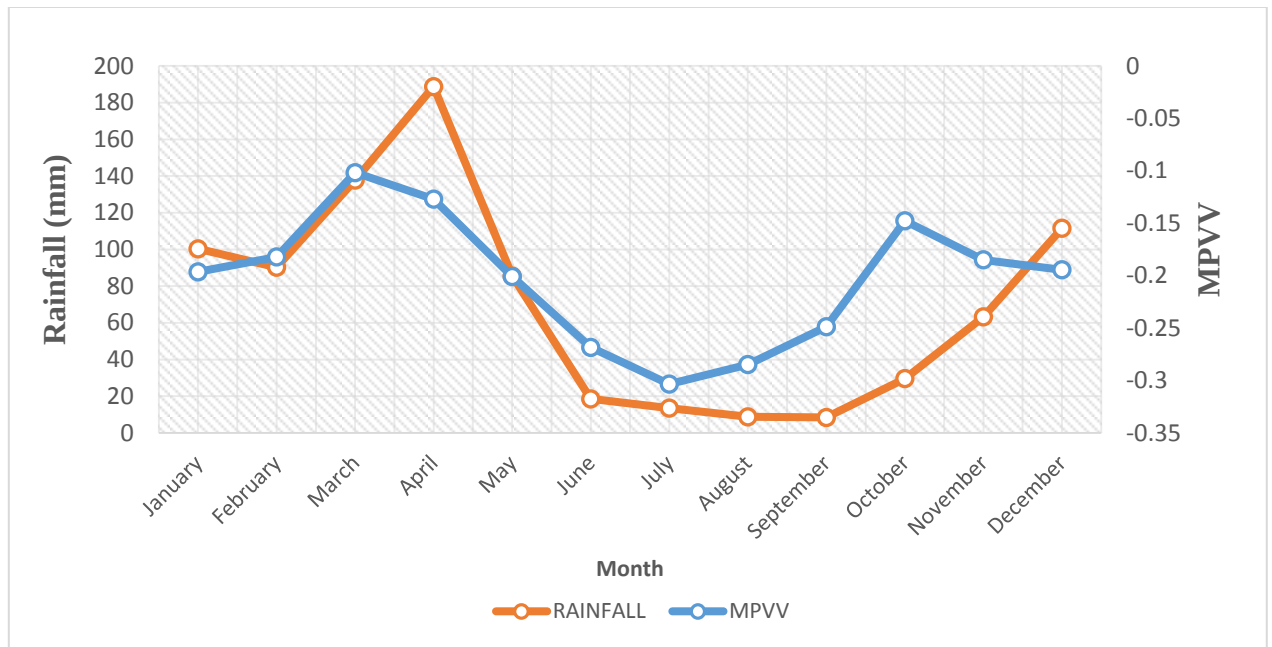


Figure 10. Annual cycle of rainfall and first component of MPVV at 700hPa calculated from 1976-2001 at Morogoro meteorological station

Table 1. Indicates p-values and Coefficients of determination (R^2) for MPV, values in bold are statistically significance at $\alpha=0.05$

Station name	First term			Second term			Third term			Total MPV		
	p-values	r	R^2	p-values	r	R^2	p-values	r	R^2	p-values	r	R^2
ARUSHA	0.912	0.04	0.001	0.755	-0.10	0.010	0.491	-0.22	0.049	0.921	0.03	0.001
DIA	0.606	-0.17	0.028	0.977	0.01	0.0001	0.828	-0.07	0.005	0.674	-0.14	0.018
BUKOBA	0.557	0.19	0.036	0.160	-0.43	0.187	0.416	0.26	0.067	0.566	0.18	0.034
DODOMA	0.819	-0.07	0.006	0.472	-0.23	0.053	0.006	-0.74	0.542	0.761	-0.10	0.010
IRINGA	0.360	-0.29	0.084	0.138	-0.45	0.207	0.013	0.69	0.478	0.371	-0.28	0.081
MBEYA	0.048	0.58	0.336	0.747	-0.10	0.011	0.338	0.30	0.092	0.073	0.54	0.287
MOROGORO	0.874	0.05	0.003	0.287	-0.33	0.112	0.332	-0.31	0.094	0.936	0.03	0.001
SONGEA	0.768	-0.10	0.009	0.559	-0.19	0.035	0.197	0.40	0.160	0.770	-0.09	0.009
TABORA	0.100	0.50	0.248	0.319	0.31	0.099	0.007	-0.73	0.537	0.101	0.50	0.246
TANGA	0.404	0.27	0.071	0.815	0.08	0.006	0.485	0.22	0.050	0.411	0.26	0.068
IGERI	0.032	0.62	0.382	0.006	0.74	0.550	0.020	0.66	0.433	0.028	0.63	0.398
ILONGA	0.994	0.001	0.0000001	0.253	-0.36	0.128	0.244	-0.36	0.133	0.970	-0.01	0.0001
KIBAHA	0.517	-0.21	0.043	0.824	-0.07	0.005	0.386	-0.28	0.076	0.526	-0.20	0.041
KIGOMA	0.471	0.23	0.053	0.029	-0.63	0.392	0.114	-0.48	0.231	0.640	0.15	0.023
LYAMUNGO	0.629	-0.16	0.024	0.076	0.53	0.281	0.441	-0.25	0.060	0.663	-0.14	0.020
MLINGANO	0.699	-0.12	0.016	0.683	0.13	0.017	0.343	0.30	0.090	0.771	-0.09	0.009
MOSHI	0.267	0.35	0.121	0.202	0.40	0.157	0.834	-0.07	0.005	0.262	0.35	0.124
MTWARA	0.017	-0.67	0.447	0.367	-0.29	0.082	0.768	-0.10	0.009	0.013	-0.69	0.479
MUSOMA	0.677	-0.13	0.018	0.471	-0.23	0.053	0.216	-0.39	0.149	0.625	-0.16	0.025
MWANZA	0.934	-0.03	0.001	0.190	-0.41	0.165	0.044	-0.59	0.348	0.807	-0.08	0.006
SAME	0.353	-0.29	0.087	0.353	-0.29	0.086	0.232	-0.37	0.140	0.350	-0.30	0.088
ZANZIBAR	0.754	-0.10	0.010	0.778	0.09	0.008	0.983	0.01	0.0001	0.776	-0.09	0.008

Table 2, indicates p-values and Coefficients of determination (R^2) for MPVV, values in bold are statistically significance at $\alpha=0.05$

Station name	First component			Second component			Third component			Magnitude of MPVV		
	p-values	r	R^2	p-values	r	R^2	p-values	r	R^2	p-values	r	R^2
ARUSHA	0.228	0.38	0.142	0.414	0.26	0.068	0.104	-0.49	0.243	0.183	0.41	0.170
DIA	0.006	0.740	0.547	0.303	0.32	0.105	0.131	0.46	0.213	0.006	0.74	0.546
BUKOB	0.406	0.264	0.070	0.504	0.21	0.046	0.727	-0.11	0.013	0.352	0.30	0.087
DODOMA	0.009	0.712	0.507	0.062	0.55	0.306	0.346	0.30	0.089	0.002	0.79	0.627
IRINGA	0.206	0.393	0.154	0.015	0.68	0.465	0.080	0.52	0.275	0.002	0.80	0.637
MBEYA	0.635	-0.153	0.023	0.363	0.29	0.083	0.211	0.39	0.152	0.503	0.21	0.046
MOROGORO	0.002	0.786	0.618	0.120	0.47	0.224	0.967	-0.01	0.0002	0.003	0.78	0.610
SONGEA	0.111	-0.484	0.234	0.876	0.05	0.003	0.245	0.36	0.132	0.308	-0.32	0.103
TABORA	0.127	0.466	0.217	0.056	0.56	0.319	0.944	-0.02	0.001	0.001	0.83	0.682
TANGA	0.269	0.347	0.120	0.264	0.35	0.123	0.165	0.43	0.183	0.057	0.56	0.316
IGERI	0.457	-0.237	0.056	0.684	0.13	0.017	0.041	-0.59	0.354	0.896	-0.04	0.002
ILONGA	0.007	0.728	0.530	0.116	0.48	0.228	0.996	0.001	0.0001	0.010	0.71	0.501
KIBAHA	0.002	0.801	0.642	0.216	0.39	0.149	0.359	0.29	0.085	0.001	0.83	0.682
KIGOMA	0.352	0.295	0.087	0.195	0.40	0.162	0.036	0.61	0.371	0.005	0.75	0.558
LYAMUNGO	0.677	-0.134	0.018	0.729	-0.11	0.012	0.208	-0.39	0.154	0.628	-0.16	0.024
MLINGANO	0.027	0.633	0.401	0.378	0.28	0.079	0.618	0.16	0.026	0.060	0.56	0.311
MOSHI	0.791	0.086	0.007	0.924	0.03	0.001	0.095	-0.50	0.254	0.801	0.08	0.007
MTWARA	0.123	0.470	0.221	0.643	0.15	0.022	0.974	-0.01	0.0001	0.398	0.27	0.072
MUSOMA	0.984	-0.007	0.00004	0.192	0.40	0.163	0.062	-0.55	0.306	0.268	0.35	0.121
MWANZA	0.423	0.256	0.065	0.031	0.62	0.386	0.083	-0.52	0.270	0.013	0.69	0.478
SAME	0.045	0.588	0.345	0.357	0.29	0.085	0.387	-0.28	0.076	0.050	0.58	0.331
ZANZIBAR	0.019	0.663	0.439	0.398	0.27	0.072	0.119	0.47	0.225	0.021	0.65	0.426

