PROBABILISTIC WEATHER FORECASTING USING BAYESIAN MODEL AVERAGING:

A CASE OF SAGCOT REGIONS

PROBABILISTIC WEATHER FORECASTING USING BAYESIAN MODEL AVERAGING:
THE CASE OF SAGCOT REGIONS

By

Emmanuel Joel

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CERTIFICATION

We, the undersigned, certify that we have read and hereby recommend for acceptance by the Mzumbe University, a research dissertation entitled: “Probabilistic Weather Forecasting Using Bayesian Model Averaging: The case of SAGCOT Regions” in fulfillment of the requirements for the award of degree of Master of Science in Applied Statistics of Mzumbe University.

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DECLARATION

I, Emmanuel Joel, hereby declare that this dissertation is my own original work and it has not been presented to any other University or Institution of Higher Learning for a similar or any other degree award.

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DEDICATION

I dedicate this study to my beloved father Joel Meliyo and my lovely mother Joyce Joel for their love, prayers, financial support and advise throughout my academic life.

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ABBREVIATIONS

AFWA	Air Force Weather Agency
ASOS	Automated Surface Observing
B.C	Before Christ
BMA	Bayesian Model Averaging
BS	Brier Score
CDF	Cumulative Density Function
CFS	Climate Forecast System
CFSR	Climate Forecasts System Reanalysis
CRPS	Continuous Ranked Probability Score
DOE	Department od Energy
E	East
ECMRWF	European Centre for Medium-Range Weather Forecasts
EMC	Environmental Modeling Center
EPS	Ensemble Prediction System
ESRL	Earth System Research Laboratory
FAA	Federal aviation Administration
GCMs	Global Climate Models
GFS	Global Forecast System
GFS-FNL	Global Forecast System- Final Reanalysis

GMP	Global Model Products
hPa	Hectopascal
IC	Initial Condition
IMD	India Metrological Department
KM	Kilometer
LAM	Limited Area Model
MAE	Mean Absolute Error
MAM	March April and May
MSE	Mean Square Error
NA	November to April
NBS	National Bureau of Statistics
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NOAA	National Oceanic and Atmospheric Administration
NOMADS	National Operational Model Archive and Distribution System
NWP	Numerical Weather Prediction
OND	October November December
PDFs	Probability Density Functions
PIT	Probability Integral Transform
PNNL	Pacific Northwest National Laboratory

PoP	Probability of Precipitation
PWF	Probabilistic Weather Forecasts
RCMs	Regional Climate Models
RD	Reanalysis Data
RD	Reanalysis Data
S	South
SAGCOT	Southern Agricultural Growth Corridor Of Tanzania
TMA	Tanzania Meteorological Agency
UN	United Nation
USA	United States of America
UTC	Universal Time Coordinate
VRH	Verification Rank Histogram
WPS	Weather Pre-processing System
WRF-ARW	Advanced Research in Weather Research Forecasts

ABSTRACT

Over the past decade Tanzania has experienced spontaneous population increase (1.556 mil annual). But the number is estimated to further increase by 2050 to 2.982 mil annual, thus Tanzania is estimated to have population of 137 millions people in 2050 (UN, 2015). The fast growing population is mainly depending on rainfed agriculture, which contribute 29 percent of the country GDP and providing employment to 65.5 percent of Tanzanians (Deloitte, 2016).

The diversity in climatic and weather activities has posed a challenge in rainfed agriculture especially on when to plant seeds. Therefore in order to promote agricultural activities, stable and reliable weather information are crucial in order for production to match with population increase.

This study explores the challenge facing the Numerical Weather Prediction (NWP) namely WRF-ARW, by creating the system of equation (ensembles) from WRF-ARW resulting from the use of different initial conditions. Ensemble allow for probabilistic forecast to take the form of predictive probability function (PDF). But, raw ensemble forecast system are finite hence they only capture some of the uncertainty of the NWP. Thus, this study used Bayesian Model Averaging (BMA) methods of postprocessing ensemble forecast to maximize the sharpness of the parameter and calibration.

The findings shows BMA method successively removes most of under disersion showed by raw ensembles. Thus, calibrated and sharp results of BMA approach resolves a number of the weaknesses of the ensemble forecasts including their under dispersion and the discrepancy between forecasts and observations. Therefore BMA can be used to attain higher consistency in the probabilistic forecasts of an operational model.

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CHAPTER ONE
BACKGROUND OF THE STUDY

1.0 Introduction

This chapter gives in-depth background of weather forecasting techniques from ages to present, statement of the problem, objective of the study and significance of the study.

1.1 Background of the study

The art of weather forecasting began with early civilization using reoccurring astronomical and meteorological events to help them monitor seasonal changes in the weather (NASA, 2002). Since then, there has been a spontaneous successive improvement on the subject of weather forecasting where in 650 B.C., predictions of short-term weather changes were based on the observation of clouds and phenomena such as haloes. Chinese astronomers were among the early developer of weather forecasts, where they invented calendar that divided the year into 24 festivals based on different types of weather in the year (Marusek, 2010). However, according to Neves (2017), philosopher such as Aristotle in 340 B.C., also wrote on the subject of weather forecast, were he included theories about formation of clouds, rain, wind, thunder and hurricanes. Aristotle observation on weather and associated errors set foundation until in 17th century during the start of the modern forecast.

Different methods and procedures where attempt to produce forecasts based on lore and personal observations. By the end of Renaissance, interests in the knowledge of atmosphere increased exponentially and different instruments were needed to further understanding in the subject of weather forecasting (Kuismanen, 2008). In the 19thcentury, the innovation of metrological instruments made possible for observation and record of data and further studies on the subject such as wind patterns and storm system. From there, roots for weather predictions and observation spreads across the globe leading to birth of synoptic weather forecasting in the 1860s (Neves, 2017).

Bjerknes (1904) introduced hydrodynamics and thermodynamics into weather forecasting. Thus the idea of predicting weather by solving the mathematical equations was formulated, current known as Numerical Weather Prediction.

Furthermore, Richardson (1922) made further exploration on exploiting differential mathematical equations on weather predictions were far advanced (Lynch, 2006). He manually calculate the change of atmospheric pressure, for the particular place and time, his predictions were 145 hPa in 6 hours. However, the prediction was totally unrealistic value and too large by two orders of magnitude due to poor computational tools. The possible answer for this unrealistic value was that some day in the dim future it was possible to advance the computations faster than the weather advances and at a cost less than the saving to mankind due to the information gained, but that is a dream"..

For centuries weather and climate has proven to be crucial in development of human activities and many sectors of economy, thus sensitivity may varies in the necessity of weather among sector from average to extreme conditions. The social and economic contributions of accurate weather forecasts are cosmic in different sectors, mostly in agricultural sector, disaster managements, transportation systems and energy sectors. According to Frei (2012), whether it is forecasting the weather, diseases or economy anticipating things to come is arguably one of the biggest human desires. By anticipating things to come we are able to plans and make desirable decisions on the unforeseen.

The current exponentially growing in computer functionality, capacity and satellite technology, gathering of data has removed constraint on the modern weather forecasting. However, even though additional factors have been added in the modeling, still uncertainty in weather forecasting remains the challenge. Uncertainties arise from the assumption of Numerical Weather Predictions (NWP) that initial and boundary conditions are the same everywhere, which is not necessarily. As the consequence, forecasts should be treated as probabilistic rather than deterministic. As Gneiting (2008) argued weather forecasts should be presented as probability distribution over future weather events.

Numerical weather prediction models are still run today, but with the change toward implementation of ensemble forecast methods. Whereas, ensemble prediction system is the group of forecasts which tackles the uncertainties of the deterministic models and give room for probabilistic forecasting. Ensemble systems are created by single or multiple runs of NWP model, with a set of different initial conditions and boundary conditions create a forecast ensemble.

However, even ensemble forecasts have problems, as they tend to exhibit systematic biases as well as dispersion errors (Bao, et. al, 2010). The ensembles therefore lack calibration and are typically under dispersed (Hamill and Colucci, 1997). To address these problems statistical methods of post processing are used to correct biases and dispersion errors with the aim of maximizing sharpness and calibration (Gneiting et al. 2007). Post processing methods such as Bayesian Model Averaging yield full predictive probability density functions (PDF's) for weather quantity of interest. Thus, ensemble system represents uncertainty of the chaotic nature of the atmosphere compared to single NWP model and post processed ensemble outperforms the raw ensemble in terms of calibration and sharpness (Gel, et. al, 2004).

1.2 Statement of the problem

Recent researches show that there is substantial evidence that climate has been changing in the recent decades (Maurel, 2014). The shocks from changes in the climate conditions have affected development in every aspect, mostly in agricultural production where production depends on climatic condition. These changes will exert additional pressure in the developing countries because majority of the countries are relying on rain-fed agriculture. In Tanzania over the past few decades has been experiencing unpredictable and unreliable patterns of rainfall, resulting to unreliable productivity and wellbeing of the population since agricultural sector is the backbone of the country economy (Mbululo, 2012). In order to address this weather challenge, most of developed and developing countries have heavily invested in the science of meteorology, were Tanzania Meteorological Agency (TMA) is given the task of provision of weather and climate information in Tanzania.

However, in most of developing countries such as Tanzania the traditional deterministic approach is the mainly method used for weather forecasting where single NWP model is used to provide the single solution of the unknown future atmospheric state in a specific time and location(PUT REFERENCE HERE). But chaotic nature of the atmosphere make it impossible to determine the realistic initial and boundary conditions for the required resolution in the NWP model due to uncertainty. Thus small errors on the initial and boundary conditions can produce inaccurate future weather forecast. That is why the predictability of the future atmospheric states is limited in time: the initial condition errors are amplified as the forecast period grows (Callado, 2013). Furthermore, others sources of errors that may affect weather forecasts may be physical parameterization, computation and observation system together limit the skill and predictability of a deterministic forecast system.

This study aims at in filling the gap in literature by using probabilistic weather forecast system, which uses ensembles forecast. Where, ensembles forecast are formulated by single or multiple runs of NWP models with a set of different initial and boundary conditions. Therefore ensemble approach produces a set of random and independent forecasts and the diversity of these forecasts represents the forecast uncertainty. However, ensemble forecasts are not able to catch the full uncertainty of numerical weather predictions and therefore often display biases and dispersion errors and thus are uncalibrated. To account for this problem, BMA statistical post processing method was used to recover intervariable and spatial dependencies from the original ensemble forecasts.

1.3 General objective

To study probabilistic weather forecasting based on ensemble prediction system using Bayesian Model Average

1.3.1 Specific objectives

i. To evaluate probability forecasts of temperature using Bayesian model averaging
ii. To evaluate probability forecast of precipitation using Bayesian model averaging

iii. To evaluate initial resolution and boundary conditions in model accuracy forecasting

1.4 Research questions

The following are the research questions;

i. What are the probabilistic forecasts of temperature using Bayesian model averaging?
ii. What are the probabilistic forecasts of precipitation using Bayesian model averaging?
iii. Does initial resolution and boundary conditions influence in model accuracy forecasting?

1.5 Significance of the study

- Weather forecasting agency

This study will help weather forecasting agencies in the country as the researcher exploit the alternative approach for weather forecasting. The researcher used probabilistic forecasts as the alternative approach for deterministic forecasts.

- Agricultural sector

The study will help agricultural sector by providing reliable and stable weather information. The stable weather forecasts helps on the timing of the commencing of cultivation up to growth, development and yields of a harvest. The study will also help in prevalence of pests and diseases, which are crucial in agricultural sector.

- Further studies

This study used BMA statistical post processing method which has been be in weather forecasting studies. . The BMA methods and exploration of other post processing methods that helps to improve the calibration and sharpness as the methods have proven to have a better performance compared to deterministic forecasts.

CHAPTER TWO
LITERATURE REVIEW

2.0 Introduction

This chapter review various arguments and findings from different authors, journals, publications and other sources of information. It covers Key terms, theories, empirical studies and conceptual framework .

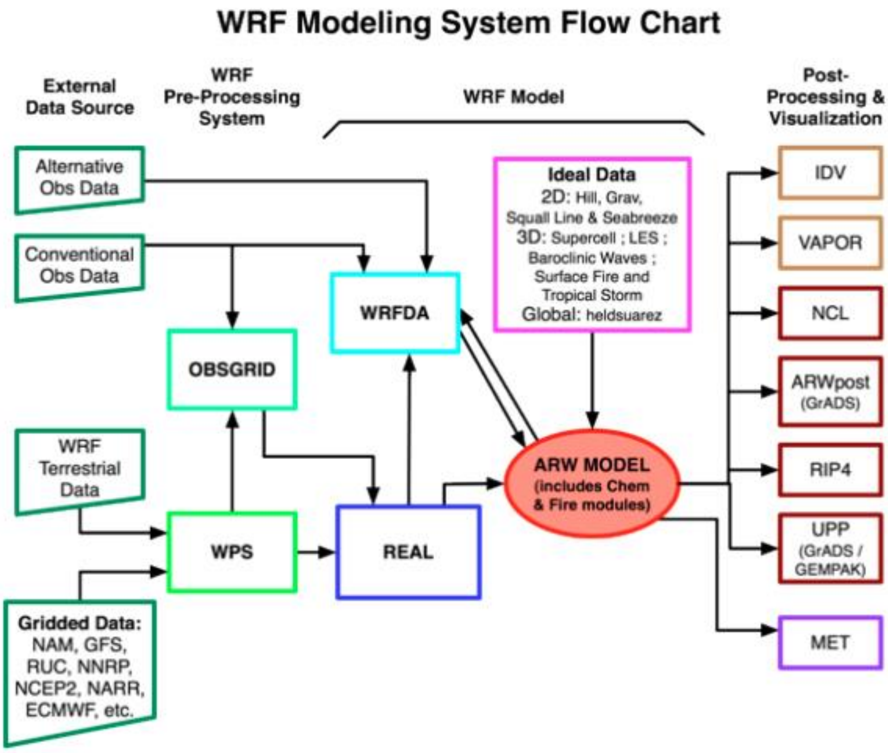
2.1 Meaning of key terms

2.1.1 WRF-ARW model

It is a supported “community model” created for both research experiment and operational forecasts with the aim of downscaling the global model forecasts to high resolutions forecasts. WRF-ARW is planned to be adaptable, state-of-the-art atmospheric simulation system that is convenient and capable on offered parallel processing platforms. The ARW is appropriate for use in different applications across scales ranging from meters to thousands of kilometers, including; Forecasting research, real-time NWP, teaching and Idealized simulation. The system software is in the public domain and is feely available for community use developed by NOAA/NCEP/EMC, NOAA/ESRL and NCAR with partnerships at DOE/PNNL, FAA, AFWA and collaborations with Universities and other Government agencies in USA and other countries (ARW modeling System Users Guide, 2012).

Figure 2.1 Show the flowchart for the WRF-ARW system from observation dataset, gridded dataset, WRF pre-processing system (WPS), WRF model to post-processing

Figure 2.1 WRF-ARW modeling System



Source: ARW modeling System Users Guide, (2012)

2.1.2 Uncertainty in Weather Forecasting

To increase both precision and effectiveness of weather forecasts, different methods have been developed to describe, calculate and where convenient quantify uncertainty. However,the aim is not to predict with certainty what is going to happen, but to better understand and represent uncertainty (Frei, 2012). There are two main sources of uncertainties in weather forecasting.

i. Uncertainty in the deterministic models:

   Deterministic models have been remarkably good tools for approximating atmospheric behavior, but these models are not complete and true representation of the governing physics. This is the result of some physical process functioning on scale too small to be presented by the deterministic models, and their effects on the forecasts over time are massive.

ii. Uncertainty in the Initial Conditions (ICs)

   According to Lorenz, (1963) assuming that deterministic models are complete and true representation of the atmospheric behavior, still we could not escape the uncertainty because of the dynamic chaos. Thus, if two deterministic forecasts are started with slightly varying Initial Condition (IC), the two solutions will eventually yield different results.

Figure 2.2 presents Lorenz system in finite time error growth for three probabilistic forecastsbeginning from distinctive points.

a. Extremecertainty and consequently a high level of confidence in the conversion to a different weathersystem.
b. A high level of certainty in the near term but then increasing uncertainty later in the prediction with a humble probability of aalteration to a different weathersystem.
c. A predictionbeginning near the transition point between systems is highly uncertain.

Figure 2.2 Finite time probabilistic prediction of the Lorenz (1963) system

Source: Palmer, (2003)

Therefore, NWP forecasts of the future atmospheric behavior will always be uncertain, and probabilistic approaches will always be needed to describe the chaotic behavior of the atmosphere (Wilks, 2006).

