UNIVERSITY OF NAIROBI

EVALUATION OF THE SKILL OF SEASONAL RAINFALL AND TEMPERATURE FORECASTS FROM GLOBAL PREDICTION MODELS OVER ETHIOPIA

BY

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DECLARATION

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

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DEDICATION

I dedicate this dissertation effort to my family and numerous friends. A special feeling of gratitude to my lovely friends Dr. Hussen Seid and his wife, Seada Abdella whose words of encouragement and constant support continue to resonate with me, inspiring determination and perseverance.

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ABSTRACT

The skill of seasonal climate predictions from global forecasting models varies considerably across different regions and seasons. Evaluating the skill of these models in forecasting temperature and rainfall for various seasons is crucial for enhancing forecast accuracy and ensuring the efficient utilization of forecast information. This study analyzed the performance of the North American Multi-Model Ensemble (NNME) and Copernicus Climate Change Service (C3S) seasonal forecast models in predicting the June-September (JJAS) and February-May (FMAM) seasonal rainfall and temperature over Ethiopia. The seasonal forecast models were evaluated for the hindcast period of 1994–2016 using the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data as a reference for rainfall and the Climatic Research Unit (CRU) for temperature. The skill assessment is conducted using the recently developed Python-based Climate Predictability Tool (PyCPT). The model predictor domains used were tropical ocean, the Western Indian Ocean, Ethiopia itself, the Atlantic and Indian Oceans at forecast time leads of 2-months, 1-month and 0-month. The models' skill assessment was performed using various skill scores such as Pearson correlation, Relative Operating Characteristics (ROC) and Ranked Probability Skill Score (RPSS).

The results show that the NMME and C3S models show varying levels of the skill of forecasted seasonal rainfall. The better performing models with the Pearson correlation greater than 0.5, ROC below score exceeding 0.7, ROC above score exceeding 0.6 and RPSS greater than 20% are CanSIPS-IC3, ECMWF-SEAS5, DWD-GCFS2P1, CMCC-SPS3P5 and METEOFRANCE8. These models show higher ability in forecasting rainfall in the JJAS season over the Central, Northeastern, Northern, Northwestern and pocket areas in the Eastern portion of Ethiopia compared to other models like, GFDL-SPEAR, RSMAS-CCSM4, NASA- GEOSS2S and NCEP-CFSv2. However, most models have low skill (Pearson correlation <0, ROC<0.5 and RPSS <0) to predict the rainfall in the JJAS season over the Southern, Southeastern, Southwestern and Western half of Ethiopia. It has been indicated that May and June initialized forecasts show better skill compared to the April initialized forecasts during the JJAS season. For effective agricultural and water management planning, the preferred choice is the May-initialized forecast. During the

FMAM season, the CanSIPS-IC3, ECMWF-SEAS5, DWD-GCFS2P1, CMCC-SPS3P5 and METEOFRANCE8 models show higher skill (Pearson correlation between 0.5 & 0.7, ROC below between 0.6 & 0.8, ROC above between 0.6 & 0.7 and RPSS between 20 & 40%) in forecasting the seasonal rainfall in the Southeastern, Southern, Central, and Eastern Ethiopia compared to other models like, RSMAS-CCSM4, NASA-GEOSS2S and NCEP-CFSv2. But their skill is lower in the Western half of Ethiopia. The 1-month lead forecast (initialized in January) exhibits a better skill compared to the 2-month and 0-month lead time forecast. The evaluation of various predictor domains' effect on forecast skill shows that the tropical domain (180°W to 180°E, 30°S to 30°N) exhibit higher skill in the JJAS and FMAM seasonal rainfall forecasts for Ethiopia when compared to other domains. It has been noted that the skill of models in forecasting the below normal rainfall are higher than the above normal rainfall for both JJAS and FMAM rainfall seasons.

The findings indicate that the models perform better in predicting temperature compared to their performance in predicting rainfall. During the JJAS season, the SPEAR, CCSM4, CFSv2, GEOSS2S, GCFS2P1, and SPS3P5 models exhibit better skill (Pearson correlation >0.6, ROC>0.8 and RPSS>40%) in predicting the seasonal temperature across much of the country, with the exceptions being in the Southeastern and Northwestern parts of the country, when compared to other models like CanSIPS-IC3, ECMWF-SEAS5, and METEOFRANCE8. During the FMAM season, the SPEAR, CanSIPS-IC3, SEAS5, CFSv2, GEOSS2S, GCFS2P1, and SPSv3P5 models display higher ability (Pearson correlation between 0.5 & 0.8, ROC below between 0.6 & 0.8, ROC above>0.7 and RPSS between 20 & 40%) in forecasting the seasonal temperature across most portions of Ethiopia, with the highest ability demonstrates in the Western half of Ethiopia. However, CCSM4 and METEOFRANCE8 models show low spatial skill in their temperature predictions. Overall, the findings of this study help to inform how a set of models could be chosen to create an objectively consolidated MME of seasonal forecast and improve the accuracy of forecasting for Ethiopia, as recommended by the WMO.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURE

LIST OF ABBREVIATIONS

AEJ	African Easterly Jet Stream
ARC2	African Rainfall Climatology version 2
AUC	Area under Curve
CanSIPS-IC3	Canadian Seasonal to Interannual Prediction System v2.1
CCA	Canonical correlation analysis
CCSM4	Community Climate System Model Version 4
CDF	Cumulative distribution function
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
C3S	Copernicus Climate Change Services
COLA-RSMAS	Center for Ocean Land Atmosphere Studies, University of Miami, and the National Center for Atmospheric Research-
CPC	Climate Prediction Center
CPT	Climate Prediction Tool
CMCC-SPS3P5	Euro-Mediterranean Center on Climate Change- seasonal prediction system 3.5
CRU	Climate Research Unit
DWD-GCFS2P1	Deutscher Wetterdienst-German Climate Forecast System 2.1
EALLJ	East African Low-Level Jet stream
ECMWF-SEAS5	European Center for Medium Range Weather Forecasts - Seasonal Forecasting system 5
ENSO	El Nino Southern Oscillation
EOF	Empirical Orthogonal Function
GCM	General Circulation model
GFCS	Global Framework for Climate Services
GFDL-SPEAR	Geophysical Fluid Dynamics Laboratory- Seamless system for Prediction and Earth System Research
GHA	Greater Horn of Africa
GPCs	Global producing Centers
GTS	Global Telecommunications System.
IRI	International Research Institute for Climate and Society
ITCZ	Inter-Tropical Convergence Zone