4.5 Summary and recommendations

The aim of this study was to compute the moist potential vorticity (MPV) and moist potential vorticity vector (MPVV) and compare their performance in describing rainfall events over different regions of Tanzania. Results indicated that MPVV perform better, in explaining the variation of rainfall than MPV. The first component and the magnitude of MPVV provide strong correlation coefficient with rainfall at significant level less than 0.05 at many stations when compared to other components. This suggest that the magnitude of MPVV and first component can be used as predictors of rainfall over different regions where they have shown strong correlation coefficient, and high coefficient of determination at significant level of 0.05. For instance, from Fig.7 to Fig. 10, the first component captured the annual cycle of rainfall over Tabora in unimodal region and Kibaha, Dar es Salaam and Morogoro in bimodal region. One can construct a transfer function between the first component of MPVV and monthly rainfall and use it to better the climate change projections for rainfall or for seasonal climate prediction. This is important especially for Tanzania where seasonal climate forecasting is based on analyzing analog years. This is the simple seasonal prediction technique based on analyzing weather maps that resemble another weather maps for different years within the season in the historical record and normally is based on subjective judgments from human eyes. This method produces fairly inaccuracy seasonal climate prediction (Huijun et al., 2015).

In this study we recommend the use of MPVV for development of empirical model for seasonal climate prediction over different regions in Tanzania. MPVV reproduce the pattern of rainfall in both bi model and unimodal region better than RCMs simulation of rainfall. Recently Luhunga et al (2016) evaluated the performance of the CORDEX RCMs to simulate climate condition of Tanzania. They found that the RCMs underestimate rainfall in March-April-May (MAM) and overestimate during October-November-December (OND) season. However, MPVV show the observed pattern of rainfall, that in MAM where there is higher rainfall total the MPVV is also higher and in OND where there is lower rainfall total the MPVV is lower too. Therefore a transfer function constructed based on MPVV may accurately predict the seasonal variation of rainfall over different regions in Tanzania.

Furthermore MPVV need to be explored more on its application to better seasonal prediction in East Africa where seasonal climate prediction depends among other techniques on simulations from the general circulation models (GCMs) forced by sea surface temperatures. However the GCMs have coarse space resolution to reproduce climate details at different regions. The results presented in this study contribute on the existing predictors that are used for development of empirical models for seasonal climate prediction. Most statistical model are constructed using predictors such as relative humidity, geo potential height, upper level wind speed (e.g. at 500hPa). These predictors suffer to reproduce at the same time the dynamics and thermodynamics of the atmosphere. However MPVV can reproduce at the same time the dynamics of the atmospheric flows (through vorticity) and thermodynamics of the atmospheric flows (through the gradient of moist entropy potential temperature).

It is important to note that the MPV and MPVV presented in this study were computed using data from the RCM driven by GCM. Therefore further studies are recommended to explore the performance of MPV and MPVV in describing rainfall events in Tanzania using data from RCM driven by ERA-Interim data. Moreover, it is recommended that MPVV should be tested on ability to reproduce interannual variability of rainfall to have more confidence to use it as predictor of rainfall events.

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Chapter 5: Moist potential vorticity vector for diagnosis of heavy rainfall events in Tanzania

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Abstract

In this paper, we modify the convective vorticity vector (CVV) which is defined as a cross product of absolute vorticity and gradient of equivalent potential temperature to moist potential vorticity vector (MPVV) defined as cross product of absolute vorticity ζ_a and the gradient of the moist-air entropy potential temperature (θ_s). The patterns of MPVV are compared with the patterns of heavy rainfall events that occurred on 20th to 22nd December, 2011 and 05th to 8th May, 2015 over different regions in Tanzania. Moreover, the article aims at assessing the relative contributions of the magnitude, horizontal and vertical components of MPVV on the observed patterns of rainfall events. Dynamic and thermodynamic variables: wind speed, temperature, atmospheric pressure and relative humidity from numerical output generated by the Weather Research and Forecasting (WRF) model running at Tanzania Meteorological Agency (TMA) were used to compute MPVV. It is found that MPVV provide accurate tracking of locations received heavy rainfall, suggesting its potential use as a dynamic tracer for heavy rainfall events in Tanzania. Finally it is found that the first and second components of MPVV contribute almost equally in tracing locations received heavy rainfall events. The magnitude of MPVV describes the locations received heavy rainfall events better than the components.

5.1 Introduction

In recent years, extreme weather events such as heavy rainfall (defined as rainfall amount realized in a day is between 64.5 to 124.4 mm) are common and have contributed to loss of lives, damage of properties, destruction of environment and other social economic livelihood of people in many countries (Hally et al., 2014 and GWHS, 2016). Tanzania has witnessed many heavy rainfall events in recent years. Table 1 bellow depicts some of the more recent heavy rainfall events which have occurred over different regions in Tanzania. Forecasting of these events is of considerable benefit to different sectors (agriculture, hydropower, health, water resources) and community at large. However, it is difficult to forecast these events accurately and reliably (CNRS, 2013 and Mahmud and Kumar, 2008). In Tanzania, the difficulty to forecast heavy rainfall is associated with the country's complex topographical landscapes, numerous large inland water bodies, variation in vegetation types and land-ocean contrast (Kijazi and Reason, 2009).

Table 1 Regions received heavy rainfall from 2011to 2015 in Tanzania

No.	Region	Lat (S)	Lon	Alt	Rainfall	Date of heavy
1	Tukuyu,	08.56	33.28	1758	232	09/11/2011
2	Dar es	06.53	39.12	53	156.4	20/12/2011
3	Iringa	07.40	35.45	1428	131	21/12/2011
4	Kizimbani,	06.13	39.13	18	130.2	19/04/2011
5	Mtwara	10.21	40.11	113	100	18/02/2011
6	Tanga	05.05	39.04	49	100.6	11/10/2011
7	Zanzibar	06.13	39.13	18	133.8	19/04/2011
8	Dar es	06.53	39.12	53	133.8	11/04/2012
9	Mwanza	02.28	32.55	1140	142	31/10/2012
10	Zanzibar	06.13	39.13	18	116.2	26/11/2012
11	Dar es	06.53	39.12	53	138.1	11/04/2014
12	Dar es	06.53	39.12	53	111.4	6/5/2015
13	Kibaha	06.50	38.38	167	88.3	6/5/2015
14	Zanzibar	06.13	39.13	18	45.5	6/5/2015

Several studies (e.g. Kapala et al., 1994; Anyah and Semazzi, 2006 and Kijazi and Reason, 2009) have analysed the drivers of heavy rainfall events over East African region in general and Tanzania in particular. Kapala et al (1994) analyzed the link between El Nino events in the equatorial Indian Ocean and the catastrophic rainfall of 1961-1962 in East

Africa. They found that, heavy rainfall over East African region is associated with large Sea Surface Temperatures (SSTs) and wind anomalies over equatorial Indian Ocean. Kijazi and Reason (2009) analysed atmospheric circulation patterns over the Indian Ocean that was linked to heavy rainfall event that occurred over northern Tanzania during the short rain of October- December (OND) season in 2006. They found that heavy rainfall during OND season of 2009 was associated with strong warming over the Indian Ocean, coupled with convective zones over the western Indian Ocean and East African region.

The above mentioned studies have analysed the impacts of large scale atmospheric circulation, atmosphere-ocean interactions and SSTs on heavy rainfall events. However, relatively less attention has been directed towards analysing the impact of local scale induced circulations from orography, land ocean contrast, difference in vegetation type and from water bodies on formation of heavy rainfall events. Furthermore the combined impact of local and large scale circulations to the atmospheric environment at which was the main cause of heavy rainfall events have not been analysed. In this study, we modify the convective vorticity vector (CVV) which is defined as a cross product of absolute vorticity and gradient of equivalent temperature to moist potential vorticity vector (MPVV) by replacing the equivalent of potential temperature with the moist-air entropy potential temperature (θ_s). The usefulness of MPVV in diagnosis of heavy rainfall event is analysed. The ultimate goal is to highlight the possibilities of using MPVV to help prediction of heavy rainfall events over different regions in Tanzania.

