UNIVERSITY OF NAIROBI

TOWARDS IMPROVING THE SKILL OF SEASONAL RAINFALL PREDICTION OVER RWANDA

BY

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DECLARATION

I declare that this dissertation is my original work and has not been submitted elsewhere for examination, award of degree or publication. Where other people's work, or my own work has been used, this has properly been acknowledged and referenced in accordance with the University of Nairobi's requirements.

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DEDICATION

I dedicate this dissertation to my beloved family; my Wife Mrs. Alice RURANGIRWA, my daughter Kelsey KEZA MUGUNGA and my parents.

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ABSTRACT

Rainfall prediction exhibits spatial and temporal variability over Rwanda. The improved seasonal rainfall prediction to reduce the climatic extreme events using dynamical and statistical models with fewer uncertainties is important to the socio-economic growth of the country.

Improving the skill of rainfall in seasonal forecast time scale over Rwanda has a huge implication for provisions of food security and water resource planning. The intent of this work, is to improve the skill of seasonal rainfall forecast over Rwanda by using statistical and dynamical methods.

The data used in this were seasonal rainfall observations, gridded rainfall dataset, global sea surface Temperatures (SSTs), and initialization data for weather research and forecasting, environmental modelling system (WRF-EMS) obtained from Global Forecasting System (GFS). Model simulation was done for the period 1981-2018 and the model output for the 30 stations was used to determine the skill of the WRF-EMS model for March to May 2018 (MAM) and September to December 2018 (SOND) over the entire country.

The Methodology employed for quality control analyses indicated that most of the data used in the study were of acceptable. The Dynamical part involved assessing the skill and accuracy of the Weather Research and Forecasting Model using measures like root mean square error (RMSE), mean absolute error (MAE), correlation and regression analysis. The statistical part involved identifying the appropriate predictors by using principal component regression, sea surface temperatures anomalies sea surface temperature gradients, specific zonal wind, Indian ocean dipole and El Nino Southern Oscillation and verification of the improved skill scores.

The results of the RMSE and MAE for the sample stations, which shows the capability of the model to give the observed precipitation, which show the smaller value the better fit for the test. The Absolute Mean Error for many stations were to 1, showing that the model had a high accuracy in producing the rainfall observation during the wet seasons. also the result shows very low Mean Absolute Square (MAE) and low Root Mean Square (RMSE) of less than one (1) for all sample stations during the two (2) wet seasons, thus the capacity of the model to produce the

rainfall observation. The results from correlations analysis indicated that the use of sea surface temperature gradient modes as predictors has advantage over grid point sea surface temperatures, and has the potential to improve seasonal rainfall forecasts for both seasons especially for the March-May season. The highest value of correlation observed with the season rainfall, and grid-point sea surface temperatures modes was 0.7 during September to December compared to 0.85 during March to May. The March-May rainfall continues to have higher potential of predictability than September-December

The results from regression analysis indicated that the methods of using SST modes would improve the prediction of rainfall season in the country especially for March to May rainfall season, such linkage were statistically significant and can contribute in improving the prediction skill of the long and short rainfall season in the country.

The results from WRF model indicate that the model simulate well the observed and the predicted rainfall at both seasons and can be use among many seasonal predictions of rainfall in Rwanda.

Results of the study show that the methods can be used to improve the skill of seasonal rainfall forecast over Rwanda which is critical to the planning, sustainable and growth of development to the socio-economic activities together with improvement of existing Early Warning System (EWS) of extreme precipitation events and contribute to weather driven disaster preparedness efforts in Rwanda.

CHAPTER ONE

1.0. INTRODUCTION

1.1. Background

Climate modeling have controlled to the advancement of models for sector-specific weather and climate application such as Agriculture, water management, Energy, Health and Disaster Risk reduction (DRR), as defined on Global Framework for Climate Services, World Meteorological Organizations (GFCS WMO, 2011).

The availability of water, energy, and other socio-economic needs in the country, like other parts of the globe, is influence by daily weather, monthly, sub-season, season, annual and inter-annual climate variability. Most of natural hazards often translate into disasters affecting the globe are linked to extreme climate events.

Anomalous rainfall events such as drought and floods are among the extreme climate evets with adverse effects on the society and economy of the region. The adverse effects resulting from a single anomalous event can linger on for a long period (ISDR 2006, WMO 2006).

Extreme climate events cannot be stopped from occurring. However, the associated impacts can be mitigated. The prediction of seasonal prediction is an important components of an early waning. The warning formulated from the skillful seasonal forecasts may contribute significantly to the prevention of climate related and natural disasters, improved production in sectors dependent on climate and effective management of the organizations depend on weather and climate (Georgakakos and Graham 2008).

The warning may also help to reduce the vulnerability of the communities and sectors frequently affected by weather and climate related hazards.

The improvement of the skill in seasonal forecasts is useful in the mitigation of climate related risks and for taking advantage of the positive aspects of the climate extremes. Most attention to address disasters in the region related to natural hazards has been given to disaster response and relief. Such a reactive approach is not suit.

Goswami BN. (2004) reported that the use of Numerical Weather Prediction (NWP) models in rainfall prediction is previously proven in various operative weather and climate forecast Centre, partly because of the demand of improved precipitation forecast given that rainfall affects various economic sectors such as farming, fisheries, transport and additional economic events. Accuracy in rainfall observing and forecasting is therefore vital to temporal and spatial variability as well as climate change studies and for agriculture applications.

In the past years, there has been a lot off request for high-resolution climate forecasts at appropriate lead times to let response in planning from different users' needs among others. GCM based seasonal prediction normally have low spatial resolution and to generate increases spatial detail, statistical or dynamical downscaling techniques are employed.

The warning formulated from the skillful seasonal forecasts may contribute significantly to the prevention of climate related natural disaster, enhanced productivity in sectors dependent on climate and efficient management of the institutions dependent on weather and climate (Georgakakos and. Graham 2008). The warnings may also help to reduce the vulnerability of the communities and sectors frequently affected by weather and climate related hazards. The improvement of the skill of seasonal forecasts is useful in the mitigation of climate related risks and for taking advantage of the positive aspects of the climate extremes.

This project work, therefore, intend on improving the skillful seasonal forecasts would be useful in reducing and managing the risks associated with seasonal rainfall extremes. They would further provide useful inputs to the improvement of early warnings of extreme rainfall events and contribute to disaster risk reduction and sustainable socio-economic development in the country. Such results would not only provide new climate risk management tools for coping with past and current climate extremes, but also experiences and lessons learnt that can be extended to addressing climate change adaptation challenges.

1.2. Statement of the Problem

The availability of food, water, energy and other socio-economic needs in Rwanda like other parts of the region is influenced by daily weather, monthly, seasonal and inter-annual climate variability, and precipitation is the most significant weather parameters that impacts socio-economic activities over the country. The country has a highly spatially variable climate because of large topographic differences and the complexity of the regional climate. This being said, the two main wet seasons are in March, April to May and September, October, November to December. While predominant moisture source for Rwanda is the Indian Ocean, some moisture is also advected from DR Congo especially during January-May.

These complexities have made forecasting Rwanda's rainfall a challenging enterprise. The uncertainty in the forecast provide to the end users and the public in general is still a challenge.

Predictability depends on the physical factors controlling each phenomenon. Extracting predictive information in space and time can allow us to unpick these complex problems and make real improvements in seasonal prediction.

Rainfall affects almost all sectors of the economy such as agriculture, forestry, hydropower production, transport, water supply and human settlement among others. These activities are highly affected by seasonal rainfall variability. There have been shortcomings in the rainfall prediction over Rwanda on seasonal timescales. It is expected that the accuracy of rainfall prediction on these timescales may improve the seasonal and sub-seasonal rainfall prediction over Rwanda. As all the sectors of the economy ranging from water resources, energy, transport, construction, health, planning and tourism depend on accurate and timely weather and climate information, forecasting is vital for proper planning. In most cases, impacts of severe climatic events are not factored in planning and decision making. The challenges to use weather and climate information include low level of education, limiting interpretation of weather/ climate information by potential users, limitation in access to the weather and early warning information, and poor dissemination of information. The research will help to develop skill in analyzing and produce reliable forecasts as early warning information and to improve the skill generated and explore better avenues for information disseminate to users.

1.3. Objectives of the Study

The general aim of this study is to improve the skillfulness of seasonal rainfall prediction over Rwanda by using statistical and dynamical methods.

In order to attain this aim, several specific objectives were pursued:

1) To assess the skillfulness of dynamical and statistical models in March, April and May (MAM) and September, October, November and December (SOND) seasonal rainfall over Rwanda
2) To identify the suitable predictors that can improve the skillfulness of seasonal rainfall forecast.
3) To assess the use of both dynamical and statistical approaches to improved skill of MAM 2018 and SOND 2018 seasonal rainfall over Rwanda.

1.4. Justification of the study

In this section the climate associated problem that motivated this study and research questions together with limitations of this study are discussed.

Rainfall is one of the main weather elements that are very important to the economy of any country. Understanding the performance of rainfall for a given season, helps in understand the circulation of the local and synoptic scale systems that may have caused the performance.

Weather and climate are the main factors influencing social economic activities including Agriculture, which is the backbone of the economy in the country, The climate associated problem that motivated this study is the significant influence of climate extreme events on the socio-economic activities within the country. Most of the social and economic activities in the region are dependent on rainfall. The day to day and seasonal characteristics of rainfall, therefore, influence almost socio-economic sectors of the region. Hence the ability to provide skillful seasonal forecasts is important for disaster preparedness and for enabling the communities to take advantage of the good times.

The study assumes that the improvements in seasonal climate forecasts may help in reducing losses of life and property, and risks in sectors dependent on rainfall since the climate forecast is an important components of early warning systems and agriculture activities in Rwanda. The seasonal climate forecasts remain the most important tools not only for the mitigation of natural climate related disasters, but also for efficient exploitation of natural resources for the improvement of well-being of the society. However, the skill of seasonal forecasts is generally low especially for the major rainfall seasons of MAM and SOND.

The limitations to simulate cross equatorial flow add to the difficulties of predicting rainfall forecasts over Rwanda from dynamical models. The efforts to improve the skill of seasonal rainfall forecast need to be encouraged.

The increase frequency and severity of severe weather and climate events such as floods and drought that have the high potential for the occurrence of climate extremes in the region need long lead time skillful predictions to enable the policy makers to make decisions to prepare the communities for the anticipated events.

The improvement of in the skill of seasonal forecasts would contribute to the desired shift in disaster response with emphasis on disaster risk reduction incorporating preparedness, mitigation and prevention with the context of sustainable development towards reducing risks and vulnerability to natural disaster (ISDR 2005). Timely and accurate weather and climate forecasts together with appropriate

Developing consistent forecasts on time with accuracy and appropriate plan in various sectors of the economy would improve the quality of forecast which in turn improve the lives of the community at large.

1.5. Area of Study

Rwanda is situated in East Africa and Central Africa, bordered by Democratic Republic of Congo (DRC) (West), Tanzania (East), Burundi (South) and Uganda (North). Rwanda lies within 1° 4′ and 2° 51′ South, 28° 53′ and 30° 53′ East, its cover an area of 26,338km^2 (Ilunga et al.2004; MINERENA 2010). has complex spatial and temporal natures of daily monthly and seasonal precipitation due to the influence of topography and the distribution of water bodies

1.5.1 Climate of Rwanda

The country is known as the land of thousand hills and has complex spatial and temporal natures of daily and seasonal precipitation due to the influence of topography and distribution of small lake within the country.

Despite being located in the tropical belt, Rwanda experiences a temperate climate and sub-divided into four climatic regions, that are varying between 900m and 4,507m (Ilunga et al. 2004). The North-western region is mountainous and volcanic with elevations over 2000m. Elevations decrease towards the central plateau (1500 -200m), and in the eastern plateau toward the border with Tanzania (less than 1500m). There are two major wet seasons in Rwanda: March, April and May (MAM) and September, October, November and December (SOND), Two dry seasons; major dry period is June to August and the shorter one running from Mid-December to Mid-February due to the North to South and vice versa movement of the Inter-Tropical Convergence Zones (ITCZ) crossing the equator twice a year in March and September respectively. Annual rainfall in the country ranges between 800-1700 mm.

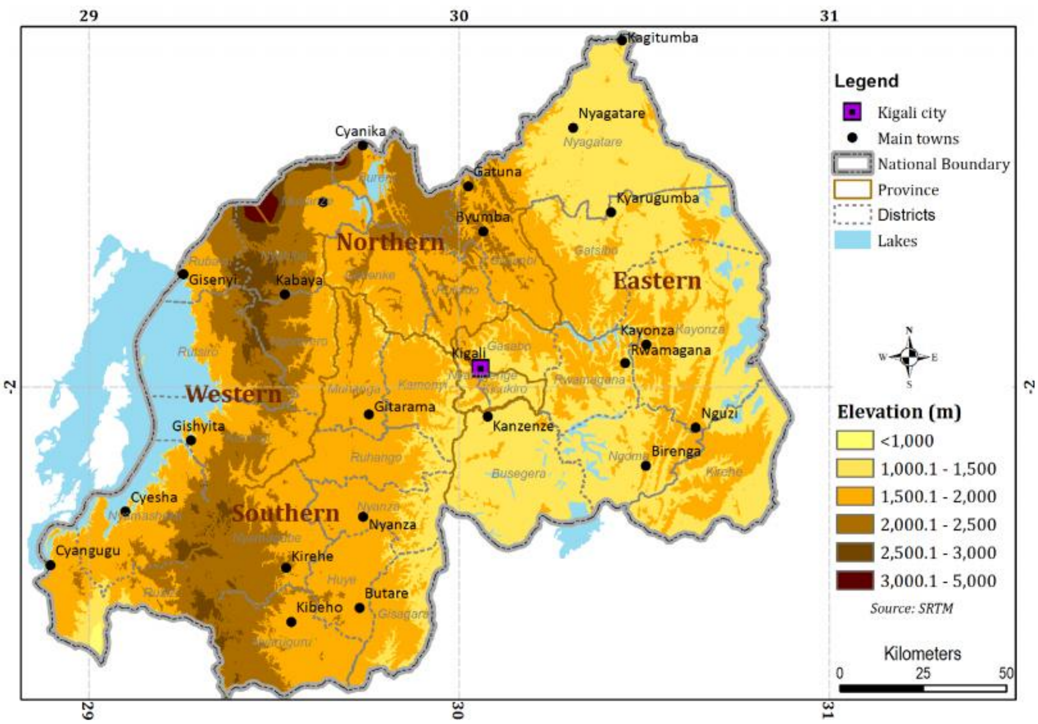

Figure 1: Spatial distribution of elevation (National Institute of Statistics of Rwanda, 2005)

Some factors that impact the rainfall over the country include: ITCZ, Congo Air Masses, Topography, large water bodies, Sub Tropical Anticyclones, Tropical Cyclones, Monsoons, ENSO, QBO and MJO

1.5.2. The Systems that impact the distribution of rainfall over Rwanda

The two major seasons mentioned in (section 1.5.1), are largely controlled by the location and intensity of Anticyclones such as St. Helena, Mascarenes, Azores and Siberian, (Ilunga et al.2004; Anyah and Semazzi 2007; Kizza et al. 2009). Rainfall in the country generally occurs during the rains seasons (MAM and SOND) as the ITCZ shifts to the equator from North to South, and vice-versa (Mutai and Ward 2000).

The ITCZ is the most system controlling the rainfall season over Rwanda. The subtropical anticyclones are regions of high pressure, which form the sources of the winds. They act as pumps of moisture into the areas of convergence. Their location and intensity influence the seasonal rainfall performance in the country. The subtropical anticyclones with important effect on the climate of the country include Azores (situated Northern Atlantic Ocean), St. Helena (situated Southern Atlantic Ocean), Mascarene (Situated in the Southern Indian Ocean) and the Arabian high pressure ridge (Situated in the Arabian Sea). The Mascarene high pressure is a major pump of moisture into the region. It is at its strongest during the Southern Winter (June-August) when it is associated with the East African high pressure Ridge, which render the wind flow over Eastern Africa mainly diffluent at lower levels. The Arabian ridge is fully developed during southern summer in the period of December-February, it is mainly associated with the diffluent flow over the region creating mainly short dry period condition in the country and little rainfall in some areas due to its topographic features. The maritime location is favorable rainfall occurrence. The St. Helena high pressure is an important pump of humidity into the area from the Congo air basin. The Congo basin is an important source of moisture for the country, which bring significant rainfall during March and May when the subtropical Anticyclones in the southern hemisphere are fully developed. The Azores high pressure is useful in the enhancement of the convergence in the region.

The tropical cyclone affecting the region form in the Arabian and southwestern India. They form in the Arabian sea region during the period March to May and in the Southern Indian during the period December-February. The tropical cyclone days over Indian ocean contains prominent decadal cycles, higher frequencies linked to Quasi Biennal Oscillation (QBO) and had positive relationships with SSTs over the entire south west India Ocean from September to March (Jury et al. 1999) suggested that the possibility of association between the occurrence of tropical cyclones and Madden Julian Oscillation (MJO). The MJO has a strong impact in the development of the tropical cyclone activities. The effects of Tropical cyclones on weather and climate of the region depend on time of the year, location of the cyclones and the associated large scale flow (Anyamba 1984, 1993). The Cyclones that move to the Mozambique channel can have adverse effects on the weather and climate of the region in March-May season which induce low level diffluent flow in the region (Anyamba 1993). However, the cyclones in the Mozambique channel during the months of December and January tend to enhance rainfall and are often associated with floods affecting the region during the period. They are characterized with the increase in pressure gradient between North Africa and Atlantic Ocean and Southwest India Ocean resulting to moist westerlies convergence over the region. It can therefore, be concluded that the effect of the tropical cyclones on region rainfall depends on the season, track and location of the cyclones.

ENSO has an important effect on precipitation over the region (Indeje et al. 2000). El Niño is linked with improved rainfall over the region especially in September to December (SOND) season. La Nina is linked with is scarce rainfall over some parts of the region. It’s also influences or impacts the onset, cessation and the peaks of seasonal rainfall (Indeje 2000).

The Indian Ocean Dipole (IOD) is the modes that have been observed to have important impact on rainfall over the region and other areas neighboring the Indian Ocean (Owiti 2005 and Omondi 2005).

Sea surface temperatures (SSTs) of the global oceans are the most frequently used predictors of seasonal rainfall. Various effort has been made to determine useful relationships between SST and seasonal rainfall over the region and other parts of the tropics that could use to predict rainfall during the seasons (Nyakwada 2003).

Enhanced/depressed seasonal rainfall over a region has been linked with the Warming and Cooling over the Western Indian Ocean (Owiti 2005) also the cooling over the Eastern Indian Ocean observed that wet/dry seasons over the region were closely associated with distinct anomalously warm/cool SSTs over parts of the western Indian/Eastern Atlantic Oceans.

The significant relationship observed among SST and seasonal rainfall over the area has motivated efforts to develop functional relationships to predict seasonal rainfall.

The SST based models have been observed to give climate outlooks for the region with useful skills. The skills of the forecasts are, however, influenced by the statistics of the weather within the season, which are dependent on internal chaotic variations (Zebiak 2003).

Mesoscale convective systems are collection of thunderstorms that act as a system. MCS are organized on a scale (on the order of 100 kilometers) larger than single thunderstorms but smaller than extratropical cyclones and are the features that influence the mesoscale weather in the western and northern region of the country. The intense insolation, circulation patterns over Lake Victoria and their interaction with large scale systems results in frequent thunderstorms and enhanced rainfall activities in the afternoon over the Western sector than the Eastern of the region. Moisture from the Congo Basin and the lake basin may be blocked from reaching the low land of the country through the action of high physical features like highlands and mountains. Action of orographic lifting may lead to wetter conditions on either side of the highland. The western parts of the Indian Ocean act as a source of moisture for the coastal areas and are also a forcing feature for mesoscale systems like the sea breeze. This is why North Western part of the country, receives abundant rainfall almost throughout the entire year.

Forcing on climate reviewed some aspects of solar forcing and found out that the effects were not strong on seasonal timescales. While the annual cycle of solar radiation is the dominant external forcing on the climate system, other external forcing like the 11-year solar cycle have been suggested though not very strong on seasonal time scales. On the internal climate forcing mechanisms, volcanoes for example, have been found to affect climate and have the potential to affect the skill of certain seasonal forecasts made after large eruptions (Robock, 2000).

CHAPTER TWO

2.0. LITERATURE REVIEW

Use of dynamical methods involves the simulation of the atmosphere land ocean interactions to forecast the future state of the atmosphere. Atmospheric general circulation models have reasonable skills in seasonal prediction during some seasons and parts of the tropics and subtropics (Janowiak 1992; Shogwe 2005) but the skill is generally low in areas where local features have significance influence on climate (Frederiksen et al. 2001). In the situation where the relationships are linear the skill of statistical and dynamical methods are comparable (Goddard et al. 2000; Kumar and Hoerling 2000).

The use of statistical methods, the SSTs anomalies are used to predict the rainfall season over East Africa and beyond (Omondi 2005; Owiti 2005). The significant relationships among SST and seasonal rainfall over the area has motivated efforts to develop functional relationships to predict rainfall during the season over the area. The skills of the forecasts are, however, influenced by the statistics of the weather within the season, which are dependent on internal chaotic variations (Zebiak 2003). The variations in correlation between rainfall and SSTs are major challenge to empirical methods since they are based on persistent relationships.