KMA MME	Korea Meteorological Administration Multi-Model Ensemble
LC-LRFMME	Lead Center for Long-Range Forecast Multi-Model Ensemble
MLR	Multiple linear regression
MME	Multimodel Ensemble
MOS	Model output statistics
NAPA	National Adaptation Program of Action
NASA-GEOSS2S	National Aeronautics and Space Administration–Goddard Earth Observing System sub seasonal to Seasonal prediction system
NCAR	National Centers for Atmospheric Research
NCEPs	National center for environmental prediction
NCEP-CFSv2	NOAA'S centers for environmental prediction, National center for environmental prediction climate forecast system version 2
NMA	National Meteorological Agency
NMHSs	National Meteorological and Hydrological Services
NMME	North American Multi-Model Ensemble
NMS	National Meteorological Services
NMSA	National Meteorological Services Agency
NCOF	National Climate Outlook Forum
NOAA	National Oceanic and Atmospheric Administration
PCR	Principal Component Régression
QBO	Quasi Biennal Oscillation
PyCPT	Python Climate Predictability Tool
ROC	Relative operating characteristics
RPSS	Ranked probability skill score
S2S	Sub seasonal to Seasonal Prediction Project
STWJ	Sub Tropical Westerly Jet stream
TAMSAT	Tropical Applications of Meteorology using Satellite and Ground-Based Observations.
TEJ	Tropical Easterly Jet stream
UEA	University of East Anglia
WMO	World Meteorological Organization

CHAPTER ONE

1. Introduction

1.1 Background

Ethiopia is one of the states more susceptible to the climate crisis and variability, with significant consequences for rural livelihoods and agricultural productivity (Kassie et al., 2013). The country is often exposed to numerous natural hazards including droughts, floods, volcanoes, and earthquakes. Floods and droughts were all severely hinder to the control of water supplies, agroeconomic growth, farming practices, and supply of food. The incidence and strength of climate changes, especially lack of rain and storms, has also increased in the country in recent decades (Zegeye, 2018). In order for information to be used in activities which reduce the adverse impacts of climate on various socio-economic sectors, accurate and trustworthy climate and weather reporting is essential.

The rainfall climatology in Ethiopia is predominantly determined by seasonal fluctuations in large-scale movement, with a component involves the latitudinal motion of the intertropical convergence zone (ITCZ). This phenomenon occurs across the broader Sahel area, extending from Sudan to Senegal (Nicholson, 1989). Seasons in Ethiopia are distinct and mostly categorized depends on the distribution and volume of rainfall. They divided in to three rainfall seasons, such as October to January (Bega), February to May (Belg) and June to September Kiremt) defined by Diro et al., 2011a, 2011b; Gissila et al., 2004; Segele & Lamb,2005; Korecha & Sorteberg, 2013. These seasonal categories are used by National Meteorological Agency (NMA) for regular seasonal climate forecasting and climatic feature monitoring.

The strength of monsoon systems and position within Ethiopia proximity, and also the convection of moisture, are the main determinants of rainfall variation. A common monsoon element for the Eastern African region, which includes Ethiopia, is the westward spread of meteorological disturbances occurring in the Arabian Sea, Indian Ocean, and southerly moisture movement (Selato & Nicholson, 2000; Lamb & Segele 2005).

The NMA seasonal forecast is generated through the analysis of past evolution and present conditions of atmospheric, oceanic, synoptic scale, and climate factors. This crucial component of seasonal forecasting techniques is defined by Diro et al., (2011c); Korecha & Barnston, (2007b). The Multivariate ENSO Index (MEI), Southern Oscillation Index (SOI), El Nino and La Nina prediction obtained from climate prediction center, and sea surface temperatures (SSTs) indices throughout the tropical Pacific Ocean are all used as NMA seasonal climate predictors (Wolter & Timlin, 1998).

The Ethiopian National Meteorological Agency seasonal forecasting which was first employed in 1987 and the technique of forecasting are based on analogue methods (using El Nino Southern Oscillation index), SST trends, numerical evaluation, and teleconnections of meteorological systems (Bekele, 1997). The analogue forecasting method is a way of predicting the climate for the forthcoming season based on similar patterns of sea surface temperature, upper-air heights of the geopotential and sea surface pressure of the past, and therefore has an influence on the skill of the forecast due to low extent of available historical data. Further, the forecast product from the consensus-based approach (analogue method) is not available in digital format, hence, it is difficult to verify it.

The NMA seasonal rainfall prediction are prepared as probabilities for regional seasonal rainfall categorized as above normal, normal, and below normal compared to the climatological normal. This is done for the country divided in to eight homogeneous rainfall regions. Its categorization depends on the usual monsoon process in each zone as well as how each region reacts spatially and temporally to important oceanic and atmospheric flow patterns (Diro et al., 2008a, 2011c; Tsidu, 2012, Gissila et al., 2004).

Farmers can choose crop varieties and seeding periods, as well as take into account the hazard of unusual occurrences in the period and reduce their effect, with the aid of accurate seasonal prediction during lead periods of numerous months. But it has been exposed that the efficacy of a certain rainfall prediction of a season is subpar due to unreliable beginning situations and model flaws both at the regional and global levels (Lavers et al., 2009; Teshome et al., 2022).