5.1.1 Motivation of the use of new moist potential vorticity vector to describe rainfall events

Heavy rainfall events, among other factors are triggered by transport and convection of large volume of water vapour. Physical variable such as moist potential vorticity (MPV), that describe both dynamics and thermodynamics aspect of water vapour can be used to diagnose and potentially predict the occurrence and distribution of heavy rainfall (Liang et al., 2010). Indeed, MPV combines the two general characteristics responsible for the rain formation: the dynamics via the vorticity component and the thermodynamics via the gradient of the moist air temperature. Zhang and Cho (1992) used MPV as a fundamental

dynamical variable to examine a four dimensional dataset obtained from an 18-hr high resolution 25km simulation of a squall line that occurred during 1200UCT 10 June- to 0600UCT 11 June 1985 in the mid latitude (Northern hemisphere). They found that the stratiform region is characterised by negative MPV and suggest that trailing stratiform precipitation could be viewed as an end of slantwise convection with pronounced moist symmetric instability (MSI). Liang et al (2010) used MPV as a diagnostic variable of heavy rainfall event that occurred in Meiyu and found that MPV is an important physical variable to reveal heavy rainfall structure and dynamic mechanisms. They also found that negative MPV correspond to the Meiyu front-wind shear line system and the negative center corresponds to the heavy rain center.

However, the scalar MPV which is derived from the dot product of absolute vorticity and gradient of moist temperature may not fully explain the complex atmospheric circulations patterns over the tropics (Zi-feng and Hui, 2012). The Coriolis parameter over the tropics is very small and is zero over the equator. Furthermore the vertical gradient of temperature over the tropics is small due to strong mixing processes. Thus the scalar MPV may not represents some dynamical patterns over the tropics, particularly close to equatorial region. For instance, Gao et al (2004) demonstrated that the vertical component of planetary vorticity in MPV computation is zero and cannot explain two dimension (2-D) equatorial atmospheric flows. Zi-feng and Hui (2012) argued that the moist potential vorticity computed from the dot product is mainly in the horizontal direction since the absolute vorticity and the gradient of temperature are small and cannot represent the atmospheric motions reasonably. Gao et al (2004) proposed the use of convective vorticity vector (CVV) to study deep convection particularly over tropical regions. However, the CVV was computed using the gradient equivalent potential temperature θ_e . It is conservative only in moist adiabatic and frictionless processes and its generalization to be used in dry atmosphere lead to annihilation of solenoidal term in its tendency equation (Schubert et al., 2001). Since the atmosphere is never completely dry or saturated, but non-uniformly saturated. Thus CVV cannot be used to study non-uniform saturated atmospheric flow and fulfil the demand to verify, at the same time, a moist and dry air conservative property and an invertibility principle. In this study we modify CVV to moist potential vorticity vector (MPVV) by replacing the equivalent potential temperature with moist-air entropy potential

temperature (θ_s). This temperature is valid for a general mixing of dry air, water vapour and all possible condensed water species (Marquet, 2011). MPVV is analysed on its ability to diagnose heavy rainfall events over different regions in Tanzania.

5.2 Data and Methodology

5.2.1 Model description, Experimental design and data from the model

The Weather Research and Forecasting (WRF) model version 3.3.1, jointly developed by the National Oceanic and Atmospheric Administration (NOAA) and National Centre for Atmospheric Research (NCAR) is used in this study. This model is a non-hydrostatic mesoscale NWP model, fully compressible and has terrain following sigma coordinates (Skamarock et al., 2008). The WRF is chosen in this study because it has been used by different researchers at government institution and universities and is currently running at Tanzania Meteorological Agency (TMA) Numerical Weather Prediction (NWP) modelling section. It features multiple dynamical cores, a 3-dimensional variation and 4-dimensional (3DVAR and 4DVAR) data assimilation system, and has software architecture that allow for computational parallelism. WRF is suitable for a broad spectrum of applications across scales ranging from meters to thousands of kilometres (Wang et al., 2008).

In this study the domain of WRF is set-up over East Africa region (8°N to 18°S ; 25°E to 52°E) (Fig.1), on a horizontal resolution of 15km, and the model has 28 vertical levels. The model was set to simulate heavy rainfall events that occurred from 20th to 22nd December 2011 and 5th to 8th May 2015 over different regions in Tanzania. The boundary condition from the National Centre for Environmental Prediction (NCEP) global forecast system (GFS) dataset with a $0.5^{\circ}\times 0.5^{\circ}$ spatial resolution were used to force the WRF. The input data has a time interval of three hours, while the output data are served at hourly interval. The simulations were initiated at 00h UTC and run for 48 hours ahead. Simulated meteorological variables: wind speed (zonal, meridional and vertical components), pressure, temperature and relative humidity at different pressure levels are used to compute MPVV.

5.2.2 Rainfall data

Rainfall as cumulated total for every 3 hours was accessed from the Tropical Rainfall Measuring Mission (TRMM). This is an international project led by the National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA). The project provides improved estimate of rainfall over tropical regions using remote sensing technique through satellite observations. The TRMM rainfall estimates used here are from TRMM 3B42V7, available at spatial resolution of 0.25^0 by 0.25^0 which is approximately 27.8 km by 27.8 km. These data were accessed from the website:

<http://giovanni.sci.gsfc.nasa.gov/giovanni/#service=TmAvMp&starttime=&endtime> and was used to map the spatial distribution of rainfall (mm/day) during 20th to 22nd December 2011 and 5th to 8th May 2015. These maps are compared with the spatial patterns of MPVV

5.2.3 Observed rainfall data

Daily accumulated rainfall (mm/day) during 20th to 22nd December 2011 and 5th to 8th May 2015 were acquired from the Tanzania Meteorological Agency (TMA). In order to compare the spatial patterns of MPVV with rainfall, the Inverse Distance Weighting (IDW) interpolation technique was used to interpolate the patterns of observed rainfall using data from 22 weather stations. For detailed description about the IDW interpolation technique a reader may consult Hartkamp et al (1999). The spatial rainfall maps generated using IDW interpolation techniques are compared with spatial patterns of MPVV.

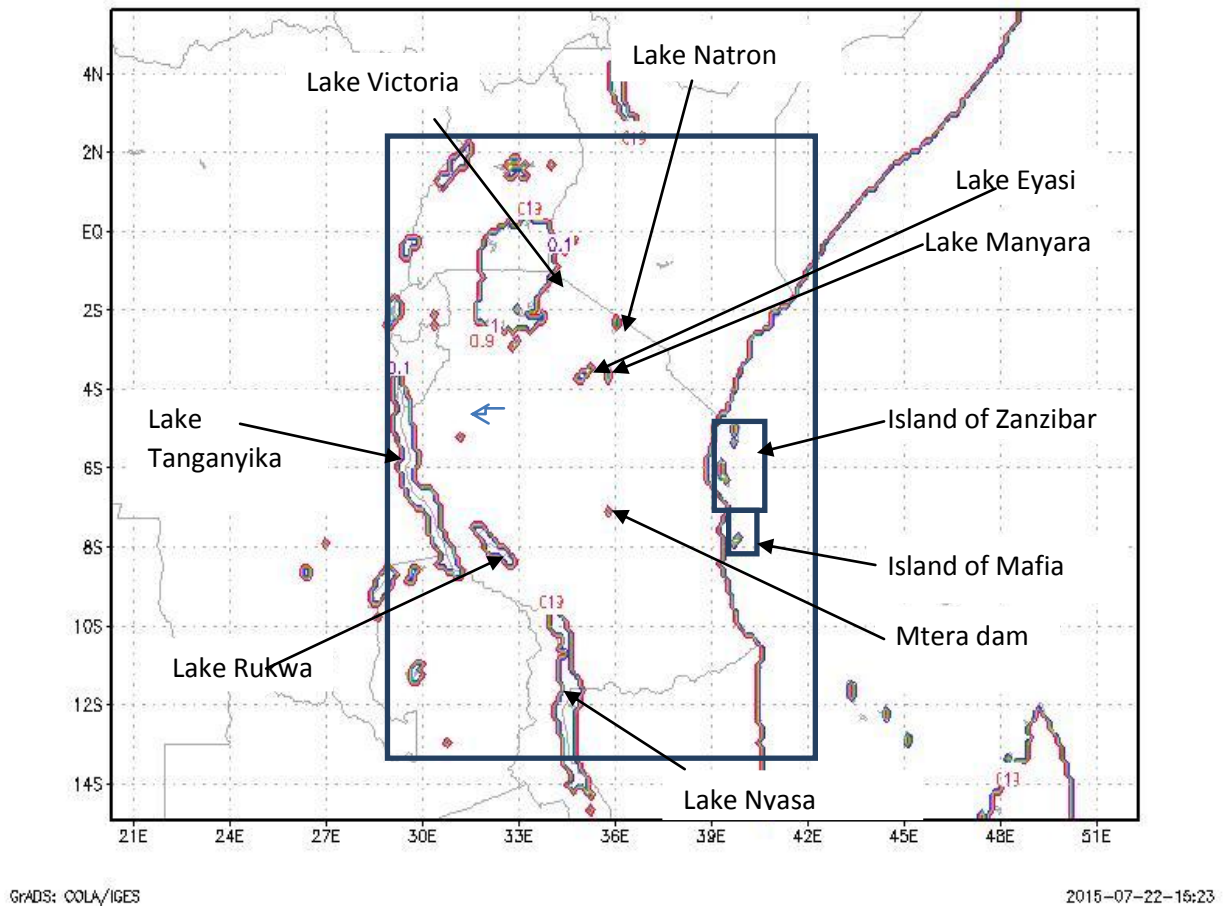


Figure 1: The topographical map in the domain where WRF is set indicating surface land cover that can be resolved by the model in the study region

5.2.4 Descriptions of rainfall events

On 20st to 22nd December 2011, there was very heavy rainfall over the city of Dar es Salaam which triggered a worst flooding event where forty three people were reported dead and many were missing. The major transportation networks of the city were destroyed by the flood. Some bridges were completely swept out and others were covered with water. The heavy rainfall event were caused by warming over the eastern, North and northwestern Australia and the prevailed surface Westerly wind, that pushed warm surface water towards western Indian Ocean. This warm surface water spread around western equatorial Indian Ocean coupled with significant warming developed over western Indian

Ocean (coast of Dar es Salaam) on 20-22 December enhanced more convection along the coastal regions. Moreover, low level convergence dominated over most regions that enhanced heavy rainfall over much parts of the country. Fig.2 indicates the cloud band over the coastal region detected from satellite image on 21-12-2011, at 0900UCT.