2.1.3 Numerical Weather Prediction

This is the approach of weather forecasting that employs a set of mathematical equations to explain the flow of fluids. These equations are interpreted into computer code and use principal equations, parameterizations of other physical processes, numerical methods and combined with initial and boundary conditions before being run over a geographical area (domain). However, nearly every step in NWP includes omissions, estimations, approximations and compromises. Thus, numerical method is the result of transformation of partial differential equation to algebraic equation, because computers can compute arithmetic but not calculus. Therefore, the aim of numerical method is to convert temporal and spatial derivatives into algebraic equations that computers can solve.

- Taylor series demonstrating transformation of equation to finite algebraic equation

$$f(v_i + \Delta v_i) = f(v_i) + \Delta v \left.\frac{\partial f}{\partial f}\right|_{v_i} + \left.\frac{\partial v^2}{2!}\frac{\partial^2 f}{\partial v^2}\right|_{v_i} + \cdots + \left.\frac{\Delta v^n}{n!}\frac{\partial^n f}{\partial v^n}\right|_{v_i}$$

- NWP model can be presented in simple form as

$$\frac{\Delta\, temperature}{\Delta t} = F(P)$$

Where;

$\Delta\, temperature$: Changes in a forecast variable at a particular point in space,

Δt: Changes in time

$F(P)$: Terms that can cause changes in temperature

The equation above demonstrate the changes in the temperature forecast during the time period t is equal to the cumulative effect of all process that force temperature to change.

However, Numerical Weather prediction models are associated with setbacks in weather forecasting. The following below explain the setbacks;

- The way in which primitive equations are derived from their complete theoretical form and converted to computer codes can contribute to errors
- The model forecast equations are simplified versions of the actual physical laws governing atmospheric processes; especially cloud processes, and atmosphere exchanges, and radiation. The physical and dynamic approximations in these equations limit the phenomena that can be predicted.
- Due to their complexity, the primitive equations must be solved numerically using algebraic approximations, rather than calculating complete analytic solutions. These numerical approximations introduce error even when the forecast equations completely describe the phenomenon of interest and even if the initial state were perfectly represented.
- Computer translations of the model forecast equations cannot contain all details at all resolutions. Therefore, some information about atmospheric fields will be missing or misrepresented in the model even if perfect observations were available and the initial state of the atmosphere were known exactly.
- Grid point and spectral methods are techniques for representing information about atmospheric variables in the model and solving the set of forecast equations. Each technique introduces different types of errors.

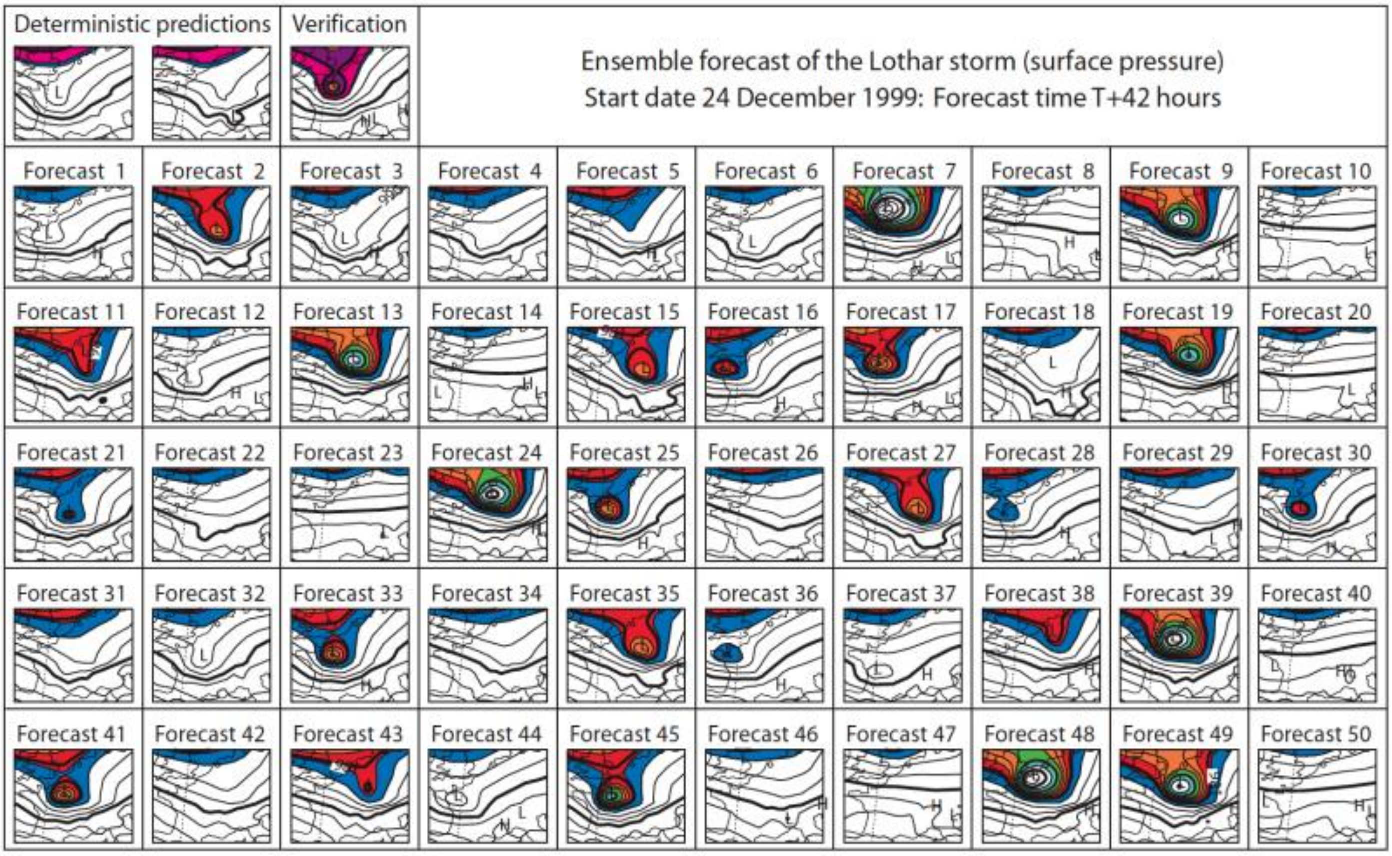
2.1.4 Ensemble Weather Prediction

Since the industrial revolution, climate and weather activities have been changing rapidly. The complexity of atmospheric parameterization and initial condition for NWP modeling has magnified difficulties in weather forecasting. Ensemble Prediction System (EPS) has emerged as alternative method of weather forecasting, were it assign the available computational resources to create a series of dynamical NWP model forecasts with different initial and boundary conditions. Thus ensemble forecasting offers the likelihood to tackle the uncertainties within the initial state and deterministic models that is the natural uncertainties in atmospheric prediction.

However no specific raw ensembleforecast from the ensemble system may be ultimately correct, several results of the ensemble output both suggest the possibility and offer the means of probabilistic forecasts. Additionally, the ensemble mean forecast normally outperforms most of the individual forecasts comprising the ensemble (Grimit and Mass, 2002).

Figure 2.2 demonstrate the significance of Ensemble Prediction System (WPS) in forecasting severe events. Whereas in December 1999,Lothar and Martin were the names given to the storms that swept across Central Europe. The destruction of the storms were massive; leaving 100 of people dead, extensive damage of infrastructures and significant economic loss. But what were the reasons for not foreseen the storms?Figure 2.2 presents the surface pressure for the 42 hours ensemble forecast generated at the European Centre for Medium-Range Weather Forecasts (ECMWF) few days before Lothar stroke Northern France. From figure 2.2 the top-left presents the operational deterministic forecast for December 26th and the validating evaluation. Nonetheless, the ECMWF operational NWP forecast completely missed the storm although given observation data for December 24th. However, unlike deterministic forecast several ensemble members projected there will be storm. In other words, the ensemble managed to capture significantly the abnormality and warn there might be a severe storm, while the best NWP forecast show normal day failing to suggest there might be severe event (Palmer, 2002).

Figure 2.3 Ensemble forecasts for Lothar storm (surface pressure) in 24 Dec 1999



Source: Palmer's, (2002)

2.2 Empirical Literature Review

The foremost desire of human is to have a prior knowledge of the unforeseen future events. Thus numerous studies have been conducted on the subject matter of weather forecasting from earlier 20 century to present day (Bjerknes, 1904; Richardson, 1922 and Frei, 2012). However, in weather activities the race of forecasting have changed in the recent decade from deterministic forecasts to probability; were forecasts must be probabilistic taking the form of PDFs over future events (Hoeting, 1999; Moller, 2014; Berrocal, et. al., 2007; Gneiting, 2005; Fraley, et. al., 2011 and Hoeting, 2008).

Inthe past fifteen years we have witnessed a radical change in the practice of weather forecasting, were ensemble prediction systems (EPS) have been implemented operationally. The following review empirical literature;

Sloughter et al. (2007) studied “Probabilistic Quantitative Precipitation Forecasting Using Bayesian Model Averaging”, where BMA is the statistical postprocessing method for creating probabilistic forecast from ensembles in the form of predictive PDFs.

In the study BMA was applied to 48 hours forecasts of 24 hours precipitation accumulation in the Northwest of Pacific for the 0000UTC rotation over the 2 years period of 1 Jan 2003 to 31 Dec 2004. Using nine-member University of Washington mesoscale ensemble (Eckel and Mass, 2005).The predictive PDFs of precipitation was evaluated by Verification Ranked Histogram (VRH) and Probability Integral Transformation (PIT) to measure the calibration, were Brier score was used to measure accuracy of the forecasts and Skills score was used to measure skills of the forecasts. Moreover, Reliability diagram, CRPS and MAE were also used to access the accuracy of forecasts.

The researcher concluded thatBayesian Model Averaging forecasts were better calibrated and sharper than the raw ensembles, which were uncalibrated. The Bayesian Model Averaging median forecasts had lower Mean Absolute Error than the ensemble median, and the Bayesian Model Averaging predictivePDFs had substantially lower CRPS than the raw ensemble.

Chmielecki and Raftery (2010) studied the application of BMA on the probabilistic visibility of forecasts. In the study the researcher used three methods to generate the PDFs for the visibility, while all methods they used BMA to post process an ensemble of visibility forecasts. These methods were applied to 12 hours ensemble forecasts from 2007 to 2008 and they were tested against observations records at Automated Surface Observing Station (ASOS) in the Pacific Northwest.

Results of the three approaches produced predictive PDFs that are calibrated and sharp compared to both climatology and raw ensembles.

Soltanzadeh et al., (2011) conducted a study on 2-m surface temperature forecasts over Iran by using Bayesian Model Averaging. The study used multi-model multi-analysis ensemble for 5 months interval, where the performance of the predictive forecasts PDFs were evaluated by using ROC and reliability diagram.The main results showed that the BMA method is the most effective at reducing but not all the under dispersion presented by the raw ensemble and thus obtain higher reliability in the probabilistic forecasts that could be used in an operational framework. Thus the use of weighted ensemble means resulted into BMA forecasts to perform nearly continually better than the best members deterministic forecast in the ensemble.

Aggarwal and Kumar (2013), conducted a comprehensive evaluation of NWP models and showed that errors in preliminary situations may be dealt successfully by slightly perturbing the observation. The model outputs with marginally different initial conditions may be averaged to get the very last output, were by doing so it improves the forecast skills.

In dynamical modeling the errors in preliminary situations arise out of wrong observation, incorrect calibration or due to finite reminiscence of the virtual device available with the researcher. These are dealt with the aid of applying perturbation to the initial commentary. Several initializations are important for chaotic gadget because errors tend to grow with time.

In recently, precipitation forecasts are normally based on forecasts ensembles from NWP models. However, even modern-day ensembles prediction systems are uncalibrated and bias, and thus the researcher proposed statistical postprocessing technique as the strategy aiming to calibrate the ensemble output.

Frei (2012) conducted a research on quantiles as the post processing method for probabilistic forecasts of precipitation.

The e study proposed a singular manner of post processing forecast ensembles for precipitation based on quantile regression. Even though traditional quantile regression has been learned to perform properly, separately fitted regressions are not constraint to be mutually steady and the approach does not yield predictive densities. To overcome this problem, the study proposed a two-step technique which model

i. The possibility of precipitation incidence by using logistic regression
ii. The precipitation quantities using log-normal distribution.

The techniques were carried out to 48 hours forecasts of 24 hours precipitation accumulation over the North American Pacific Northwest while using college of Washington mesoscale ensemble.

The ensuing probabilistic forecasts end up producing calibrated than the individual ensemble (deterministic forecasts) and a reference forecast (climatological).

Bhowmik and Prasad, (2008) conducted a research on Limited Area Model (LAM) forecasts with the aim of improving India Meteorological Department (IMD) operational forecasts. Meteorological Department of India has been using a LAM on operational basis for the forecast up to 48 hours with lateral boundary conditions from the Global Spectral Model (GSM) (T-80) run of the National Center for Medium Range Weather Forecasting (NCMRWF).

In the study, modifications were made to make the model flexible and delinking it from the NCMRWF. By doing that it allowed the use of initial and boundary conditions directly from other source. Thus the researcher used datasets from Global Forecast System (GFS) with 100Km resolution.

The difference between the modified model, operational model and the observation were evaluated quantitatively. The modified model, which was the result of improved resolution of LAM and use of better initial and boundary condition (GFS) ended up been capable of providing reliable numerical guidance on the occurrence of heavy precipitation in the interval of 48 to 72 hours.

Moller et al., (2013) proposed the use of BMA and copulas as the post processing methods for ensemble forecasts in order to acquire a combined prognostic distribution of weather. They applied existing BMA postprocessing approaches to acquire estimated marginal distributions. However, implementing of these approaches individually produce no information concerning the joint distribution. In order to counter the problem the researchers used Gaussian copula, which give a simple technique for recuperating the dependence that are lost in the estimation of the ensemble BMA marginal.

These approaches were applied to 48 hours forecasts of five weather variables using the eight membersof University of Washington mesoscale ensembles. The method sused improvement in the dependencies between weather variables as the results; they improved calibration and sharpness on both the individual ensembles.

Palmer (1999), conducted a study on “predicting uncertainty in forecasts of weather and climate”. The unpredictability in weather forecasting arises from the vast dimensionality of the climate system, thus in the study researcher proposed a techniques that generated ensemble perturbations that capture the uncertainty. Strength where placed on the use of singular-vector approaches to regulate the linearly unstable component of the initial probability density function. And operational ensembles prediction systems for days, seasons and decades were evaluated.

Findings show that, ensemble forecasts can be used as input to a simple decision-model analysis. But, probability forecasts of weather and climate have greater potential economic value than corresponding single deterministic forecasts with uncertain accuracy.

Moller (2014), evaluated the use of postprocessing methods in weather forecasting. The researcher argued that, currently emphasis has been put into the uses of ensemble prediction system in weather forecasting. However, uncertainty in NWP system has proven difficulty for ensemble forecasts to capture the true unforeseen nature of initial and boundary conditions to be used in the modeling process. To account for this problem the researcher introduced BMA and EMOS statistical postprocessing methods to improve inter variable and spatial dependencies from the novel ensemble forecasts.

The multivariate post processing procedure that was used to models inter-variable dependence uses the UWME 8-member forecast ensemble over the North West region of the US. While the spatial post processing procedures was applied to temperature forecasts of the ECMWF 50-member ensemble over Germany. The findings showed both multivariate and spatial approaches yield excellent calibration and sharpness results in comparison to individual ensemble. Furthermore, the techniques were able to capture the spatial structure of observed fields.

Berrocal et al., (2007) applied probabilistic weather forecasts in the winter road maintenance in USA. During winter seasons in USA icing became challenging especial to the department of transportation. Thus, anti-icing (chemicals) is crucial during winter season, although given the nature of anti-icing agents precision in forecasts of the road ice is essential. Currently, anti-icing assessments are generally based on deterministic weather forecasts. However the costs of the two types of inaccuracy are highly unequal because the cost of a road closure due to ice is much greater than that of taking anti-icing measures. As a result, the researchers proposed the use of probabilistic forecasts in order to optimize decision- making.

The researchers used two approaches for forecasting the probability of ice;

i. Deterministic numerical weather predictions

   This method was used to generate the predictive PDFs of temperature and precipitation. The results were used to formulate the probability of ice, defined as the occurrence of precipitation when the temperature is below freezing.

ii. Bayesian method via Markov Chain Monte Carlo

   This method was used to estimate the model parameters of the spatial dependence between forecast errors at different locations.

Both approaches were evaluated to compare their probabilistic forecasts with observations of ice formation for Interstate Highway 90 in Washington State in USA for the 2003 to 2004 and 2004 to 2005 winter seasons. The findings showed that using probabilistic forecasts could be used to save a significant budget compared with deterministic forecasts.