Recently, WMO designated several advanced climate centers worldwide as Global Producing Centers providing seasonal and long-range prediction (Otieno et al., 2014; Stockdale et al., 2010). At several seasonal forecast conferences, WMO encouraged for Hydrological and Meteorological offices to use objective forecasting methods (WMO, 2020). The consensus prediction technique did not provide sufficient evidence to demonstrate its applicability across various industries.

International Research Institute for climate and society developed the Climate Predictability Tool (CPT) which is basically a software for making seasonal forecasts over various global areas and validating those forecasts (Mason, 2011). Following WMO's advice, the next generation sub seasonal and seasonal prediction method has currently been established and deployed for numerous nations across the globe (Acharya et al., 2021, 2022; Munoz et al., 2019). NMA is able to produce and provide tailored weather and climate numerical results that are pertinent for appropriate government judgment on various stages by using python next generation seasonal prediction methods.

1.2 Statement of the Problem

Ethiopia is one of the most vulnerable nations to the consequences of climate change and fluctuation (Bezu, 2020). Weather and climate linked natural disasters such as floods and droughts are becoming increasing enormously also with greater intensity, and impacting on the community and means of subsistence for society in Ethiopia. Accurate and reliable climate knowledge is vital information to enable people in the country to cope with spatial and temporal differences of climate and reduce the effect of weather and climate related disasters.

Climate models are an important tool for predicting future climate conditions, but their accuracy varies depending on the region and season due to the intricate interplay of various elements of earth climate pattern and the way individual models are designed. Different regions have unique weather patterns that can be impacted through numerous aspects, including ocean currents, terrain as well as atmospheric circulation. Similarly, different seasons have distinct weather patterns that can be influenced by factors such as pressure and wind patterns. Evaluating the performance of prediction models for various areas and seasons is vital to identify skillful models for specific regions and seasons. This helps advance forecast skill and improve the effective acceptance of forecast information.

Despite significant advancements in computer models and observational technologies in recent years, there remain significant challenges in accurately forecasting weather and climate variables at national and local levels. Factors such as model biases, incomplete data, and the inherent complexity and unpredictability of climatic and weather patterns all participate to uncertainty and errors in these predictions.

The primary emphasis of this research investigation was to evaluate how effectively global prediction models can be used to predict the key climate variables in Ethiopia. Specifically, the problem is to evaluate the accuracy and consistency of these systems in forecasting rainfall and temperature as well as to identify the best predictor domain for the different rainfall seasons over the country. This problem is important because accurate weather and climate predictions are essential for just a variety of uses from agriculture and energy management to disaster preparedness and public safety.

Overall, this research will improve our knowledge of the strengths and limitations of present global models in predicting rainfall and temperature over Ethiopia, and provide insights into the best/skillful models, forecast lead times and predictor domains for the different rainfall seasons.

1.3 Research Questions

1. How well do the global prediction models predict rainfall and temperature over Ethiopia in different rainfall seasons?
2. Which predictor domain has the greatest influence on the seasonal rainfall variability in Ethiopia?
3. What is the influence of lead time on the forecast accuracy?

1.4 Objectives

The goal of this research is to evaluate the skill of global prediction models over Ethiopia in predicting rainfall and temperature for the different seasons using different predictor domains and forecast lead-times.

To achieve the above overall objective, the following particular objectives were pursued:

i. Analyze the skill of the global forecast models in predicting rainfall and temperature in Ethiopia for two rainfall seasons and identify the skill of models.

ii. Analyze the sensitivity of the forecast skill to the different predictor domains to identify the most preferred predictor domain for the different rainfall seasons over Ethiopia.
iii. To evaluate the influence of lead time on the forecast accuracy.

1.5 Justification for the Research

Agriculture, the major contributor to Ethiopia's economy, is heavily dependent on rainfall. However, the seasonal variation in rainfall linked to climate events impacts farming products. Hence, understanding the skill of seasonal prediction would provide information for emergency alert advice to consumers of climatic products for readiness to reduce the disruptive effects caused by climate events (Jolliffe & Stephenson, 2012a). The use of dynamical models in forecasting has made it possible to provide early warning information. The single model may not adequately provide sufficient skill for the forecasts; hence, ensemble model approaches are better suited to improve the skill and accuracy of seasonal forecast (Palmer et al., 2004).

Evaluating the accuracy of Global Climate Model (GCM) within Ethiopia will improve the National Climate Outlook Form (NCOF) processes by minimizing any prejudice in the prediction method; it should ultimately lead to advances in the prediction technique. Accurate prediction would be helpful to policy makers, stakeholders and rain dependent sector. Application of a forecasting system that benefits from the best available multi-model forecasts and generates skillful forecasts over Ethiopia would provide a useful contribution to the climate monitoring and early warning sectors. Creating consensus seasonal climate outlooks at the regional level using the output of the GCMs, has strengthened the ongoing regional efforts aimed at mitigating the adverse impacts of climate extremes. As a result, this has led to an enhancement in the accuracy and reliability of the predictions.

CHAPTER TWO

2. Literature Review

This segment contains a review of past studies, briefly discussing climate modeling , global climate forecast, seasonal climate forecasts over Ethiopia, forecasting skill and calibration, and Next Generation (NextGen) regional forecasting system.

2.1 Climate Modelling

A climate model is a computer program that uses climate model governing equations and quantitative techniques to predict climate and weather of the earth, which includes snow, air and ocean. The models applicable for forecasting the upcoming weather and climate, also simulate historical situations. Climate modeling and seasonal forecasting are widely used as a tool to predict and understand the extremes of the climate conditions. To address the challenges common with GCMs the uses of climate modeling and downscaling of climate information to users have been employed. Downscaling is done through the use of climate models using statistical, dynamical or combination of both models (Eastwick et al., 2008; Landman et al., 2009). Currently, a product of GCMs from world meteorological organization GPCs as well as other dynamical modeling Centers are being downscaled using regression-based models. Nevertheless, models based on sea surface temperature are typically afforded more credence in producing the subjective forecast (Mason & Chidzambwa, 2009). Palmer et al., (2000) introduced and tested the concept of MME forecast as a means to address the challenges posed by sensitivity and ambiguity to parameterization and primary situations commonly observed at many General Circulation Models (GCMs). The purpose of this approach is to advance forecasting accuracy.