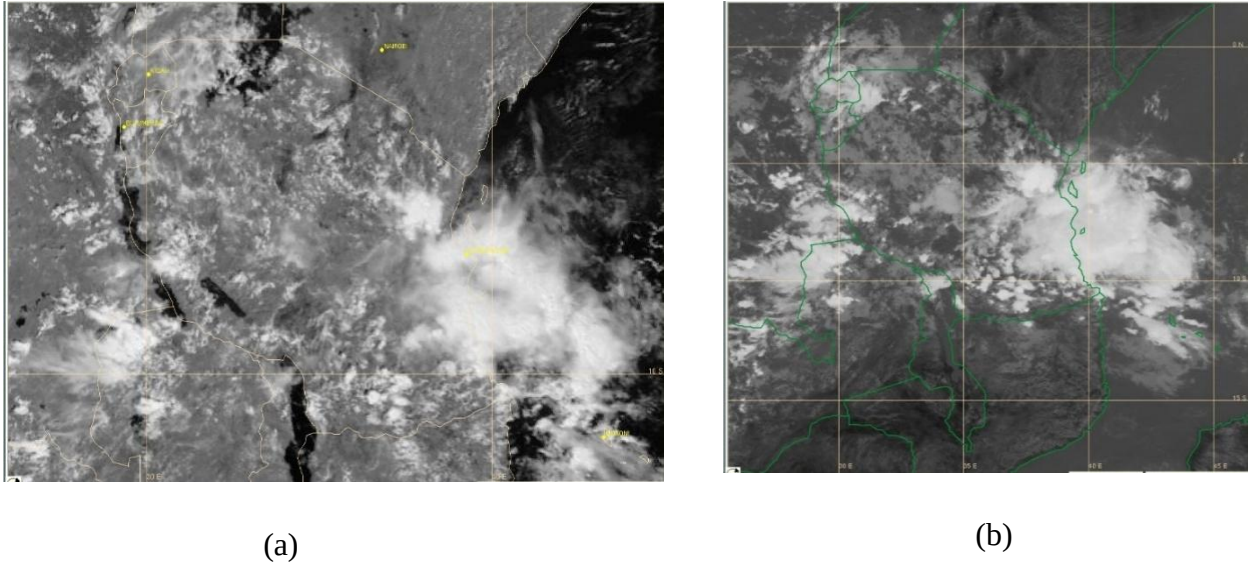


Figure 2: Satellite image (a) visible band (b) infra-red band on 21-12-2011, at 0900UCT

On 6th May 2015, the city of Dar es Salaam received heavy rainfall of 111.4mm in 24-hours. Kibaha region received 88.3mm in 24-hours, while Zanzibar reported 45.5mm in 24-hours. On the 7th May 2015, rainfall of 60.2 mm, 52.5 mm, 49.7mm, 41.4 mm and 37.4mm were reported at Mahenge, Dar es Salaam, Kibaha, Zanzibar and Mtwara regions respectively. These rainfalls were influenced by the enhancement of the inter-tropical convergence zone (ITCZ) over Tanzania, and significant moisture flux over the coastal belt coupled with low level convergence that triggered deep convection over most regions.

5.2.5 Modification of CVV to MPVV

We start by defining the moist air entropic potential temperature. The moist air entropy potential temperature θ_s is defined in Marquet (2011) as

$$\theta_s \equiv (\theta_s)_1 \left(\frac{T}{T_r} \right)^{\gamma q_t} \left(\frac{p}{p_r} \right)^{-k \delta q_t} \left(\frac{r_r}{r_v} \right)^{\gamma q_t} \frac{(1 + \eta r_v)^{k(1 + \delta q_t)}}{(1 + \eta r_r)^{k \delta q_t}}, \quad (1)$$

$$(\theta_s)_1 = \theta \exp(\Lambda_r q_t) \exp\left(-\frac{L_v q_l + L_s q_i}{c_{pd} T}\right), \quad (2)$$

where $\Lambda_r = \frac{(s_v^0 - s_d^0)}{c_{pd}} \approx 5.87$ is a key quantity. It is mentioned in Marquet (2011) that Λ_r depends on the standard entropies of water vapour and dry air (s_v^0) and (s_d^0). It is also mentioned that $(\theta_s)_1$ is a good approximation of θ_s . For detailed derivation of θ_s please refer to Marquet (2011, 2014, 2015).

Another parameter to use in computation of MPVV is density ρ which is defined from equation of state as

$$\rho = \frac{p}{\theta(\rho, p) R_d} \left(\frac{p_0}{p}\right)^k, \quad (3)$$

where p is atmospheric pressure (in Pa) at different level, p_0 is atmospheric pressure at reference level, $\theta(\rho, p)$ is potential temperature in this case θ_s is used to account for moist air, R_d is specific gas constant for dry air and $k = \frac{R_d}{C_p}$, C_p is specific heat capacity at constant pressure. The last parameter used for computing MPVV is the absolute vorticity which is defined as

$$\zeta_a = -\frac{\partial v}{\partial z} i + \frac{\partial u}{\partial z} j + (\zeta + f) k, \quad (4)$$

where ζ is the relative vorticity defined as $\zeta = \frac{\partial v}{\partial x} - \frac{\partial u}{\partial y} + \frac{u}{a} \tan(\varphi)$, where a is the radius

of the earth and φ is the latitude, f is the coriolis parameter defined as $f = 2\Omega \sin(\Omega)$.

MPVV is defined as

$$\begin{aligned}
 MPVV(\theta_s) &= \frac{\zeta \times \nabla \theta_s}{\rho} = \frac{1}{\rho} \begin{pmatrix} -\frac{\partial v}{\partial z} \\ \frac{\partial u}{\partial z} \\ (\zeta + f) \end{pmatrix} \times \begin{pmatrix} \frac{\partial \theta_s}{\partial x} \\ \frac{\partial \theta_s}{\partial y} \\ \frac{\partial \theta_s}{\partial z} \end{pmatrix} = \frac{1}{\rho} \begin{pmatrix} \frac{\partial u}{\partial z} \frac{\partial \theta_s}{\partial z} - (\zeta + f) \frac{\partial \theta_s}{\partial y} \\ \frac{\partial v}{\partial z} \frac{\partial \theta_s}{\partial z} + (\zeta + f) \frac{\partial \theta_s}{\partial x} \\ -\frac{\partial v}{\partial z} \frac{\partial \theta_s}{\partial y} - \frac{\partial u}{\partial z} \frac{\partial \theta_s}{\partial x} \end{pmatrix} = \\
 &\begin{pmatrix} MPVV_x \\ MPVV_y \\ MPVV_z \end{pmatrix}, \tag{5}
 \end{aligned}$$

Considering the hydrostatic equilibrium $\partial/\partial z = -\rho g \partial/\partial p$, Eq.5 can be re-written as

$$\text{First component } MPVV_x = \rho g^2 \frac{\partial u}{\partial p} \frac{\partial \theta_s}{\partial p} - \frac{(\zeta + f)}{\rho} \frac{\partial \theta_s}{\partial y}, \tag{6}$$

$$\text{Second component } MPVV_y = \rho g^2 \frac{\partial v}{\partial p} \frac{\partial \theta_s}{\partial p} + \frac{(\zeta + f)}{\rho} \frac{\partial \theta_s}{\partial x}, \tag{7}$$

$$\text{The third component } MPVV_z = g \frac{\partial v}{\partial p} \frac{\partial \theta_s}{\partial y} + \frac{\partial u}{\partial p} \frac{\partial \theta_s}{\partial x}, \tag{8}$$

The magnitude of MPVV is written as

$$|MPVV| = \sqrt{(MPVV_x)^2 + (MPVV_y)^2 + (MPVV_z)^2}. \tag{9}$$

5.3 Results and discussion

In this study we analyse whether MPVV can serve as diagnostic variable of heavy rainfall events over different regions of Tanzania. This is achieved by comparing the spatial patterns of MPVV and rainfall. Starting with the first case, Fig.3 shows the distribution of rainfall estimate derived from satellite, where subplot 3 (a) and 3 (b) respectively represent accumulated rainfall estimates on 20th and 21st of December, 2011. While subplot 3 (c) is 48-hour accumulated rainfall estimates from 20th to 21st December, 2011. It is seen that the distribution of rainfall almost covered the whole domain of Tanzania. However, there are

differences in rainfall intensity across the regions. The coastal regions and southwestern highlands received larger amount of rainfall compared to Northern regions and northeastern highlands. The maximum 24-hours accumulated rainfall is seen over Dar es Salaam (Fig.3 (a) and (b)). These rainfall estimates from satellite collocate with observed rainfall in Fig.4, where maximum rainfall of about 156 mm was measured over Dar es Salaam weather station on 20th December, 2011. Further, figure 4 also show most of the regions which received rainfall above 22 mm on 20th December, 2011.