(Shukla 1998) shows that the Sea surface temperatures are potential predictors for the achievement of long-range climate prediction from dynamical methods especially in parts of the tropics where the relationships are strong.

(Livezy et al. 1996) shown that the improvement in the skills of seasonal forecasts from dynamical methods have been observed from the use of two tier approach of atmospheric general circulations models.

(Mason et al. 1999) reported that the use of ensemble methods, which involves the integration of an atmospheric general circulation models (AGCMs) with various primary conditions to obtain probabilistic data about the future conditions and to offer an estimation of the natural variability integral in the atmosphere, has shown further improvements in the skills of seasonal prediction from dynamical methods.

A latest study has revealed possible skilled experimental forecast of the MJO, with suitable leading periods of about 12 to 20 days (Wheeler, 2001). Such skillfulness is obviously better than a total number of present and preceding operating Numerical Weather Prediction (NWP) will be appropriate for the withdrawal of the MJO indicator from the output of the global NWP models.

(Sagero, 2012) described good predicting skill of Environmental Monitoring System Weather Research Forecasting (EMS-WRF) model for 3days predictions of rain over Kenya for small thresholds but unsuccessful forecast the incidence of rainstorms particularly on the coastline zone.

(J. Mutemi, 2003) shows that skillfulness of the model is more advanced during El Niño Southern Oscillation (ENSO) while large Sea Surface Temperature (SST) values are initiate over various areas of the equatorial tropics region.

(J. Ininda, 2008) shows that the advancement of rainfall during the season forecast through by using Model Output Statistics (MOS) and downscaled ECHAM predictions model over Tanzania that shown that the model was skillful in simulate observed mean climatological circulation and the yearly precipitation pattern over Tanzania and the skillfulness of simulating were high in October, November and December rainfall period while during March to May was low.

Epstein (1969) developed a stochastic dynamic prediction scheme that included a forecast equation for probability distribution of the atmosphere variables. Because of the size of the problem this method is unfeasible except for the simplest models

Lilly, 1990 did a study on NWP and found that at high resolution; convection is explicitly resolved, meaning that clouds and precipitation are entirely represented through additional prognostic equations which account for the microphysical and thermos-dynamical transformations associated with water phase changes. Moreover, high resolution allows for a much complete demonstration of the orographic forcing, known to play a key role at the mesoscale.

Willmott and Matsuura (2009) proposed that Root Mean Square Error (RMSE) is adequate normal model presentation and can be a confusing value of mean error, and as a result the Mean

Absolute Error (MAE) can be a well measure for the purpose. but near the concerns over using RMSE raised are usable, the future anticipation of RMSE in favor of MAE is not the result.

CHAPTER THREE

3.0. DATA AND METHODOLOGY

The section is dedicated to the discussion of the data and model used in this study and several approaches used to accomplish the aims of the study**.**

3.1. DATA

Data used this study include observed rainfall obtained from Rwanda Meteorology Agency, Sea Surface Temperature data (SST) from National Centre for Environment Prediction/ Climate Prediction Centre (NCEP/CPC) of the National Oceanic and Atmospheric Administration (NOAA), and WRF datasets which constitute the initialization data for the WRF-EMS model obtained from the Global Forecasting Model.

3.1.1. Rainfall data

This study used the monthly totals observations rainfall data which were obtained from Meteo Rwanda, historical data of 1981 to 2018 for thirteen (13) Agro Synoptic stations scattered across the country.

Despite loss of data or information during a shocking period in its history Meteo Rwanda and IRI have been working together to implement the Enhancing National Climate Services (ENACTS) in Rwanda to recover all the data until 2010. Then Meteo Rwanda start a series of training to recover complete dataset by using ENACTS system.

Table 1*: *List of Meteorological Station in Rwanda and their Coordinates for the Period (1981-2018) Source: Meteo Rwanda Metadata

N$^{\underline{O}}$.	STATIONS NAME	DISTRICTS	ALTITUDE	LATITUDE	LONGITUDE
1.	KIGALI	KICUKIRO	1490 m	01^o 36’S	30^o 08’E
2.	BYUMBA	GICUMBI	2235 m	01^o 26’S	30^o 03’E
3.	RUBENGERA	KARONGI	1473 m	01^o 49’S	30^o 26’E
4.	BUSOGO	MUSANZE	2100 m	01^o 34’S	29^o 33’E
5.	RUHENGERI	MUSANZE	1878 m	01^{o}29’S	29^o 33’E
6.	KIBUNGO	NGOMA	1706 m	02^o 29’S	29^o 46’E
7.	NYAGATARE	NYAGATARE	1706 m	01^o 47’S	30^o 19’E
8.	GIKONGORO	NYAMAGABE	1377 m	02^o 28’S	30^o 34’E
9.	GITEGA	NYARUGENGE	1567 m	01^o 59’S	30^o 04’E
10.	GISENYI	RUBAVU	1554 m	01^o 40’S	29^o 15’E
11.	BYIMANA	RUHANGO	1750 m	02^o 10’S	29^o 25’E
12.	KAMEMBE	RUSIZI	1591 m	02^o 28’S	28^o 55’E
13.	KAWANGIRE	KAYONZA	1473 m	01^o 49’S	30^o 26’E

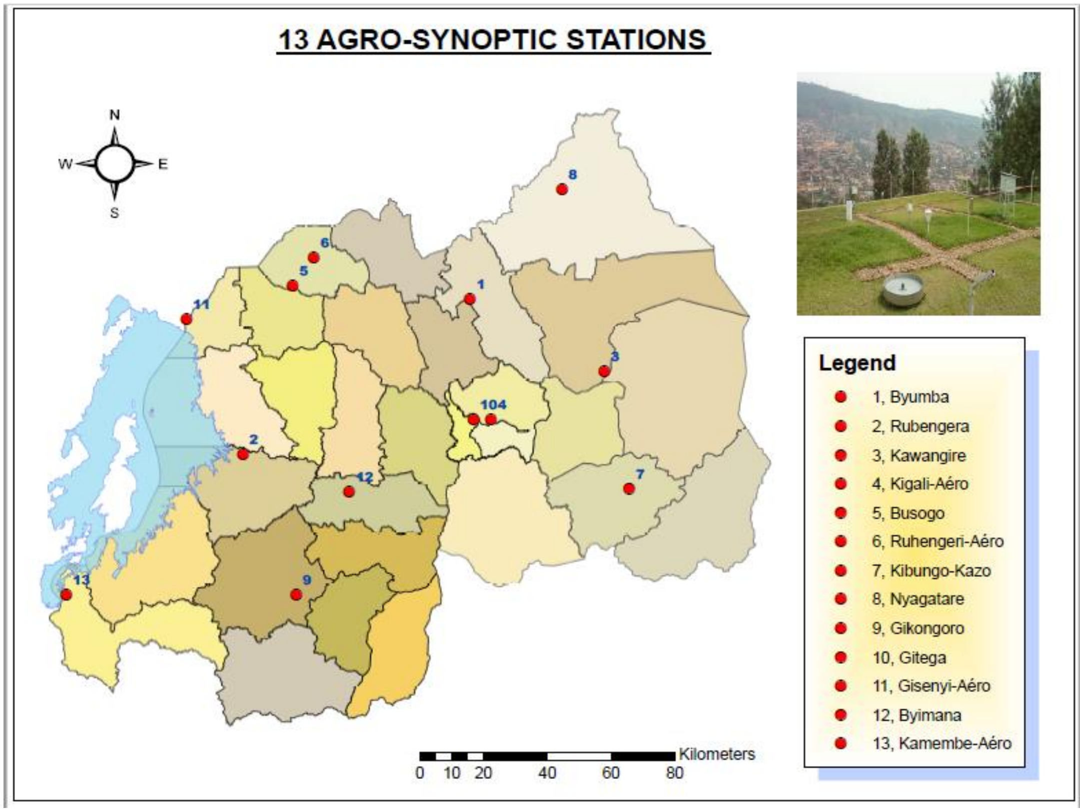

Figure 2: Spatial Map of the Rainfall Stations used over the study area. Meteo Rwanda, (2016)

3.1.2. WRF Datasets

For this study, the CFSv2 datasets was used in the WRF model. The datasets are available from the website, monthly datasets of the two seasons March, April to May (MAM) and September, October, November and December (SOND) of the year 1981 to 2018 were downloaded.

3.1.3. Sea Surface Temperature data

SST are widely used as a key predictor in most climate prediction models due to the long period of persistence of the SST anomalies (Omondi 2005). The data were obtained from NCEP/CPC for the period of 1981 to 2018.

3.1.4. Quality Control of the Data

The quality control of the estimated data was also investigated; the mass curve analysis was used to plot the cumulative climatological records against time. The total seasonal rainfall data for each station were cumulated and plotted against the years. An almost straight line shows the data are homogeneous.

3.2. METHODOLOGY

This section outlines the key analysis approaches adopted in the study.

3.2.1. Weather Research and Forecasting (WRF) experimental design

Running WRF requires the inputs datasets, the primary phase is the datasets to be downloaded. With additional more datasets accessible from Weather Research Forecasting (WRF) website. In this study CFSv2 datasets were used, consisting of pressure levels and surface fluxes.

In the Weather Research Forecasting (WRF) Model, parameterizations comprise radiation transmitted over the atmosphere incoming solar radiation and outgoing terrestrial radiation, planetary boundary layer and surface layer convective PBL during the day and stable PBL at night, turbulence and diffusion, cumulus convection on dynamic mass-flux approach with updraft/downdrafts and entrainment/detrainment, microphysics of clouds and precipitation interactions among hydrometeors, vapor, and the environment also hydrometeors form on cloud condensation nuclei (CCN) in supersaturated environments also interaction with Earth's surface.

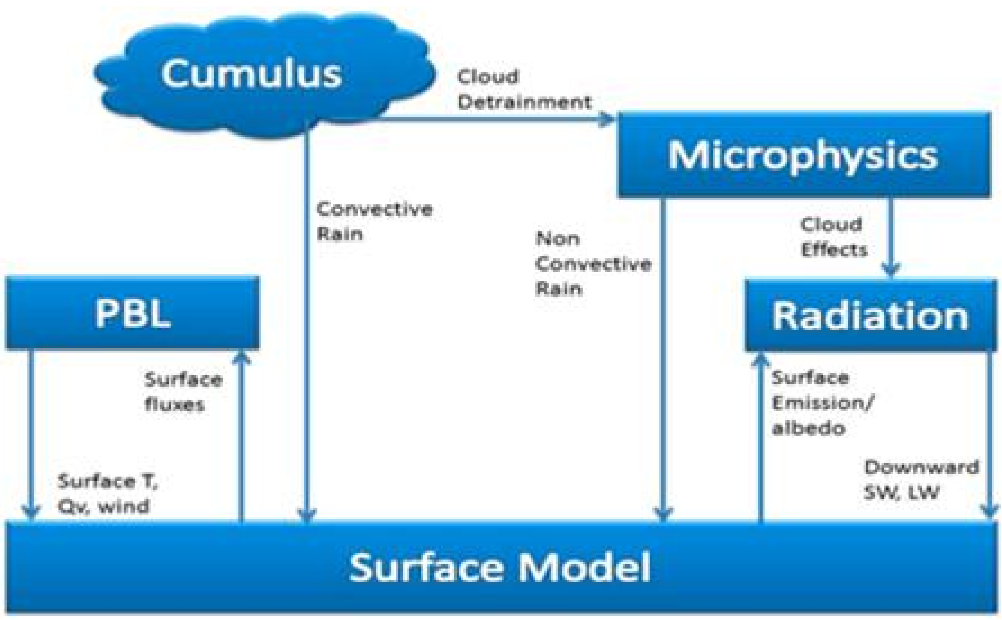

Figure 3: Interactions between WRF parameterization schemes (source: Physical parameterization notes)

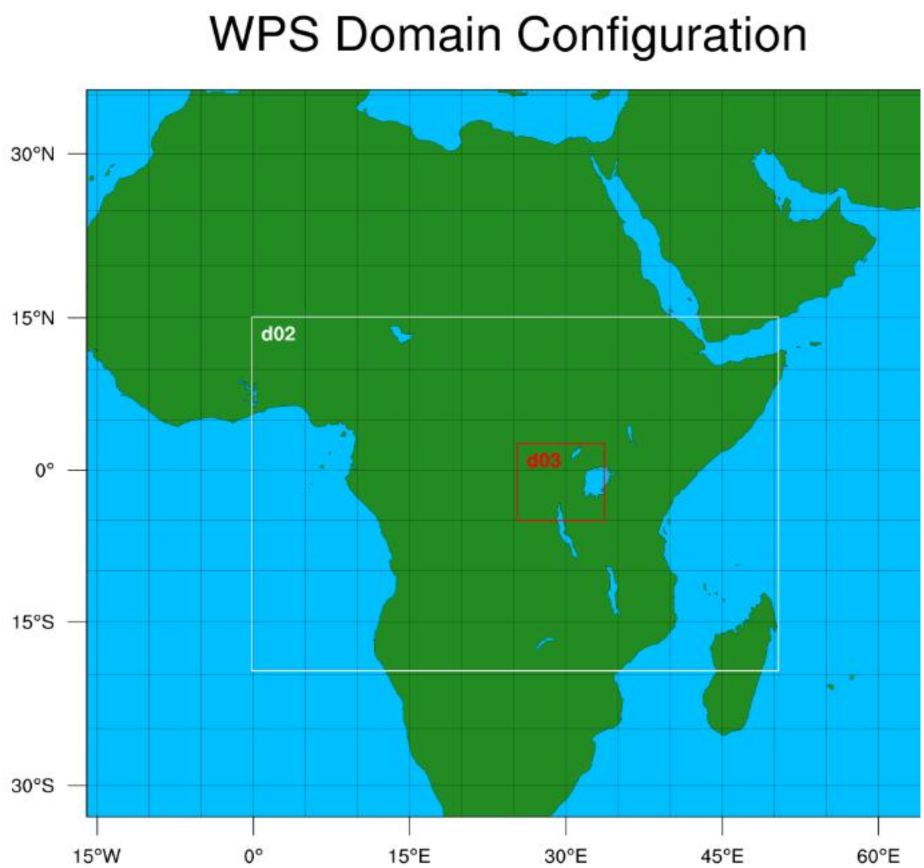

Figure 4: Configuration of the domain used for WRF simulation over the study area (1st domain 36km, 2nd domain 12km and 3rd domain 4km)

Interest on nested domains: The above map show the domain of the model used. horizontal resolution od 36km is the first (1st) domain, the second (2nd) as intermediate has 12 km and 3rd domain 4 km. Experimental domain is 0 °-50.0 °E and 15.0 °S-20.0 °N. With a horizontal grid ranging from the Eastern Atlantic to the East African coast of Indian Ocean.

The domains are centered over Rwanda that characterize the regional-scale flows and to determine the complex movements of the region.

3.2.2. Assess the Model skill and Measure of Accuracy

The section presents the several methods that were used to measure the skill of the model. This approaches include Mean Absolute Error (MAE), root mean square error analysis (RMSE), correlation analysis and regression analysis. Brief descriptions are discussed in the next section.

3.2.2.1. Mean Absolute Errors (MAE) and Root Mean Square Error (RMSE)

The Root Mean Squared Error (RMSE) is the difference among the forecasted and observed rainfall. It is overall best ratio of the model presentation for the reason that of the weighting of forecasted to its observed rainfall especially when we have extreme values. For a perfect model, the RMSE must approach zero. Accurate models have low systematic RMSE. The advantage of this measure skill is that it retains the unit of the forecast variable, but its advantage is that it favors model forecasts that underestimate variability, also RMSE can over amplify the importance of a single large error (Brier and Allan 1951).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{obs,i} - X_{pred,i}\right)^2}{N}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

In Equation 1, $X_{obs,i}$ is observation values and $X_{pred,i}$ is the forecast value i and N is the total number of observation pairs, observed value. i= 1, 2, 3…N. ranges from 0 to ∞. Perfect score is zero (0). The minor the Error the better the fit test, the greater the RMSE the worst the fit test.

Mean Absolute Error **(MAE)** measures how far the forecast values are away from observed values. It is computed as shown in Equation 2.

$$MAE = \frac{1}{N}\sum_{i=1}^{n} |X_{pred,i} - X_{obs,i}| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

In Equation 2, $X_{obs,i}$ is observed values and $X_{pred,i}$ is the predicted values i and N is the total number of observation sets, observation value. i= 1, 2, 3…N. It varies from 0 to ∞. good score is zero (0).

3.2.2.2. Correlation Analysis

The basic methods for searching for predictors are based on correlation concepts that attempt to develop some correlation coefficient that quantify the associations between some independent variables and dependent variables to be predicted. Correlation analysis examines the relationship between pairs of variables namely the independent variables (X) and dependent variables (Y). The degree of relationships between pair of variables X predicted and X observed are often quantified using correlation coefficient.

This simple correlation coefficient between two variables (r) a predict values *($X_{pred,\ i}$)* and the equivalent observed *($Y_{obs,\ i}$)* may be expressed as (r) correlation coefficient:

$$r = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(X_{pred,i} - \overline{X}_{\iota}\right)\left(X_{obs,i} - \overline{X}_{\iota}\right)}{\sqrt{\left[\frac{1}{N}\sum_{i=0}^{N}\left(X_{pred,i} - \overline{X}_{\iota}\right)^{2} . \frac{1}{N}\sum_{i=0}^{N}\left(\mathrm{X}_{\mathrm{obs,i}} - \overline{\mathrm{X}}_{\mathrm{i}}\right)^{2}\right]}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In the Equation (3) X_i symbolizes the ith predicted value, X_i is the ith observation value,$\overline{X}_i$ and $\overline{X}_i$ are examples average for model output and observation data and N the number of observation pairs i= 1, 2, 3…N.

The value of i lies between -1 and +1, if the value is +1.0, then X_i predicted and X_i observed are perfectly correlated, while it is zero when there is no relationship between two variables, a value of -1.0 denotes a perfect inverse linear relationship. The linear relationship was determined in both seasonal and monthly bases at various lags. The significant correlation coefficient indicated the predictive potential (Wilks, 1995).

The only disadvantage of this method is that it does not have the ability to recognize strong non-linear relationship between X_i predicted and X_i observed.

The correlation analysis alone is not sufficient to delineate linkages between multiple dependent/ independent variables. It is also weak in identifying linkages that are not temporally symmetrical, for example, high linkages with maximum sea surface temperatures (SST) values but no linkages with minimum sea surface temperature (SST) values. The computed correlation coefficient (r) was tested for significance using the t-test summarized by the equation 4:

$$\boldsymbol{t_{n-2} = r\sqrt{\frac{n-2}{1-r^2}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Equation 4, $\boldsymbol{t_{n-2}}$ is the student $\boldsymbol{t}$ – test value with **n-2** degrees of freedom and n is the length of records. If r = 0, this quantity has a “t-test” with “n-2” degrees of freedom. The details $\boldsymbol{t}$ – test can be obtained in many standard references (WMO 1966; Wilks 2006).

3.2.2.3. Performance of Regression Model

Regression analysis is a statistical method for estimating the relations between variables. Multiple linear regression (MLR) analysis aims to produce predicted values of a dependent variable from a linear set of principal predictors that well define the collective variability of independent variables. To create a statistical forecast system, one must first identify the potential predictors (mutually uncorrelated) that are strongly related to the predictands. Then statistical forecast models are built by relating the predictors to the observation anomaly. MLR is the most used statistical technique that describe the link among one continuous dependent variable and two or more independent variables.

The multiple linear regression models are given by Equation 5:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots\ldots + \beta_k X_k + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

In Equation 5, Y is the dependent value and the values of the independent variables are $X_1, X_2, \ldots\ldots . X_k$ and $\beta_1, \beta_2, \ldots . \beta_k$ are the model regression parameters connecting to the predictors $X_1, X_2, \ldots . X_k$ and ε is an error values.

To evaluate individual significance level, we used the derived regression equations by using stepwise multiple linear regression which comprise in the equation. F ratio is the ration of two mean square values. If the null hypothesis is true, you expect F to have a value close to 1.0 most of the time, a large F ratio means that the variation among group means is more than you would expect to see by chance.

The p-value less than 0.05, means that there is a significant difference when is over 0.05, there no significant relation between two variables.

3.2.3. Assessment of the appropriate Predictors

A number of predictors were selected for the prediction like; Sea Surface Temperature anomalies (SSTa), Indian Ocean Dipole (IOD) El-Nino Southern Oscillation Index (ENSO), and SST gradients (Nyakwada *et al* 2009), Quasi Biennal Oscillation (QBO), Maiden Julian Oscillation (MJO). This study was used new methods during MAM and SOND seasons.