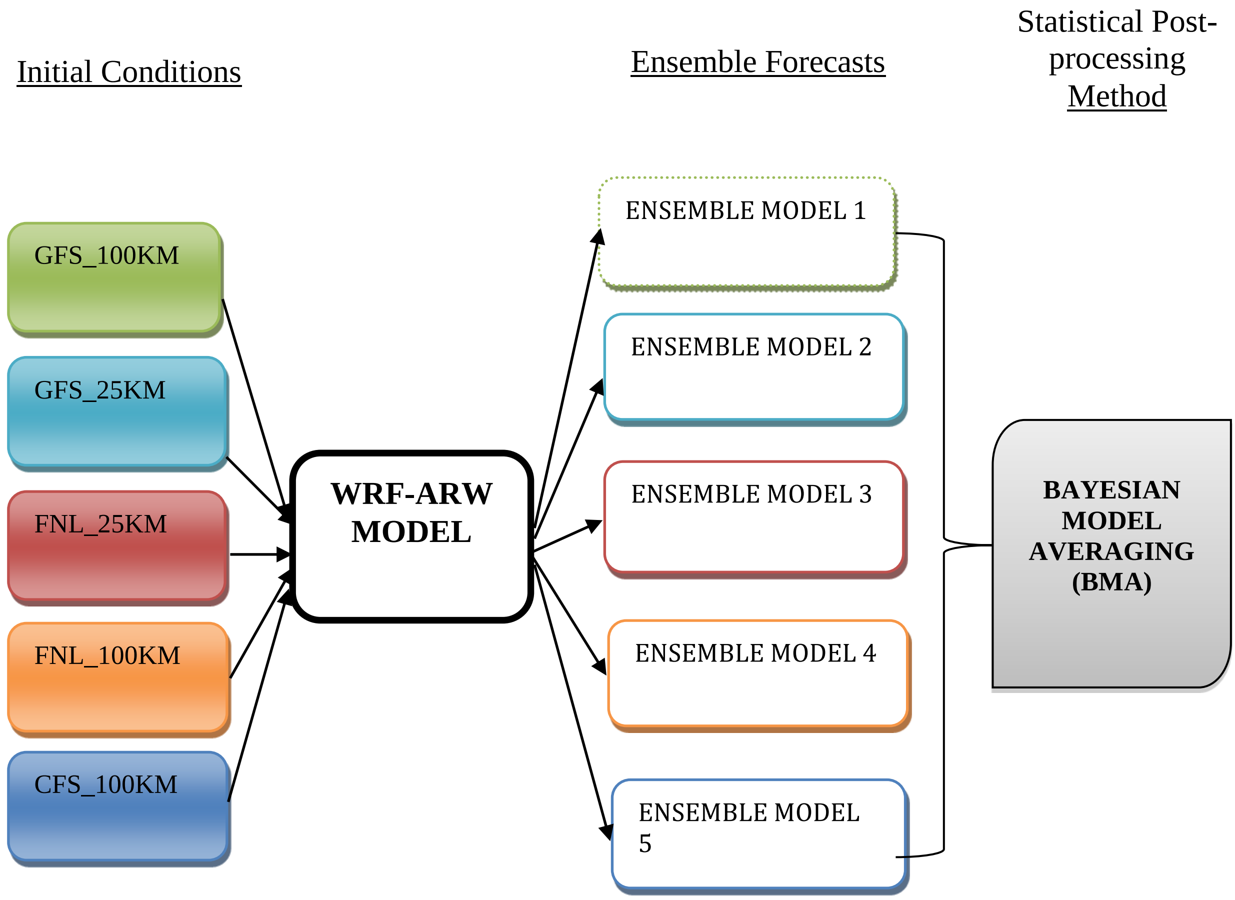
2.3 Conceptual framework

Ensemble Prediction System (EPS) forecasts are designed in different ways, in this study EPS forecasts were generated by running one NWP model (WRF-ARW) while use different Global Climate Models (GPM) as varying initial conditions.

Like deterministic forecasts, ensemble prediction systems faces similar problems in producing calibrated forecasts. However, raw ensembles are nothing but deterministic simplification of the atmospheric reality, since the process of selecting Initial Condition (IC) fails to randomly sample the current atmospheric state. Therefore, raw ensembles forecasts capture certain amount of uncertainties that are involved in the weather prediction.

To solve the problems associated with raw ensembles, researcher used Bayesian Model Averaging as statistical postprocessing method in order toproduce forecasts which are calibrated, that is probability forecasts in form of predictive PDFs over the future weather events.

Figure 2.3 Conceptual Framework



Source: Research design, (2018)

CHAPTER THREE
RESEARCH METHODOLOGY

3.0 Introduction

This chapter provided the information on the methods that were used to create ensembles forecasts for parameters (precipitation and temperature) on the SAGCOT regions of Tanzania. However, narration of the study area and boundary for the data to be clipped and geoprocessing environment set were discussed. methods for preparing both forecasts and observation data for analysis were as well described.

This chapter also discussed the methods used in downscaling the data from global scale. Moreover, description of different initial and boundary condition that were used with their spatial resolution in relation to coordinate system and projection that cover the study area were explained. After preparation of data, elaboration for statistical postprocessing methods (BMA) that were used to evaluate the raw ensembles will be specified.

3.1 Research design

According to Churchill (2002) research design is a master plan specifying methods and procedures for collecting and analyzing the required data. In order to fulfill the study,the research design was used to obtain the required information. Kothari (2006) defines descriptive case study research design concerted with describing the characteristics of a particular individual or of a group, and determining the frequency with which something occurs or it's associated with something else.

The researcher will use descriptive research design, because in descriptive design major emphasis is describing the characteristics, specific predictions and narration of facts concerning individuals and groups.

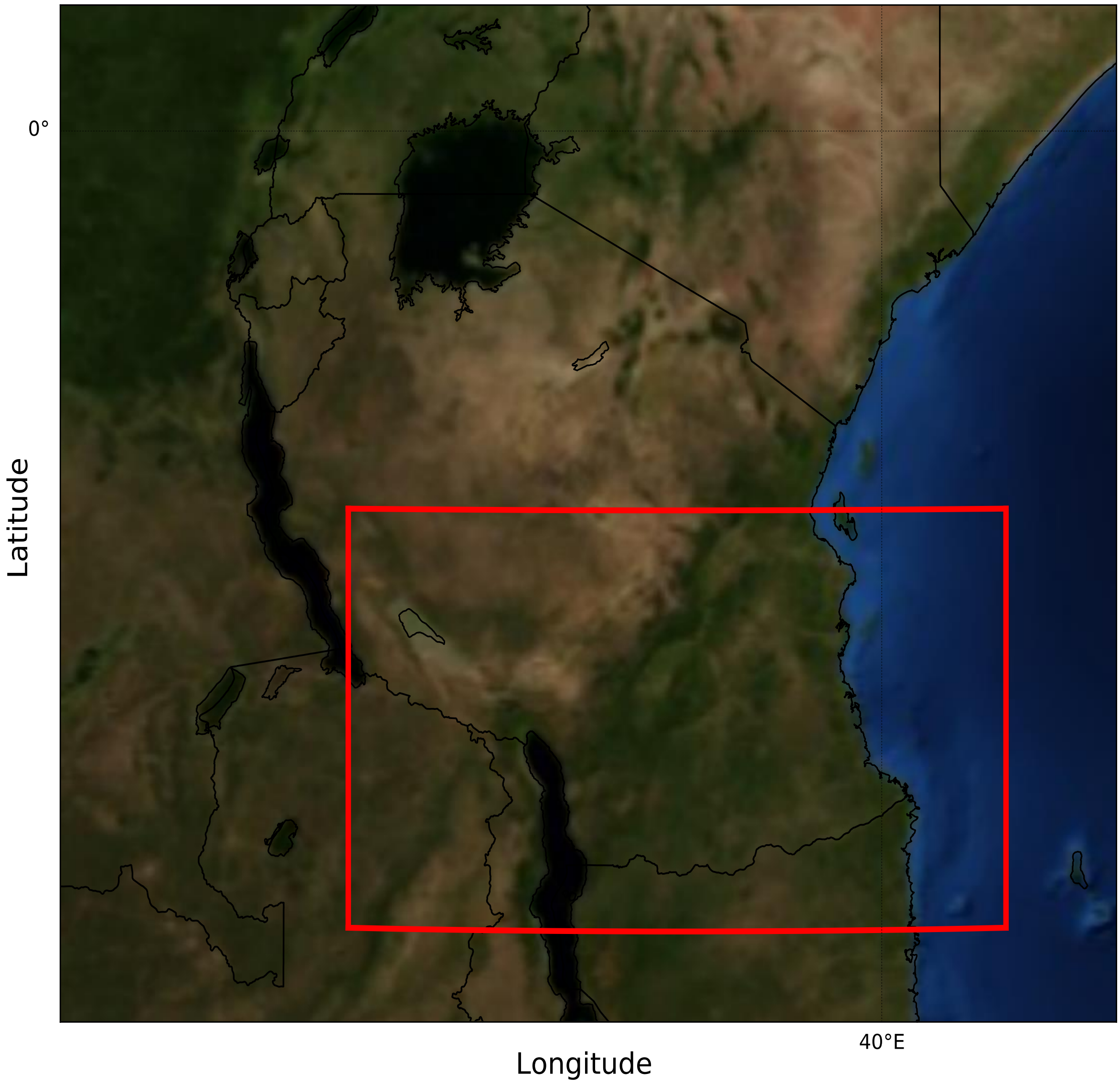
3. 2 Description of the study area

Tanzania is roughly located in East Africa between latitudes $1°$ and $12°$ S and longitudes $29°$ and $41°$ E, with the area approximately 945,000 km^2. The vast size of the country yield to different geographical and topographical features which resulting to different rainfall patterns and variety of temperature in the country. The two major rainfall seasons that are characterized in Tanzania mainland are namely; bimodal and unimodal seasons. Bimodal rainfalls seasons are divided into long and short rainfalls, where the long rainfalls are starting from March to May (MAM) locally known as "*masika*", and short rainfall seasons are starting from October to December (OND) locally know as "*vuli*". Unimodel seasons are characterized with single long rainfall starting from November to April (NA). In Tanzania areas for unimodal areas are southern, southwestern highlands, central and western areas while bimodal areas in Tanzania include northern eastern highlands, Lake Victoria basin, northern coast areas and northern areas.

Moreover, distribution of temperature in the country followed pattern of altitude. Areas around Coastal regions (Dar es Salaam) have high temperature due to low altitude from the sea level, and low temperature in Southern highlands and part of Northern regions such as Njombe and Kilimanjaro respectively due to high altitude from the sea level.

In this study, the experiments from WRF-ARW model focused on Southern of Tanzania area between latitudes $5°$ and $12°$ S and longitudes $30°$ and $41°$ E, with objective of evaluating SAGCOT regions. SAGCOT regions are characterized with low lands, mountains and river basins, which offers potential for agricultural activates. Where month of Marchwas chosen because was found to be the maximum month of rainfall around the SAGCOT regions.

Figure 3.1 Domain of the study



Source: Research design, (2018)

3.3 Data and data sources

The study used the sample of 15 different precipitation and temperature days (01 to 15 March 2017). The study used forecasts and observation data, both of which were collected for the same forecast time and duration over the same location.

3.3.1 Observations data for rainfall and temperature

The study used daily observations for rainfall and temperature covered the period of 15 days i.e. from 0000UTC 01 to 16 March 2017 for 6 meteorological stations. These data were obtained from Tanzania Meteorological Agency (TMA) headquarters located at Dar es Salaam.

Table 3.1 Weather stations

No.	Station	Latitude	Longitude
1	Morogoro	-6.90	37.70
2	Mahenge	-8.60	36.70
3	Iringa	-7.70	35.70
4	Mbeya	-8.90	33.40
5	Songea	-10.68	35.58
6	Sumbawanga	-8.00	31.60

Source: Research findings, (2018)

3.3.2 Initial and boundary conditions

Initial and boundary conditions used in WRF-ARW model are the following:

- Global Forecast System (GFS) datasets

The Global Forecast System is the weather forecast modeling that produced gridded dataset that cover the entire earth, produced by Centers for Environmental Prediction (NCEP). The GFS take into consideration varieties of variables;ranging from topographical to atmospherically variables in the production of forecast sum of which are atmospheric ozone, precipitation, winds, elevation, solar radiation, vegetation type and temperatures. In the study GFS gridded datasets between 00Z01032017-00Z15032017 with horizontal resolution of 0.25 degree (approx. 25km) and 1 degree (approx. 100km) were downloaded as initial conditions for WRF-ARW downscaling. Both datasetswere available at 3 hours interval in the first 10 days and 6 hours interval in the last 5 days, at National Operational Model Archive and Distribution System (NOMADS).

- Final Analysis (GFS- FNL) Data Sets

Final Analysis (FNL) and GFS models are related were both models are products of NCEP. However, these models yield different products from the same data assimilation and forecast system. The difference is the result of Final Analysis model (FNL) incorporates about 10 percent more observations than GFS; resulting from delay of 60 to 90 minutes of FNL in the initialization so that model can include all of the available observations data. In the study, FNL gridded datasets between

00Z01032017-00Z15032017 with horizontal resolution of 0.25degree (approx. 25km) and 1 degree (approx. 100km) were downloaded as initial conditions for WRF_ARW downscaling. Both datasets were available at 6 hours interval, at National Operational Model Archive and Distribution System (NOMADS).

- Climate Forecast System (CFS) Data Sets

In the study CFS datasets will be downloaded in between 01 and 16 March 2017 with horizontal resolution of 1 degree (approx. 100km) in Surface and Radioactive Fluxes (FLX) and 0.5 degree (approx. 25km) in Pressure Level Data (PGB) were they all are available at 6 hours interval.

3.4 Experimental of the model

Since forecast datasets from Global Forecast Products and Reanalysis Data are produced in low resolutions i.e. 50km and 100km, experiments was conducted to downscale to high resolution on the study area during the research period.

Experiment was conducted by using the Advanced Research WRF version 3.9 covering the study domain with the aim of analysis SAGCOT regions specifically; Morogoro, Iringa, Mbeya, Rukwa and Ruvuma regions in the period of 0000UTC 01 to 16 March 2017. The resolution for the WRF-ARW experiment used in the study was 10km.

3.4.1 Reanalysis Data for WRF Model Initialization

In order to initialize the WRF model for the Southern and Eastern of Tanzania regions presented in figure 3.1, both global model products and reanalysis data provided the required meteorological fields for initial and boundary conditions. Three Global Model Products (GMP) and Reanalysis Data (RD) at different resolution were used to initialize the WRF experiments for SAGCOT regions in the period of March 2017:

- Global Forecast System (GFS) the product of The National Centers for Environmental Prediction (NCEP) at 25km and 100km resolution, all are available at 3 hours interval in the first 10 days and 6 hours interval in the last 6 days.

- Final Analysis (FNL) the product of NCEP with data from National Operational Model Archive and Distribution System (NOMADS) at 25km and 100km spatial resolution all available at 6 hours interval.
- The NCEP Climate Forecasts System Reanalysis (CFSR) at 100km resolution in Surface and Radioactive Fluxes (FLX) and 25km in Pressure Level Data (PGB) were they all are available at 6 hours interval.

3.5 Statistical postprocessing method for ensemble forecasts

Numerical Weather Predictions (NWP) is the standard methods of weather forecast based on single model selection. These methods ignore models uncertainty and lead to underestimation of uncertainty when making inference (Hoeting et al., 1999). To tackle the problem of uncertainty in the model, system of equations resulting from the use of WRF-ARW with different initial resolutionand boundary conditions were used to create ensembles, which provided the best possible solution in the inferences.

Ensemblesforecasts allow for probabilistic forecast taking the form of predictive probability function (PDF). But, raw ensemble forecast system are finite hence they does not provide full PDFs for continuous quantities (Moller, 2013). However, Ensemble Prediction System (EPS) has evidenced shown systematic errors (forecast errors) similarly to those in NWP. Where most of raw ensemble shows a positive spread-error correlation, while at the same time being uncalibrated (Feldmann, 2012), therefore they only capture some of the uncertainty of the atmospheric state.In the study the researcher used Bayesian Model Averaging (BMA) as the method of postprocessing to maximize sharpness of the parameter and calibration.

3.5.1 Bayesian Model Averaging

BMA is a standard statistical approach for combining competing statistical models and has a broad application in e.g. social, economic, financial and health sciences (Hoeting et al., 1999). Its advantage over other techniques, such as conventional regression analysis, is based on the fact that BMA makes use of multiple models, in contrast to methods which solely use a single model that is deemed to be the best. Only using a single model often leads to an underestimation of the uncertainty in the process of model selection. In this study, the researcher follow the extension of BMA from statistical models to dynamical models, for the purpose of producing calibrated and sharp predictive distributions (Raftery et al., 2005).