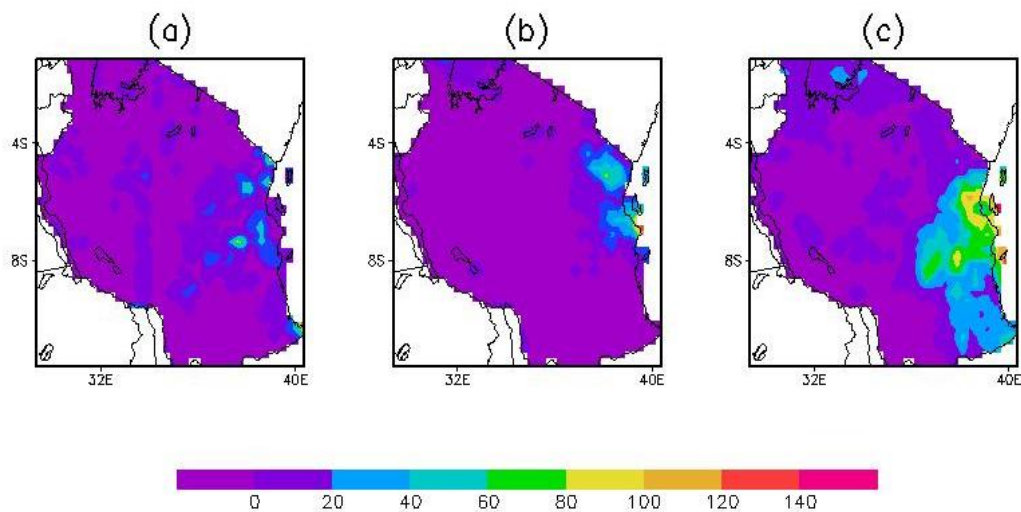


Figure 3: Rainfall in mm/day (a) 20/12/2011 (b) 21/12/2011 (c) 20-21/12/2011

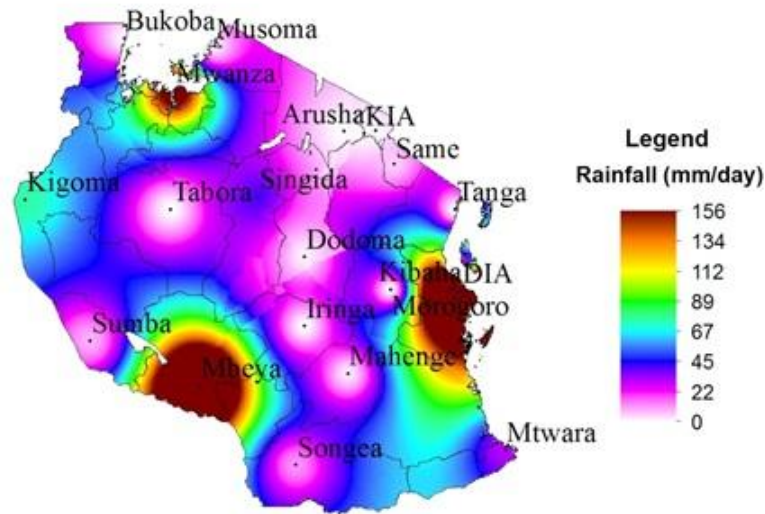


Figure 4: Distribution of observed interpolated rainfall data over different regions in Tanzania on 20-12-2011

The distribution of the MPVV share similar patterns to that of rainfall areas. Fig. 5 shows the distribution of the first component of MPVV, where subplot 5 (a) and 5 (b) presents the first component of MPVV at 700hPa on 20th and 21st December 2011 respectively, while subplot 5 (c) is the 48-hour average of MPVV at 700hPa. The reason why we calculate MPVV at 700hPa level and compare with the rainfall areas is due to the fact that, this level is commonly used for diagnosis of rainfall triggering systems over the tropics, particularly in Tanzania. Thus the behaviour of MPVV computed at this level is expected to better represent the pattern of rainfall over different regions compared to MPVV at other levels. The positive values of MPVV are seen distributed almost over the whole domain of Tanzania (Fig.5 (a)). This collocates with the distribution of rainfall in Fig.3 (a). Positive values of MPVV extended from Congo to western part of Tanzania, where they extended again to northern and southern regions. This distribution may have contributed to the observed high amount of rainfall over the southwestern highlands, where high ground topography may be enhancing convection processes and over southern part of Lake Victoria, where lake-land contrast may be triggering convection activity. However, a negative band of MPVV is seen along the coast (Fig.5 (a)). This band is surrounded by positive values of MPVV, where maximum values are seen over the Indian Ocean. Fig.

5(b) shows the band of negative MPVV extends from the coast to inland, this indicates convective processes over the coast regions reduced on 21st of December 2011.

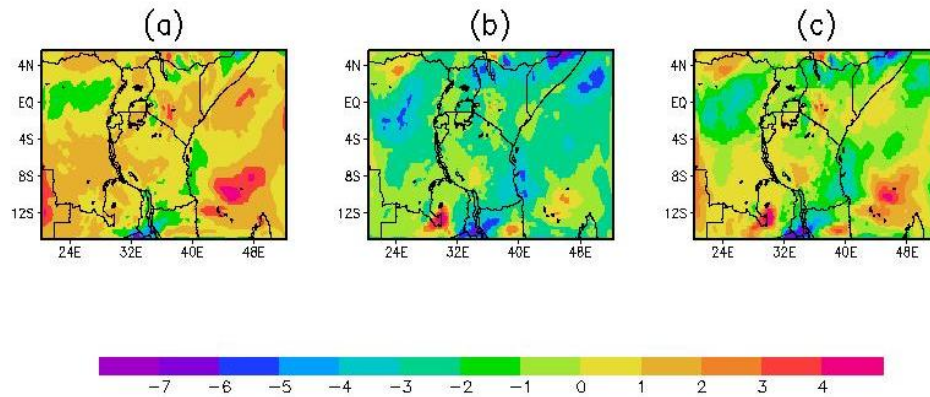


Figure 5: Spatial distribution of the first component of the moist potential vorticity vector (in PV-units) on (a) 20/12/2011 (b) 21/12/2011 (c) 20-21/12/2011

Fig. 6 shows the distribution of the second component of MPVV, where subplot 6 (a) and 6 (b) present the patterns of MPVV on 20th and 21st, December 2011 respectively. Subplot 6 (c) is the average of the second component of MPVV from 20th to 21st December 2011. The distributions of the second component of MPVV collocate with the distribution of rainfall locations. Positive values of MPVV are distributed almost over the whole of Tanzania. Similar to what was observed with the first component, the coastal region is dominated with negative value of MPVV which are surrounded with positive values of MPVV. From figure 6 (a), maximum positive values of MPVV are seen over southwestern highland and southern part of the lake Victoria region and parts of central regions this correspond to high rainfall over those areas.

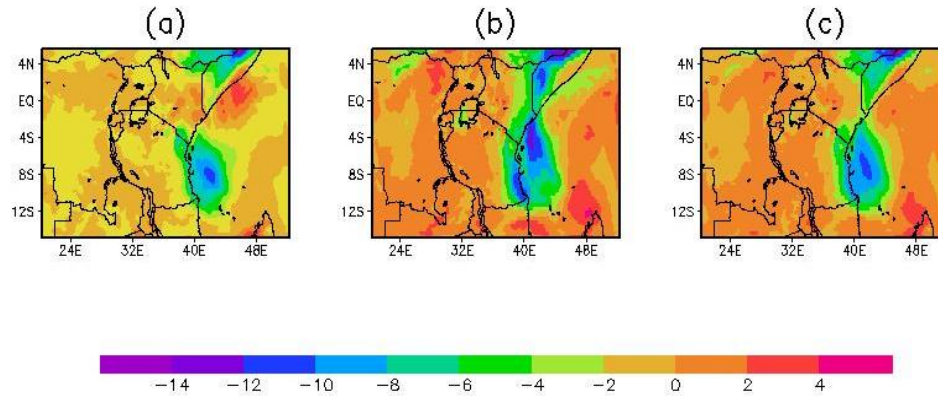


Figure 6: Similar to figure 5 but for the second component of the moist potential vorticity vector (in PV-units) on (a) 20/12/2011 (b) 21/12/2011 (c) 20-21/12/2011

The distribution of the third component of MPVV is shown in Fig. 7. From this figure it can be seen that subplot 7 (a) and subplot 7 (b) which represents the patterns of the third component of MPVV on 20th and 21st December 2011 respectively are dominated with positive values. The 48-hour average of the third component of MPVV shows that the country was dominated with small positive values MPVV (Fig 7 (c)).