3.2.3.1 Sea Surface Temperature Gradients

The use of sea surface temperature (SSTG) gradients could give good representation of the dynamic forces of the general circulation. The use of sea surface temperature gradients is motivated by their influence on the atmospheric circulation, nearly of the Sea Surface Temperature gradients (SSTG) that have been recognized to impact climate of the region and beyond include the Zonal SST gradients in the Indian ocean associated with the IOD (Owiti 2005), the zonal SST gradient in the pacific and the zonal and meridional SST gradients in the Atlantic ocean are linked through teleconnections with large-scale atmospheric circulation such as the Walker and Hadley cells. The zonal and meridional SST gradients have a strong signature on the climate of the tropical areas. A complete illustration of sea surface temperature gradient is representing in the Equation 6 below.

$$SSTG(t) = A(t)_{ij} - B(t)_{ij} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(6)}$$

In Equation 6, *A* and *B* represent standardized anomalies of averages SST for the regions A and B. small i is represent latitude and j is representing longitude. The zonal and meridional gradients are calculated in the direction of the arrows as shown in Figure 5.

Table 2: Computation of Meridional and Zonal SST gradient modes that had the highest associations with seasonal rainfall over East Africa.

Ocean	Region	LATITUDE	LONGITUDE	COMPUTATION	GRADIENT NAME
PACIFIC	A B	5N-5S 5N-5S	120W-90W 150E-180E	B-A	ZPAC
INDIAN	C D	5N-5S 5N-5S	80E-100E 40E-60E	D-C	ZIND
ATLANTIC AND INDIAN	G K	40-30N 20-30S	40W-10W 20W-15E	G-K	MAB3
	L	10N-20N	40W-15W	L-F	MAB4
	D	5N-5S	40E-60E	E-D	ZAF

3.2.3.2 Madden Julian Oscillation

The Madden Julian Oscillation (MJO) is an intra-seasonal wave originating in the Tropics which results in changes of atmospheric and oceanic conditions and have a typical period/ cycle of approximately 30-60 days and propagate eastward. The MJO has direct and indirect sensible weather impacts nearly everywhere around the globe, The MJO has direct impacts on ENSO, tropical cyclone activity and other tropical waves. Influence of the MJO on the predictive skillfulness of extreme rainfall is frequently more in when the MJO is active and has greater convection occurring over the western hemisphere, Africa and/ or the western India Ocean than during the inactive phases of oscillation (Jones et al 2001). In the western hemisphere the main contribution to RMM1, 2 comes from zonal winds as the contribution from outgoing long wave radiation (OLR) is small outside the Indian Ocean. (Madden and Julian, 1971)

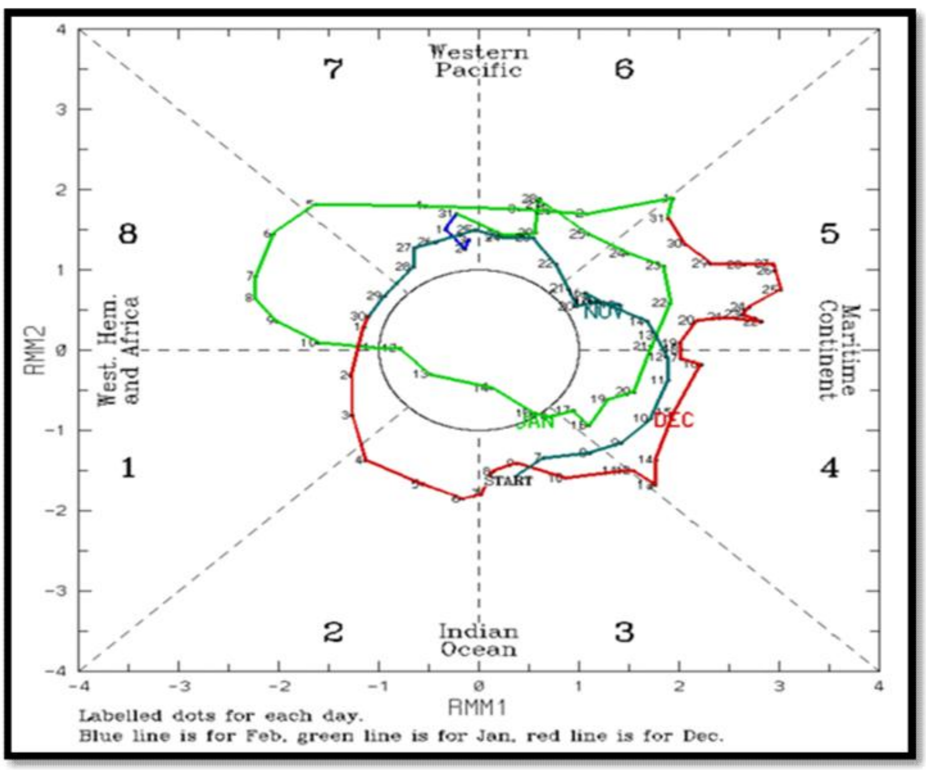

Figure 5: MJO phase for December 2018 to February 2019

(Source: Bureau of Meteorology Australia http://www.bom.gov.au/climate/mjo)

3.2.3.3. Principal Component Regression

Principal component regression (PCR) is a method of analysis that is centered on principal components analysis (PCA) it consider regressing the dependent variables on the predictors field derived using the method of EOF (Empirical orthogonal function) /Principal component analysis. It used the method that can be divided into three steps

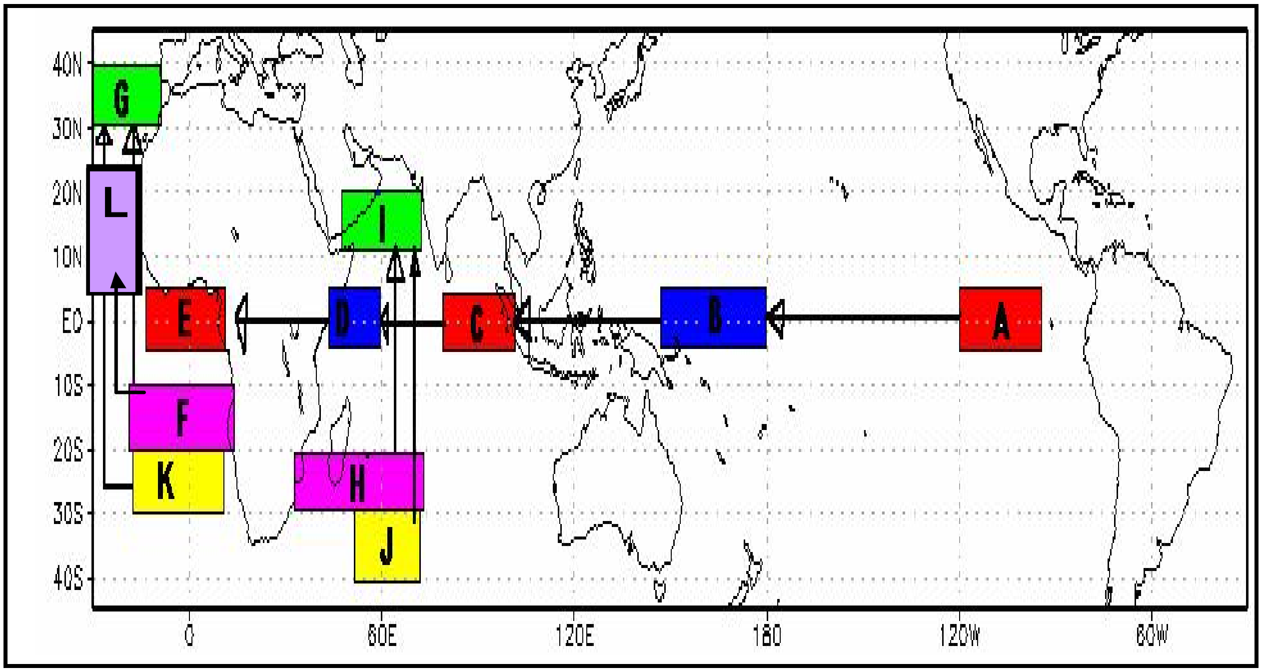

Figure 6: The Positions used to compute the sea surface temperature Gradient modes that had the highest relationships with seasonal rainfall over East Africa

Nyakwada (2009) used PCA techniques to identify modes for individual oceans and combined Indian-Atlantic that were used to identify the core centers that were used to construct SST gradient modes (see Figure 6 and Table 2 and 3).

Figure 6 provides the areas used to calculate the meridional and zonal sea surface temperature gradient that have the highest associations by seasonal precipitation over the region.

Computation of the other zonal and meridional modes was done in a similar manner using the grid points indicated in Table 3.

Table 3: The Computation of the other Sea Surface Temperature Modes that had significant Relationships with Seasonal Rainfall over East Africa.

OCEAN	REGION	LONGITUDE	LATITUDE	GRADIENT COMPUTATION	GRADIENT NAMES
	D	50E-60E	0-10S		
	C	110E-20E	0-10S	D-C	ZIND
	D	40E-50E	10N-30S		
Indian Ocean	C	90E-130E	0-20S	I-H	ZIND
	G	20W-15E	10-20S	G-K	MAB1
Atlantic Ocean	K	20W-15E	20-30S	L-F	MAB2
	L	40-15W	20-10N	G-L	MAB5

3.2.4. Verification of the improved Skill Scores

The verification of improved skill scores uses to analyze the analyze the association among the model outputs statistics and the rainfall observation values. 3x3 contingency table were used to calculate the skill scores. Verification of forecast is the method of measuring the quality of a prediction, in instance it should give you information about the nature of predicted bias, Jolliffe, (2003).

Table 4: 3 by 3 Likelihood Table Events Observed and Predicted

	Event Forecasted				TOTAL
Event Observed		BN	NN	AB	
	BN	A	B	C	M
	NN	D	E	F	N
	AB	G	H	I	O
TOTAL		J	K	L	T

BN: below Normal, **NN:** Near Normal and **AB:** Above Normal

3.2.4.1. Bias Score

The bias corresponds between forecast and mean observation. The bias score calculates the proportion of the frequency of predicted rainfall events to the frequency of observed rainfall events. It shows whether the predicted system has a tendency to Bias < 1 below expectation or above expectation (Bias>1) rainfall events. Varies from 0 to ∞ the good score is 1 (100%). Range: 0 to ∞, perfect score=1

$$\text{BIAS} = \begin{cases} \frac{J}{M}\,(\text{Below Normal}) \\ \frac{L}{O}\,(\text{Above Normall}) \\ \frac{K}{N}\,(\text{Near Normal}) \end{cases} \quad (7)$$

3.2.4.2. Probability of Detection

PoD provides an ordinary calculation to the quantity of precipitation occurs and predicted by the model. It's sensitive to misses events and hits, only can be improved by over forecasting, ranges are from 0 to 1 and the perfect score is 1 (100%).

$$\text{POD} = \begin{cases} 100 * \frac{A}{M}(\textit{Below Normal}) \\ 100 * \frac{I}{O}(\textit{Above Normal}) \\ 100 * \frac{E}{N}(\quad \textit{Normal}) \end{cases} \quad (8)$$

The limitation of PoD is that you can have a high score for one category because of a systematic bias, rather than because of real skill and conversely you can have a low score for a different category again because of a systematic bias. For example, if you have 30 years of observations, and 10 each are below normal, near normal and above normal, but your forecast method has a dry bias, it may have forecast that 20 of the 30 years are dry 10 are near normal and none are wet. 10 of those 20 dry forecast years may coincide with the 10 dry observations giving a PoD of 1 for that category, but clearly the forecast is picking dry more frequently than observed.

3.2.4.3. False Alarm Ratio

FAR provides an ordinary relative calculation of the tendency of the models to predicted category of rainfall where none was observed. It's function of false alarms and hits only, can be improved by under forecasting.   Range is from 0 to 1 and the good score is zero (0).

$$FAR = \begin{cases} 100 - 100 * \frac{A}{J}(Below \quad Normal) \\ 100 - 100 * \frac{I}{L}(Above \quad Normal) \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (9)$$

3.2.4.4. Heidke Skill Score

The HSS derived from the elements in the contingency table that used to establish the performance of the models that gives the accuracy of the forecast relative to random chance and measures the fraction of correct forecasts after eliminating the forecasts correct due to purely random chance, is also the technique that calculate the percentage of accurate predictions after removing the predicted that could be exact due to random coincidence. Range is -∞ to 1 and perfect score is 1 (100%). skill level less than zero in the prediction is poor to the climatology.

The mathematical expression of HSS

3.2.4.5. Post agreement

Post agreement is a supplement of FAR (PA= 1 – FAR), is not widely used and is complex to false alarms and hits. It varies from 0 to 1 and the good score is one (1) (100%).

It has an advantage of being simple and intuitive and disadvantage it can mislead when it is heavenly subjective by the best common category.

$$PAG = \frac{A}{(J+L)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

CHAPTER FOUR

4.0. RESULTS AND DISCUSSION

4.1. Introduction

The chapter presents the results that were obtained from various methods that were presented in chapter 3 above that address the aims of this study. These objectives include, improvement of the WRF model skills during the rainfall seasons of March-May (MAM) and September to December (SOND) 2918. By using Absolute Mean Error, Root Mean Square Error, correlation analysis, regression analysis and identification of the suitable predictors that may increase the skillfulness of the statistical seasonal rain forecast and verification approached to hindcast the prediction of seasonal rainfall:

4.2. Data Quality Control

Figure 7 and Figure 8 give examples of mass curves that were used to test for the homogeneity of the records during MAM and SOND. The mass curves showed that generally only straight single line could be fitted to cumulative rainfall records, which is indicative of homogeneity of the records used in the study. The quality of the estimated data the mass curve analysis that involves the plotting of cumulative climatological records against time.

In general, the quality control analyses showed that most of the records used were of good quality. These data made the base of most of the analyses that were accepted to investigate various specific objectives in this study. The results of the homogeneity test which were achieved by the use of single mass curves.

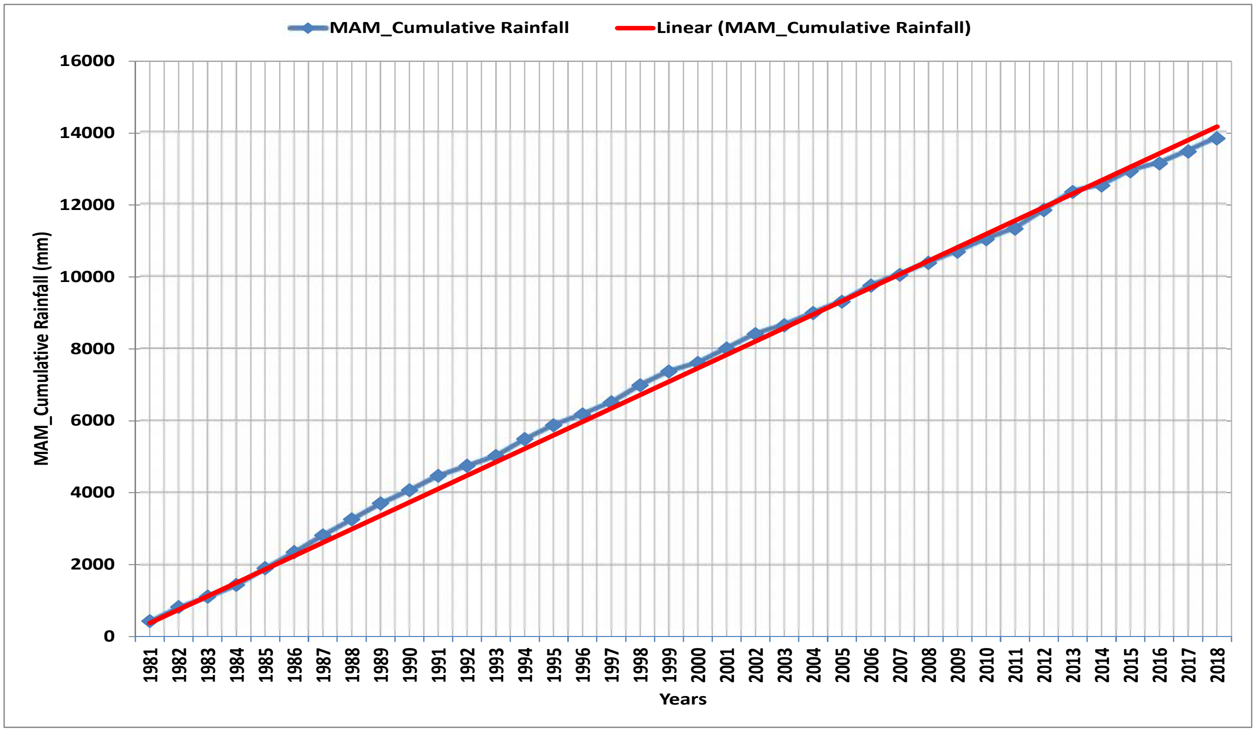

Figure 7: Plot of cumulative MAM long rainfall season (mm) over Kigali (1981-2018)

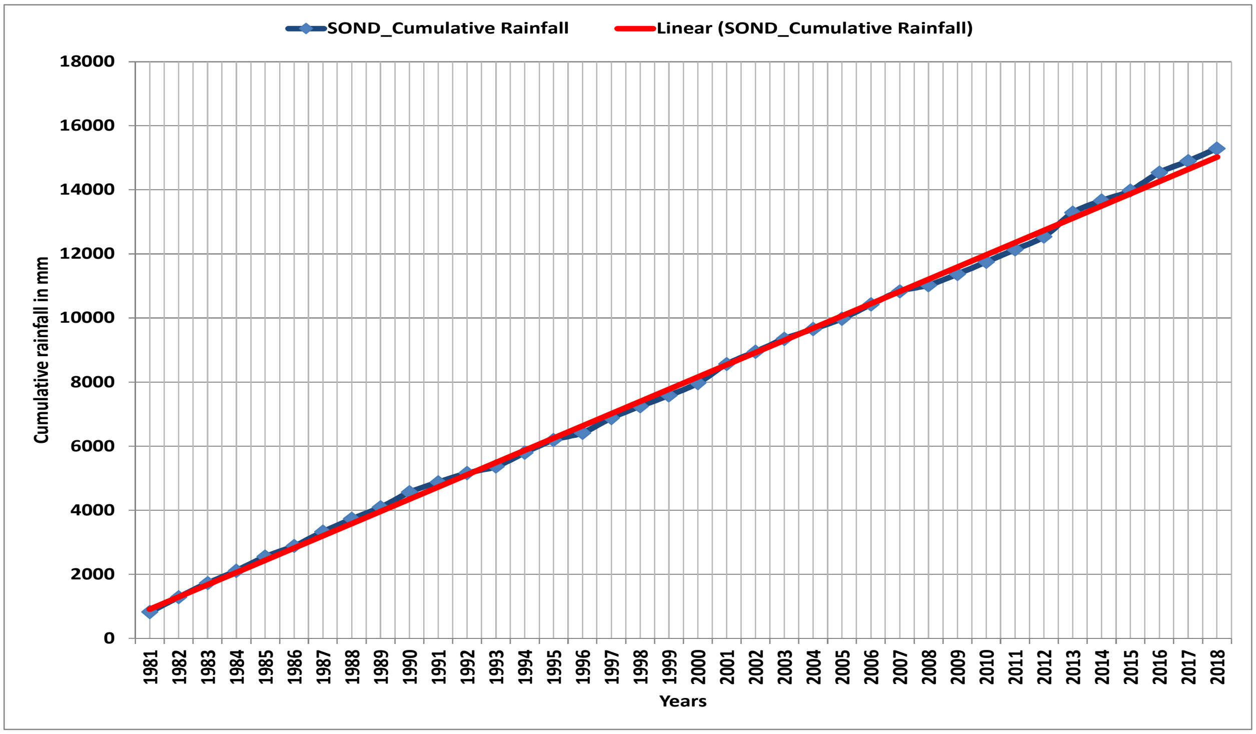

Figure 8: Plot of cumulative SOND short rainfall season (mm) over Kigali (1981-2018)

4.3. Assess the Weather Research Forecasting (WRF) model in MAM and SOND 2018 rainfall seasons

By assessing the performance of Weather Research Forecasting (WRF) model during the two season seasonal rainfall prediction namely (MAM_2018) and (SOND_2018).

4.3.1. Performance of the WRF Model during MAM 2018

Figure 9 (a and b) show the spatial pattern of the rainfall simulated by WRF model and the observed rainfall of March to May 2018 season for the country. The figure shows that the rains were highly enhanced, both timely and spatial countrywide. It’s evident that the model simulates very well the general nature of the spatial rainfall distribution. It however failed to capture the fine details as in the observed seasonal rainfall total (Figure 9 b) where the model under-estimated the rainfall over the south and eastern parts of the country and over-estimated the rains over the Western part of the country. This shows the deficiency in the model to reproduce the effects of small scale systems that may have been responsible for rainfall in some parts of the country during MAM 2018 season.