Enhancing the precision of seasonal forecasting models' predictions relies on their capacity to accurately simulate essential elements of the climate system, such as convection, atmospheric boundary layers, ocean mixing, and land surface mechanisms. Properly handling these parameters, along with various other processes, is essential to enhance the forecast skill of dynamic models, as discussed by Latif et al., (2001).

The method of multiple linear regression is used to predict the result of a parameter by considering the values of two or more additional factors. Sometimes, this is simply known as multiple regression, which is an expansion of linear regression. The factors used to anticipate the value of a dependent variable are referred to as independent variables, while the variable being forecasted is called the dependent variable. Mathematical calculation of multiple linear regression formulas is refer to Equation (1).

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \ldots + \beta_p x_{i,p} + \epsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \, Equation\ (1)$$

Where, i = n, observations. y_i, is the dependent variable, β_0 is constant value (y, intercept), a numerical value of y if x_i and x_2 are zero (0). β_1 and β_2 are the coefficients associated with the independent variables $x_{i,1}$ and$x_{i,2}$, respectively. For individually independent variable's slope coefficient is represented by β_p, while the random error term is represented by ϵ.

2.2 Global Climate Forecast

Weather and climate forecast is a probabilistic or deterministic expression about the upcoming spatial and chronological weather and climate situations. It relies on the scientific comprehension of the dynamical and physical mechanisms that control future developments. Climatic prediction involves forecasts on different timescales and is utilized for long-term strategy, emergency alert of possible risks, and response to climatic fluctuations and changes (Hewitt et al., 2015). The system for functional seasonal predictions has improved with approval of WMO global producing center-long range forecast (LRF) in 2006 and LC-LRFMME (Lead Center for Long-Range Forecast Multi-Model Ensemble) in 2009. Currently, 13 approved global producing centers for long-range forecasts produce seasonal predictions on a monthly basis. Data from these forecasts is collected by LC-LRFMME (WMO-chosen center), which generate a consolidated seasonal prediction using multi-model techniques (Graham et al., 2011).

Predictability is more consistent across various climate elements compared to the reported skill, implying that there is potential for enhancing model predictions, despite encountering regional and seasonal differences. The estimation of potential predictability remains fairly stable, regardless of the model chosen. Generally, models with higher predictability across different areas tend to exhibit superior forecast skill (Becker et al., 2014).

The employment of seasonal ensemble prediction, which involves multiple models, consistently yields superior outcomes compared to the conventional deterministic forecasting method. Utilizing statistical analysis with data from Global Climate Models (GCM), the model output statistics approach effectively rectifies systematic errors present in GCM fields, including spatial shifts. Additionally, the scales down climatic information when simulations and observations differ in spatial resolution (Beraki, 2015).

The ensemble multi-model forecasting method generates more accurate predictions of rainfall and temperature in contrast to singular models. It has been demonstrated to be particularly effective in quantifying prediction uncertainty resulting from ambiguity in model design and initialization (WMO, 2017). Numerous worldwide joint research projects, including functional European and North American methods, are developed on the multimodel techniques. The NMME is a functional multimodel sub seasonal and seasonal prediction methods contains coupled models from United States modelling institutions, such NOAA/NCEPs, NOAA/GFDL, IRI's, NCAR, NASA and MSC (Kirtman, Min, Infanti, Kinter, Paolino, Zhang, Van Den Dool, Saha, Mendez, Becker, et al., 2014). Currently, this method transmits seasonal to interannual forecasts in real time according to the NOAA-CPC functional timeline. Data on hindcast and observed predictions are easily accessible as well as presented graphically by CPC. Also, operational forecasters are currently using NMME forecasts as advice, this data can be found at (http://www.cpc.ncep.noaa.gov/products/NMME/).

The Korea Meteorological Administration MME is a functional multimodel seasonal prediction method, which is made up of models obtained from 12 GPCs. Hindcast and actual time forecast data is easily accessible online on (http://www.wmolc.org). Since 1982, climatic research unit at University of East Anglia has made accessible gridded datasets of surface temperature data for areas of land, as well as mean for both the Northern and Southern Hemispheres and the entire world.

Numerous research studies have investigated the forecast capabilities of models over Ethiopia. Previous investigations were based on NMME models and an earlier version of the data. For instance, Teshome et al., (2022) study assessed the predictive proficiency of the NMME in

Ethiopia for the JJAS season. Employing CCA and RMSE, the study revealed that NMME models adeptly forecast JJAS seasonal rainfall in northern, northeastern, and central parts of Ethiopia, but displaying very low ability in Southwestern and western regions. In a similar vein, Acharya et al., (2021) study introduces the Next Generation seasonal forecast method to improve climate services in Ethiopia through NMME. Utilizing a CMME method with advanced GCM from the NMME project, NextGen demonstrates superior probabilistic and deterministic performance in forecasting Bega rainfall in comparison to JJAS and FMAM rainy areas.

2.3 Seasonal Climate Forecast over Ethiopia

Seasonal forecasting is a process of predicting climate for upcoming seasons, then specifically, how much, anticipated climate will vary from past years. It provides climate information from one to four months and the prediction include rainfall and temperature outlooks, its information is important to the users and judgements. WMO implemented the Global Framework for Climate Services (GFCS) in 2009, gives climate information that endorses private and public users worldwide, provincial and sectoral levels (WMO, 2020).