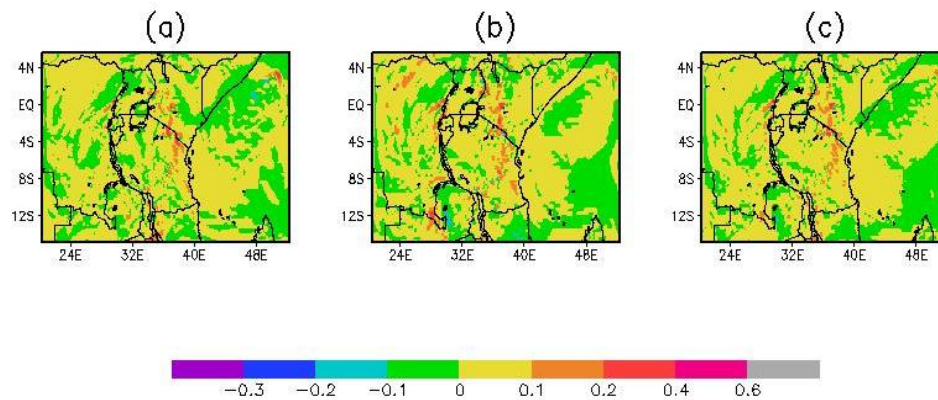


Figure 7: Similar like figure 6 but for third component of the moist potential vorticity vector (in PV-units) on (a) 20/12/2011 (b) 21/12/2011 (c) 20-21/12/2011

The magnitude of the MPVV shown in Fig.8 indicates that the band of maximum values of MPVV is located over the coastal regions. This band bear different shapes, on 20th December, it is oriented in south-eastern direction touching the coast, with maximum values of MPVV located close to Dar es Salaam. This collocated with the observed heavy rainfall over that region that triggered catastrophic flooding event. On 21st December 2011,

the band of maximum magnitude of MPVV is oriented parallel to the coast but also touches most regions along the coast. This collocated with the observed rainfall over the coastal regions. Generally it is seen that the area close to maximum values of the magnitude of MPVV experienced heavy rainfall (Fig.8 (a), Fig.3 (a) and Fig.4). To compare the strength of convective systems along the coast regions between day 20th and 21st it can be seen that convection processes were stronger along the coastal regions on 20th than on 21st of December, 2011.

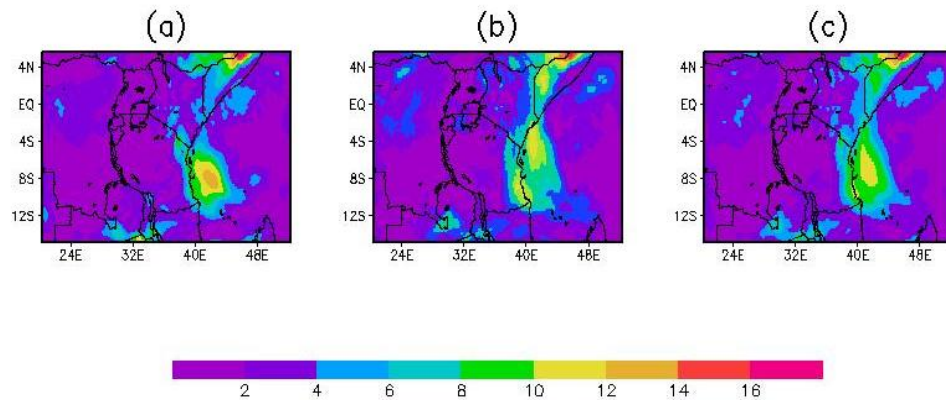


Figure 8: The magnitude of the moist potential vorticity vector (in PV-units) on (a) 20/12/2011 (b) 21/12/2011 (c) 20-21/12/2011

The second case analysed in this study is that occurred on 5th to 7th May, 2015. Fig. 9 present distribution of rainfall estimates from the satellite, where subplot 9 (a), 9 (b) and 9 (c) presents rainfall distribution on 5th, 6th and 7th May 2015 respectively. It can be seen that most areas received rainfall on the 5th where the coastal region received more rain compared to the other regions (Fig.9 (a)). On the 6th the amount of rainfall has increased over coastal regions, when the city of Dar es Salaam received heavy rainfall which triggered catastrophic flooding. On the 7th rainfall has increased over the entire coastal regions.

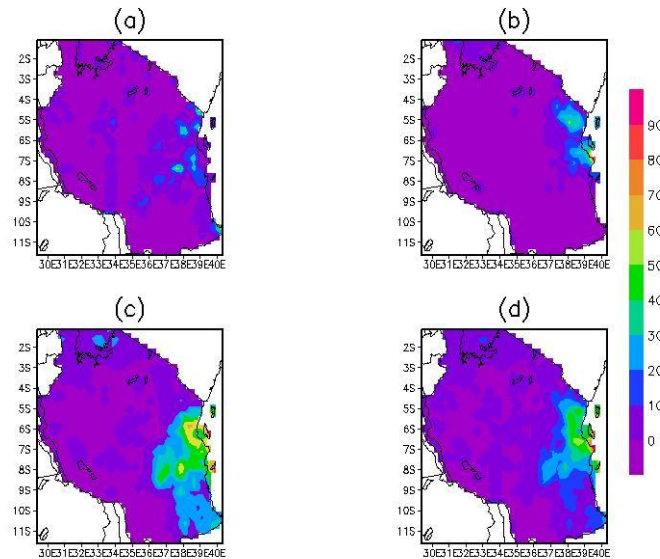


Figure 9: Rainfall in mm/day (a) 5/5/2015 (b) 6/5/2015 (c) 7/5/2015 (d) 5-7/5/2015

Fig.10, 11, 12 represents the distribution of observed rainfall over different regions. These figures present similar patterns as the satellite rainfall estimates. However, the amount of rainfall estimated by satellite is lower than that from the weather stations. The coastal region received more rainfall than other regions and the city of Dar es Salaam received about 111mm of rain on 6th May 2015.

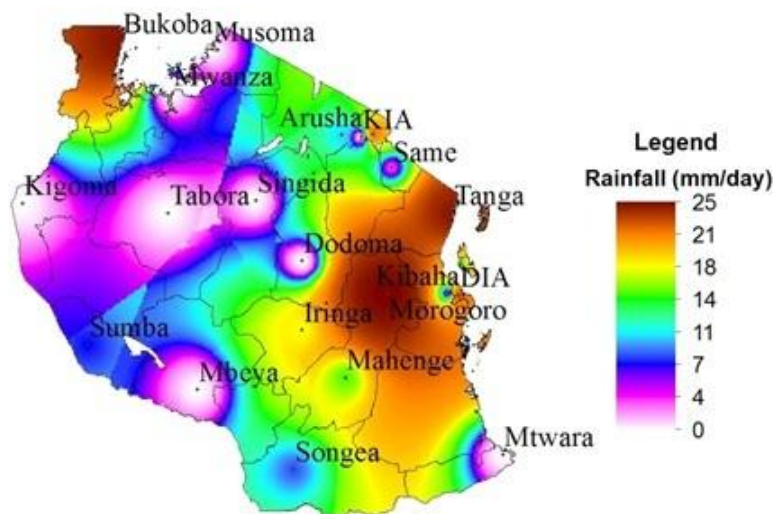


Figure 10: Distribution of observed rainfall over different regions in Tanzania on 5-5-2015

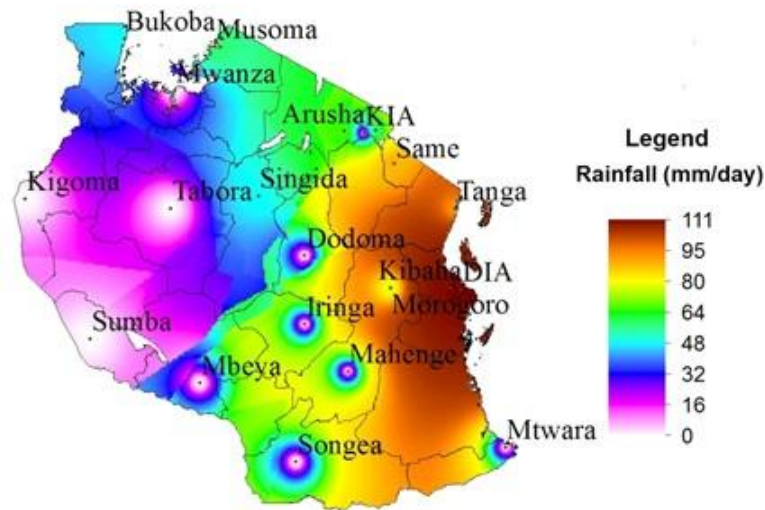


Figure 2 Distribution of observed rainfall over different regions in Tanzania on 6-5-2015