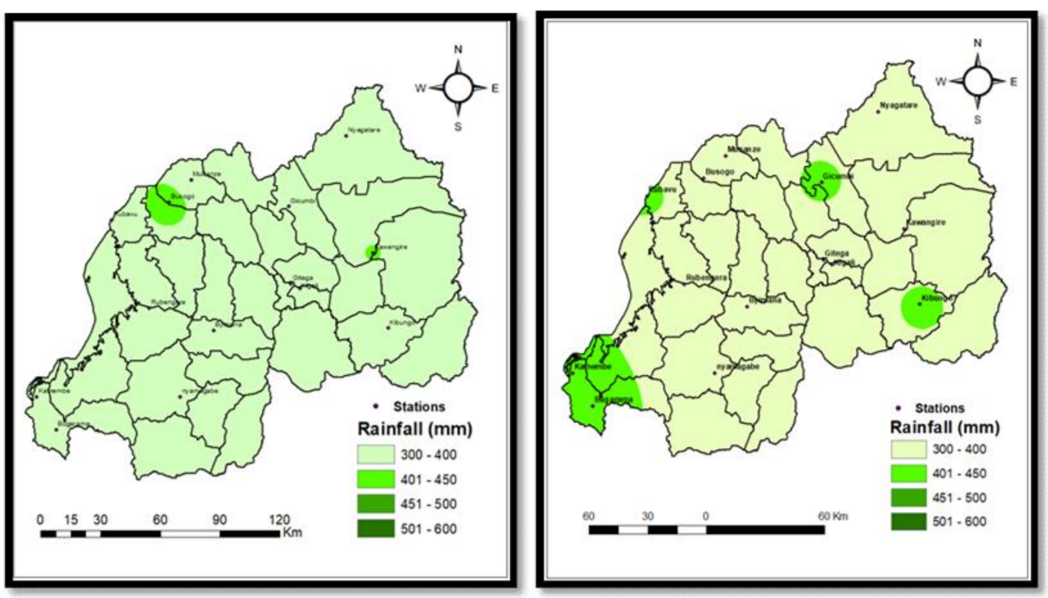

Figure 9: The spatial distribution of observed (a) and predicted (b) rainfall (mm) green is high rainfall amount and light green and light yellow are the lowest rainfall amount over Rwanda using the WRF model during the MAM long rainfall season of 2018

4.3.2. Performance of the WRF Model during SOND 2018

Figure 10 (a and b) show the spatial pattern of the rainfall simulated by the WRF model and the observed rainfall of September to December 2018 seasonal for the country. The model over-estimated the rainfall amount compared to the observed rainfall during SOND 2018, especially in the Western parts of the country, both in time and space. In those figures, it's evident that the model simulates very well the general nature of the spatial rainfall distribution; it however captures large part of the region compare with less details (Figure 10 b) where the model over-estimated the rainfall total over the whole country. This shows the deficiency in the model to reproduce the effects of mesoscale and small scale systems at seasonal time scale that may have been responsible for rainfall in the country during SOND 2018 season. that the model simulates very well

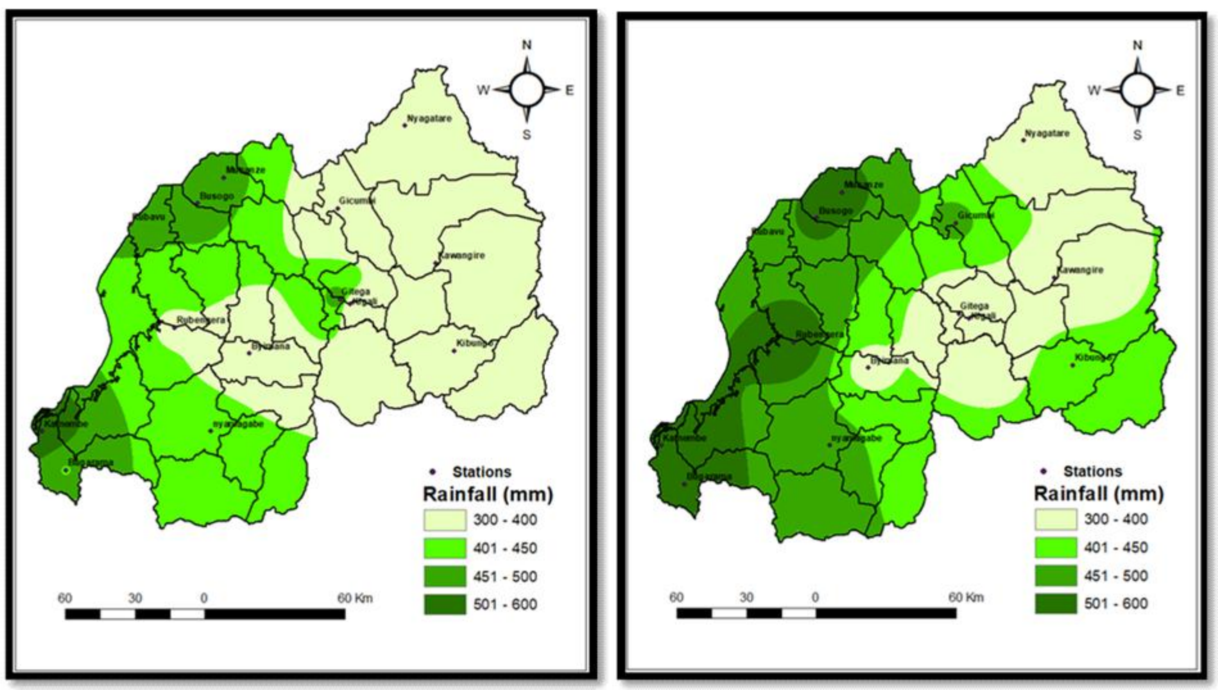

Figure 10: The spatial distribution of observed (a) and predicted (b) rainfall (mm), dark green and light green is high rainfall amount and light yellow is the lowest rainfall amount over Rwanda using the WRF model during the SOND short rainfall season of 2018

4.4. Results of the skill of the Statistical Model

This section highlights the analysis from several methods that were used to assess model skill. The skill was evaluated by using mean absolute error (MAE), root mean square, Correlation Analysis and Performance of Regression Analysis.

4.4.1. Result from Root Mean Square Error and Mean Absolute Error

Table 5 presents the results of the RMSE and MAE for 10 sample stations, which show the ability of the model to produce the rainfall observed. The smaller the RMSE and MAE the improved the fit test. The value calculated of absolute mean error for more stations were closer than one (1), that showing that the accuracy of the model was good in producing the observed rainfall during the wet seasons. The outcomes of the models show very small values of less than 1 for all sample stations during the two seasons for RMSE and MAE, this identify the capability of the model to produce the observed rainfall, expect Kibungo and Gikongoro stations during MAM season and Kigali during SOND season that RMSE exceed 1.

Table 5: Computation results of RMSE and MAE during MAM and SOND season

Station Names	MAM-RMSE	MAM-MAE	SOND-RMSE	SOND-MAE
Byumba (Gicumbi)	0.86	0.51	0.56	0.74
Gisenyi (Rubavu)	0.73	0.52	0.67	0.60
Kamembe (Rusizi)	0.94	0.54	0.98	0.65
Rubengera (Karongi)	0.87	0.53	0.34	0.79
Kigali Airport (Kigali)	0.91	0.52	1.10	0.51
Ruhengeri (Musanze)	0.89	0.55	0.56	0.75
Kibungo (Ngoma)	1.32	0.60	0.92	0.62
Nyagatare	0.91	0.52	0.78	0.69
Gikongoro (Nyamagabe)	1.23	0.61	0.96	0.81
Byimana (Ruhango)	0.45	0.57	0.79	0.76

4.4.2. Results from Correlation of Analysis

This section presents the results that were obtained when the rainfall for the two wet seasons was subjected to correlation analysis between the observed rainfall and SST indices. Significant correlations were found with various regions of the global oceans. The relationship was found to be stronger when the SSTs were lagged one month and thus the choice of using the August SST anomalies during SOND and February SST anomalies during MAM (March-May) seasons.

4.4.2.1. Result from correlation of global SSTs indices with MAM rainfall seasonal.

Figure 11 shows the spatial pattern of lagged SST Indices of the global Ocean areas with significant lag-correlation value between MAM (March-May) rainfall and February global SST's for the period 1981-2018 were determined and used as areas of potential predictors.

Significant correlation values of **(| r | = 0.85)** were identified in the Pacific, Atlantic and Indian Oceans as indicated in the Table 6. Examples of spatial correlations between February SST anomalies and MAM rainfall are shown in Figure 11. All the events used in this section were within the 37 years period 1981-2018 as shown in the Table 6.

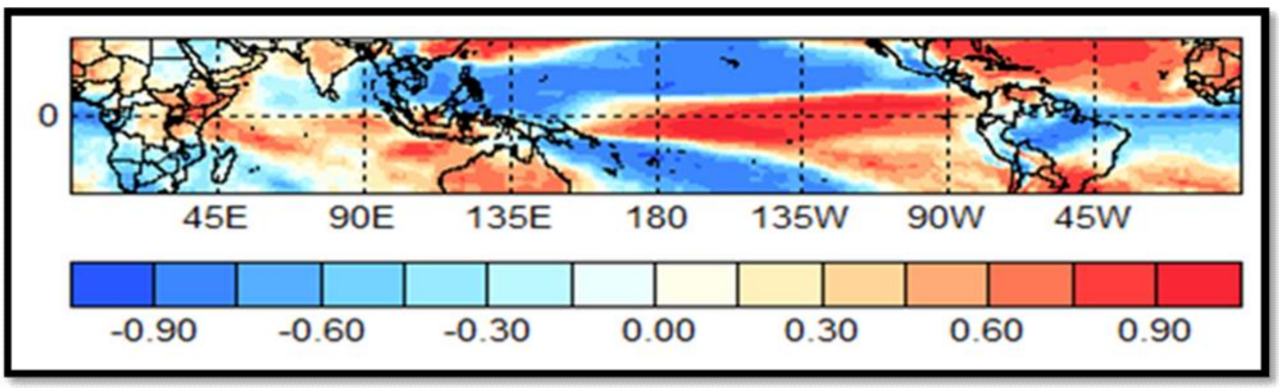

Figure 11: Average Global Map showing the Spatial pattern of Correlation coefficient between model and observed rainfall during MAM season over Rwanda

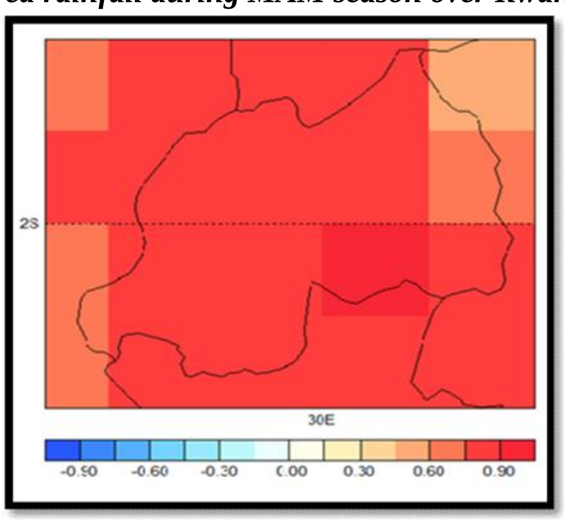

Figure 12: Spatial distribution of the Pearson's correlation coefficient of 0.85 between the modeled and observed rainfall during the MAM 2018 season over Rwanda

Table 6: Locations of Significant MAM SST Predictors for various stations over the Study Area

Stations	Pacific Ocean	Indian Ocean	Atlantic Ocean	Correlation
Kigali	160°W-90°W			0.5-0.7
	45°S-40°S			0.4-0.5
Rusizi	120°W-90°W	60°E-90°E		0.6-0.8
	45°S-40°S	10°S-10°N		0.5-0.6
Musanze	150°W-110°W			0.3-0.5
	30°S-10°S			0.3-0.6
Gicumbi		50°E-60°E;		0.2-0.4
		5°S-10°N;30°S-10°S		0.2-0.3
Nyagatare		40°E-60°E	10°W-20°E	0.2-0.5
		40°S-15°S	30°S-10°S	-0.3-0.4
Ngoma			10°W-30°E	0.2-0.6
			30°S-10°S	0.2-0.3
Ruhango	120°W-90°W			0.4-0.7
	45°S-40°S			0.3-0.5
Karongi		45°E-90°E		0.5-0.8
		15°S-10°N		0.2-0.4
Rubavu	120°W-140°W	30°E-60°E		0.4-0.6
	30°S-05°S	10°S-10°N		0.3.0.7
Nyamagabe	90°W-120°W	30°E-60°E		0.5-0.8
	45°S-60°S	10°S-20°N		0.6-0.7

4.4.2.2. Result from correlation of global SSTs indices with SOND rainfall seasonal

Figure 13 shows the spatial pattern of lagged SST Indices of the global Ocean areas with significant lag-correlation value between SOND (September-December) rainfall and August global SST's for the period 1981 - 2018 which were determined and used as areas of potential predictors. Significant correlation values of **(| r | = 0.70)** were identified in the Pacific, and Indian Oceans as indicated in the Table 7.

Examples of spatial correlations between August SST anomalies and SOND rainfall are shown in Figure 13. All the events used in this section were within the 37 Years period 1981-2018.

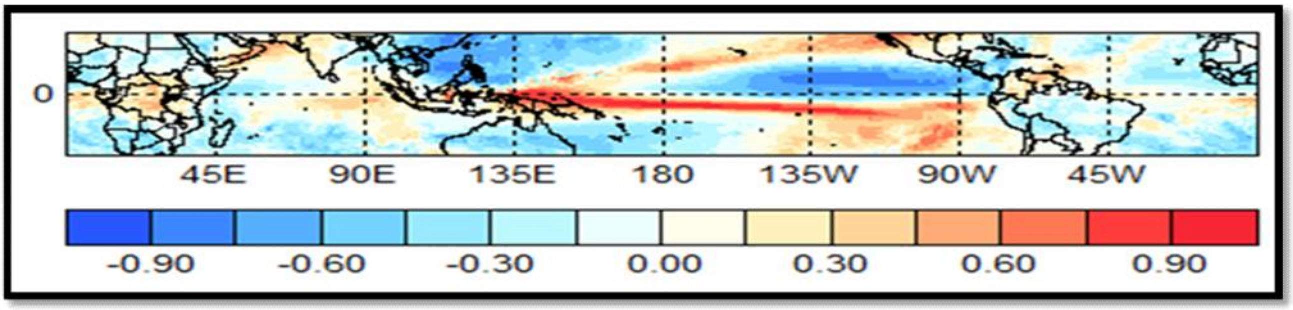

Figure 13: Average Global Map showing the Spatial Correlation coefficient between model and observed rainfall during SOND season over Rwanda

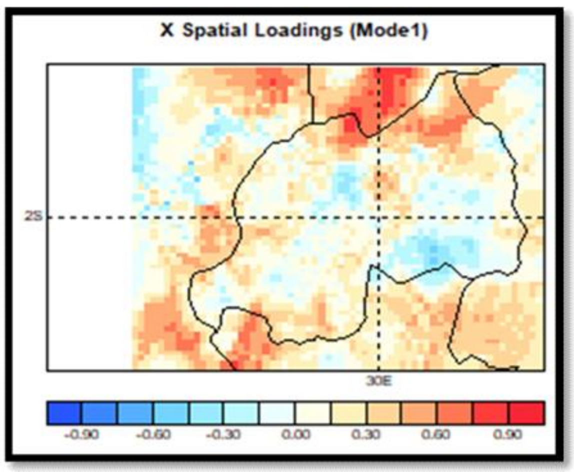

Figure 14: Spatial distribution of the Pearson's correlation coefficient of 0.70 between the modeled and observed rainfall during the SOND 2018 season over Rwanda

Table 7: Locations of Significant SOND SST Predictors for various stations over the Study Area

Stations	Pacific	Indian	Correlation
Kigali	135°W-90°W	50°E-70°E	0.3-0.4
	45°S-40°S	20°S-10°N	0.4-0.5

Rusizi	100^oW-140^oW		0.3-0.4
	15^oS-20^oS		0.4-0.5
Musanze	110^oW-140^oW		0.3-0.5
	20^oS-10^oS		0.2-0.3
Gicumbi		90^oE-120^oE	0.2-0.4
		5^0S-10^oN	0.2-0.3
Nyagatare	10^oS-15^oN	50^oE-60^oE	0.2-0.5
	60^oE-120^oE	30^oS-15^oS	0.3-0.4
Ngoma		30^oE-90^oE	0.4-0.6
		20^oS-35^oS	0.2-0.3
Ruhango		5^oS-10^oN	0.3-0.5
		70^oE-120^oE	0.2-0.4
Karongi		30^oS-10^oS	0.3-0.4
		50^oE-60^oE	0.2-0.6
Rubavu		30^oE-60^oE	0.4-0.6
		10^oS-10^oN	0.2-0.3
Nyamagabe		45^oE-90^oE	0.3-0.4
		15^oS-10^oN	0.4-0.5

4.4.3. Results of the skill of the Regression Model

In this section the results from regression analysis of MAM and SOND rainfall and various predictors are discussed. The details of the regression analysis methods were presented in section 3.2.2.3 and the details of the SST gradients that are significantly correlated with Rwanda rainfall are presented in Section 3.2.3.1.

Table 8: Regression analysis table for F-Ratio, P-Value and Root Mean Square error (R^2) of the Model skill for MAM 2018 Season

Representative Stations	F- RATIO	P-Value	R^2
Gicumbi (Byumba)	0.99	0.000	75.0%
Rubavu (Gisenyi)	0.67	0.001	68.1%
Rusizi (Kamembe)	0.69	0.000	68.8%
Karongi (Rubengera)	0.95	0.000	74.4%
Kigali Airport	0.56	0.002	64.9%
Musanze (Ruhengeri)	0.91	0.000	75.5%
Ngoma (Kibungo)	0.34	0.011	57.7
Nyagatare	0.93	0.000	73.8%
Nyamagabe (Gikongoro)	0.74	0.000	68.0%
Ruhango (Byimana)	0.86	0.000	72.5%

Table **8** gives the summary of the results from regression analysis between the observed rainfall and some few predictors that highly predicted MAM rainfall when the regression model was run to completion. The results indicate that the skill was relatively high with coefficients explaining more than 57.7 % of the variance and fairly high F-ratio at 95% confidence level. To demonstrate the skill of the models developed, two approaches were adopted. The first one involved training (fitting) the regression model for data within the period 1981-2010, The period 2011-2018 was then used to test the model skill. The second method compared the forecasts and observations through verification for the specific station. This provides prediction estimate for all the years, the statistical results for the individual seasons and overall summary of the whole study area are presented in Table **29** and **30**.

Figures **15 – 24** showed that the models captured fairly well the observed rainfall during the training and verification periods with R^2 ranging between 57.7% to 75.5% means good fit of the model and F-ratio 0.39 to 0.99, Ruhengeri station in Musanze district had the highest R^2 of 75.5% means good fit of the model and F-ratio 0.91 (Table **8**).

Table 9: Regression analysis for F-Ratio, P-Value and Root Mean Square (R^2) of the Model skill for SOND 2018 Season

Stations Representative	F- RATIO	P	R^2
Gicumbi (Byumba)	0.62	0.09	49.0%
Rubavu (Gisenyi)	0.44	0.09	42.0%
Rusizi (Kamembe)	0.76	0.04	58.0%
Karongi (Rubengera)	0.34	0.08	53.2%
Kigali Airport	0.84	0.09	34.6%
Musanze (Ruhengeri)	0.39	0.03	33.7%
Ngoma (Kibungo)	0.41	0.02	43.5%
Nyagatare	0.54	0.04	58.0%
Nyamagabe (Gikongoro)	0.67	0.04	57.1%

Table **9** gives the summary of the results from regression analysis between the observed rainfall and some few predictors that predicted SOND rainfall when the regression model was run to completion. The results indicate that the skill was relatively slight low with coefficients explaining that 57.7 % of the variance and fairly F-ratio at 67% confidence level.

The models captured fairly well the observed rainfall during the training and verification periods with coefficient of determination ranging between 34.0% to 58.0% means slight good fit of the model and F-ratio 0.41 to 0.39, Ruhengeri station in Musanze district had the lowest R^2 of 33.7% means bad fit of the model and F-ratio 0.41 during SOND.

Regression model results of observed and predicted are depicted by Figure **15-24**. Figure **15** for instance shows the regression model for Gicumbi as represented by Byumba station. The training period (1981-2010) show consistency between observed and predicted rainfall while in the verification period (2011-2018), the forecasted values are explained at 75.0% (R^2=75.0%). It is apparent from the figures that although the model is capable to capture the general direction of extreme rainfall, there are significant differences between observed and predicted anomalies. It also evident from the figure that the predicted model was not able to capture some of the extreme rainfall peaks well due to variability in the weather/climate.

4.5. Results of the Models verification

4.5.1. Inter-annual variation of observed and model rainfall during MAM season

Figures **15-24** show the observed and forecast rainfall anomalies during MAM for the country (Station one to station ten). For instance, Figure **15** shows that the forecast compare well with the observed values with R^2 of 75.5%. This means the model is a better fit to the observed values.