In meteorology, season is a time of year, because airmass that influences a region exhibits consistency in weather and climate variables (Désalmand, 1998). Since 1987, the NMA has been issuing operational seasonal predictions through an analogue approach for three seasons: Kiremt, Belg, and Bega (Diro et al., 2011; Korecha & Barnston, 2007a). The analogue technique and the evaluation of NMA operational seasonal rainfall prediction for Kiremt and Belg from 1999–2011 are recorded in Korecha & Sorteberg, (2013). NMA has categorized Ethiopia into eight homogenous precipitation zones. This categorization depends on each region's characteristic monsoon systems and their influence on the main atmospheric and oceanic circulation systems in terms of both space and time (Diro et al., 2008a, 2009; Gissila et al., 2004).

The NMA generates seasonal rainfall forecasts by assessing the likelihood of the seasonal rainfall being categorized as above, near, and below the average across 8 consistent rainfall areas (as shown in Figure 1). This categorization is determined by considering the precipitation generating mechanisms that impact each region and how they respond to main oceanic and atmospheric circulation systems, taking into account spatial and temporal patterns.

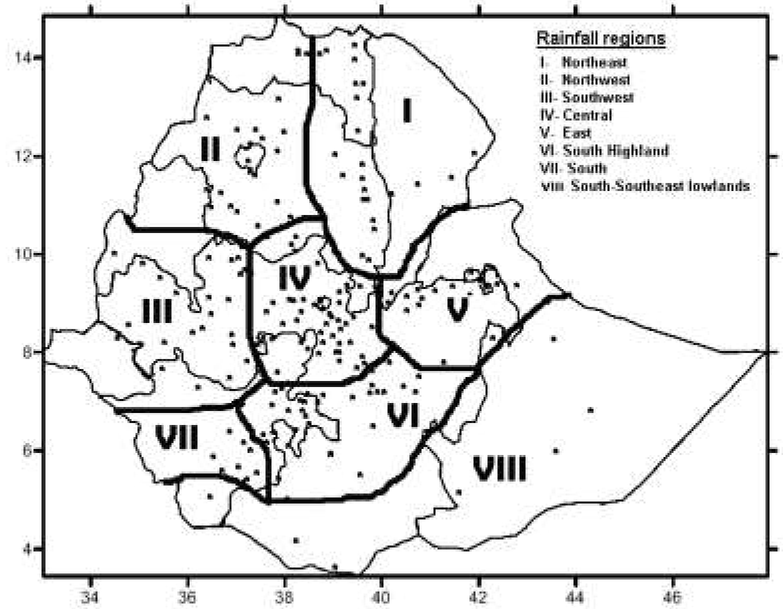

Figure 1: Rainfall regimes over Ethiopia
Source (https://cgspace.cgiar.org/handle/10568/107813)

There are a number of examples of oceans, such as Pacific, Indian and Atlantic Oceans are associated with various teleconnection patterns, which result in different climate anomalies in different regions of Ethiopia Diro et al., (2011c); Segele & Lamb, (2005). ENSO indices have been correctly recognized as effective pre-season predictors, and as a result, they have served as the foundation for Ethiopia's analogue forecasting methods (Korecha & Barnston, 2007b). Ethiopian rainfall is influenced by changes in La Nina, El Nino, location of African easterly jet and Indian monsoon (Diro et al., 2008b). The Teleconnection with extensive global systems like ENSO) and the Indian Ocean Dipole, along with regional systems, has been identified as a significant factor in shaping climate patterns across Greater Horn of Africa, including Ethiopia (MacLeod et al., 2021) .

The regional influences on the seasonal to inter seasonal climate trends over Ethiopian have been identified by NMA. These include the surface pressure systems across the Southern and Eastern Atlantic Oceans, the Mediterranean Sea, south and north Indian Oceans, Red Sea, southwest and north Indian Oceans, and the positive or negative phases of the IOD (Gissila et al., 2004; Gonfa, 1996; NMSA, 1996; Shanko & Camberlin, 1998). Korecha & Barnston, (2007b), studied climatological elements affecting rainfall over Ethiopia, including the meridional movement of the

ITCZ; the creation of warm lows in the Sahara and Arabian landmass; the development of sub-tropical high pressure over the Azores; the circulation of cross equatorial humidity from the Central , Southern, and equatorial parts of the tropical Africa, Indian Ocean, and the Atlantic Ocean, respectively; the low-level Somali jet and circulation of upper level tropical easterly jet over Ethiopia.

(Diro et al., (2011a), Studied the EALLJ, TEJ, Azores high, African easterly jet (AEJ), moisture anomalous in the Red Sea too Gulf of Guinea, ITCZ, ENSO and low-level wind abnormality from Atlantic and Indian ocean are the large-scale attributes linked to anomalous rain during Kiremt rainy season over Ethiopia. Likewise, during the Belg rain season large scale attributes connected to rainfall anomalies, such as STWJ, ENSO, Arabian High, ITCZ, low level wind abnormality from Indian and Atlantic Ocean and moisture anomaly over Eastern Africa

2.4 Assessment of Forecasting Skill

The common method for examining the forecasting ability of prediction systems is by comparing the hindcast with observations for the historical period. The accuracy of several seasonal forecasting systems has been evaluated through hindcast analysis (Bunzel et al., 2016; Bushuk et al., 2017; Krikken et al., 2016). Abnormal correlation coefficients of non-stationary time sequence for every targeting month of year at the initialized time are the main metrics used to measure the prediction performance. Additionally, they are compared to the effectiveness of considerably basic anomalous endurance prediction techniques. The ability in forecasting precipitation was at its highest during the one month initialized forecast and declined quickly afterward. Meanwhile, the skill in predicting temperature was notably higher overall and demonstrated better retention in extended lead times, indicating a more robust form of temporal persistence (Roy et al., 2020). (Shukla et al., 2019) examined the forecasts for temperature and rainfall made by 8 NMME models concerning East Africa. Their results revealed that temperature predictions showed greater effectiveness compared to precipitation forecasts. The latter exhibited a certain level of accuracy, but only within a limited area of the domain.