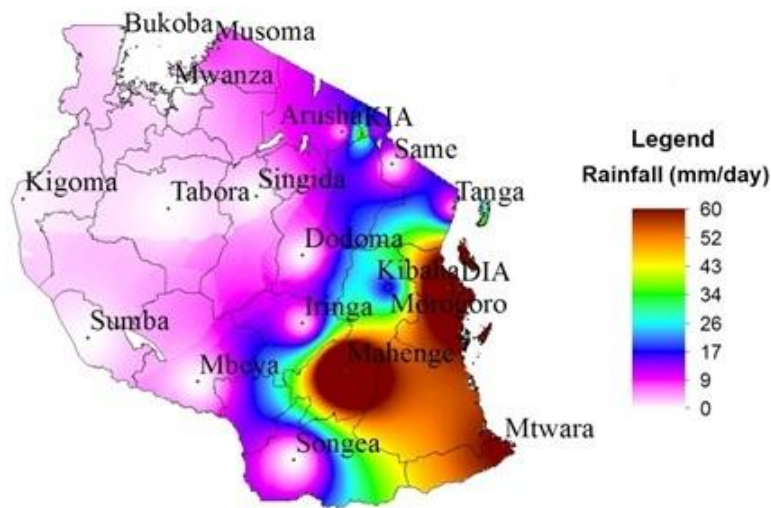


Figure 3 Distribution of observed rainfall over different regions in Tanzania on 7-5-2011

The patterns of MPVV follow similar patterns to that of the rainfall. Fig.13 shows the distribution of the first component of MPVV, where on 5th positive values of MPVV dominate almost over the entire domain of Tanzania with maximum values located over the northern coast. However, on 6th the positive values of MPVV squeezed to form a kidney shape, extending from northern to parts of southern coastal regions. This band of positive values of MPVV contributed to heavy rainfall over Dar es Salaam. On the 7th the

band of positive values of MPVV over the coast relaxed and moved to parts of southwestern high grounds. This might contributed to heavy rainfall events observed over Mahenge (Fig.13).

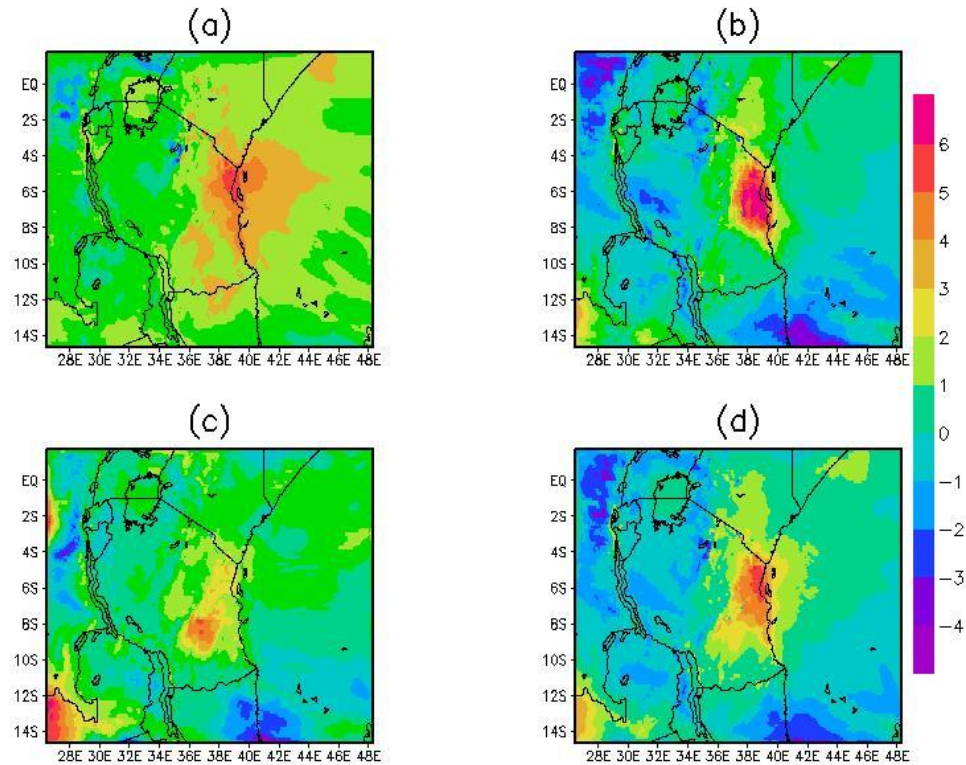


Figure 13: the first component of the moist potential vorticity vector (in PV-units) (a) at 2015:5:5:00-2015:5:5:22 (b) 2015:5:5:22-2015:5:6:21 (c) 2015:5:6:21-2015:5:7:20 (d) 2015:5:5:00-2015:5:7:20

The distribution of second component of the MPVV is shown on Fig. 14. Similar pattern to that of the first component is seen. However, the second component shows that on 5th the maximum positive values were located close to northern Tanzania Kenya boarder. It moved over northern coast on the 6th and influenced heavy rainfall over those areas. On the 7th the entire coast was dominated with positive values of the second component of MPVV. The third component of MPVV shows little contribution to observed rainfall as it indicates the country was dominated with small positive values of MPVV on the 6th without showing the regions with maximum values especially to the area where received maximum rainfall (Fig.15).

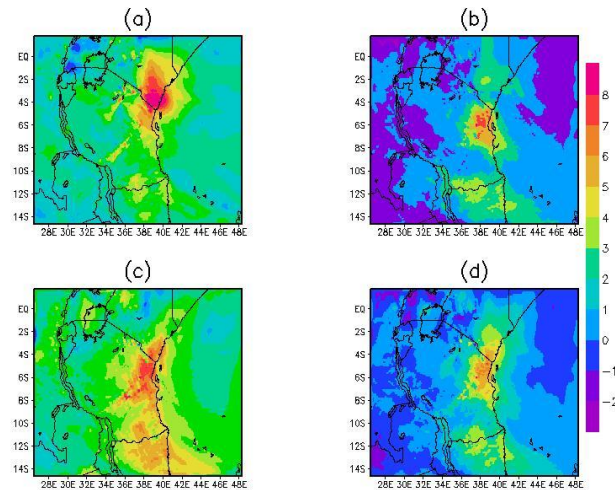


Figure 14: the second component of the moist potential vorticity vector (in PV-units) (a) at 2015:5:5:00-2015:5:5:22 (b) 2015:5:5:22-2015:5:6:21 (c) 2015:5:6:21-2015:5:7:20 (d) 2015:5:5:00-2015:5:7:20

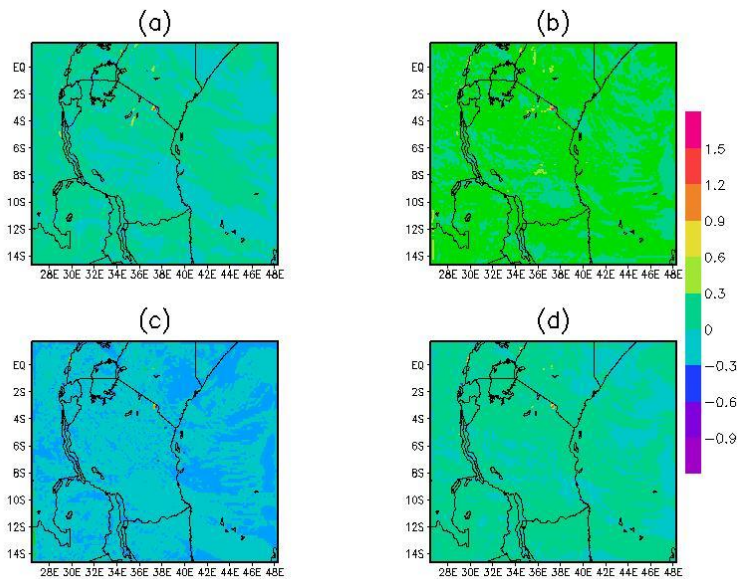


Figure 15: the third component of the moist potential vorticity vector (in PV-units) (a) at 2015:5:5:00-2015:5:5:22 (b) 2015:5:5:22-2015:5:6:21 (c) 2015:5:6:21-2015:5:7:20 (d) 2015:5:5:00-2015:5:7:20

The magnitude of MPVV shows that maximum values of MPVV were located on the northern Tanzania to Kenya boarder on the 5th, it then moved to touch the entire northern coast of Tanzania on the 6th (Fig.16). In general the areas with maximum values of the

magnitude of MPVV collocated with areas received heavy rainfall. This gives more confidence that MPVV can be used to diagnose the occurrences of heavy rainfall.