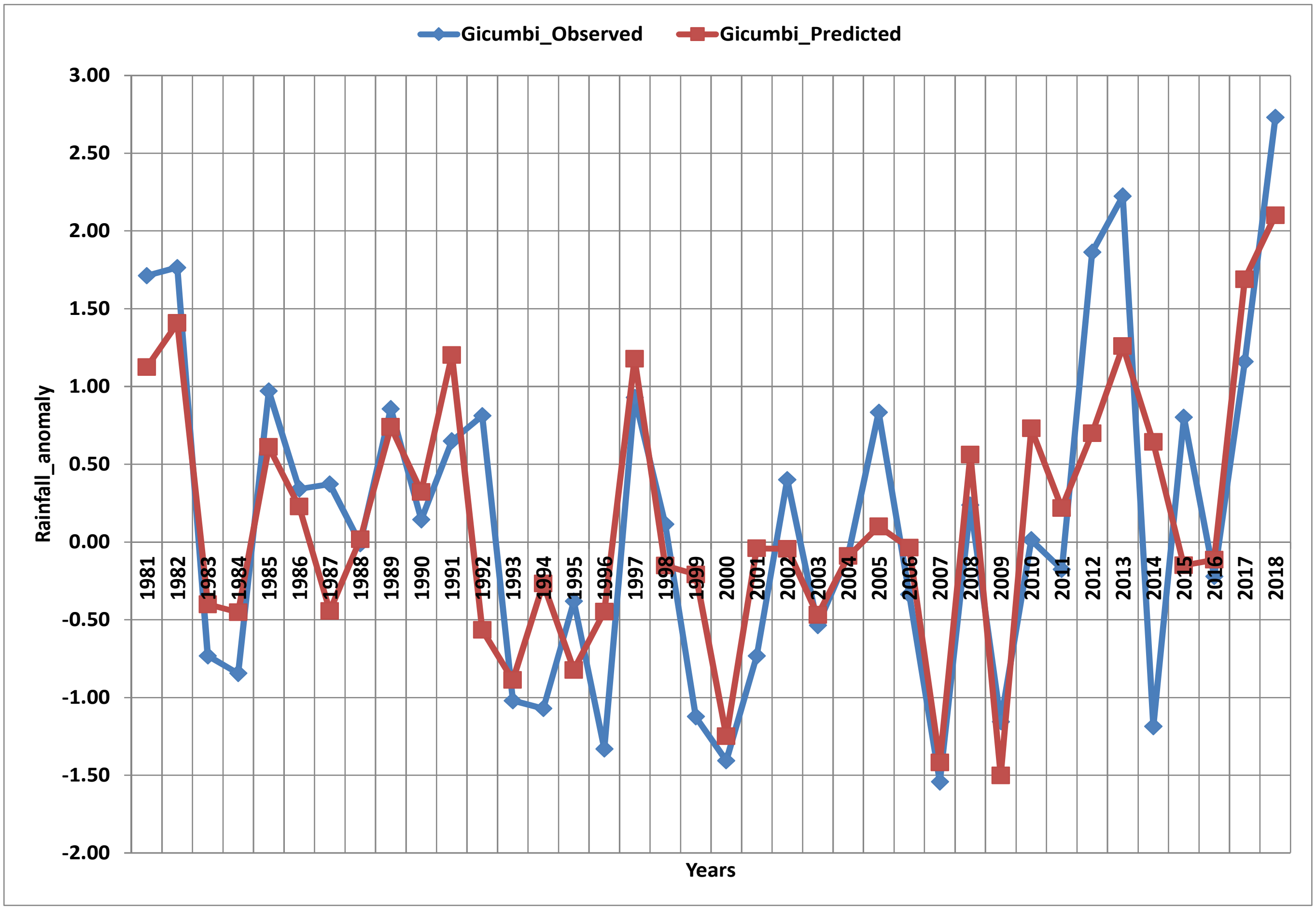

Figure 15: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Gicumbi (represented by Byumba station between 1981 and 2018)

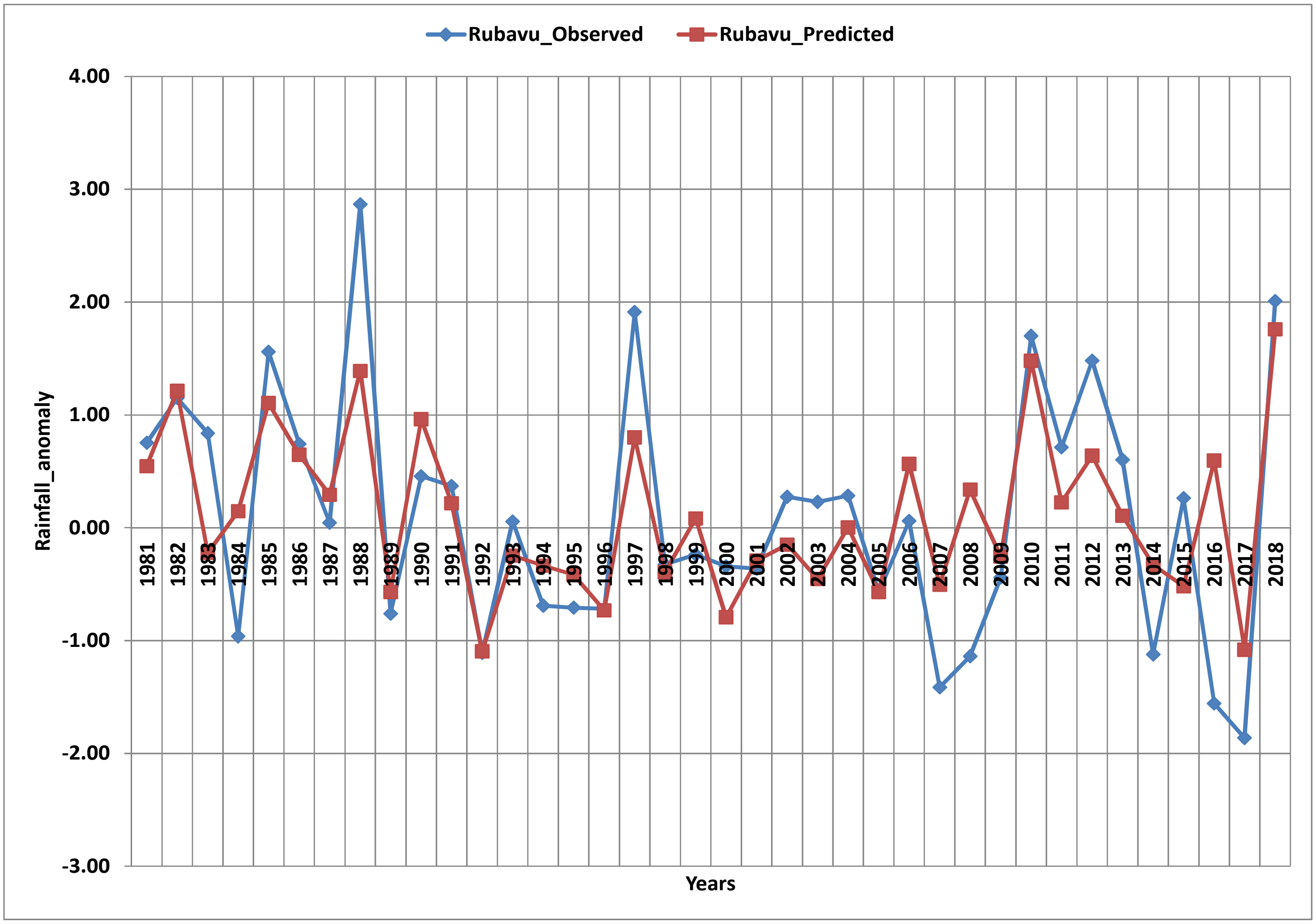

Figure 16: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Rubavu (represented by Gisenyi station between 1981 and 2018)

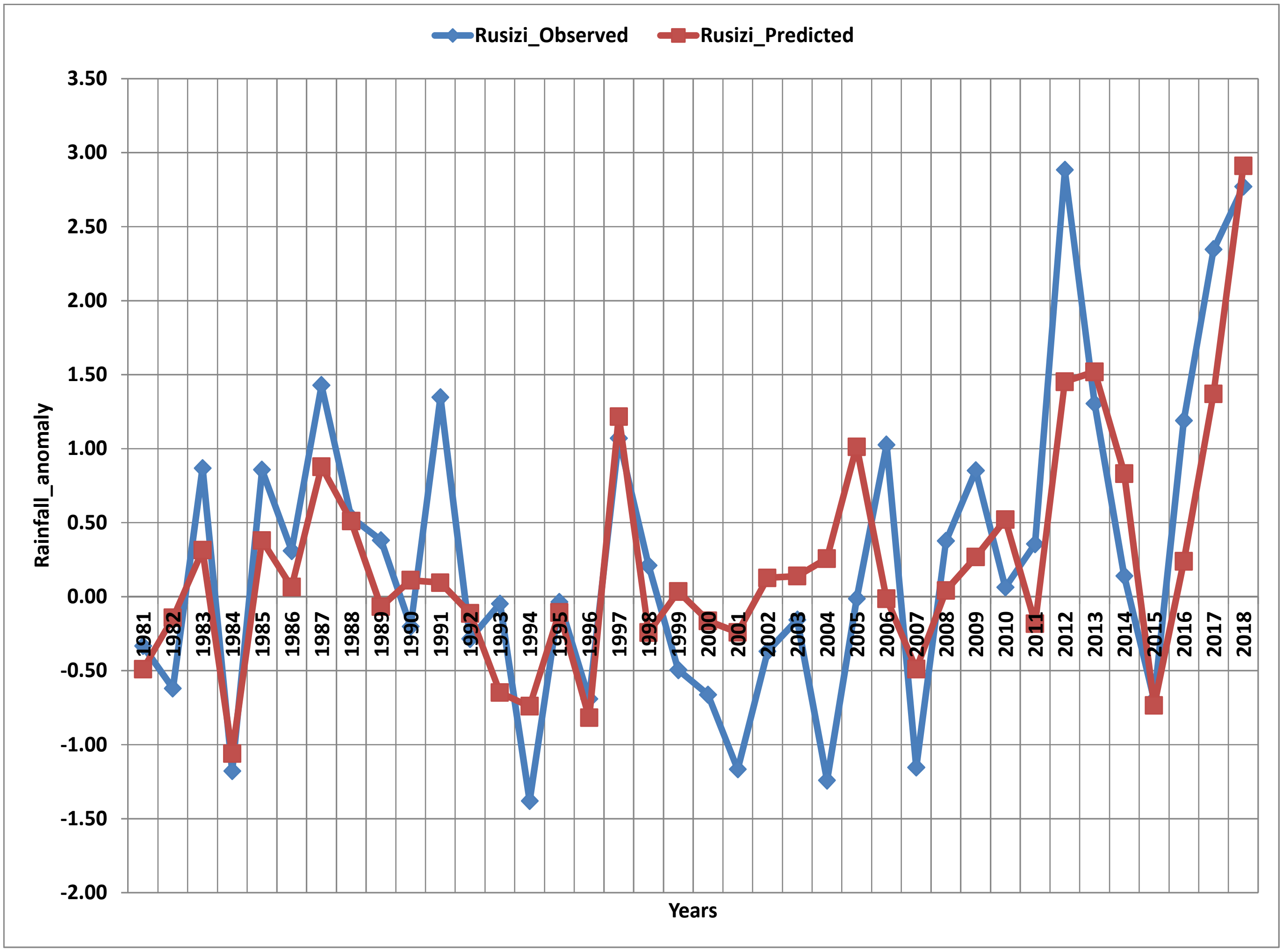

Figure 17: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Rusizi (represented by Kamembe station between 1981 and 2018)

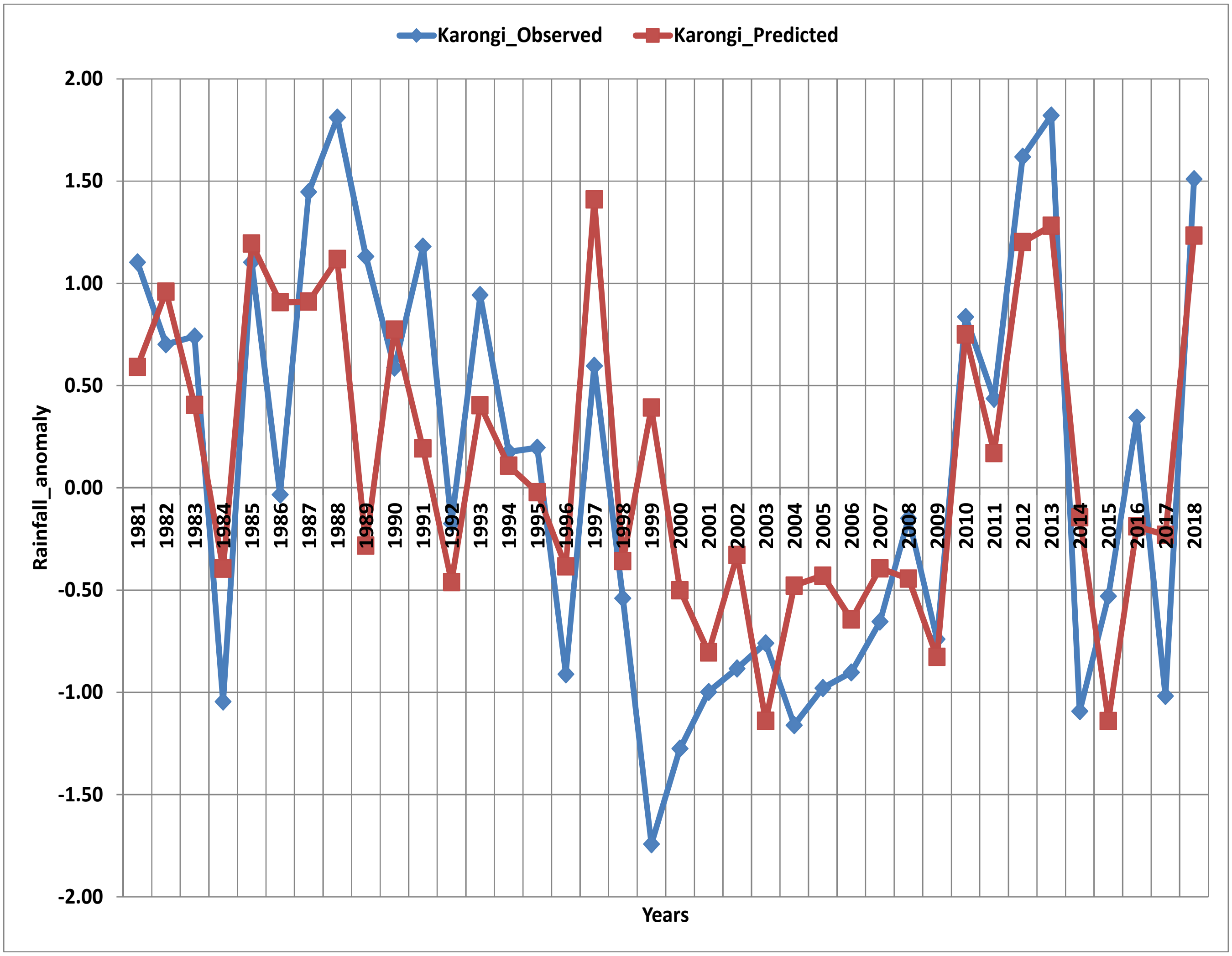

Figure 18: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Karongi (represented by Rubengera station between 1981 and 2018)

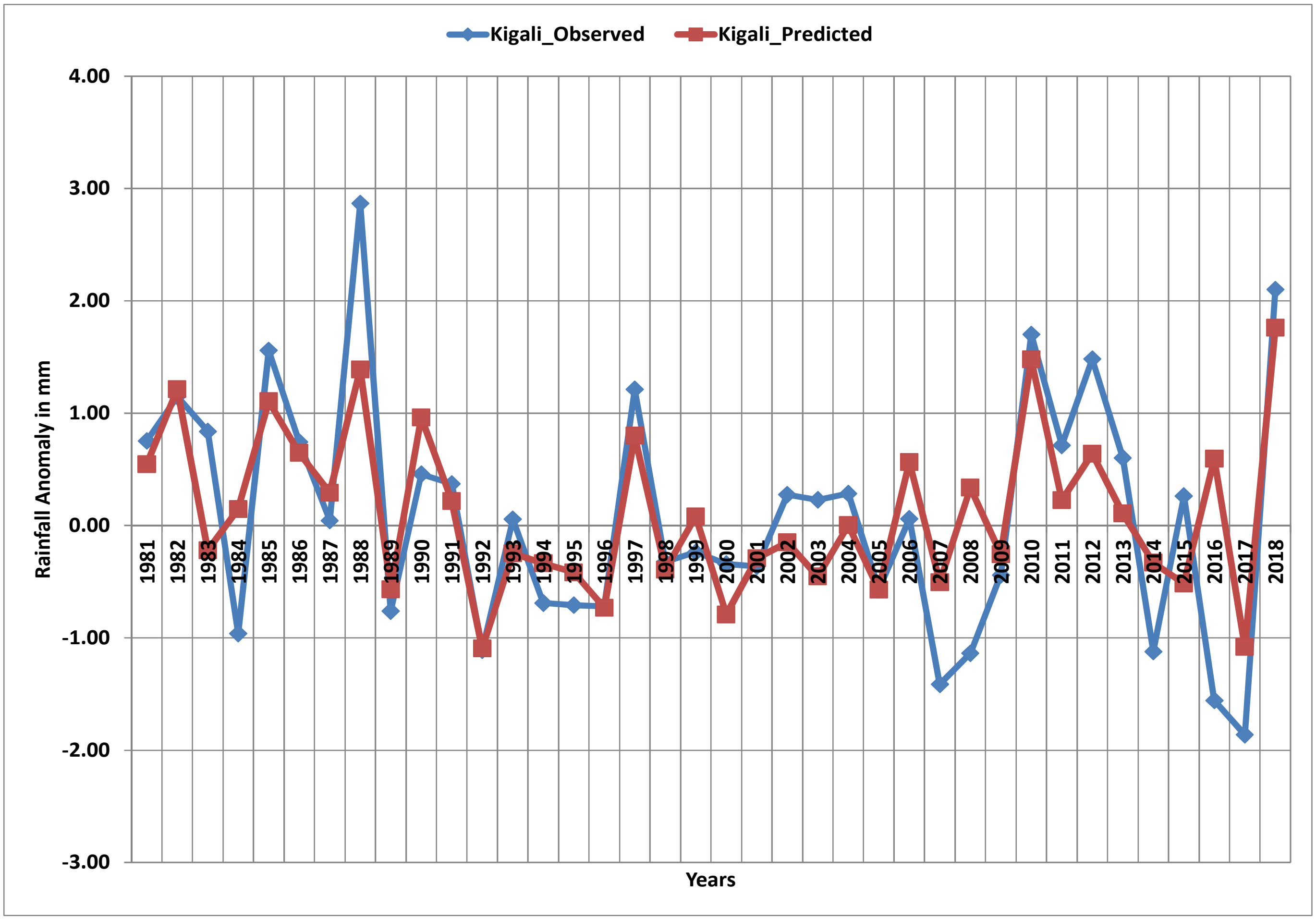

Figure 19: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Kigali (represented by Kigali Airport station between 1981 and 2018)

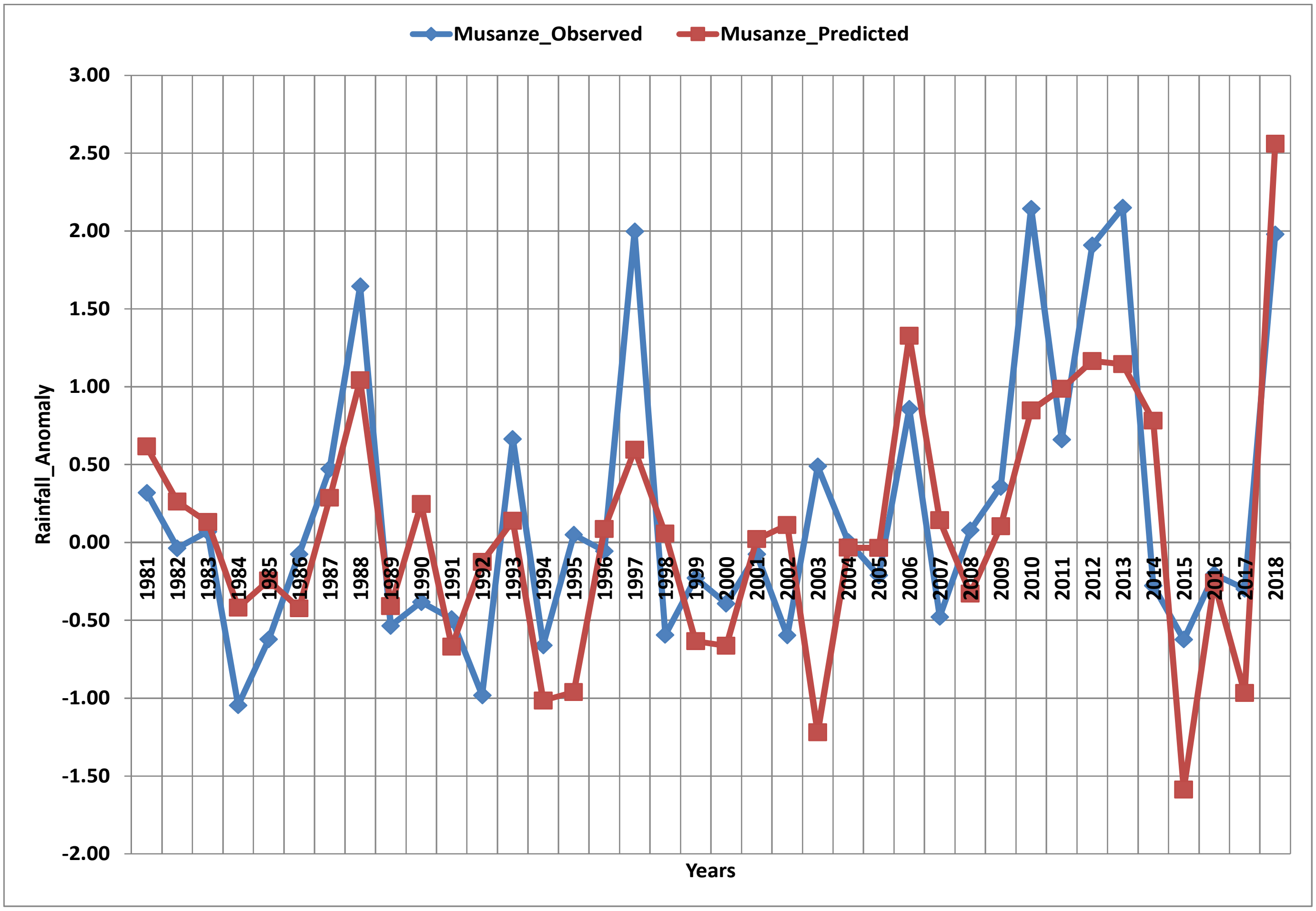

Figure 20: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Musanze (represented by Ruhengeri station between 1981 and 2018)