The following demonstrate how BMA was used to statistically post-process forecastsof ensemble that is transforming ensemble output into well-calibrated probabilistic forecasts in form of predictive PDFs of future weather quantities.

3.5.1 BMA for temperature

Let y_s denotes the weather quantity of interest and $f_1, f_2, f_3, ..., f_M$ represents the ensembles forecast of a quantity y_s for a given time and location.

In the case of a quantity y_s to be forecast on the basis of training data y^T using M statistical models $f_1, f_2, f_3, ..., f_M$ the law of total probability tells us that the forecast PDF, $P(y_s)$ is given by

$$p\left(y_s\right) = \sum_{m-1}^{m} p\left(y_s \mid f_m\right) p\left(f_m \mid y_s^T\right)$$

where,

$$p\left(f_m \mid y_m^T\right) = \frac{p\left(y_s^T \mid f_m\right) p\left(f_m\right)}{\sum_{m=1}^{m} p\left(y_s^T \mid f_m\right) p\left(y_s^T\right)}$$

is posterior distribution of ensembles forecast and the likelihood distribution is given as

$$p(y_s \mid f_M) = \int p\left(y_s \mid \theta_m, f_m\right) p\left(\theta_m, f_m\right) \partial\theta_m$$

Therefore, $p\left(y_s \mid f_m\right)$ is the forecast PDF base on the model f_m, and $p\left(f_m \mid y_s^T\right)$ is the posterior probability of model f_m being correct given the training data, and reflects how well model f_m fits the training data. The posterior model probabilities add up to one, so that $\sum_{M=1}^{M} p(f_M \mid y^T) = 1$, and can view as weights.

The Bayesian Model Averaging PDFs gives each individual model, weighted by their posterior model probabilities. From the models, we extend BMA to dynamical models, where for a given forecast ensembles there exist the best model that we do not know. From given equation given that f_M is the best forecast in the ensemble, then the BMA predictive model is given by

$$p(y_s \mid f_1, f_2, f_3, \ldots, f_M) = \sum_{M=1}^{M} w_M g_M (y_s \mid f_M)$$

where w_M is the posterior probability of the forecast M being the best one and is based on forecast M's performance in the training period and since w_M probabilities are nonnegative thus they sum up to 1 , that is, $w_M = \sum_{M=1}^{M} p(f_M \mid y_s^T) = 1$.In BMA model, normal distribution will be used to model temperature. Therefore, linear function of the temperature forecast is presented in form of $v_M + q_M f_M$ for each ensemble member. Moreover, v_M and q_M are the bias correlated parameters, where $g_M (y_s \mid f_M)$ is a normal predictive density function (PDF) with mean $v_M + q_M f_M$ and standard deviation σ. Thus, BMA predictive function is written:

$$p(y_s \mid f_1, f_2, \ldots, f_M) = \sum_{M=1}^{M} w_M (v_M + q_M f_M)$$

And the overall variance of quantity of interest in BMA is given by

$$Var\left(y_s \mid f_{1s}, f_{2s}, \ldots, f_{Ms}\right) = \sum_{M=1}^{M} w_M \left(\left(v_M + q_{Ms}\right) - \sum_{M=1}^{M} w_M (v_M + q_M f_{Ms}) \right)^2 + \sigma^2$$

where between and within forecast variance are presented in the above expression respectively.

3.5.1.2BMA for Precipitation

For pressure, wind speed and temperature, the conditional PDF can be fit reasonably using normal distribution. However, for precipitation conditional PDF cannot fit using normal distribution. This is because distributions of accumulated precipitation are highly skewed i.e. nonnegative, were one of the assumption of normal distribution is distribution are suppose to be normally distributed.

However, Sloughter et al. (2007) propose to model the component PDF of precipitation as discrete and continuous mixture distribution to account for the large number of zero observation in precipitation. Where the probability of precipitation (PoP) is modeled as the function of forecast using logistic regression with a power transformation of the forecast as the predictor variable. And the predictive PDF of the amount of precipitation is specified as a gamma distribution.

The following demonstrate how BMA was used to statistically post-process forecastsof ensemble that is transforming ensemble output into well-calibrated probabilistic forecasts in form of predictive PDFs of future weather quantities. Thus, according to Sloughter et al. (2007) gamma distribution $\Gamma(\alpha,\beta)$ is parameterized in terms of sharp parameter α and scale parameter β, given the amount of precipitation is greater than zero. Then the BMA predictive PDF is given as the mixture of distribution

$$g_M\left(y \mid f_M\right) = P\left(Y_s = 0 \mid f_m\right) \mathrm{I}_{\{y=0\}} + P\left(Y_s \rangle 0 \mid f_m\right) h_m\left(y_s \mid f_m\right) \mathrm{I}_{\{y>0\}}$$

where y is the cube root of precipitation amount, h_M denotes a gamma density in terms of the cube root of precipitation amount and $\mathrm{I}_{\{y \in D\}}$ the indicator function with $\{ \mathrm{I}_{\{y \in D\}} = 1$ if $y \in D$ for a desired set D and $\mathrm{I}_{\{y \in D\}} = 0$ for $y \notin A$.

The probability of zero precipitation is modeled with a logistic regression approach where the predictor variable is defined as cube root of the original forecasts

$$p(Y = 0 \mid f_M) = \frac{\exp\left(v_{0m} + v_{1m} f_m^{1/3} + v_{2m} \delta_m\right)}{1 + \exp\left(v_{0m} + v_{1m} f_m^{1/3} + v_{2m} \delta_m\right)}$$

where $f_m^{1/3}$ is the power transformed forecast f_m, and δ_m is an indicator variable, that is equal to one of $f_m = 0$ and $\delta_m = 0$ otherwise. The probability $p(y = 0 \mid f_m)$ defined the probability of nonzero precipitation given f_m, conditional on f_m providing the best forecast in the ensemble.

The predictive PDF $g_m(y \mid f_m)$ of the cube root of the precipitation amount y, given that it is positive, is specified as a gamma distribution

$$g_m(y \mid f_m) = \frac{1}{\beta_m^{\alpha_m}\Gamma(\alpha_m)} y^{\alpha_m - 1} \exp\left(-\frac{y}{\beta}\right)$$

where $\alpha_m = \frac{\mu_m^2}{\sigma_m^2}$ is the sharp parameter and $\beta_m = \frac{\sigma_m^2}{\mu_m^2}$ is the scale parameter of the gamma distribution. The mean and variance of the gamma distribution are $v_{0m} + v_{1m} f^{1/3}{}_m$ and $c_0 + c_1 f_m$ respectively.

Table3.2 The ensemble BMA kernel functions for temperature and precipitation

Variable	Range	Kernel	Mean	Variance
Temperature	$y \in \mathbb{R}$	$N(\mu_m, \sigma_m^2)$	$v_{0m} + v_{1m} f_m$	σ^2
Precipitation amount	$y^{1/3} \in \mathbb{R}_+$	$\Gamma(\sigma_m, \beta_m)$	$v_{0m} + v_{1m} f^{1/3}{}_m$	$c_0 + c_1 f_m$

Source: Research design, (2018)

Table 3.2 provides the summary for the BMA models that were used in this study and their properties. Estimation for these BMA models wasimplemented in R package ensembleBMA (R Development Core Team, 2011 and Fraley et al., 2011).

3.6 Verification measures for probabilistic forecasts

The use of BMA as the statistical postprocessing methods hasnormally increased the possibility of well-calibrated probabilistic forecasts, in form of (PDFs) over forthcoming weather quantities(Wilks, 2006).Thus, it is critical to assess the predictive ability of these forecasts in the study.

According to the analyticalexample of Gneiting et al. (2007), the objective was to maximize the sharpness of a probabilistic forecast subjected to its calibration. The following are the methods used to evaluate the prognostic performance of probabilistic forecasts of raw ensembles and BMA for postprocessing method.

3.6.1 Verification of Raw Ensembles

3.6.1.1 Brier Score (Measures Accuracy)

This is the common and widely method used to measure the accuracy of probabilistic forecasts of dichotomous events(Toth and Kalnay, 1997). In the study Brier Score was used to measures MSE of the probability forecasts, considering that the observation is 1 if the event occurs, and that the observation is 0 if the event does not occur. The BS averages the squared differences between pairs of forecast probabilities $\alpha_j$and the successive binary observationsδ_j,the following is the formula for calculating Brier Score

$$BS = \frac{1}{N}\sum_{j=1}^{N}\left(\alpha_j - \delta_j\right)^2$$

where;

$j$is thenumber of the N forecast-event pairs.

However, the BS can take values in the range $0 \leq BS \leq 1$, and is negatively oriented, i.e. perfect forecasts exhibit BS = 0. Less precise forecasts show higher Brier scores; note however that it weights large errors more than small ones.

3.6.1.2 Reliability Diagram (Measure calibration)

These are graphical devices that sanction immediate visual analysis of unrestricted and restricted biases that may be exhibited by the forecasts. They show the full joint distribution of forecasts and observations for probability forecasts of the binary in terms of its calibration-refinement factorization.

Reliability diagram were used to measures the agreement between predictand probabilities and observed frequencies, in order to measure if the forecasts are calibrated. In order to obtain a perfect calibration, the binned forecast probabilities and the observed frequencies should be equal, and the plotted points should lie on the diagonal.

3.6.2 Evaluation of probabilistic forecasts

3.6.2.1 Mean Absolute Error (MAE)

In the study MAE wasused to specify the mean absolute difference between the predictive median and the realizing observations. The following below show the distribution of MAE

$$mae(D, \vartheta) = \frac{1}{N}\sum_{i=1}^{N}|\mu_i - \vartheta_i|$$

where$\mu_i$is the median of the predictive distribution.

3.6.2.2 The Verification Rank Histogramand Probability Integral Transform (Measure calibration)

This method was used to evaluate raw ensemble forecasts by plotting the frequency of the observations ranks within the forecast ensembles. The distributions of histogramsplotshelps in the interpretation were skewed histograms indicate a certain bias and calibrated ensembles produce a uniform histogram.

However it is important to note that, a uniform histogram does not essentially denote a skilled forecast, thus rank uniformity is crucial but not sufficient criterion for defining that an ensemble is reliable.

Moreover, probability integral histogram was used to measure the calibration of the density forecasts. If the anticipated distribution H is identical to a hypothetical “true” distribution, the value of the predictive CDF on the observation x has a uniform distribution

$$p = H(x) \sim U(0,1)$$

For perfect calibration, the histogram of all PIT values p, computed for all forecasts has to show a flat form. Deviations from uniformity can be used to diagnose aggregate deficiencies, as they are both smooth to understand and to interpret. A U-formed histogram shows overconfidence, in that the spread of the underlying predictive distribution is simply too small, and the predictive distribution is under-dispersed. An over-dispersed distribution reveals itself in a hump-fashioned diagram, with too many observations inside the middle of the distribution.

3.6.2.3 Scoring Rules (Measure accuracy)

Wilks (2006), defined Scoring rules as the methods thatmeasures accuracy of the density forecasts by assigning penalties depending on forecast accuracy, and can be used to compare competing forecasting methods. In the study the researcher used continuous ranked probability score to assess the calibration and sharpness simultaneously.CRPS is expressed by

$$crps(D, \vartheta) = \int_{-\infty}^{\infty} (F(y) - I\{y \geq \vartheta\})^2 dy,$$

where

F is the cumulative density function related with the predictive distribution D, and ϑ is the observation.

In the ensemble forecasts, the predictive distribution D_{ens}places a point mass of $\frac{1}{N}$ of the ensemble members $\vartheta_1, \vartheta_2, \ldots, \vartheta_N \in R$, the CRPS can be assessed as

$$crps(PP_{ens}, \vartheta) = \frac{1}{N}\sum_{j=1}^{N}\left|\vartheta_j - \vartheta_i\right| - \frac{1}{2N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left|\vartheta_j - \vartheta_i\right|$$

But for the normal distribution with parameters$N(\mu, \sigma^2)$ there exists a closed form of the CRPS with the distribution

$$crps(N(\mu, \sigma^2), \vartheta) = \sigma\left\{\frac{\vartheta - \mu}{\sigma}\left[2\,\Phi\left(\frac{\vartheta - \mu}{\sigma}\right) - 1\right] + 2\varphi\left(\frac{\vartheta - \mu}{\sigma}\right) - \frac{1}{\sqrt{\pi}}\right\}$$

where Φ (.) and $\varphi(.)$are the cumulative and probability density function of the normal distribution respectively (Gneiting et al., 2005).

CHAPTER FOUR
PRESENTATION AND DISCUSSION OF FINDINGS

4.0 Background of the findings

Regional Climate Models (RCMs) are the commonly used methods for downscaling, which generate high-resolution information about estimated climate changes situations from Global Climate Models (GCM). Thus RCM produces high-resolution in a particular region by solving the atmospheric weather equations governing the region while using GCM output as the initial and boundary conditions. And postulate highly resolved climatic information that the GCM cannot capture.

The increasing climatic and weather changes have demanded for high-resolution information's, where precipitation and temperature have become the key variables of interest in different sectors mainly agriculture in Tanzania.

Table 4.1 Summary of the GCM used in the formulation of raw ensembles

Global Climate Model	Resolution	Produced
GFS	25Km and100Km	Centers for Environmental Prediction (NCEP)
GFS-FNL	25Km and 100Km	Centers for Environmental Prediction (NCEP)
CFS	FLX-50Km/ PGB-100Km	Centers for Environmental Prediction (NCEP)

Source: Research findings (2018)

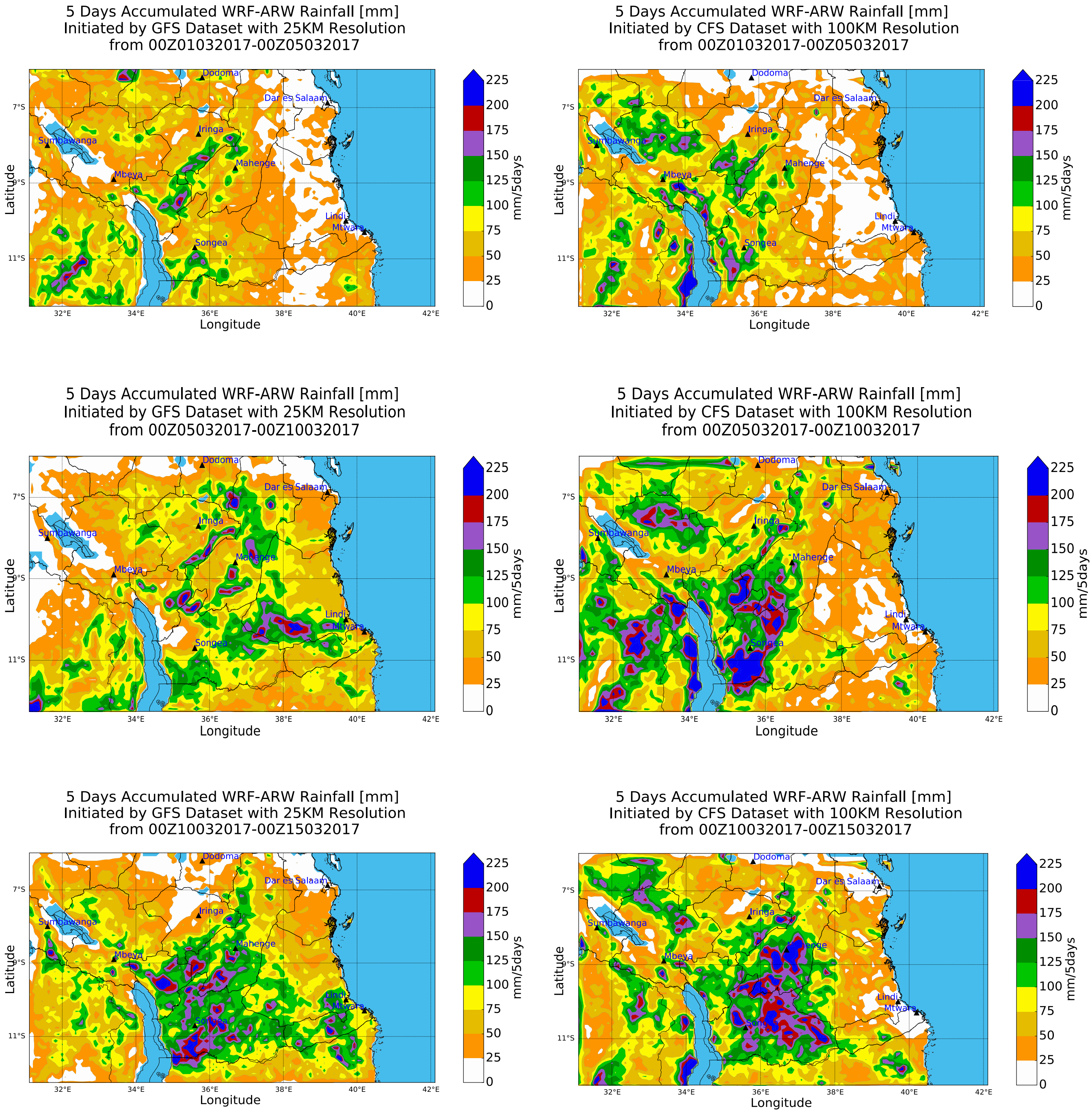
4.1 Evaluation of initial and boundary conditions resolutions in model accuracy forecasting

4.1.1 Five days accumulated WRF-ARW rainfall (mm) Initiated by GFS dataset and CFS

The objective of this study was to evaluate the initial and boundary conditions resolutions in model accuracy forecasting. Where initial conditions for raw ensembles forecasts of precipitation were assessed to measure the influence of resolution in model accuracy forecasting.