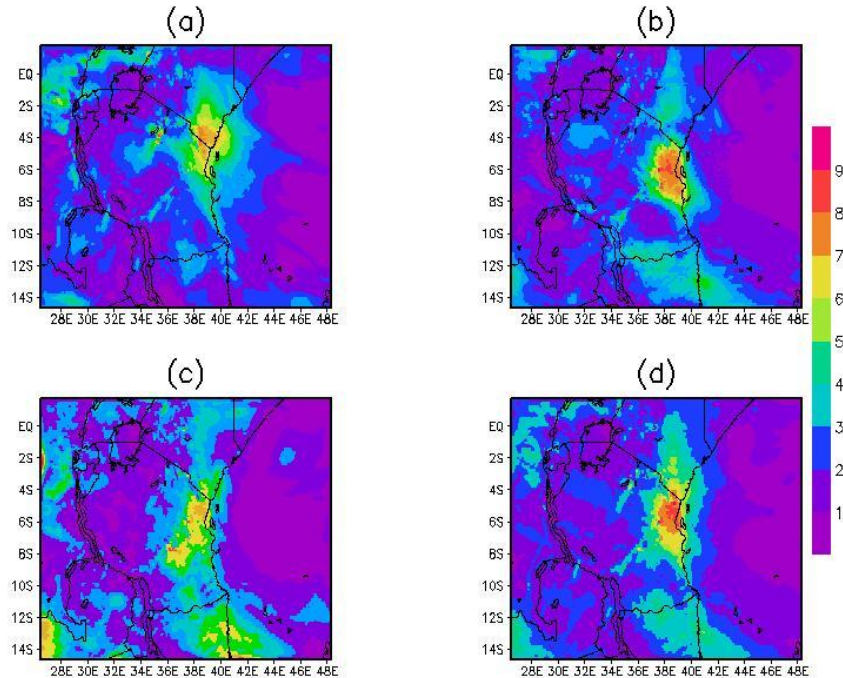


Figure 16: The magnitude of moist potential vorticity vector (in PV-units) (a) at 2015:5:5:00-2015:5:5:22 (b) 2015:5:5:22-2015:5:6:21 (c) 2015:5:6:21-2015:5:7:20 (d) 2015:5:5:00-2015:5:7:20

5.4 Conclusion and recommendations

In this study we have analysed the possibilities to use MPVV as diagnostic variable of heavy rainfall events in Tanzania. It is found that MPVV can serve as a diagnostic variable of heavy rainfall events over different regions in Tanzania. The first, second components of MPVV and the magnitude contribute almost equally to locate the areas which received heavy rainfall. Maximum values of MPVV are found to coincide with the areas with heavy rainfall. Although we get good relation between MPVV with heavy rainfall but only five days data was used, therefore we recommend more studies to be done to validate the usefulness of MPVV. Furthermore it might be interesting if MPVV can be tested to be used as a predictor in climate change studies to help in downscaling climate change projections.

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Chapter 6: Summary and recommendations

Agriculture is a main driver of Tanzania economy and is predicted to be severally impacted by climate change (e.g. Mwandosya et al., 1998; Agrawala et al., 2003; INC, Ernhart and Twena, 2006; IPCC, 2007; Enfors and Gordon, 2008; Thornton et al., 2009; 2010; Arndt et al., 2011; Ahmed et al., 2011; Müller et al., 2011; and Rowhani et al., 2011). However, assessments from these studies are subject to uncertainties due to fact that, climate change projections used to drive the crop models were derived directly from the General Circulation Models (GCMs). These models classically run at spatial resolution of 300km or more such that their climate change projections cannot be used directly for impact studies at regional and sub-regional scales. Recently, Masson and Knutti, (2011) and Ramirez-Villegas and Challinor, (2012) argues that GCMs coarse resolution severely limits the direct application of their output in regional and sub-regional decision making. The limitation of direct use of GCMs outputs in regional and sub-regional decision making call into questions of the many prior evaluation of climate change impact on rainfed crop production, in Tanzania. Furthermore, adaptation and mitigation policies that were developed based on GCMs simulations are not realistic and might pose significant challenges for anticipatory adaptation in the country. Therefore, credible evaluation of climate change impacts on rainfed crop production using high resolution Regional Climate Models (RCMs) in Tanzania is urgently required. The RCMs can simulate local conditions in greater details over a limited region (Danis et al., 2002).

The main aim of this thesis was to evaluate the impacts of climate change on rainfed maize production in the Wami-Ruvu basin of Tanzania. This basin is one of most important maize production area in Tanzania. High-resolution climate change simulations for current climate condition (1971-2000) as well as future climate change projections (2010-2039), (2040-2069) and (2070-2099), using two Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5 were used to drive the Crop–Environment–Resource–Synthesis (CERES)-Maize model incorporated within the Decision Support System for Agro-technological Transfer (DSSAT 4.5).

To achieve the main aim of the thesis, four objectives were analysed. The first evaluated the performance of CORDEX regional climate models in simulating present climate condition of Tanzania, the second objective to assess the impact of climate change on rainfed maize production in the Wami-Ruvu basin of Tanzania using a process-based crop model the Decision Support System for Agro-technological Transfer (DSSAT) and high resolution climate change simulation from three regional climate models (RCMs) driven by three different General Circulation Models (GCMs). The models used to drive DSSAT were chosen after the first research objective. The third objective was to evaluate the possibility of using the moist potential vorticity (MPV) and moist potential vorticity vector (MPVV) as predictor of rainfall events to help in downscaling of climate change projections or in developing empirical statistical model for seasonal rainfall prediction. This is important since rainfall is normally poorly simulated by most climate models (MacKellar et al., 2014, Endris et al., 2014, and Chris et al 2015). The fourth objective tested the MPVV on its usefulness in describing heavy rainfall events in Tanzania.

The major findings of the first objective are that the RCMs from the CORDEX capture the annual cycle of minimum temperature (TN), maximum temperature (TX) and rainfall well, however, underestimate and overestimate the amount of rainfall in March–April–May (MAM) and October–November–December (OND) seasons respectively. The RCMs reproduced the interannual variations of TN, TX, and rainfall. The source of uncertainties can be analysed when the same RCM is driven by different GCMs and different RCMs are driven by same GCM simulate TN, TX, and rainfall differently. It is found that the biases and errors from the RCMs and driving GCMs contribute roughly equally. Overall, the evaluation finds reasonable (although variable) model skill in representing mean climate, interannual variability, and temperature trends, suggesting the potential use of CORDEX RCMs in simulating TN, TX and rainfall over Tanzania.

The findings of the second objective showed that due to climate change, the length of growing season and future maize yields over Wami-Ruvu basin will decrease under both RCP4.5 and RCP8.5 at the current, mid and end of the centuries. However, the projected yields estimates and the length of growing season differ from model to model highlighting the uncertainties associated with the projections. Climate data from the ensemble average

of five model members was constructed to address the issue of uncertainties from individual climate models and used to drive DSSAT. Results showed that due to climate change future maize yields over Wami-Ruvu basin will slightly increase relative to the baseline during current century under RCP 4.5 and RCP 8.5. Meanwhile, maize yields will decline in the mid and end centuries. The spatial distribution shows that more decline in maize yields are projected over lower altitude regions due to projected increase in temperatures and decreased rainfall in those areas. The eastern part of the basin will feature more decrease in maize yields, while central parts of the basin and the western side of the basin will experience increase in maize yields during current, mid and end centuries under RCP 4.5 and RCP 8.5. The main reason for decrease and increase maize yields is the projected increase in temperatures that will reduce the length of growing seasons and hence affecting maize productivity.

The findings of the third objective show that the patterns of MPVV compared better with rainfall than the MPV. The statistical relationship between MPVV and MPV against observed rainfall data from 22 synoptic meteorological stations using Pearson correlation coefficient indicate that MPVV bears strong and statistically significant correlation coefficient to rainfall than MPV suggesting its potential use as the predictor of rainfall events in Tanzania.

The findings of the fourth objective are that MPVV compared well with the observed rainfall event, providing accurate tracking of location received heavy rainfall, suggesting its potential use as a dynamic tracer for heavy rainfall events over different regions in Tanzania. Finally, it is found that first, second components and the magnitude of MPVV provides better tracking of the locations received heavy rainfall events compared to the third component.

The following are the general recommendation in this thesis

- The use of MPVV as diagnostic variable of heavy rainfall events in Tanzania deserves more experimentations. It is important to explore the use of MPVV to better prediction of extreme heavy rainfall events that affect all dimension of food security in different regions of Tanzania.

- The use of MPVV as predictor of rainfall in seasonal climate modelling and to better the climate change projections need more studies. MPVV need to be tested on its ability to reproduce daily and inter-annual variation of rainfall. Moreover, it is important that MPVV is tested in predicting seasonal rainfall over different regions of Tanzania.
- In evaluation the impacts of climate change on maize production in the Wami-Ruvu basin of Tanzania, it was assumed that all agronomical and management practices were constant. More research is needed to see how the impacts of climate change will affect rainfed maize production in the Wami-Ruvu basin under different agronomical and management practices. Furthermore, it is recommended more research geared towards minimizing the uncertainties and necessary for designing effective and adequate adaptation strategies that will enhance and sustain maize production in the context of the projected climate change over Wami-Ruvu basin.

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