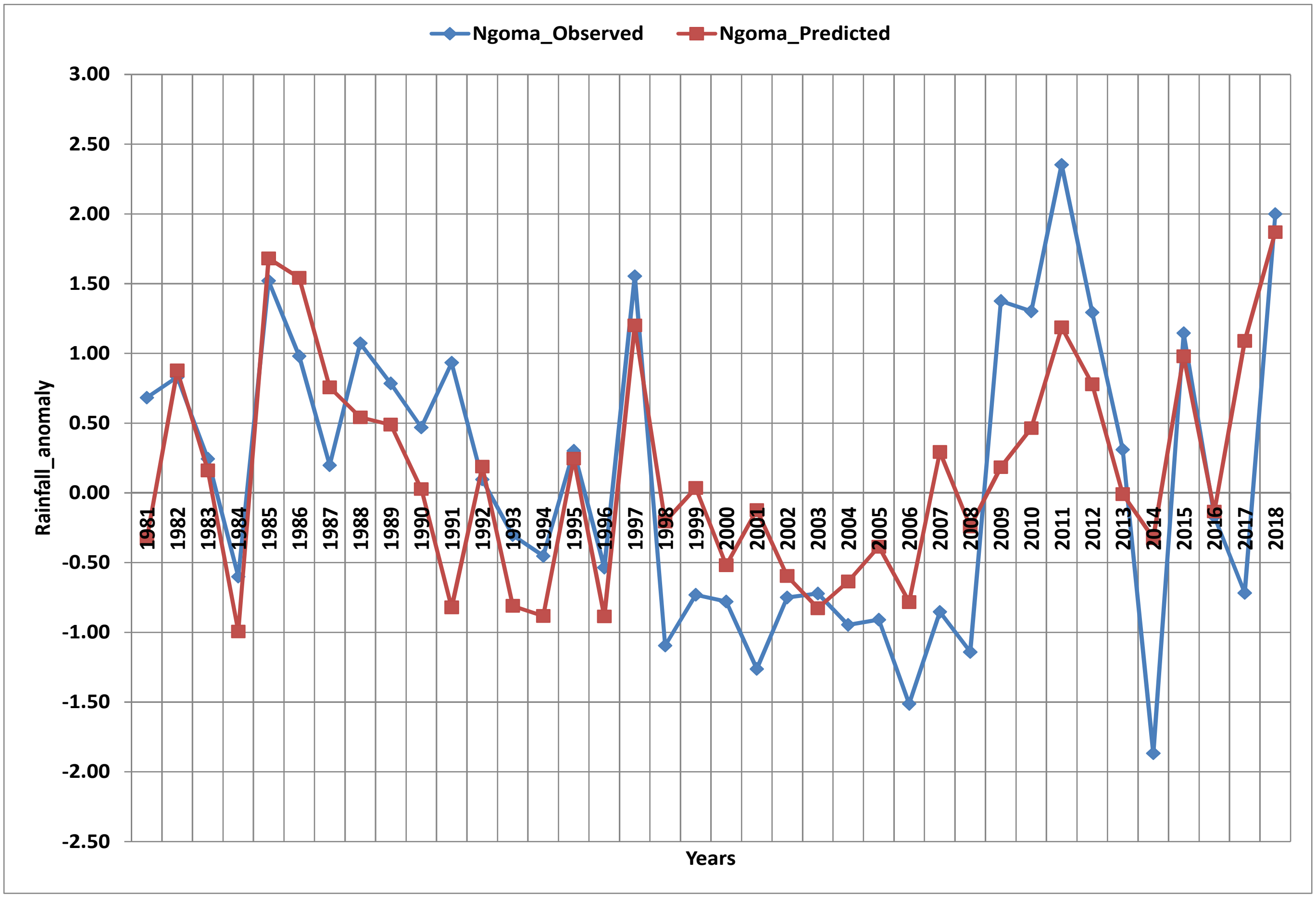

Figure 21: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Ngoma (represented by Kibungo station between 1981 and 2018)

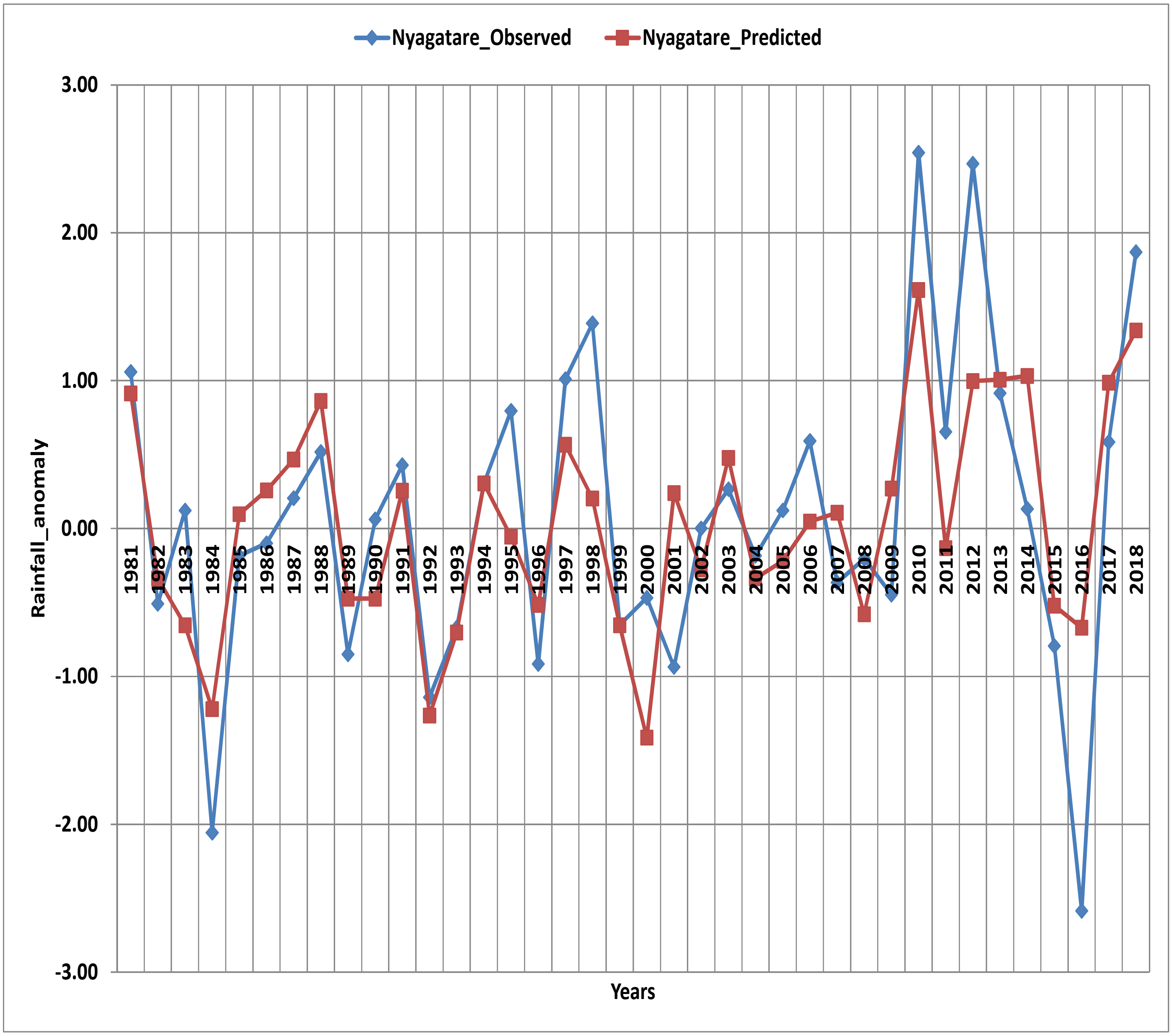

Figure 22: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Nyagatare (represented by Nyagatare station between 1981 and 2018)

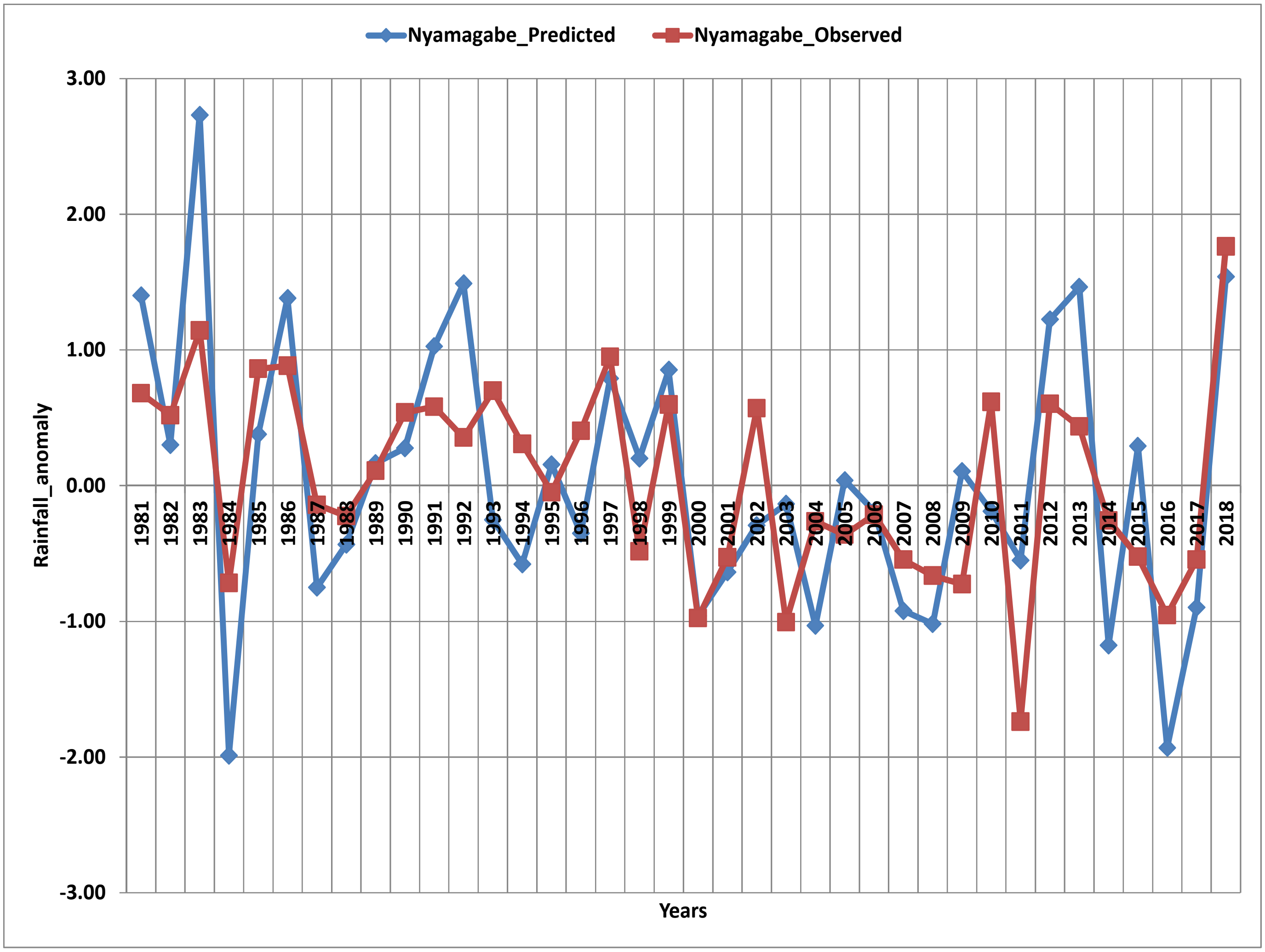

Figure 23: Time series of Predicted and Observed rainfall anomalies during MAM seasons for Nyamagabe (represented by Gikongoro station between 1981 and 2018)

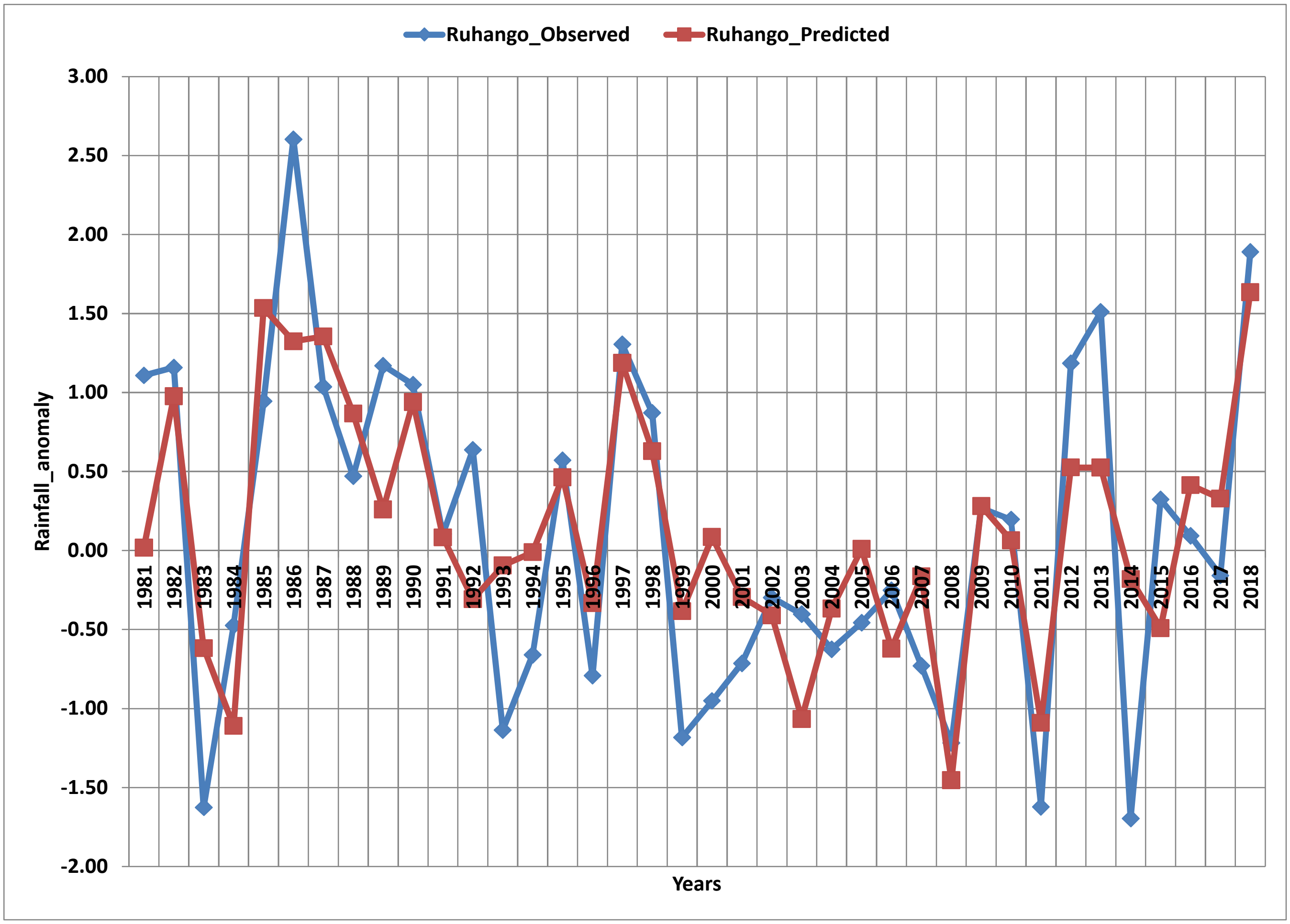

Figure 24:* *Time series of Predicted and Observed rainfall anomalies during MAM seasons for Ruhango (represented by Byimana station between 1981 and 2018)

4.5.2. Inter-annual variation of observed and models during SOND season rainfall

Figures **25-33** below shows the observed and forecast rainfall anomalies during SOND for all the stations. For instance, Figure **25** shows that the forecast compare well with the observed values with R^2 of 49%. This means the model is a better fit to the observed values.

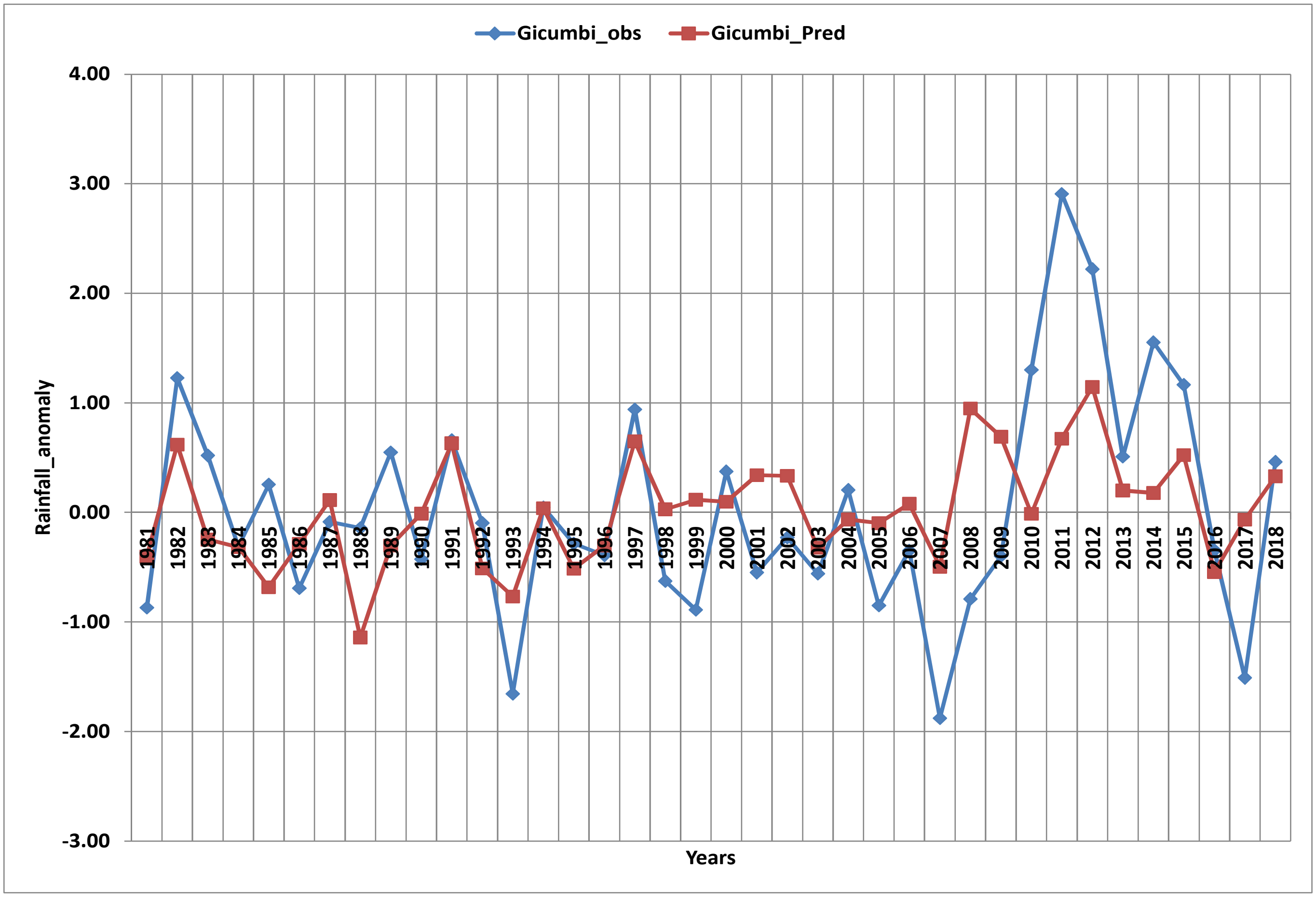

Figure 25: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Gicumbi (represented by Byumba station between 1981 and 2018)