The results are presented in figure 4.1 below which shows the maps for 5 days accumulated rainfall (mm) initiated by GFS (left column) with 25KM resolution andCFS (right column) with 100KM resolution. Both forecasts show spontaneous increase of precipitation from 1 to 15 March 2017, while CFS forecasts shows more rainfall in the region Southern Highlands with up to 225 mm. GFS forecasts show more dry and shallow rainfall in the coastal regions during the first 10 days and high rainfall in the Southern Highlands during the 10^{th} to 15^{th} March 2017, while central regions received shallow rainfall (less than 50mm).

Figure 4.1 Five days accumulated WRF-ARW rainfall (mm)

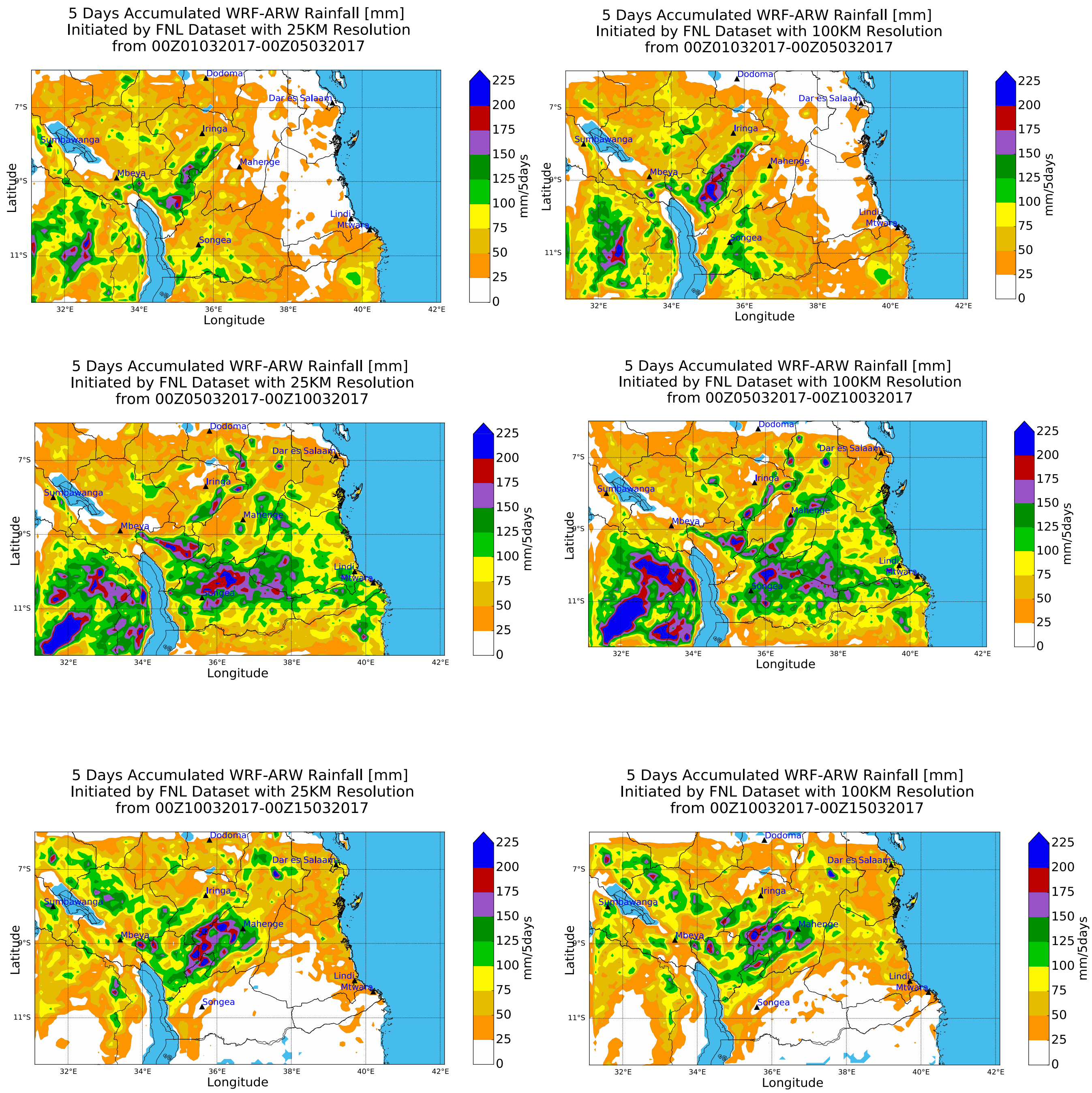


Source: Research findings (2018)

4.1.2 Five days accumulated WRF-ARW rainfall (mm) Initiated by FNL dataset

Figure 4.2 below shows the maps for five days accumulated rainfall (mm) initiated by FNL (left column) with 25KM resolutionand FNL (right column) with 100KM resolution. From the maps both forecasts show shallow precipitation and dry areas across coastal regions from 1st to 5th March 2017, and between 10th to 15th March 2017. However, during 5th to 10th March 2017 both forecasts show heavy rainfall in Southern highlands with up to 225 mm and shallow rainfall across other regions.

Figure 4.2 Five days accumulated WRF-ARW rainfall (mm)



Source: Research findings (2018)

4.1.3 Pearson Correlation matrix of precipitation between raw ensembles and observation

In order to assess the initial and boundary condition used, the Pearson correlation matrix was calculated to measure the degree of relationship between the raw ensembles forecasts and observations.

Table 4.2 presents the results of Person correlation matrix, were the findings shows there is poor correlation between individual raw ensembles and observation. As the highest correlation between raw ensemble forecast (GFS_25KM) and observation was 18 percent. Thus, based on the correlation findings, GFS_25KM provides calibrated and sharpness forecasts on precipitation compared to other raw ensembles used.

Table 4.2 Correlation matrix for 24h accumulation precipitation of raw ensembles and observation

	GFS_25KM	GFS_100KM	CFS_100KM	FNL_25KM	FNL_100KM	obs
GFS_25KM	1.00	-0.06	0.36	0.096	0.12	0.18
GFS_100KM	-0.056	1	0.13	0.087	0.19	-0.04
CFS_100KM	0.36	0.13	1	0.19	0.13	-0.06
FNL_25KM	0.10	0.09	0.19	1	0.70	0.11
FNL_100KM	0.12	0.19	0.13	0.70	1	0.15
obs	0.18	-0.04	-0.06	0.11	0.15	1

Source: Research findings, (2018)

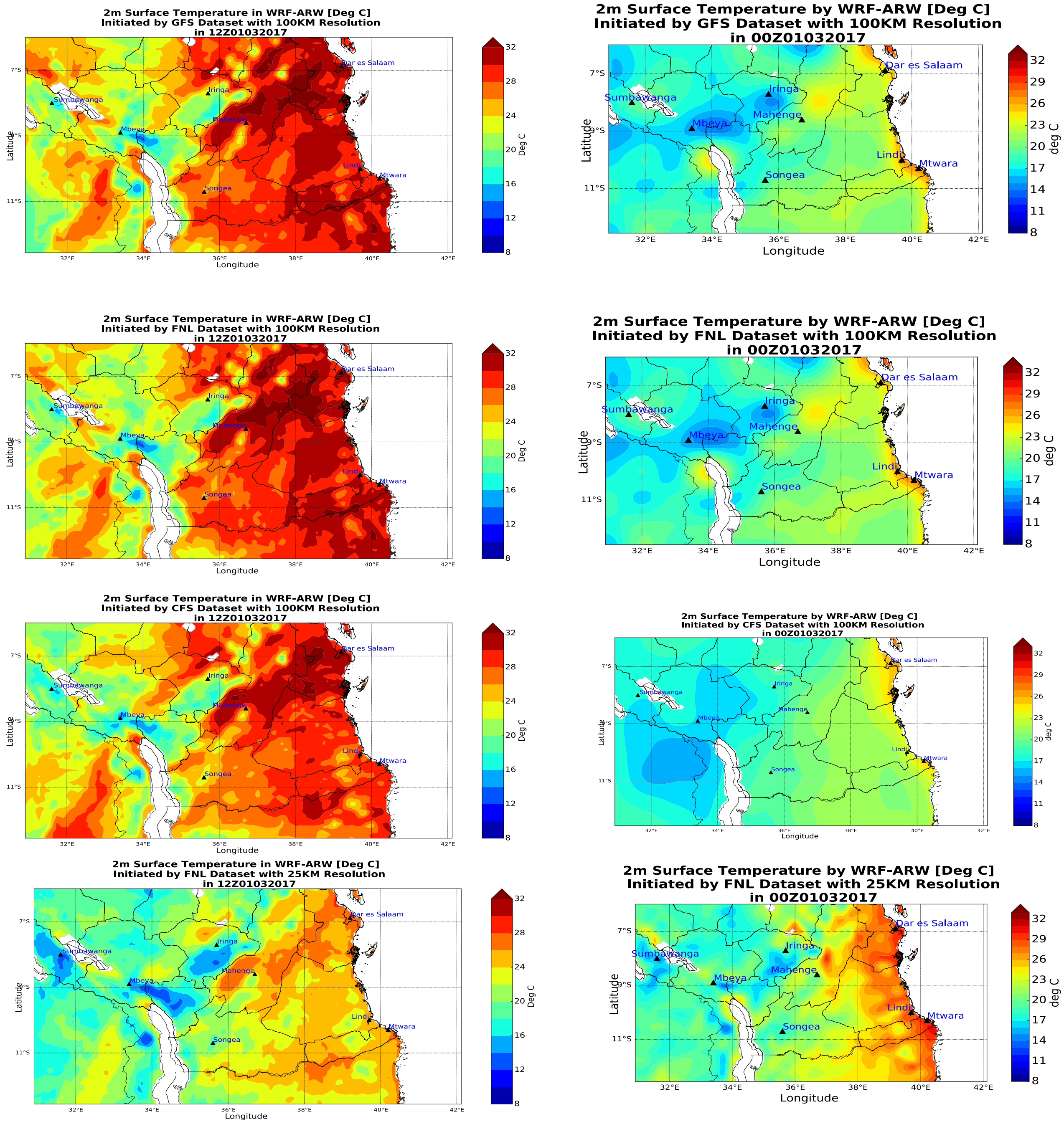
4.2 Maximum and minimum 2m surface temperature

The initial conditions for raw ensembles forecasts of temperature were also assessed to measure the influence of resolution in model accuracy forecasting.

Results in figure 4.3 below show maps for maximum (12Z01032017) and minimum (00Z01032017) temperature initiated by GFS_100KM, CFS_100KM and FNL_25KM resolution. Forecasts initiated by GFS, CFS and FNL with 100KM resolution show similar results in the maximum forecasts. The forecasts show high temperature around the coastal regions, with more than 30 ℃ in regions such as Dar es Salaam and part of Morogoro while other remaining parts of the regions ranging from 16 ℃ to 25 ℃. However, while vast coastal areas shows high temperature during the day the maps show low temperature around southern highlands with up to 16 ℃ at Mbeya region.

The GFS, CFS and FNL with 100KM resolution forecasts show similar results in the minimum forecasts, where areas around southern highlands have temperature ranging from 12 ℃ to 20 ℃. In the coastal areas the results show temperature ranging from 20 ℃ to 26 ℃.The spatial variability in initial condition and resolution used in weather forecast is portrayed by the results of FNL_25KM forecasts. The high resolution of the initial condition used helped the forecasts to provide detailed results. The results show the maximum temperature ranging from 23 ℃ to 30 ℃ around the coastal regions and 12 ℃ to 20 ℃ around Southern highlands.

Figure 4.3 2m surface temperature by WRF-ARW (Deg °C) at 00Z10032017



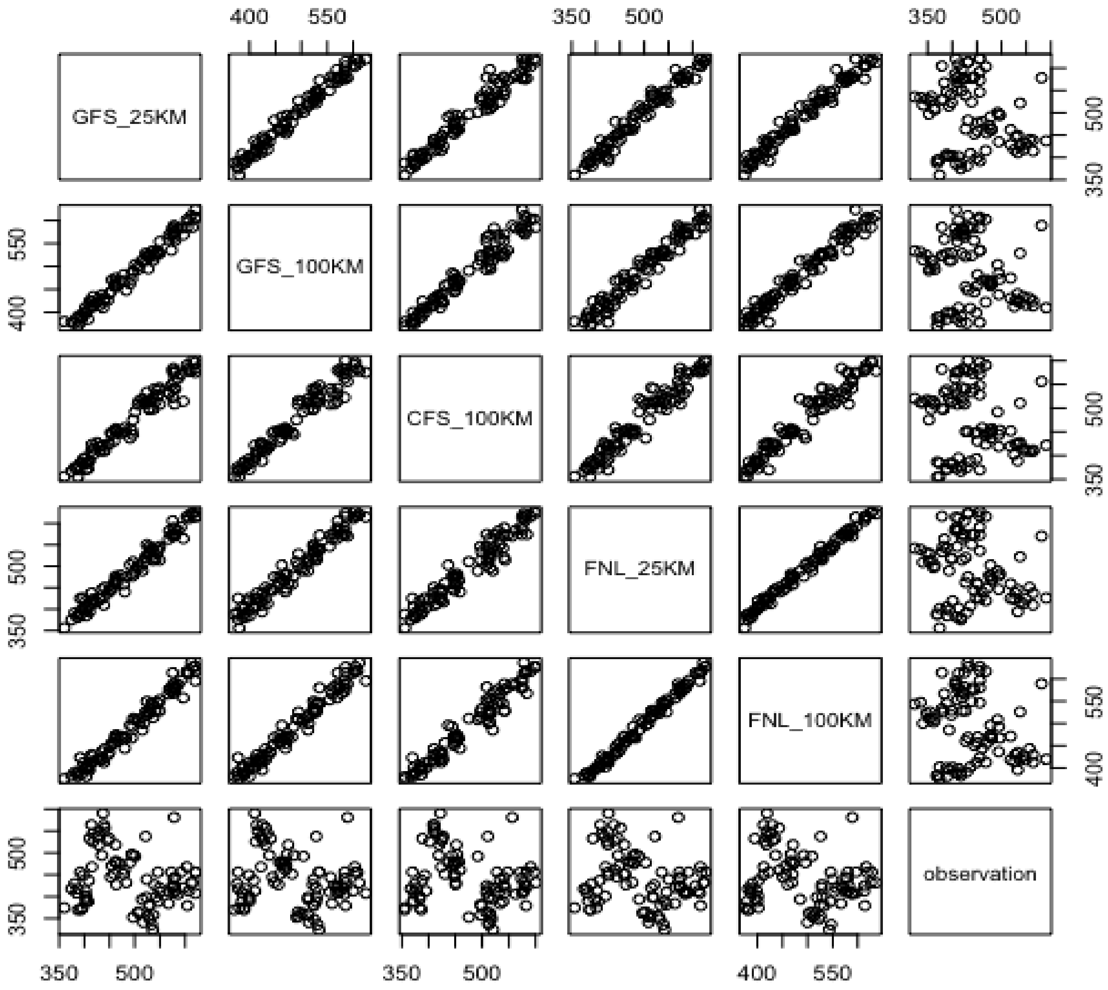
Source: Research findings (2018)

4.2.1 Temperature correlation between raw ensembles and observation

In order to assess the initial and boundary condition used, correlation plot was used to assess the relationship between the raw ensembles forecasts and observations.

Figure 4.4 presents the results of correlation, were the findings shows there is high correlation (90% and above) between raw ensembles forecasts and uniform distribution between raw ensembles forecasts and observation.

Figure 4.4 Correlation between raw ensembles and observation



Source: Research findings (2018)

4.3 Choice of Training Days

From the ensembles created the variables of interests (temperature and precipitations) were fitted using forecasts and observations data from a rolling training period. Where training data are used in the forecast on any given day, were N are the most recent days available. In standard, a longer training period moderates the statistical adaptability in the parameter estimation. Nonetheless, if a long training period is chosen the model losses adaptive to atmospheric changes.