2.4.1 Forecast calibration

Calibration depends on the statistical coherence observed when comparing observed data with the distributional forecast. It might be a difficult issue in a detrended climate, if the hindcast method does not accurately capture important dynamics. CCA is a multivariate statistical method used to examine the relationships between two sets of variables. CCA used to identify the linear combinations within each set of variables that have the highest correlation with each other across the sets. Which is a trend based multidimensional linear regression technique within observed actual anomalies and domain of the model for calibration of rainfall forecast from general circulation models. The Trend-Based Multiple Linear Regression (MLR) technique is employed across model domains and actual anomalies to calibrate rainfall forecasts derived from GCMs. This approach allows the projection of genuine spatial and temporal trends expected within the general circulation models (Barnston & Tippett, 2017; Tippett et al., 2003). By keeping small selection of empirical orthogonal function modes (EOFs), minimizes the enormous dimension of the actual datasets and supports in the prevention of prediction error (Yu et al., 1997).

2.5 Next Generation (NextGen) regional forecasting system

The World Meteorological Organization's latest seasonal forecast guideline prefers and advises using an objective seasonal prediction technique. This approach is characterized by a clear, replicable, and meticulously defined set of procedures that enable the quantitative assessment of prediction reliability (WMO, 2020). NextGen seasonal rainfall and temperature prediction methods is a scientific and objective technique. This allows validation, synthesis and verifying the objective weather and climate predictions made by global climate models such as NMME, C3S, and S2S. It is a multimodel strategy that uses systematic methods for scheming, applying, establishing also validating objective seasonal climate predictions. This method involves determining the significant decision factors by users and examining their fundamental causes, drivers of predictability, and potential predictors for the main appropriate factors. If prediction ability is sufficient, Next generation aids in choice of the best dynamic models for the selected area through evaluation methods and helps the production of multimodel, empirically validated forecasts at sub seasonal and seasonal periods (Acharya et al., 2021, 2022; Munoz et al., 2019).

CHAPTER THREE

3. Data and Methodology

This segment contains an overview of study area, climatology, data, applied model, and the diverse methods employed to accomplish both the overall and specific objectives of the research.

3.1 Description of the Study Area

This subsection presents on the description of study area based on the location and climate characteristics of Ethiopia.

3.1.1 Location

Ethiopia is a country in the Horn of Africa that is bordered by Somalia to the south and east, Eritrea to the north, Djibouti to the east, Kenya to the south, and Sudan to the west. Its geographic coordinates are 3-15° N and 33-48° E. It encompasses an area of approximately 1.14 million km^2 and is characterized by a landscape associated by high, rocky flat plains and rim lowland areas. The country's land elevation spans from 160 meters below sea level (at the Northern end of the Rift Valley) to 4600 meters above sea level (in the Northern mountainous area), with a population of over 85 million inhabitants (Korecha and Sorteberg, 2013). Figure 2 depicts the study region together with the distribution of meteorological stations.

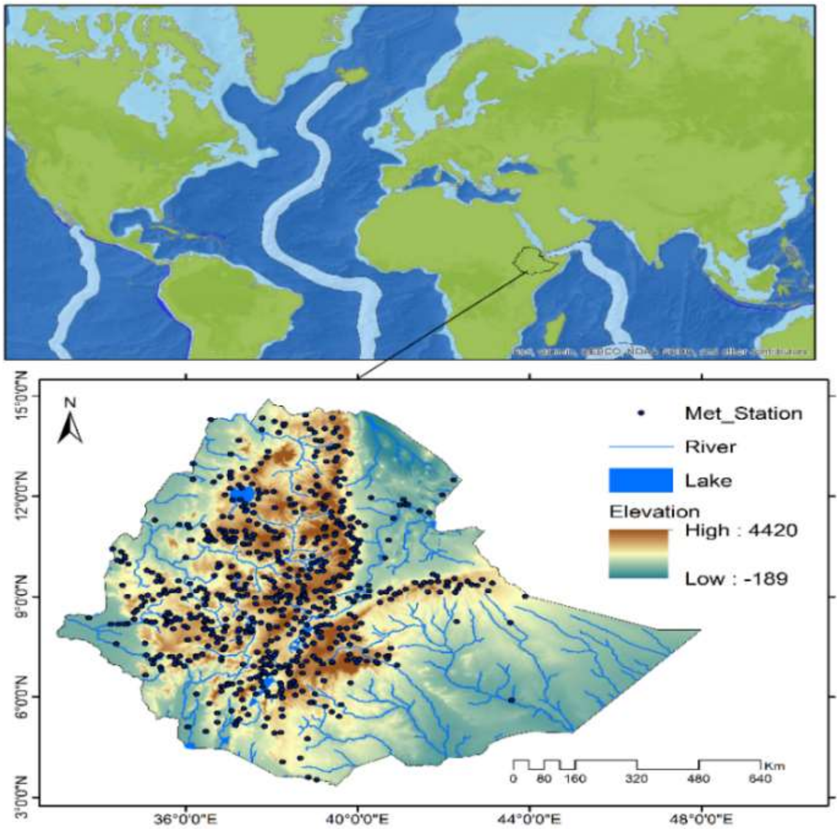

Figure 2: Location, Topography and Distribution of Meteorological stations in Ethiopia

3.1.2 Climate of the study area

The climate in Ethiopia is normally warm in the south and Northeastern lowland areas, although significantly colder in its massive middle highland areas. In these high-altitude locations, average temperature from 15 to 20 °C, while the lowland areas experience temperatures of 25 to 30 °C (Gashaw & Mahari, 2014). The movement of the ITCZ is mostly responsible for Ethiopia's seasonal precipitation. When the ITCZ is mostly in the Northern location, the majority of the country experiences one primary rainy season lasting from June to September. Additionally, some areas over the Central and Northern Ethiopia experience a second rainy period from February to May that is erratic and significantly less rainy. The Southern parts of the country experience two rainy seasons, which occur due to the movement of the ITCZ over the southern regions. In these regions, the months from March to May constitute the major rainy period which produces a rainfall range of 100 to 200 mm in each month. Conversely, a less rainy period occurs from October to January (Fazzini et al., 2015; Legesse Gebre, 2015). Ethiopian rainfall seasons are:-