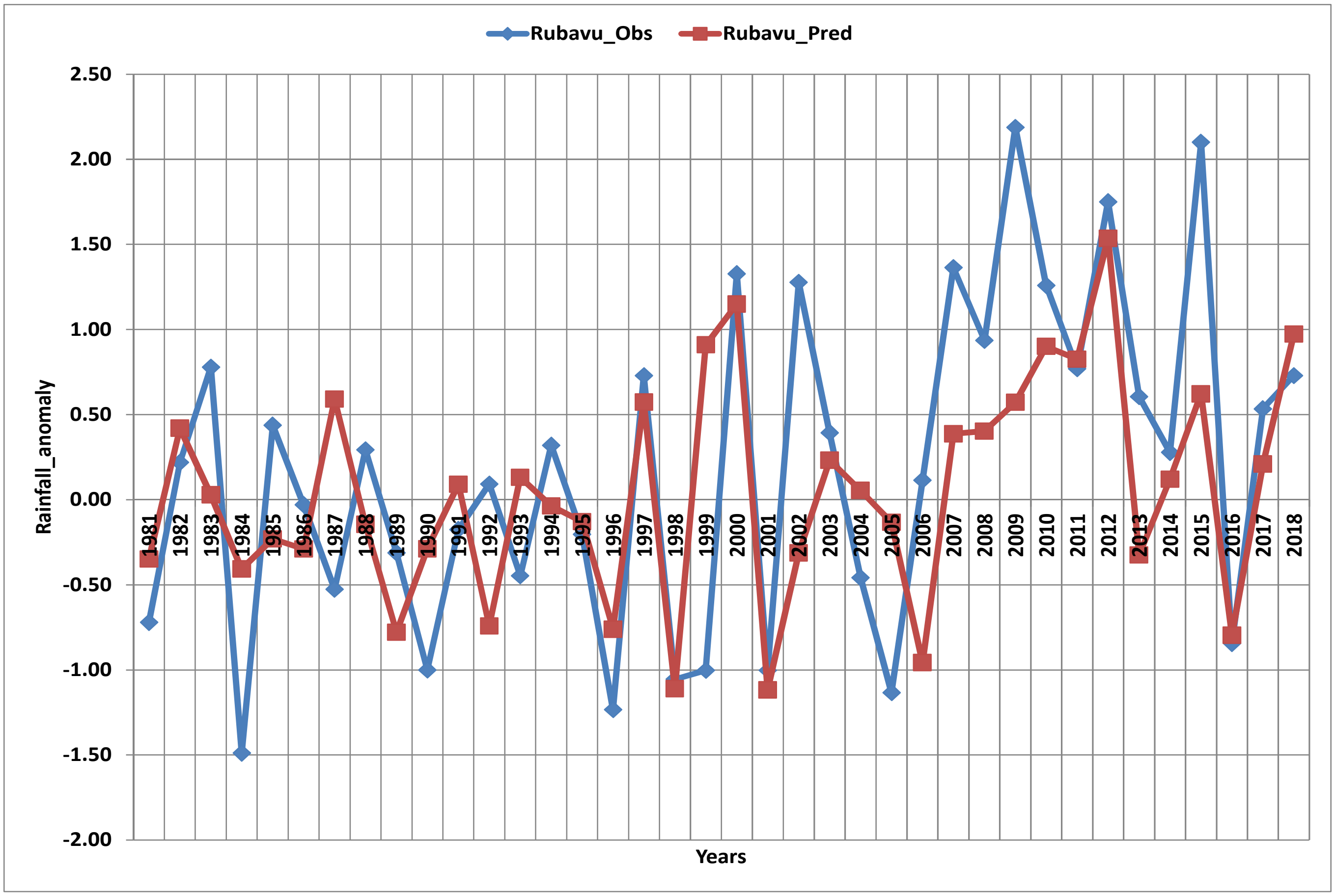

Figure 26: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Rubavu (represented by Rubavu station between 1981 and 2018)

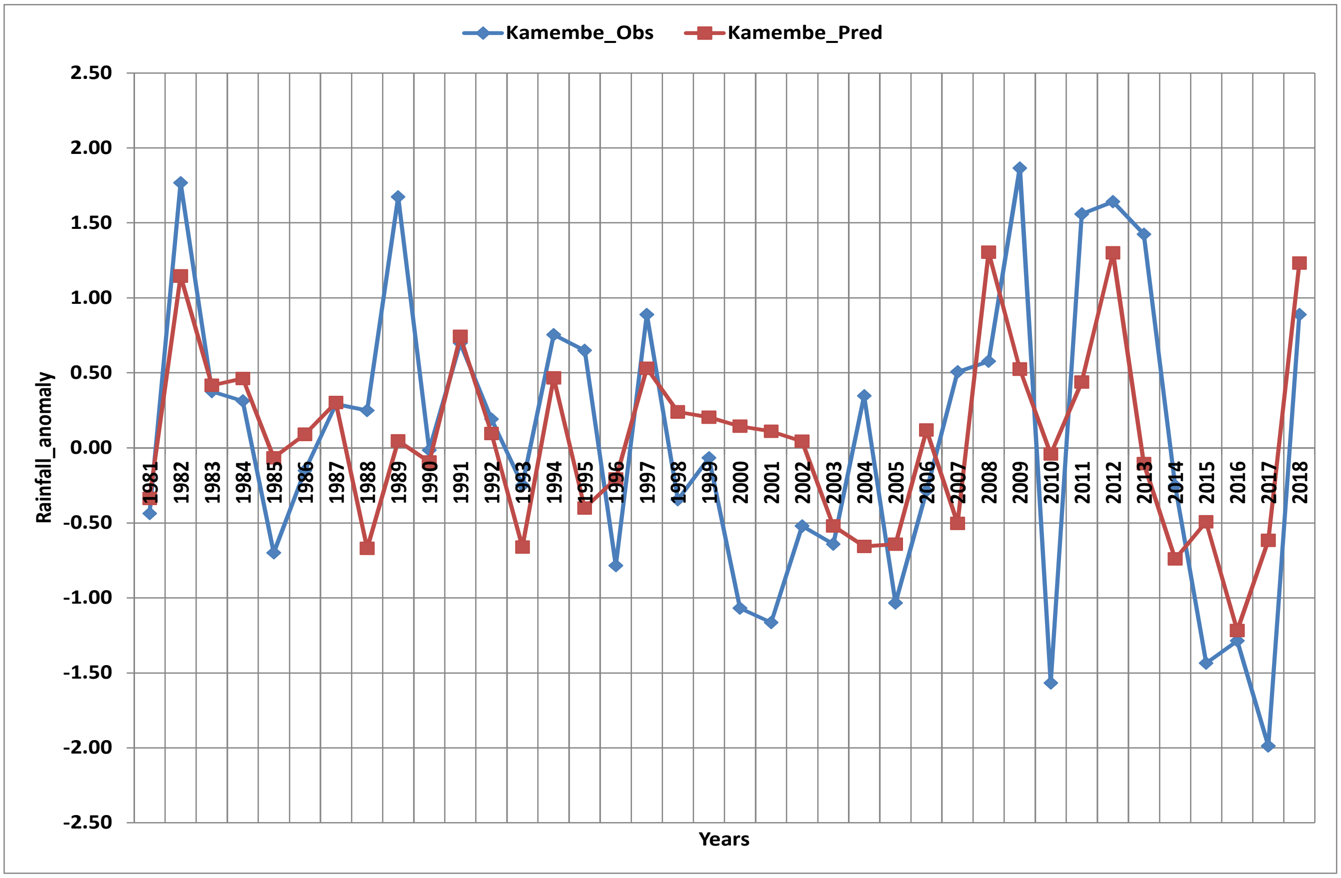

Figure 27: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Rusizi (represented by Kamembe station between 1981 and 2018)

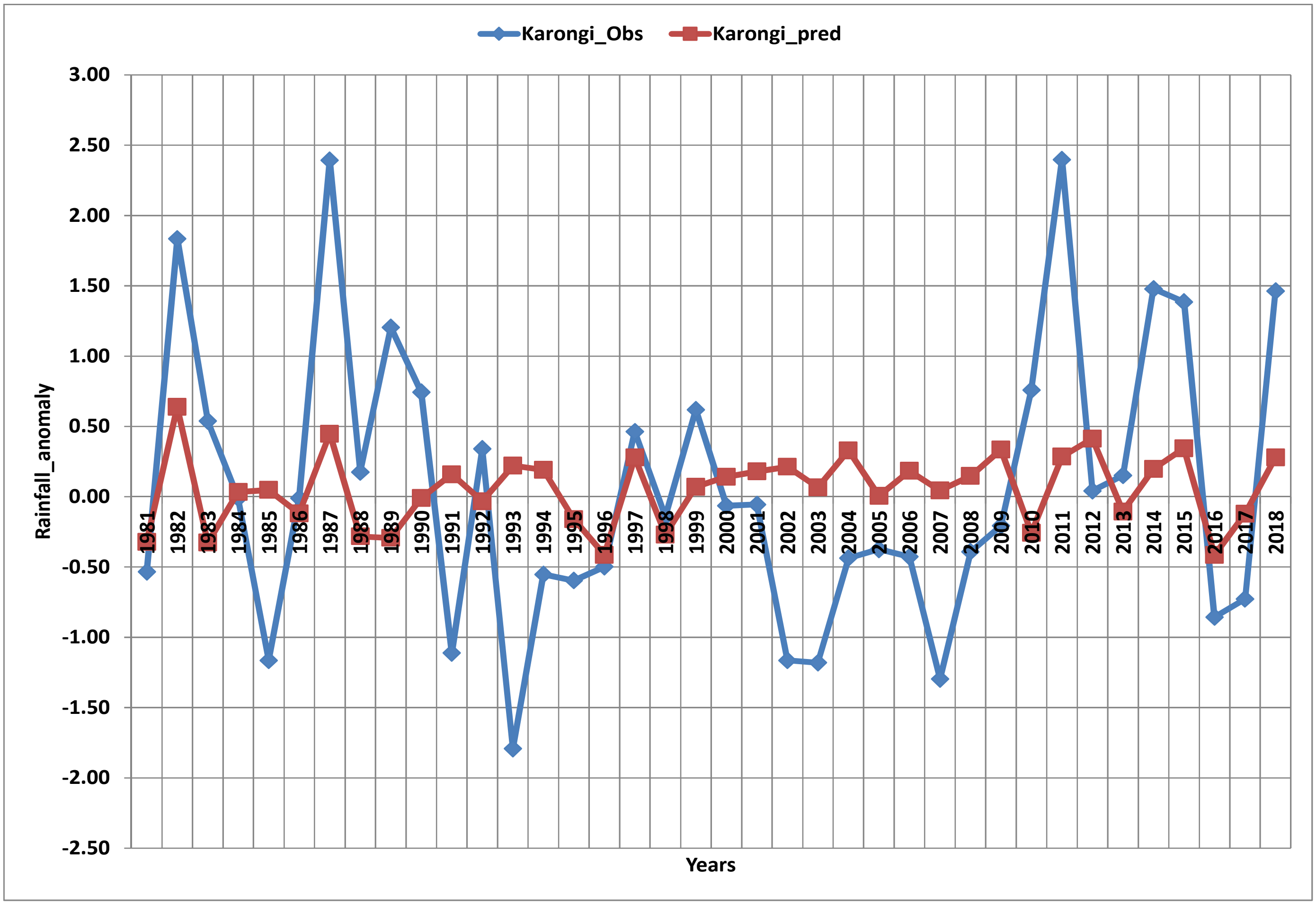

Figure 28: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Karongi (represented by Rubengera station between 1981 and 2018)

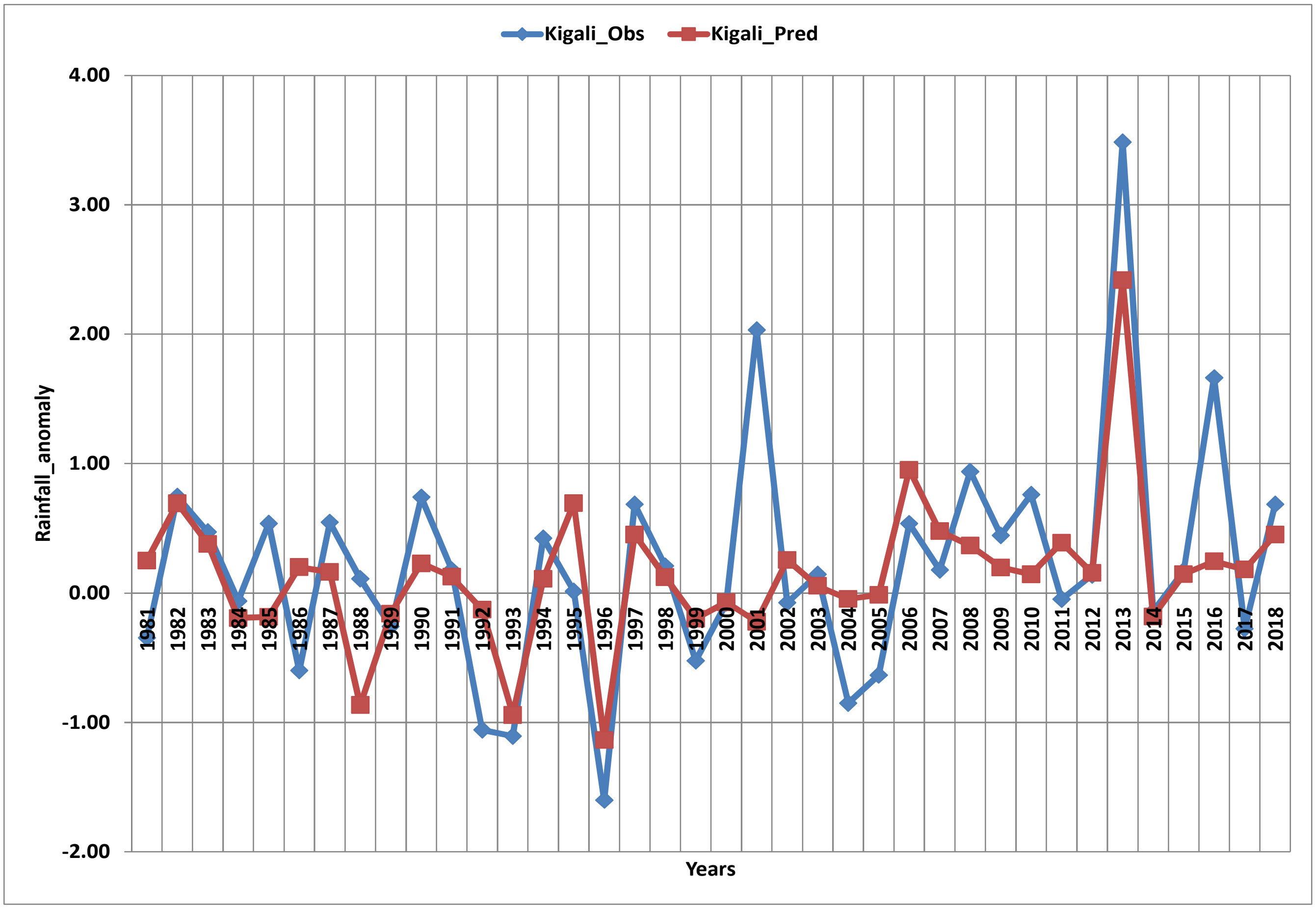

Figure 29: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Kigali (represented by Kigali Airport station between 1981 and 2018)

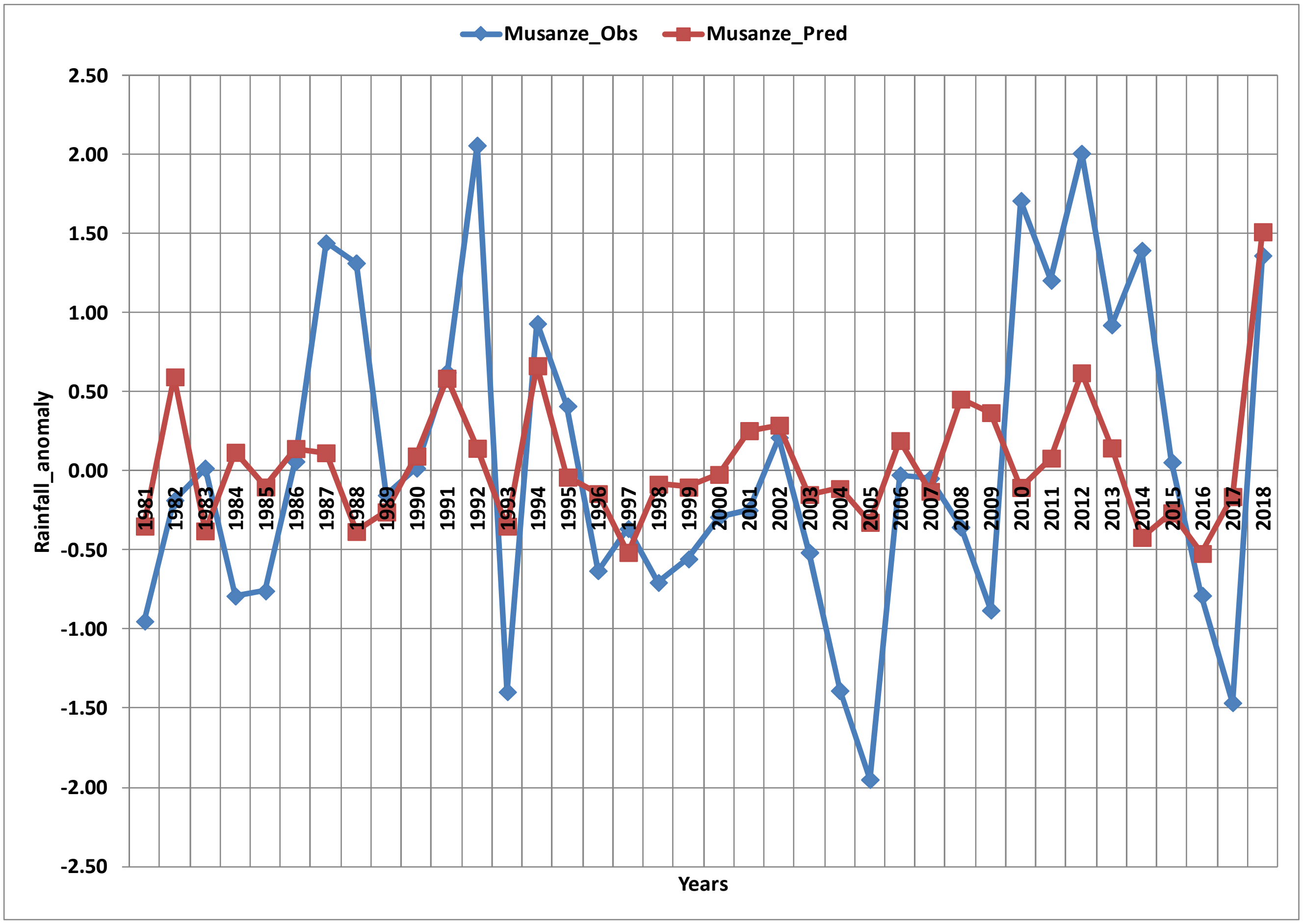

Figure 30: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Musanze (represented by Ruhengeri station between 1981 and 2018)

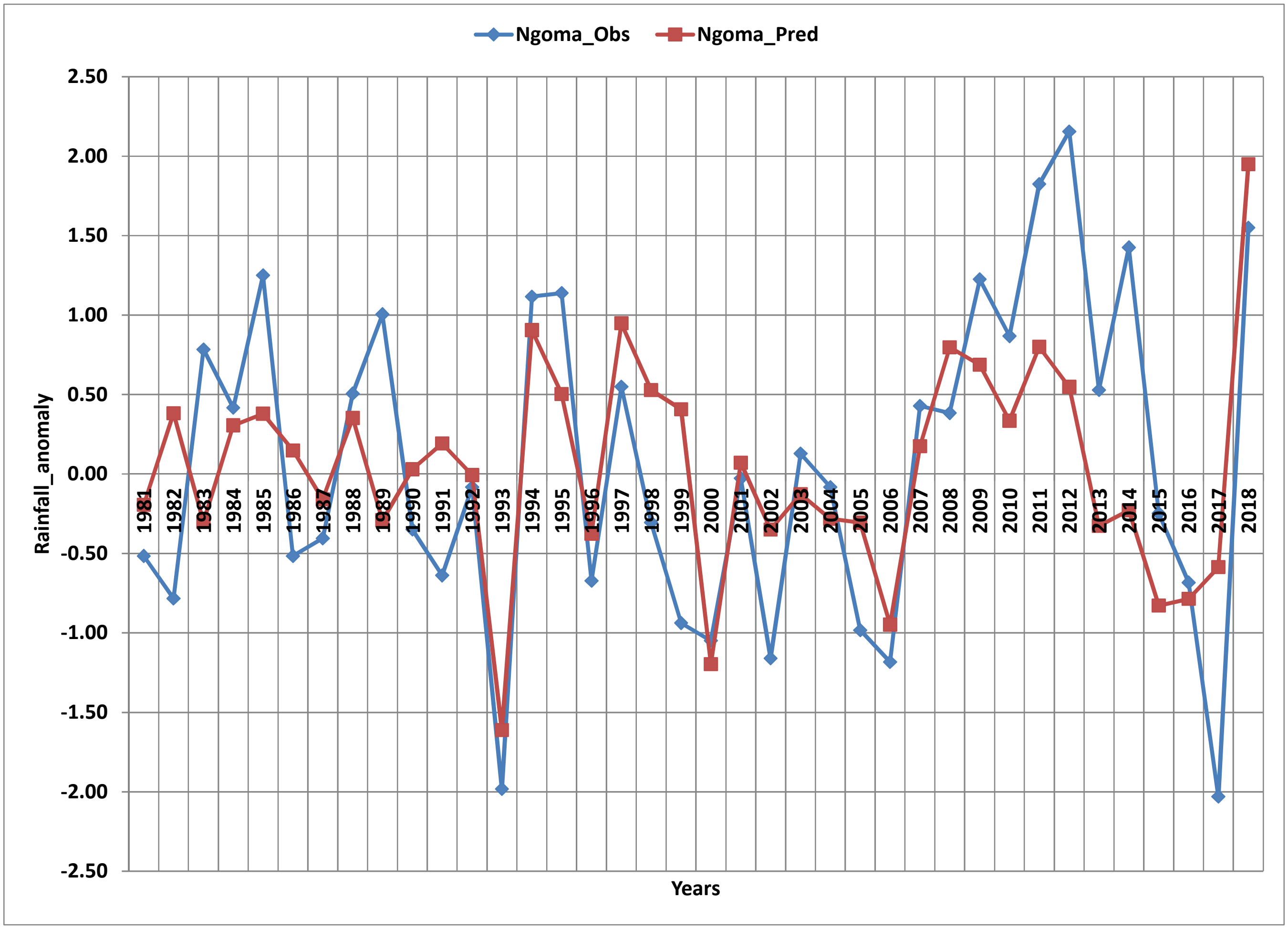

Figure 31: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Ngoma (represented by Kibungo station between 1981 and 2018)