In the study, the researcher computed the average continuous ranked probability score (CRPS) for the probabilistic forecasts and mean absolute error (MAE) of the deterministic forecasts in order to make conversant judgment about the length of the training period.

However, the number of days used in the experiment was 15 days, and the results of the CRPS and the MAE decrease (improve) as the length of the training period N increases up to 10 days, and thereafter they increase (deteriorate). Thus, the researcher used a training period of N = 10 days.

4.4 To evaluate the temperature forecast using Bayesian Model Averaging (BMA)

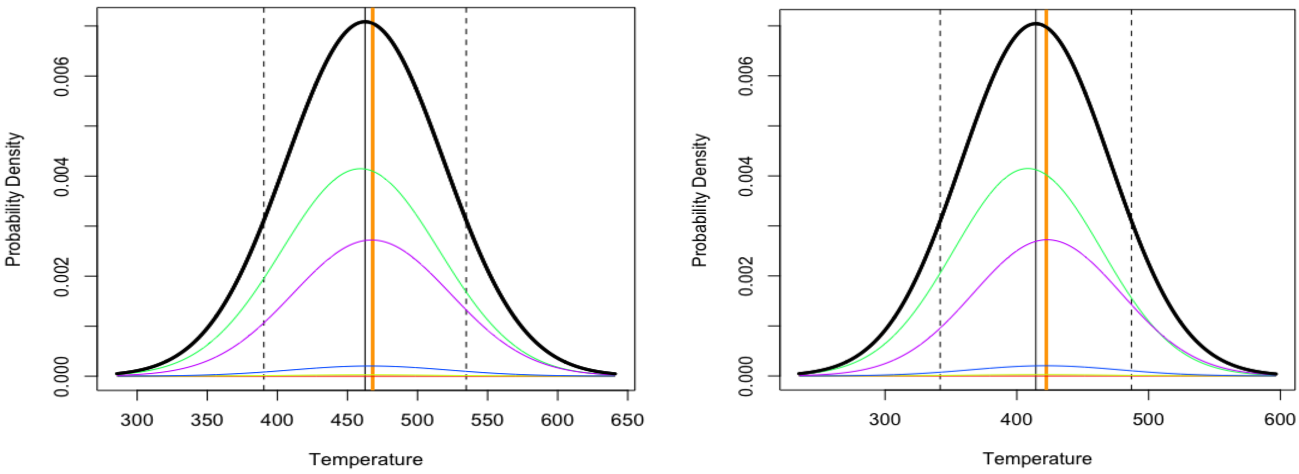
The researcher investigated the performance of Bayesian Model Averaging (BMA) method over raw ensembles on 2-meter surface temperature. The members of ensemble forecasts were created in the experiment using WRF-ARW from 00Z01032017 to 00Z15032017. While datasets from GFS, CFS and FNL were used while changing the initial and boundary conditions in order to created raw ensemble forecasts.

4.4.1 Sharpness of the predictive PDFs

In the study the researcher analyzed BMA by using the optimal lengths of 10 days as the training periods to estimate the parameters of ensembles and BMA predictive distributions for 2m temperatures. The parameters were comparedto assess the performances of raw ensembles and BMA post-processed forecasts using optimal training period lengths.

Figure 4.5 show the BMA predictive probability density function (PDFs), where the upper solid curve is the BMA PDF of the 2m surface temperature. The lower curves are the components of the BMA PDF, while the dashed vertical line represents the first and last deciles. Median forecast is presented by vertical black line and the solid vertical line (orange line) represents the verifying observation. Therefore, the sharpness of the predictive PDFs of the methods used is presented in the figure below.

Figure 4.5 BMA predictive distributions for temperature (in ℃) valid at March 10, 2017



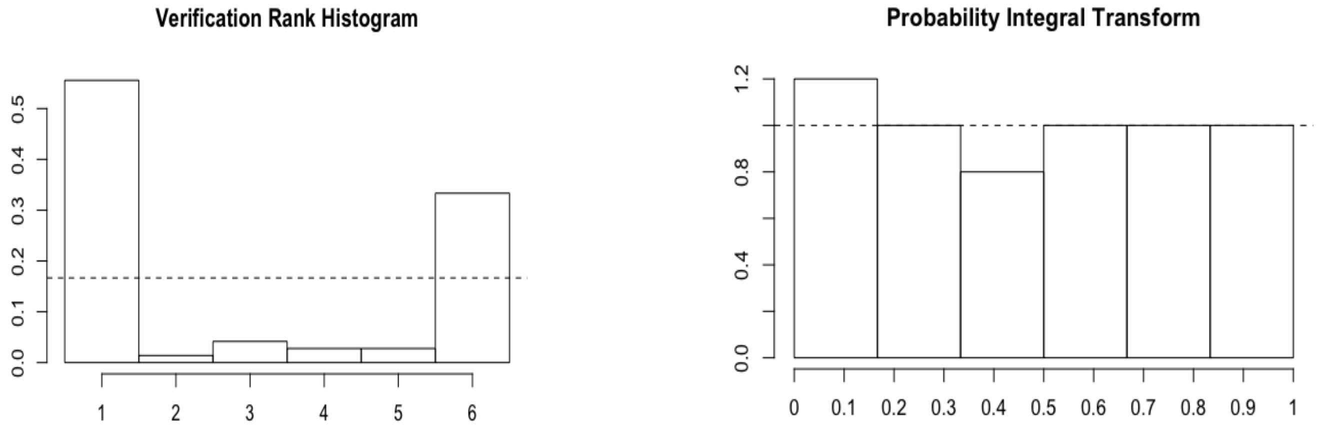
Source: Research findings (2018)

4.4.2 Calibration of the predictive PDFs

Figure 4.6 shows the verification rank histogram (VRH) for the raw ensembles forecasts and the probability integral transform (PIT) histogram for the ensembles forecastsdistributions which were used in maximizing the sharpness of the predictive density functions.

For the verification rank histogram, the u shape of the VRH indicates lack of calibration. It shows that the raw ensembles are under dispersed, since the verifying observations fall either above or below of the ensemble range. The PIT histogram for the post- processed BMA forecast on the other hand shows substantially better-calibrated results, reflected by a uniform distributed histogram.

Figure 4.6 Verification rank histogram for the raw ensemble forecast, and PIT for the BMA forecast distributions of 2m surface temperature



Source: Research findings (2018)

4.4.3 Assessing the predictive performance of raw ensembles and BMA

Table 4.3, presents method used in assessing the predictive performance of the postprocessing method of ensembles forecast. In the study the researcher compared the values of Brier Score for probability of precipitation forecasts, MAE and CRPS for quantitative precipitation forecasts of raw ensembles and BMA. In order to assesses the predictive performance of individual forecasts and BMA.

The findings shows that ensemble forecast had poor skill compared to BMA as the value of MAE for raw ensembles was higher (94.44) compared to that of BMA (43.72). Furthermore, the value of CRPS for ensembles (89.14) was highercompared to that of BMA (47.74) indicating poor performance of individual ensembles in forecasting. The values of BMA present good skill at both higher and lower thresholds,while raw ensembles showing poor skills (twice the value of BMA). Thus, a good skill of postprocessing methods indicates that BMA is the useful for identifying a risk of severe temperature anomalies.

Table 4.3 MAE and CRPS

	MAE	CRPS
Ensemble	94.44	89.14
BMA	43.72	47.74

Source: Research findings (2018)

4.5 Probabilistic forecasts of precipitation using Bayesian model averaging

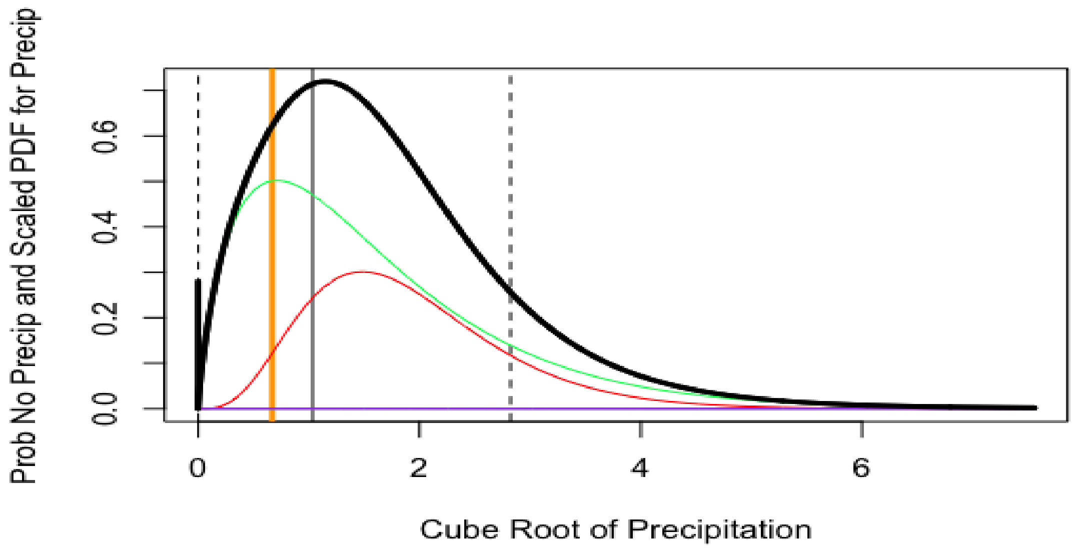
Bayesian Model Averaging as postprocessing method was applied to 48 hours forecasts of 24 hours precipitation accumulation in the SAGCOT regionon 10 March 2017, using the five ensembles members created in the study. In the forecast 6 stations and 15 days of observation data from TMA were used in each region located at SAGCOT regions.

In order to measure the predictive performance of raw ensembles and BMA forecasts

4.5.1 Sharpness of the predictive PDFs

Figure 4.7 show the BMA predictive probability density function (PDFs), where the thick vertical line at zero represents the BMA estimate of the probability of no precipitation (29%), the upper solid curve is the BMA PDF of the precipitation amount given that it is nonzero. The lower curves are the components of the BMA PDF, while the dashed vertical line represents the 90th percentile. Median forecast is presented by vertical black line and the solid vertical line (orange line) represents the verifying observation.

Figure 4.7 BMA-fitted PDFs for 10 March 2017



Source: Research findings (2018)

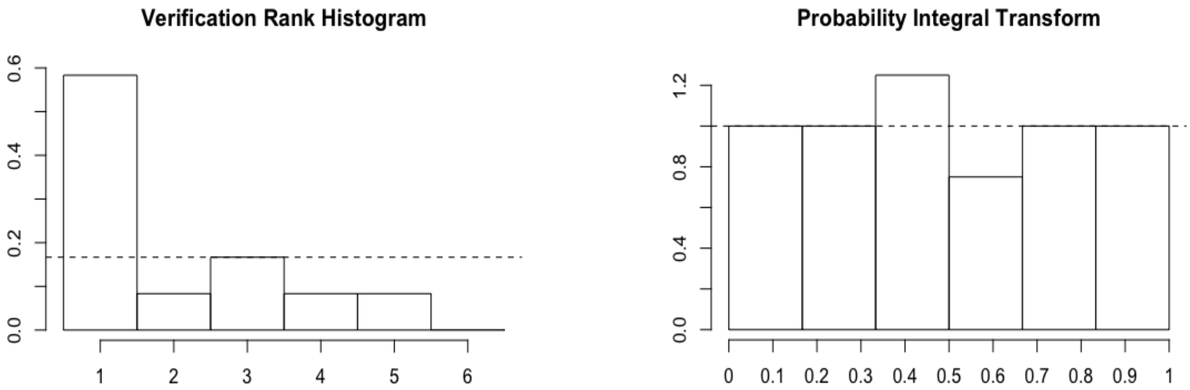
4.5.2 Calibration of the predictive PDFs

According to Gneiting et al. (2005), assessing forecasts of quantitative precipitation intends to maximize the sharpness of the predictive probability density function (PDFs) focused to calibration. Figure 4.8, shows the verification rank histogram (VRH) for the raw ensembles forecasts and the probability integral transform (PIT) histogram for the ensembles forecasts distributions.

For the verification rank histogram, there were incidences where the observed value was zero (no precipitation), and one or more forecasts were also zero. To find a rank in these situations, the observation rank was randomly selected between zero and the number of forecasts equal to zero. In order to calculate the values for the PIT histogram, the BMA cumulative distribution function was evaluated at its corresponding observation. In the case of an observation of zero, a value was randomly drawn between zero and the probability of no precipitation.

The histogram for the raw ensembles forecasts shows lack of calibration. Precisely, it shows that the raw ensembles are under dispersed, that is, too many observations fall out of the ensemble range. The PIT histogram for the post- processed BMA forecast on the other hand shows substantially calibrated results, reflected by a homogeneously distribution of the histogram.

Figure 4.8 Verification rank histogram for the raw ensemble forecast, and PIT for the BMA forecast distributions of precipitation accumulation



Source: Research findings (2018)

4.5.3 Assessing the predictive performance of raw ensembles and BMA

Table 4.4 show methods used in assessing the predictive performance of the postprocessing methods of ensembles forecasts. In the study the researcher compared the values of Brier Score for probability of precipitation forecasts, MAE and CRPS for quantitative precipitation forecasts of raw ensembles and BMA. In order to assesses the predictive performance of individual forecasts and BMA method while all values were measured in millimeters.

The findings shows that ensemble forecast had poor skill compared to BMA as the value of MAE for raw ensembles was higher (12.7) compared to that of BMA (6.3). Furthermore, the value of CRPS for ensembles (10.82) was highercompared to that of BMA (4.84) indicating poor performance of individual ensembles in forecasting. The result further shows the values of brier score at different thresholds. The values of BMA present good skill at both higher and lower thresholds,while raw ensembles showing poor skills (twice the value of BMA). Thus, a good skill of postprocessing methods indicates that BMA is the useful method for identifying a risk of severe precipitation occurrences.

Table 4.4 Brier scores (BS), and MAE and CRPS

	Thresholds	climatology	ensemble	logistic	bma
MAE		11.9	12.71	6.32	
CPRS			10.82		4.84
BS	0.0	0.24	0.41	0.24	0.26
BS	0.1	0.24	0.43	0.24	0.26
BS	0.2	0.25	0.47	0.25	0.27
BS	0.3	0.25	0.55	0.24	0.28
BS	0.4	0.25	0.54	0.24	0.28
BS	0.5	0.25	0.54	0.24	0.27

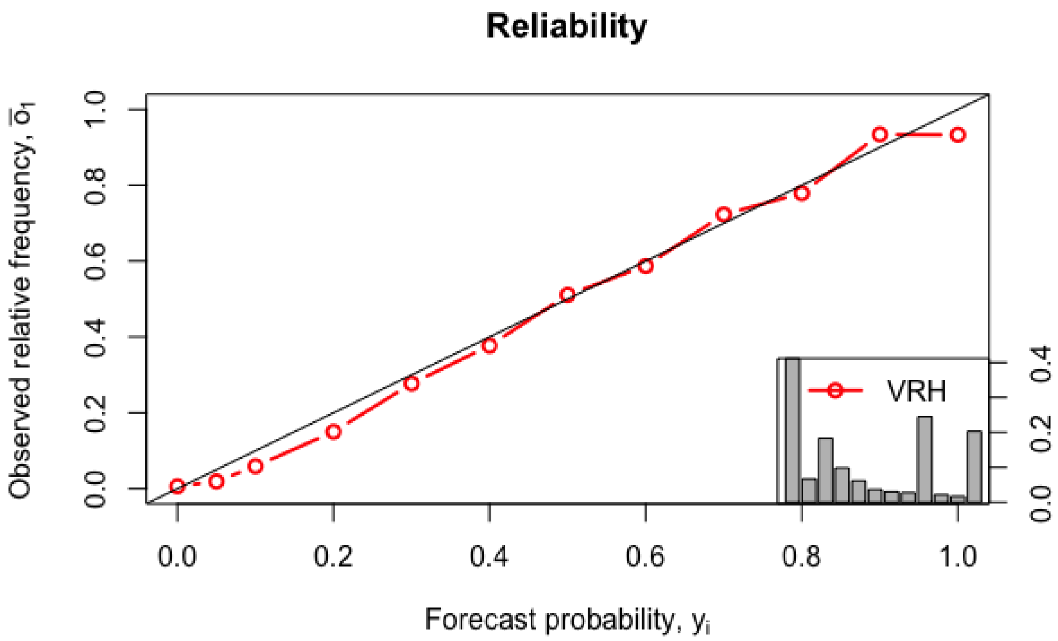
Source: Research findings, (2018)

4.5.4 Reliability of the forecasts

Reliability diagrams provide further knowledge by evaluating how closely the forecast probabilities of an event resemble to the actual chance of observing the event.