Bega, which extends from October through January, is characterized by cold and dry conditions. While tropical depressions rarely form over the Arabian Sea, there are instances when they move towards the Horn of Africa, leading to occasional unexpected rainfall in various regions. During this season, several prominent weather patterns emerge, including the dry and cool northeasterly monsoon, the seasonal Siberian High, and the northern hemispheric subtropical anticyclones. These arid air currents originate from multiple sources, such as the Saharan anticyclone, a ridge of high pressure extending from the Arabian region towards Ethiopia, and extensive surface pressure in Siberia and central Asia. Through this time the weather is sunny, muggy and cool in the morning and nights (Gonfa, 1996; NMSA, 1996).

Belg signifies the short rainy season, spanning from February to May. It is marked by a combination of dry and rainy days. The weather system during the Belg over the region is determined by the interplay of mid-latitude and tropical weather systems. The primary monsoon pattern is manifested through the intrusion of a substantial and deep trough into the easterly circulation towards lower latitudes, along with the southward shift of the westerly jet at higher altitudes. In these seasons the major systems include the heat low in South Sudan, creation and spreading of perturbations in the Mediterranean Sea, easterly tides, high pressure in Arabian Sea, connection of mid latitude depressions and tropical systems, which is sometimes preceded by troughs and subtropical jet, as well as sporadic evolution of Red Sea convergence Zone (RSCZ) (Gonfa, 1996; NMSA, 1996). From February to May the secondary rainy season over the northeastern, central and highlands of the southern and eastern parts of the country shown in Figure 3. This is the main rainy season across the lowlands of Southern and Southeastern parts of the country.

Kiremt is a primarily wet season that lasts from June to September. The dominant weather systems throughout this season are the ITCZ and the humid southwest monsoon circulation from Southern hemisphere. The commencement of rainfall and its spatial distribution are linked to the ITCZ cycle and strength of Southern hemispheric anticyclones (Fekadu, 2015; Segele & Lamb, 2005; Tadesse, 1994). Figure 3 presents the distribution of seasonal mean rainfall over Ethiopia depicted by Climate Hazards Group InfraRed Precipitation with Station (CHIRPs) data. In Ethiopia, the primary rainfall season happens JJAS when a country experiences higher rainfall levels in most regions, specifically, the Northwestern, Western, and Central parts of Ethiopia. This period of rainfall significantly contributes to sustaining agricultural operations and the management of water resources.

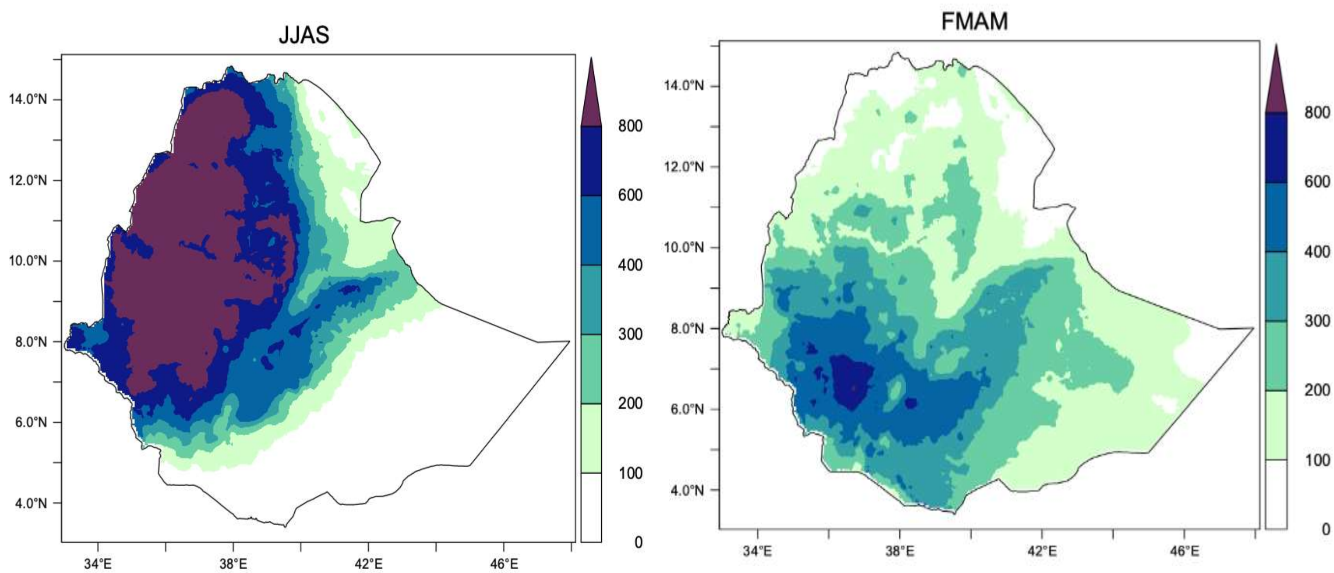

Figure 3: Climatology of June-September rainfall in mm (left panel) and February to May (right panel) taken from CHIRPS data 1994-2016.

In the Kiremt (JJAS) season the climatology of mean temperatures over Ethiopia (presented in Figure 4) experiences a significant increase in precipitation, and temperatures tend to be cooler compared to other seasons. The temperature in Ethiopia during the Kiremt season varies depends on the areas and altitude. The diverse topography of the country, including both highlands and lowlands, leads to variations in climate and temperature across the entire nation. Over the highlands, which include areas like Addis Ababa and the Northern part of the country, temperatures are milder due to the higher elevations. In the lowlands of Eastern and Southeastern Ethiopia, temperatures can be significantly higher during the JJAS season.