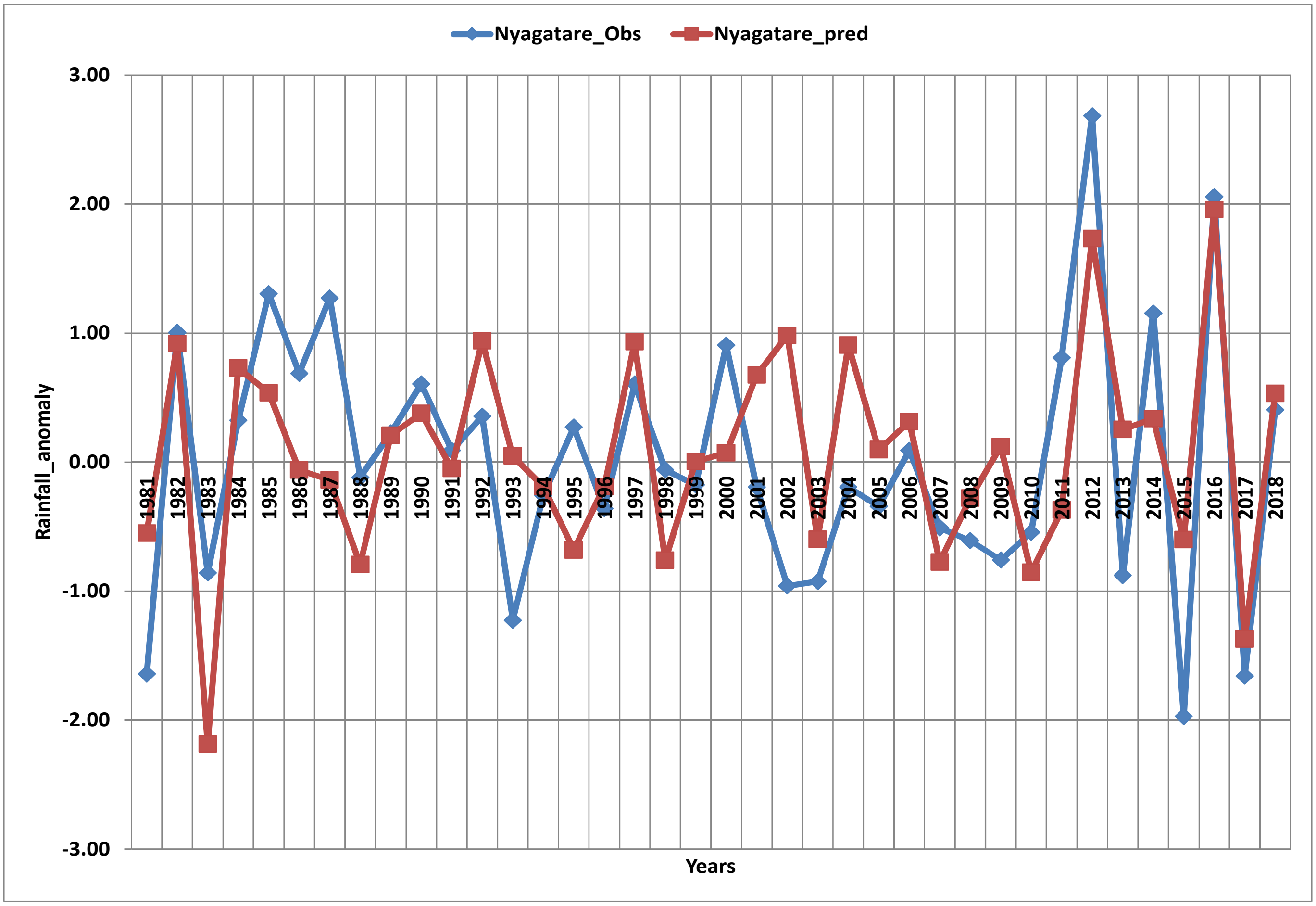

Figure 32: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Nyagatare (represented by Nyagatare station between 1981 and 2018)

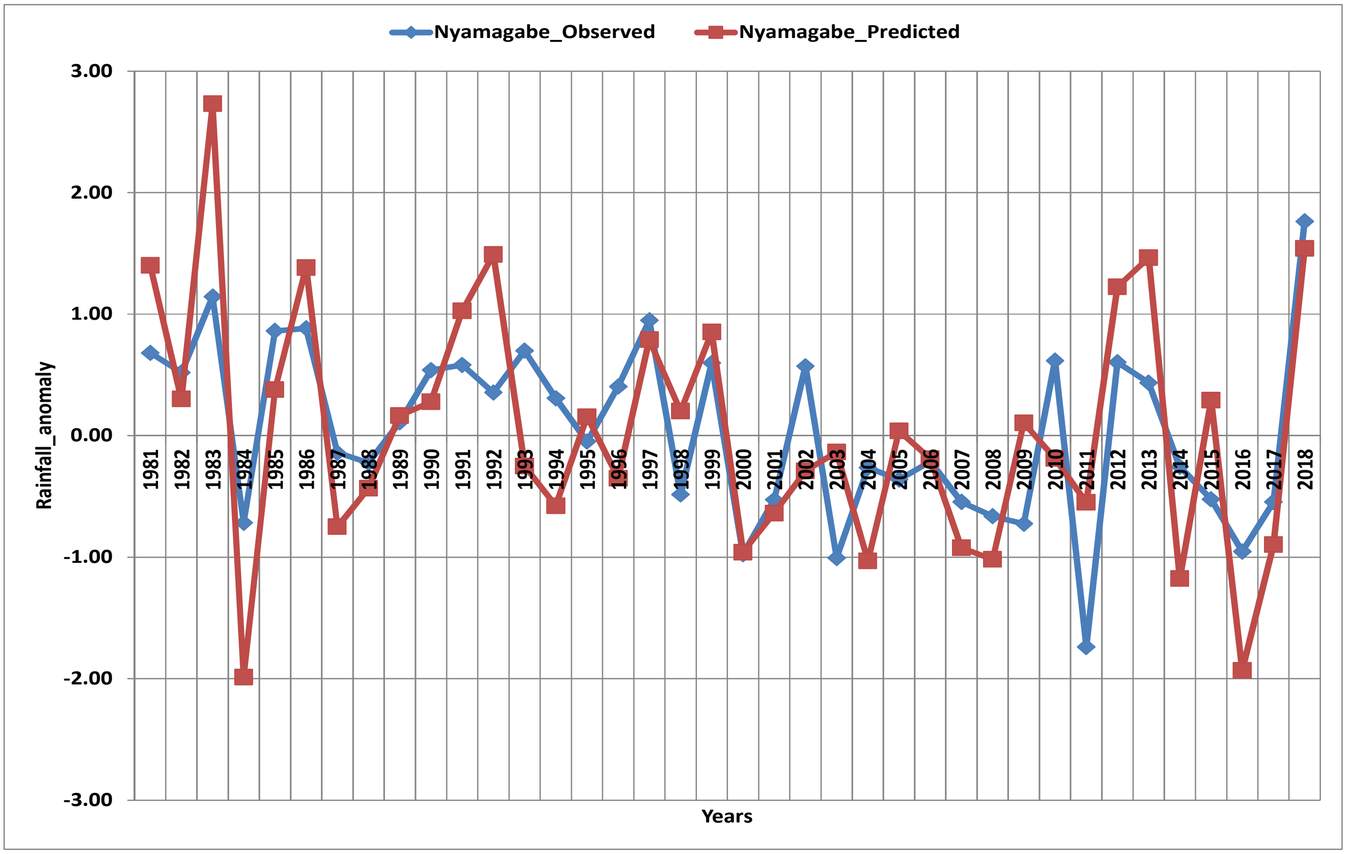

Figure 33: Time series of Predicted and Observed rainfall anomalies during SOND seasons for Nyamagabe (represented by Gikongoro station between 1981 and 2018)

4.6. Results of the Model Verification using Contingency Tables

Table 10 shows the results for Percent correct, probability of detection (PoD), Bias, Heidke skill score (HSS) and the false alarm ratio (FAR) calculated from the 3 by 3 contingency tables that were used to decide on the probability of occurrence of the Below Normal (BN), Normal (N) and Above Normal (AN) rainfall categories during MAM and SOND.

Tercile ranking was used to group the observations or forecasts in the various categories. E.g. the below-normal rainfall category is delineated from the lowest one third of the ranked rainfall anomalies. The various contingency results are presented in Table **10** and **11**. The parameter is the MAM and SOND rainfall and is categorized as BN (Below Normal), N (Normal) and AN (Above Normal).

The percentage scores forecast in all categories was found to be moderate between 51.4% and 67.6% during MAM in most stations apart from Kibungo station that had 43.2%,

During MAM the post agreement were found to be biased towards forecasting extremes events, the maximum proportion of correct percentage for forecasting dry was 80%, while highest for normal category was 55.6 % and 88.9 % for wet, During MAM the False-alarm Ratio were mixed with lowest at 18.2% and highest at 85.7%,

The probability of detection (or hit rate) for MAM was good for all stations expect Kibungo station, which got the lowest value under below normal category where it is 9.1% which show below normal category (or under forecast) compare to the expected.

The results from Bias score of below normal, normal and above normal categories the ratio of the frequency was nearly perfect in all categories during MAM. During SOND the percent correct found to be moderately below between 27.0% and 54.1%.

Post agreement, during SOND the models found to be biased towards forecasting extreme below, the lowest score at 0.0%. The occurrences of forecasted-wet and observed–dry were found to fall between 0 % and 40 % except for Kibungo station, while occurrences of forecasted-dry and observed-wet fall between 0% and 11.1 %. During SOND the False-alarm Ratio were mixed with the lowest at 7.2% and highest at 71.4%,

The probability of detection or hit rate for SOND was slight good to all stations expect Musanze station got the lowest value under below normal category where it is 8.9% which show the under forecast below normal category compare to the expected.

For Bias the ratio of the frequency was perfect in all categories during SOND which showed over forecast over Kibungo station.

In the case of all stations the forecasts show better than climatology but Kibungo station show slight less than climatology and all the scores are above zero and the frequency of the forecast events are tending to be perfect, means that near normal to above normal rainfall events for all the stations expect for Kibungo station the forecast event is tending to near normal to below normal rainfall events in general.

Table 10: Highest Skill Scores for Stations during March to May (MAM)

Scores		PA (%)	FAR (%)	POD (%)	BIAS	CSI	HSS
GICUMBI (59.5%)	B	80.0	20.0	36.4	0.45	0.33	0.387
	N	45.0		75.0	1.67	0.39	
	A	75.0	25.0	64.3	0.86	0.53	
RUBAVU (54.1%)	B	63.6	36.4	53.8	0.85	0.41	0.313
	N	35.7		45.5	1.27	0.25	
	A	66.7	33.3	61.5	0.92	0.47	
RUSIZI (54.1%)	B	70.0	25.0	54.5	0.73	0.46	0.321
	N	35.3		54.5	1.55	0.27	
	A	66.7	33.4	53.3	0.80	0.42	
KARONGI (45.9%)	B	40.0	60.0	16.7	0.42	0.13	0.180
	N	34.8		61.5	1.77	0.29	
	A	77.8	22.2	58.3	0.75	0.50	
KIGALI (54.1%)	B	63.6	36.4	53.8	0.85	0.41	0.313
	N	35.7		45.5	1.27	0.25	
	A	66.7	33.3	61.5	0.92	0.47	
MUSANZE (56.8%)	B	50.0	50.0	54.5	1.09	0.35	0.351
	N	50.0		30.8	0.62	0.24	
	A	64.7	35.3	84.6	1.31	0.58	
NGOMA (43.2%)	B	14.3	85.7	9.1	0.64	0.06	0.139
	N	31.6		46.2	1.46	0.23	
	A	81.8	18.2	69.3	0.85	0.60	
NYAGATARE (67.6%)	B	69.2	30.8	75.0	1.08	0.56	0.509
	N	55.6		45.5	0.82	0.33	
	A	73.3	26.7	78.6	1.07	0.61	
NYAMAGABE (62.2%)	B	61.5	38.5	57.1	0.93	0.42	0.422
	N	42.9		30.0	0.70	0.21	
	A	70.6	29.4	92.3	1.31	0.67	
RUHANGO (51.4%)	B	63.6	57.1	25.0	0.58	0.19	0.263
	N	35.7		61.5	1.62	0.31	
	A	66.7	22.2	66.7	0.75	0.62	

Scores: Percentages of the Models Accuracy, PA: Post Agreement, FAR: False Alarm Ratio, POD: Probability of Detection, CSI: Critical Success Index and HSS: Heidke Skill Score.

Table 11: Highest skill scores for the stations during September to December (SOND)

Scores		PA (%)	FAR (%)	POD (%)	BIAS	CSI	HSS
GICUMBI (40.5%)	B	28.6	71.4	18.2	0.64	0.13	0.077
	N	20.0		18.2	0.91	0.11	
	A	55.0	45.0	73.3	1.33	0.46	
RUBAVU (54.1%)	B	57.7	42.9	36.4	0.64	0.29	0.312
	N	38.9		63.6	1.64	0.32	
	A	75.0	25.0	60.0	0.80	0.50	
RUSIZI (54.1%)	B	45.5	54.5	38.5	0.85	0.26	0.318
	N	41.2		63.6	1.55	0.33	
	A	88.9	11.1	61.5	0.69	0.57	
KARONGI (27.0%)	B	31.9	07.2	10.4	0.43	0.13	0.122
	N	15.4		18.2	1.18	0.09	
	A	33.3	66.7	57.1	1.71	0.27	
KIGALI (48.6%)	B	60.0	40.0	50.0	0.83	0.38	0.221
	N	40.9		69.2	1.69	0.35	
	A	60.0	40.0	25.0	0.42	0.21	
MUSANZE (40.5%)	B	34.9	21.8	0.89	0.45	0.27	0.109
	N	28.9		54.5	1.91	0.23	
	A	56.3	48.8	64.3	1.14	0.43	
NGOMA (51.4%)	B	85.7	14.3	50.0	0.58	0.46	0.285
	N	36.4		72.7	2.00	0.32	
	A	62.5	37.5	35.7	0.57	0.29	
NYAGATARE (54.1%)	B	58.3	41.7	53.8	0.92	0.39	0.310
	N	41.7		50.0	1.20	0.29	
	A	61.5	38.5	57.1	0.93	0.42	

Scores: Percentages of the Models Accuracy, PA: Post Agreement, FAR: False Alarm Ratio, POD: Probability of Detection, CSI: Critical Success Index and **HSS**: Heidke Skill Score.

CHAPTER FIVE

5.0. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter compose of a summary of the results that were obtained from various analysis. It also highlights the major conclusions that were drawn from various results. Some recommendations are also given for future extension of this study.

5.1. Summary and Conclusion

It is recognized that seasonal rainfall extreme events influence the social and economic activities, and are associated with the majority of disasters affecting the region. Seasonal rainfall forecasts could help society, economic institutions and governments to minimize the negative impacts and take advantage of the positive aspects of extreme rainfall events. Seasonal rainfall forecasts are important inputs for climate early warnings and the improvements in the skills of the forecasts could contribute to the improvement of early warnings of climate extremes. Such forecasts would contribute to disaster risk reduction including enhanced economic development, food production and water resource management among other climate related activities.

The main aim of the study was to improve the skill of seasonal rainfall prediction over the country through the use of statistical and dynamical methods. The data used in this study include data from NCEP/NOAA from 1981-2017, and WRF datasets which constitute the initialization data for the WRF-EMS model obtained from the Global Forecasting Model.

The methodology employed in the study involved performance of weather research forecasting, to assess the model skill and measure of accuracy which include mean absolute error (MAE), root mean square error (RMSE), correlation analysis, regression analysis, identification of appropriate predictors by using principal component regression, sea surface temperature gradients, El Nino southern oscillation, zonal wind, Indian ocean Dipole, sea surface and verification of the improved skill scores.

The performance of WRF model shows that the rains were highly enhanced, countrywide both in time and space, over most parts of the country. It is evident that the model simulates well the general nature of the spatial rainfall distribution. The model under-estimated the rainfall over the

South Eastern part of the country and over-estimated the rains over the south western part of the country during March to May (MAM 2018) seasonal rainfall during September to December (SOND 2018) the model simulate well the general nature of the spatial rainfall distribution; but showed enhanced rainfall over a larger part of the region. The model over-estimated the rainfall amount over the whole country.

The analysis of the mean absolute and root mean square errors for rainfall during both seasons were closer than 1 over most locations.

The results from regression analysis showed that the results in the training period (1981-2010) were largely consistent with the observed rainfall. In the verification period, the forecasted values were more skillful during MAM than during SOND.

The results from correlation analysis between the observed and predicted rainfall indicated that the rainfall in the long rainfall season the MAM had Significant high correlation values of $r = 0.85$ and in the short rainfall season the SOND correlation values of $r = 0.70$. Such linkages were statistically significant and can contribute in improving the prediction skill of the long and short rainfall season in the country.

The ENSO indices during the preceding month of August could provide good predictive skill in September to December short rainfall season (SOND). in the short rainfall season the linkage with ENSO signals is stronger compared with long rainfall season.

Results from verification values show that the observed and forecast rainfall anomalies for various stations compare well with the observed values with the coefficient of determination R^2 ranging from 57.7 to 75.5%, the model fit the observations well during MAM and SOND.

From the spatial distribution of rainfall, it can be seen that WRF Model can produce well the general pattern during the wet season. WRF model could be used with assurance for predictions of seasonal rainfall in the country. This was achieved by assessing the skill of the quantitative operational forecasts against observations and determine the extent to which the new generation models products simulate rainfall variability over the country.

The results of the study can be used to improve seasonal rainfall forecasts especially for the major rainfall season of March-May. The skillful seasonal forecasts would be useful in reducing and managing the risks associated with seasonal rainfall extremes. They would provide useful inputs to the improvement of early warnings of extreme rainfall events and contribute to disaster risk reduction in the region. Such results would not only provide new climate risk management tools for coping with past and current climate extremes, but also experiences and lessons that can be extended to addressing climate change adaptation challenges.

5.2. Recommendations

The study the recommendations presented from this study address issues related to target climate research scientists and seasonal forecasting community, policy makers and providers of services and infrastructure that need accurate forecast information, and the general public users of long range rainfall forecasts.

5.2.1. Recommendations to the climate institutions and scientists

Thestudy was carried out using observational data and gridded data from ENACTS with emphasize on supporting country to have reliable quality climate information suitable for national and local and local decision making, so it is essential to all stakeholders, especially scientists and climate institutions, to preserve the data for the benefits of future analysis into decision making by improving availability, access to, and use of climate information.

The statistical and dynamical model analysis techniques adopted assumed linear relationships so We recommend that Meteo Rwanda to tests further model techniques developed here and consider using them in future during the seasonal rainfall analysis. More research is needed so as to determine the most appropriate model which can be used to predict seasonal rainfall for the country.

5.2.2. Recommendation to policy makers

One of the most important components of numerical weather prediction is initialization. Initialization is dependent on the quality of the observational data. The network of the stations over the country is very sparse due to the topography of the region. For this cause, strategy must put in place to increase the number of stations and policy-makers have to work towards increase the networks of the stations and placing them strategically. weather observing stations strictures must be position on grids for easier assessment with the models output and set aside adequate financial resources for maintaining instruments also provide resources for capacity building to support research, skilled human resources among others.

5.2.3. Recommendations to all users of climate information and prediction products

We recommend enhanced education and awareness of the users in order to enable them understand well the benefits of optimum use of climate information in planning and management of the specific sectors. It is necessary for the users to work closely with climate scientists in assessing economic values of the specific forecasts that are provided by the National Meteorology Agency and various climate centres. This will enable the downscaling of products to meet the needs of specific users. The users of climate information should work closely with the climate experts in developing detailed climate information relevant to their applications. This can be achieved through the survey of the user needs, for example, the climate events to which the productivity of a given sector is vulnerable, the forecast quality required by specific sector, and the cost and the losses involved in the application of climate information.

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