The results of the study in the figure 4.9 show that the reliability curves have positive slope, representing that as the forecast probability of the event occurring increases, so too does the verified chance of observing the event. The forecasts therefore have some reliability. However, the slope is less than the diagonal, indicating less than perfect reliability. When an upper-quintile precipitation category has a forecast probability equal to 65% the actual chance of observing the event is closer to 60%.The knowledge comprised from reliability diagrams may therefore be used to create estimated adjustments to the forecast probabilities displayed in the forecast maps.

Figure 4.9 Reliability diagram



Source: Research findings (2018)

4.6 Discussion of findings

This section provides the researcher's discussions concerning the major findings of the study.

4.6.1 Probabilistic Forecasts of temperature using Bayesian model Averaging

Forthe postprocessed ensemble forecasts, the researcher applied BMA model to calibrate the probabilistic forecasts of surface temperature as similar studies have suggestedSoltanzadeh et. al.,(2011),Gneiting, (2011),Chmielecki & Raftery, (2010).

However, the findings of BMA model were evaluated to assess the calibration.In that process researcher adopt VRH and PIT asRafter et al., (2005) argued that probabilistic forecasts can be assessed by using Verification Ranked Histogram (VRH) and Probability Integral Transform.

Figure 4.6 shows a comparison between the two methods used to assess the calibration of probabilistic forecasts. The U-shape in the distribution of VRF indicated that raw ensembles were uncalibratedwhile the distribution of PIT histograms showed uniform distribution indicating BMA forecast was calibrated. Therefore, the results showed that, postprocessed ensemble forecasts produces better and calibrated results which can be used to estimate the future events of the weather parameters These results presented similar findings as Callado et. al., (2013),Gneiting et. al., (2005),Fraley & Raftery, (2010), Berrocal et. al., (2007)and Fraley et. al., (2011).

Moreover, MAE and CRPS were used to verify the probabilistic forecasts of temperature. The decrease in the value of MAE and CRPS between raw ensemble and Bayesian model averaging in the table 4.3 quantify the advantage of postprocessing in temperature forecasting. The decrease in the valueof MAE and CRPS is the indicator of good performance of the BMA model. Toth and Kalnay, (1997); Baran et. al., (2014) presented similar findings that BMA forecasts produces stable and reliable forecasts compared to raw ensemble.

4.6.2 Probabilistic precipitation Forecasts using Bayesian model Averaging

In the study BMA was also used to assess the predictive PDFs of precipitation forecasts. Where measures were taken to evaluate the predictive capability of the BMA (calibration) compared to the individual ensemble forecasts.This approach is supported by other researchers (Hamill, et.al., 1997, 2004; Chmielecki & Raftery, 2005 and Sloughter et. al., 2007) how have demonstrated the use of statistical postprocesing in producing precipitation forecasts.

Figure 4.8 shows the comparison between PIT and VRH diagrams, which were used to evaluate the sharpness and calibration of the post processed ensemble forecast. The PIT diagram showed more consistent and uniform distribution compared to histograms for VRH diagram. These findings present similar findings as Berrocal, et. al., (2007), Hamill, et. al., (2004), Hamill & Colucci, (1997) and Moller, (2014) have observed the post processed forecasts produces better results compared to raw ensembles.

But also, MAE and CRPS and Brier Score were used to verify the postprocessed ensemble forecast of precipitation. Table 4.4 show BMA outperform raw ensemble and climatological output by producing lower value of MAE and CRPS. These finds are supported by other researchers (Sloughter, et. al., 2007; Gneiting, et. al., 2007; Berrocal, et. al., 2007) were postprocessed forecasts were able to capture more uncertainty of the future forecasts compared to individual and climatological output.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5. 0 Introduction

This chapter is divided into three parts which provide summary of the study findings, conclusion and recommendation on the probabilistic weather forecasting using Bayesian model averaging.

5.1 Summary

The main objective of the study was to evaluate probabilistic weather forecasting using Bayesian model averaging. The probabilistic forecasts were carried out at Southern Agriculture Growth Corridor of Tanzania (SAGCOT) regions namely; Morogoro, Iringa, Mbeya, Rukwa and Ruvuma.

The experiment was set up in a manner that it could be used in real time operations. The BMA was trained on current attainments of the forecast residuals, and then applied to the successive forecasts in the 15 days test period. Based on the results of the experiments, 10 days gap was chosen as the training period for temperature and precipitation datasets. The results of the study showed the contribution of probabilistic weather forecasting by producing accurate, sharpness, skilled and consistent results compared to deterministic forecasts.

5.2 Conclusion

The study was carried out to evaluate the probabilistic weather forecasting using Bayesian model averaging. In this chapter conclusion are based on the research objectives and results of the study.

The findings shows initial condition resolution and boundary conditions have impact on the forecasts outcome. In the study different initial conditions were analyzed and the findings show high resolution present more details or information on a particular geographical location (domain) on the forecast compared to low resolution. Thus high-resolution initial conditions are more appropriate, as they reflect the observation compared to low resolution initial conditions.

Furthermore, BMA statistical postprocessing method was used to evaluate the probabilistic forecasts of temperature and precipitation. The findings shows BMA method successively removes most of underdisersion showed by raw ensembles. Thus, calibrated and sharp results of BMA approach resolves a number of the weaknesses of the ensemble forecasts including their underdispersion and the discrepancy between forecasts and observations. Therefore BMA can be used to attain higher consistency in the probabilistic forecasts of an operational model.

5.3 Recommendation

This dissertation covers multidisciplinary studies ranging from mathematical modeling, science of meteorology to statistical analysis. Therefore the study suggest that mathematical, meteorology and statistical communities they should collaborate to design a reliable and stable statistical prost processing model which can be used to provide more reliable forecasts, as the findings has shown BMA produced better forecasts compared to deterministic forecasts.

Furthermore, in order to understand the potential of probabilistic weather forecasting, the data from whole country should be used in the experiment to understand the predictive distribution of the parameters compared to observation.

5.4 Policy implication of the study

- **Stakeholders and other NGOs**

The study urges that, policy makers and other stakeholders such as Government, NGOs and private sectors who are dealing with weather forecasting to take consideration in the adoption of Probabilistic Weather Forecasts (PWF) approach. The PWF techniques ensure calibrated and sharp forecasts which resolves a number of the weaknesses of the deterministic forecasts including; underdispersion and the discrepancy.

5.5 Limitation of the study

- **Resource for Weather Modeling**

In the study WRF-ARW was used during modeling of weather forecasts, where the researcher faced the challenges of shortage of computation power. The process of weather forecasting requires modern computer with high number of processor. Also, modeling process required massive storage of the data resulting from large files of initial conditions and the NetCDF output file, as the whole study used more than 4 Terabytes.

- **Setting of ensembles forecasts**

The process of creating ensembles forecasts was among the challenges that the researcher faced during the study. The process of forecasting 15 days when using WRF-ARW model and GSF datasets with 25km resolution as initial condition uses 23 hours in Macbook Pro 2011, core i5 with 500GB hard disc. Thus, creating 6 members of ensembles and interpolation of the datasets required time and online tutorial on weather forecasting knowledge.

- **Programming languages**

Poor programming skills were the main challenge during the study. Programming language were necessary during the study as WRF-ARW model for weather were command based oriented. Python and bash were the main language necessary for communicating with WRF-ARW output file (NetCDF). Furthermore, interpolation of the output also required programming skills.

5.6Area for further research

The main objective of the study was to evaluate the probabilistic weather forecast using Bayesian model averaging in order to provide a stable and reliable weather forecasts. But in order to flourish agricultural sector, stable and reliable weather forecasts alone are not enough. Reliable and stable weather information provide awareness to famers when to plant, but do not provide information on what to plant. Thus, the researcher suggests other studies should be conducted on the integration of soil properties and probabilistic weather forecasting using Bayesian model. The finding will solve the questions of when to plant and what to plant at the same time.

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APPENDIX

Python script used to create Domain of the study

```
#!/usr/bin/python
# coding: utf8
from __future__ import unicode_literals
import numpy as np

import sys,getopt
from netCDF4 import Dataset  # we dont have this library. use scipy instead
#from scipy.io import netcdf
import matplotlib
#matplotlib.use('Agg')          #required for the CRON job. Says, "do not open plot in a window"??
import matplotlib.pyplot as plt
import numpy as np
import os
from datetime import datetime, timedelta
from mpl_toolkits.basemap import Basemap, maskoceans
from matplotlib.colors import LinearSegmentedColormap
from mpl_toolkits.axes_grid1 import make_axes_locatable
import matplotlib.axes as maxes
import linecache
import matplotlib as mpl

fig = plt.figure()
ax = fig.add_subplot(111)
mpl.rcParams[u'figure.figsize'] = [10, 8]
mpl.rcParams[u'figure.dpi'] = 600

params = {'axes.labelsize': 20,
'text.fontsize': 20,
'legend.fontsize': 20,
```

```
'xtick.labelsize': 20,
'ytick.labelsize': 20,
'text.usetex': False,
'font.size':20}
plt.rcParams.update(params)

### Get Domain 1 WPS directory
file_name =
('/media/nzape/520AAE5F0AAE3FB9/MZUMBE/WRF_GFS25KM/wrfout_d01_2017-03-01_00:00:00')
cdf = Dataset(file_name,'r')
print cdf.variables
height = cdf.variables['HGT'][0,:,:]
landmask = cdf.variables['LANDMASK'][0,:,:]
height = height.copy()
ter_lat = cdf.variables['XLAT'][0]
ter_lat = ter_lat.copy()
ter_lon = cdf.variables['XLONG'][0]
ter_lon = ter_lon.copy()
cdf.close()
# Set water area to -99 in height variable. This will make it blue
height[landmask==0] = -99

## Full_domain
bot_left_lat  = ter_lat[0][0]
bot_left_lon  = ter_lon[0][0]
top_right_lat = ter_lat[-1][-1]
top_right_lon = ter_lon[-1][-1]

#scale figure size to bigger image
N = 2
params = plt.gcf()
```

```
plSize = params.get_size_inches()
params.set_size_inches((plSize[0]*N, plSize[1]*N))

print bot_left_lat , bot_left_lon, top_right_lat, top_right_lon
MP = 'merc'

#if MP == 'merc':
   ## Map in cylindrical projection (data points may apear skewed)
#m = Basemap(projection='merc',lat_0=-5.990005,lon_0=35.978,resolution='h',area_thresh=0.1,26, llcrnrlat=-14,urcrnrlon=46, urcrnrlat=3)
m = Basemap(resolution='f', # c, l, i, h, f or None
projection='merc',lat_0=-5.0, lon_0=-36, area_thresh=1000,llcrnrlon=26, llcrnrlat=-14,urcrnrlon=44, urcrnrlat=2)

# This sets the standard grid point structure at full resolution
# Converts WRF lat and long to the maps x an y coordinate
ter_x,ter_y = m(ter_lon,ter_lat)

# Turn ocean points to a really low number so we can plot it as blue, not green
masked_height = maskoceans(ter_x,ter_y,height,inlands=False,resolution='l')
masked_height.data[masked_height.data==0]=-99
m.drawstates(color='k', linewidth=.8)
m.drawcoastlines(color='k')
m.drawcountries(color='k', linewidth=1.25)
m.bluemarble()

#Plot Domain 1 Box
m.drawgreatcircle(ter_lon[0,0], ter_lat[0,0],ter_lon[0,-1], ter_lat[0,-1], color='r', linewidth='4')
m.drawgreatcircle(ter_lon[-1,0], ter_lat[-1,0],ter_lon[-1,-1], ter_lat[-1,-1], color='r', linewidth='4')
```

```
m.drawgreatcircle(ter_lon[0,0], ter_lat[0,0],ter_lon[-1,0],ter_lat[-1,0], color='r', linewidth='4')
m.drawgreatcircle(ter_lon[0,-1], ter_lat[0,-1],ter_lon[-1,-1], ter_lat[-1,-1], color='r', linewidth='4')

#m.fillcontinents(color='#f2f2f2',lake_color='#46bcec')
#m.drawmapboundary(fill_color='#46bcec')
m.drawcoastlines()
m.drawparallels(np.arange(-40,50,20), labels=[1,0,0,0], linewidth=0.1,fontsize=14)
m.drawmeridians(np.arange(-20,90,20), labels=[0,0,0,1] ,linewidth=0.1,fontsize=14)

ax.set_xlabel('Longitude ',labelpad=20)
ax.set_ylabel('Latitude ',labelpad=20)
print 'saving'
plt.savefig('best_single_domains11.pdf',bbox_inches='tight')
plt.show()
print ""
```

1. Python script used to save temperature data from WRF-ARW output (NetCDF file)

```
#!/usr/bin/python
# coding: utf8
from scipy.interpolate import interp1d
import numpy as np
import matplotlib.pyplot as plt
from netCDF4 import Dataset
from pylab import*
import sys,os

params = {'axes.labelsize': 14,
'text.fontsize': 14,
'legend.fontsize': 14,
'xtick.labelsize': 14,
'ytick.labelsize': 14,
'text.usetex': False,
'font.size':14}
plt.rcParams.update(params)

#jnia = {'name': 'MWANZA, TZ', 'lat': -2.50, 'lon': 32.90}
#jnia = {'name': 'BUKOBA, TZ', 'lat':-1.30, 'lon': 31.80}
#jnia = {'name': 'MUSOMA, TZ', 'lat': -1.5, 'lon': 33.8}
#jnia= {'name':  'KIGOMA, TZ', 'lat': -4.90, 'lon': 29.60}
#jnia = {'name': 'TABORA, TZ', 'lat': -5.08, 'lon': 32.83}
#jnia = {'name': 'SAME, TZ', 'lat': -4.10, 'lon': 37.70}
jnia = {'name': 'SUMBA, TZ', 'lat': -8.00, 'lon': 31.60}
#jnia= {'name':  'DODOMA, TZ', 'lat': -6.20, 'lon': 35.80}
#jnia = {'name': 'HANDENI, TZ', 'lat': -5.40, 'lon': 38.00}
#jnia = {'name': 'MOSHI, TZ', 'lat': -3.35, 'lon': 37.33}
#jnia = {'name': 'ARUSHA, TZ', 'lat': -3.40, 'lon': 36.60}
```

```
#jnia = {'name': 'JNIA, TZ', 'lat': -6.87, 'lon': 39.20}
#jnia = {'name': 'MAHENGE, TZ', 'lat': -8.60, 'lon': 36.70}
#jnia = {'name': 'MBEYA, TZ', 'lat': -8.90, 'lon': 33.40}
#jnia = {'name': 'IRINGA, TZ', 'lat': -7.70, 'lon': 35.70}
#jnia = {'name': 'SONGEA, TZ', 'lat': -10.68, 'lon': 35.58}
#jnia = {'name': 'MTWARA, TZ', 'lat': -10.30, 'lon': 40.20}
#jnia = {'name': 'LINDI, TZ', 'lat': -10.00, 'lon': 39.70}
#jnia = {'name': 'ZANZIBAR, TZ', 'lat': -6.10, 'lon': 39.20}
#jnia = {'name': 'PEMBA, TZ', 'lat': -5.07, 'lon': 39.72}
#jnia = {'name': 'SHY, TZ', 'lat': -3.5, 'lon': 33.40}
#jnia = {'name': 'KAHAMA, TZ', 'lat': -3.84, 'lon': 32.56}
#jnia = {'name': 'MOROGORO, TZ', 'lat': -6.90, 'lon': 37.70}

print "EXTRACTING DATA AT THE GIVEN LONGITUDE AND LATITUDE"

f = Dataset('/home/joel/WRF/mzumbe/MZUMBE/CFS100KM/wrfout_d01_2017-
03-01_00:00:00', 'r')
time = f.variables['Times'][:,0]
lons = f.variables['XLONG'][0,0,:]
lats = f.variables['XLAT'][0,:,0]
#stemps =
np.subtract(np.add(f.variables['T2'][:],6.5*f.variables['HGT'][:]/1000.),273.15)
#stemps = np.add(f.variables['RAINNC'],f.variables['RAINC'])
#stemps = np.divide(f.variables['PSFC'],100)
#stemps =
f.variables['PSFC'][:,:,:]*np.exp(9.81/(287.0*f.variables['T2'][:,:,:])*f.variables['HGT
'][:,:,:])*0.01 + (6.7*f.variables['HGT'][:,:,:]/1000.)
stemps = np.subtract(f.variables['T2'],273.15)
f.close()
y= np.abs(lats - jnia['lat']).argmin()
x = np.abs(lons -jnia['lon']).argmin()
p = zeros(stemps.shape[0])                    #Copying data only for points x and y
```

```
p = stemps[:,y,x]

print y, x
length = len(time)
print p



import csv
os.system("/bin/rm -f Sumbawanga_tem.csv")
with open('Sumbawanga_tem.csv', 'w') as fl:
        writer = csv.writer(fl, delimiter='\t')
        writer.writerows(zip(p))

sys.stdout.close()
```

2. Python script used to save precipitation data from WRF-ARW output (NetCDF file)

```
#!/usr/bin/env python
# coding: utf8
#from __future__ import print_function
#from Scientific.IO.NetCDF import NetCDFFile as Dataset
import numpy as np
from scipy.io import netcdf

#from netCDF4 import MFDataset

#from netCDF4 import MFDataset
jnia = {'name': 'SUMBA, TZ', 'lat': -8.00, 'lon': 31.60}
jnia = {'name': 'MAHENGE, TZ', 'lat': -8.60, 'lon': 36.70}
jnia = {'name': 'MBEYA, TZ', 'lat': -8.90, 'lon': 33.40}
jnia = {'name': 'IRINGA, TZ', 'lat': -7.70, 'lon': 35.70}
jnia = {'name': 'SONGEA, TZ', 'lat': -10.68, 'lon': 35.58}
jnia = {'name': 'MOROGORO, TZ', 'lat': -6.90, 'lon': 37.70}

#os.chdir('/media/gribmap/New Volume/2015/May_2015')

f=netcdf.netcdf_file("/home/host/WRF/DATA/DOMAINS/pwani/wrfout25KM_d01
_2017-11-06_06:00:00","r")

#f = MFDataset(['/media/gribmap/New Volume/2015/May_2015/wrfout_d01_2015-
05-03_06%3A00%3A00_237','/media/gribmap/New
Volume/2015/May_2015/wrfout_d01_2015-05-03_06%3A00%3A00_832'])

#print f.variables
sfcRain = np.add(f.variables['RAINNC'][:,:,:],f.variables['RAINC'][:,:,:])
lons = f.variables['XLONG'][0,0,:]
lats = f.variables['XLAT'][0,:,0]
```

```
y= np.abs(lats - jnia['lat']).argmin()
x = np.abs(lons -jnia['lon']).argmin()
data = np.zeros(sfcRain.shape[0])                    #Copying data only for points x and y
data = sfcRain[:,y,x]


length = len(data)



#*****************************************
# Write text file
#*****************************************

filename = "MORO_.txt"

# Open the file
fd = open(filename, "w")



for i in np.arange(length):

        if i==0:
                prev_total = data[i]
        else:
                prev_total = data[i-1]

        total_accum = data[i]

        prec_tend = total_accum - prev_total

        #print "%i\t%6.1f" % (i, prec_tend)
```

```
        # Write values in file

        fd.write("%i\t%.2f\n" % (i, prec_tend))

# Close file
fd.close()
```

3. Python script used to plot precipitation from WRF-ARW output (NetCDF file)

```
#!/usr/bin/python
# coding: utf8

from __future__ import unicode_literals

from matplotlib import pyplot as plt
from mpl_toolkits import basemap
from mpl_toolkits.basemap import Basemap, cm
#from Scientific.IO.NetCDF import NetCDFFile as Dataset
from netCDF4 import Dataset
import pylab
import numpy as np
import sys,getopt,os
import matplotlib as mpl
from datetime import datetime
import matplotlib
#matplotlib.use('agg')
from matplotlib.colors import LinearSegmentedColormap
from mpl_toolkits.axes_grid import make_axes_locatable
import matplotlib.axes as maxes
from datetime import datetime, timedelta
```

```
fig = plt.figure()
ax = fig.add_subplot(111)
mpl.rcParams[u'figure.figsize'] = [10, 8]
mpl.rcParams[u'figure.dpi'] = 600
params = {'axes.labelsize': 24,
'text.fontsize': 24,
'legend.fontsize': 24,
'xtick.labelsize': 24,
'ytick.labelsize': 24,
'text.usetex': False,
'font.size':24}
plt.rcParams.update(params)
# Set the default domain to be d02
dom = 'd01_10KM'
var = 'all'
export_flag = 0
restart_time = 0


# Open dataset
f = Dataset('/home/joel/WRF/mzumbe/MZUMBE/WRF100KM/wrfout_d01_2017-
03-01_00:00:00','r')

# Printing variables

print ' '
print ' '
print '----------------------------------------------------------'
for i,variable in enumerate(f.variables):
        print '   '+str(i),variable
        if i == 60:
                current_variable = variable
```

```
#         if i==112:
#                     current_variable = variable
print ' '
print 'Variable: ', current_variable.upper()
#print 'File name:  ', f

#scale figure size to bigger image
N = 2
params = plt.gcf()
plSize = params.get_size_inches()
params.set_size_inches((plSize[0]*N, plSize[1]*N))

# Extract data
lon = f.variables['XLONG'][0,0,:]
lat = f.variables['XLAT'][0,:,0]
#T = np.add(f.variables['RAINNC'][360,:,:],f.variables['RAINC'][360,:,:])-
np.add(f.variables['RAINNC'][240,:,:],f.variables['RAINC'][240,:,:])
T=np.add(f.variables['RAINNC'][120,:,:],f.variables['RAINC'][120,:,:])
landmask = f.variables['LANDMASK'][0].copy()
# I like to set the water points to a negative elevation so that the color
# map will plot the water as blue
times = f.variables['Times']
data = f.variables['U10']
T[landmask==0] = -99
print lat.max()

latidx=(lat>-11.0) & (lat<-3)
lonidx=(lon>36.0) & (lon<=43)

m=Basemap(projection='merc',lat_0=-
5.457,lon_0=35.62,resolution='h',area_thresh=0.1,llcrnrlon=lon.min()+0.2,
llcrnrlat=lat.min()+0.3,urcrnrlon=lon.max(), urcrnrlat=lat.max())
```

```
m.drawcoastlines(color='0.15')
#m.drawlsmask(land_color='#00441b',ocean_color='#8be5e5',lakes=True)
m.drawstates()
m.drawcountries()
m.drawparallels(np.arange(-13,2,2), labels=[1,0,0,0], color="black",
linewidth=0.2,fontsize=14)
m.drawmeridians(np.arange(28,46,2), labels=[0,0,0,1],
color="black",linewidth=0.2,fontsize=14)
m.drawmapboundary(fill_color='#46bcec')
m.readshapefile('/home/joel/WRF/Shapefiles/TANZANIA', 'areas')
ax.set_xlabel('Longitude ',labelpad=25)
ax.set_ylabel('Latitude ',labelpad=25)

lons = [ 31.60, 35.80, 39.20, 36.70, 33.40, 35.70, 35.60, 40.20, 39.70]
lats = [ -8.00, -6.20,-6.87,  -8.60, -8.90, -7.70, -10.70, -10.30, -10.00]
names = ["Sumbawanga","Dodoma","Dar es
Salaam","Mahenge","Mbeya","Iringa","Songea","Mtwara","Lindi"]

x, y = m(lons, lats)
m.plot(x, y, '^', color='k',markersize=10)

for i in range(len(names)):
print i
if i<1:
plt.text(x[i]+150000, y[i],
names[i],fontsize=17,fontweight='normal',ha='right',va='bottom',color='blue')
elif i==2:
plt.text(x[i]-150, y[i],
names[i],fontsize=17,fontweight='normal',ha='right',va='bottom',color='blue')
elif i>6:
plt.text(x[i]-150, y[i]+50,
names[i],fontsize=17,fontweight='normal',ha='right',va='bottom',color='blue')
```

```
else:
plt.text(x[i]+1000, y[i]+10,
names[i],fontsize=17,fontweight='normal',ha='left',va='bottom',color='blue')

for time in range(len(data[:,0,0])):
        timestr = ''.join(times[time])
        wrf_time = datetime.strptime(timestr,'%Y-%m-%d_%H:%M:%S')
        print wrf_time

def makePlot(field, lat, lon):
        # this function makes a lat/lon plot of given field
        #    plt.figure(figsize=[14,6])



        field,lon = basemap.addcyclic(field,lon)
        #field,lon = basemap.shiftgrid(180,field,lon,start=False)

        lon,lat = np.meshgrid(lon,lat)
        x,y = m(lon,lat)
        # Colorbar with EA Precip colors  #white #fdfdfd ,red #bc0000
        tz_precip_colors = [
        "#fdfdfd",  # 0 - 0.5 mm
           "#fd9500",  # 0.5 - 8 mm
           "#e5bc00",  # 8 - 16 mm
           "#fdf802",  # 16- 24 mm
           "#01c501",  # 24 -32 mm
           "#008e00",  # 32 -40 mm
           "#9854c6",  # 40 -50 mm
           "#bc0000",  # 50 -60 mm
           "#0300f4",  # 60+
      ]
        PCP_LEVELS = [0.0,25,50,75,100,125,150,175,200,225]
```

```
precip_colormap = matplotlib.colors.ListedColormap(tz_precip_colors)

        norm = matplotlib.colors.BoundaryNorm(PCP_LEVELS, 9)
        PRECIP=plt.contourf(x,y,field,PCP_LEVELS,cmap=precip_colormap,norm=
norm,extend='max')
                #cbar=m.colorbar(cf,location='bottom',pad="7%").set_label('deg C')
        cbar=m.colorbar(PRECIP,location='right',pad="7%").set_label('mm/5days')
    #PCP_LEVELS = [0.0,25,50,75,100,125,150,175,200,225]
    #precip_colormap = matplotlib.colors.ListedColormap(tz_precip_colors)

        #norm = matplotlib.colors.BoundaryNorm(PCP_LEVELS, 9)
        #PRECIP=plt.contourf(x,y,field,PCP_LEVELS,cmap=precip_colormap,norm
=norm,extend='max')
                #cbar=m.colorbar(cf,location='bottom',pad="7%").set_label('deg C')
        #cbar=m.colorbar(PRECIP,location='right',pad="7%").set_label('mm/5days')

        #plt.title('Rainfall [mm] at SAGCOT REGIONS \nWRF-DA March 05-10,
2017 00:00z',
    #  fontsize=24,bbox=dict(facecolor='white', alpha=0.65),\
        #x=0.5,y=1.0,weight = 'normal',style='oblique', stretch='normal',
family='sans-serif')
        #plt.title('24hrs Accumulated WRF-ARW rainfall [mm]\n Initiated by GFS
dataset with 50KM resolution.\n')
        plt.title('5 Days Accumulated WRF-ARW Rainfall [mm]\n Initiated by FNL
Dataset with 100KM Resolution\n from 00Z01032017-00Z05032017\n')
        file_id = '%s_f%02d' % (dom, restart_time)
        filename = '%s_first_FIVE_DAYS_FNL.pdf' % (file_id)
        plt.savefig(filename,bbox_inches='tight') # Saves the figure with small
margins
        #plt.xlabel('Average fot 3 days from 18-12-2011 to 21-12-2011',fontsize=14)

        #if export_flag == 1:
```

```
#	os.system('convert -render -flatten %s %s.gif' % (filename, file_id))
#(26 AWS)
#	os.system('rm -f %s' % filename)

makePlot(T,lat,lon)

plt.show()
plt.close()
```

Packages required

```
library(“ensembleBMA”)
library(“chron”)
library(“fields”)
library(“spam”)
library(“dotCall64”)
library(“grid”)
library(“maps”)
library(“proxy”)
library(“dtw”)
library(“MASS”)
library(“boot”)
library(“CircStats”)
```

R script used for objective 1

iv. **To evaluate probability forecasts of temperature using Bayesian model averaging**

```
##***Loading the data and naming of the data srftData***#######
srft<- read.csv(file.choose(), sep = ",")##srft are surface temperature data

##creating member lebels
memberLabels<
c("GFS_25KM","GFS_100KM","CFS_100KM","FNL_25KM","FNL_100KM")

##**surface temperature dataset to be used in mdeling**##
srftData<- ensembleData(forecasts = srft[,memberLabels],
dates = srft$dates, observations = srft$observation,
latitude = srft$latitude, longitude = srft$longitude)

#####****BMA FORECASTING OF TEMPERATURE*******####

#forecasting temperature for 24h
```

```
temp1003017<- trainingData( srftData, trainingDays = 10,
date  = "2017031000")

temp1003017Fit<- fitBMAnormal( temp1003017)

tempTestFit<- ensembleBMAnormal( tempTestData, trainingDays = 10) ##USED

###Assessment of BMA forecast for temperature ####****
####**********VERIFICATION OF THE MODEL*************####
```

1. Sharpness of the predictive PDFs

```
##Plot the Predictive Distribution Function for ensemble forecasting models
plot(tempTestFit, tempTestData)
```

2. Calibration of the PDFs

```
####Verification Rank Histogram*****
use= ensembleValidDates(tempTestData)>="2017031000"
verifRankHist(ensembleForecasts(tempTestData[use,]),dataVerifObs(tempTestData[
use,]))

###Probability Integral Transformation*****
tempTestFit<- ensembleBMAnormal( tempTestData, trainingDays = 10)
###From the BMA model used
tempTestFitPIT<- pit( tempTestFit, tempTestData)##PIT values
tempTestFitPITHist= pitHist(tempTestFit,tempTestData) ## PIT Plot
```

3. Assessment of predictive performance of Raw ensembles and BMA

```
#####*********************** Mean Absolute Error********#########
MAE( tempTestFit, tempTestData)
```

####****Formulation of CRPS for temperature *******#########
y= tempTestData[seq(5,90,5),]

###observation are in column 7 in the tempTestData
EmmaCRPSobs = y[,7]
####Forecast columns for ensembles forecasts are in the column 1 to 5
Emmaeps = y[,1:5]

######*******************CRPS calculation**********#########
calculationC= crpsDecomposition(EmmaCRPSobs,Emmaeps)

#####CRPS with alpha and beta Resampling indices##########
EmmanObs<-length(EmmaCRPSobs)

Emmai<-sample(seq(EmmanObs),EmmanObs,replace=TRUE)

#########*************Final CRPS Results***********##########
Finalcrps<-
crpsFromAlphaBeta(calculationC$alpha[Emmai,],calculationC$beta[Emmai,],calculationC$heaviside0[Emmai],calculationC$heavisideN[Emmai])

R script for objective #2

v. **To evaluate probability forecast of precipitation using Bayesian model averaging**

##*Loading the precipitation data and creation of the dataset precTestData*##
prec= read.csv(file.choose())

###** Now we create lebel members for precipitation dataset***###
memberLabels<-
c("GFS_25KM","GFS_100KM","CFS_100KM","FNL_25KM","FNL_100KM")

```
###***From the datadet prec we create PrecTestData for Modeling**###
precTestData<- ensembleData( forecasts = precTest[,memberLabels],
dates = precTest[,"dates"],
observations = precTest[,"observation"],
station = precTest[,"station"],
forecastHour = 48,
initializationTime = "00")

### ***BMA Precipitation forecast ***####
precTestFit<- ensembleBMAgamma0( precTestData, trainingDays = 10)



###Assessment of BMA forecast of precipitation ####****
####**********VERIFICATION OF THE MODEL**************####
```

1. Sharpness of the predictive PDFs

```
##Plot the Predictive Distribution Function for ensemble forecasting models

plot(precTestFit,precTestData)
```

2. Calibration of the PDFs

```
####Verification Rank Histogram*****
use= ensembleValidDates(precTestData)>="2017031000"
verifRankHist(ensembleForecasts(precTestData[use,]),dataVerifObs(precTestData[use,]))

###Probability Integral Transformation*****
precTestFit<- ensembleBMAgamma0( precTestData, trainingDays = 10)

###From the BMA model used
precTestFitPIT<- pit( precTestFit, precTestData)##PIT values
```

```
precTestFitPITHist= pitHist(precTestFit,precTestData) ## PIT Plot
```

3. Assessment of predictive performance of Raw ensembles and BMA of precipitation

```
#####*********************** Mean Absolute Error*******##########
MAE( precTestFit, precTestData)

####****Formulation of CRPS for prec *******#########
y= precTestData[seq(5,90,5),]

###observation are in column 7 in the precTestData
CRPSobs = y[,7]

####Forecast columns for ensembles forecasts are in the column 1 to 5
eps = y[,1:5]


######******************CRPS calculation*********#########
calculationC= crpsDecomposition(CRPSobs,eps)

#####CRPS with alpha and beta Resampling indices#########
nObs<-length(CRPSobs)

i<-sample(seq(nObs),nObs,replace=TRUE)

########*************Final CRPS Results**********#########
crps<-
crpsFromAlphaBeta(calculationC$alpha[i,],calculationC$beta[i,],calculationC$heaviside0[i],calculationC$heavisideN[i])
```

```
########*********Calculation of Brier Score of precipitation****######

brierScore(precTestFit,precTestData,thresholds = seq(from=0, to=.5, by = .1))


################################################################
##############***** OBJECTIVE NUMBER 3******************###
################################################################
cor(tempCorrelation))
plot(tempcorrelation)
```