Figure 4 illustrates the climatology of Belg temperatures in Ethiopia, which cover from February to May. Temperatures vary across a country, with cooler conditions in the highland regions and hotter temperatures in lowland areas, reaching above 30 °C in some places.

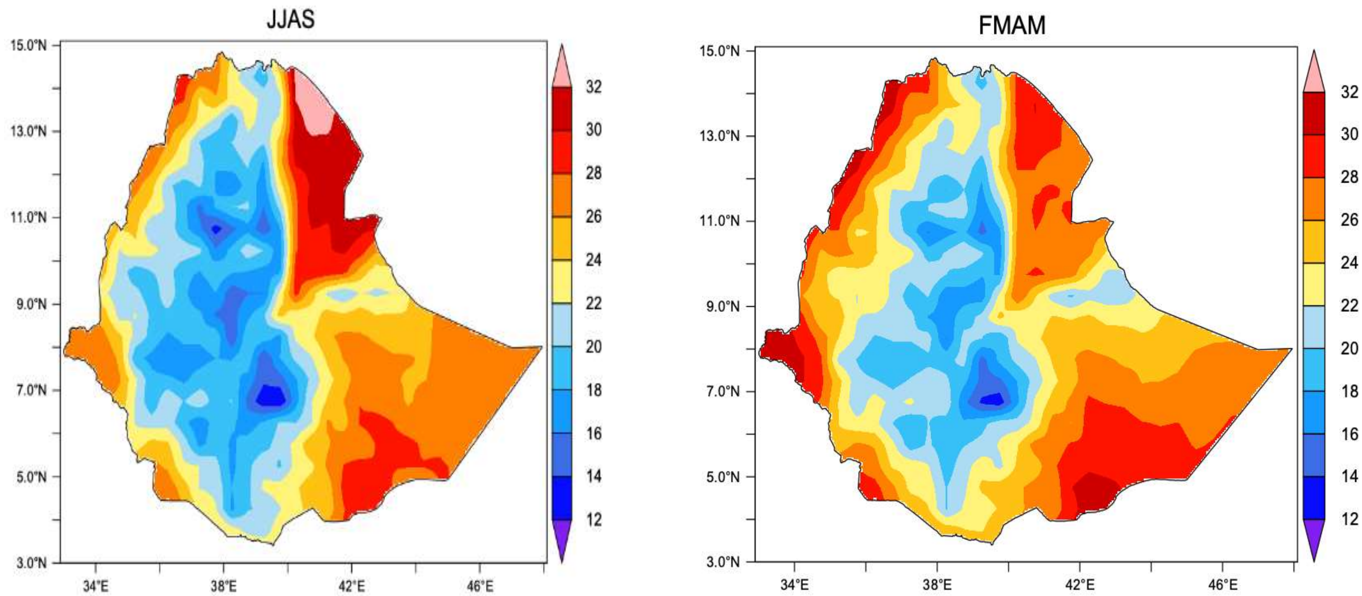

Figure 4: Climatology of Mean temperature (°C) of June-September (left panel) and during February-May (right panel) using CHIRPS data 1994-2016.

3.2 Data

3.2.1 Observed data

To address the proposed research questions, this study utilized gridded precipitation data from CHIRPS version 2.0 datasets. CHIRPS is a blend of 0.05° satellite data and the actual observed data was used to generate gridded rainfall data (Funk et al., 2015) . CHIRPS dataset spans from 1981 to the current date and has undergone validation across various regions of East Africa. The CHIRPS validation was based on comparisons with observed and satellite rainfall data from sources such as Tropical Applications of Meteorology using Satellite and Ground-Based Observations (TAMSAT) and African Rainfall Climatology version 2 (ARC2)(Dinku et al., 2018). The validation outcomes display that CHIRPS outperformed ARC2 and TAMSAT in terms of greater accuracy and lower biases, especially at monthly and ten days timelines. Therefore, CHIRPS is deemed appropriate for use as the baseline precipitation database.

In this research, gridded temperature data from the Climate Research Unit (CRU) datasets at the University of East Anglia (UEA) were utilized. Since 1982, the UEA has provided gridded datasets of observed mean temperature data over all land areas of the world except Antarctica. The CRU gridded Time Series is a commonly utilized climate dataset organized on a grid with a resolution of 0.5° latitude by 0.5° longitude. These datasets, the most recent of which is CRUTEM3, were created using information/data collected from meteorological stations located all over the globe, most of which are managed by NMHSs. NMHSs share this data over the CLIMAT network, which is a member of the WMO Global Telecommunications System (GTS). The study utilized monthly observed data for rainfall and mean temperature from 1994 up to 2016.

3.2.2 Model data

For the intent of this study, the data were acquired from the IRI data library (https://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/) and Copernicus climate change services (C3S) data store (https://cds.climate.copernicus.eu/cdsapp#!/dataset/seasonal-monthly-single-levels?tab=form). The IRI data library contains hindcast and real time forecasts from the NMME including National Aeronautics and Space Administration-Goddard Earth Observing System sub seasonal to Seasonal prediction system (NASA-GEOSS2S), Canadian Seasonal to Interannual Prediction System v2.1 (CanSIPS-IC3), Geophysical Fluid Dynamics Laboratory-Seamless system for Prediction and Earth System Research (GFDL-SPEAR), National Oceanic and Atmospheric Administration (NOAA) centers for environmental prediction, National centers for environmental prediction climate forecast system version 2 (NCEP-CFSv2) and Community Climate System Model Version 4 (CCSM4). The Copernicus climate change services (C3S) data store consists of hindcast and real-time forecast data from European models such as European Center for Medium Range Weather Forecasts system 5 (ECMWF-SEAS5), Euro-Mediterranean Center on Climate Change- seasonal prediction system 3.5 (CMCC-SPS3P5), Deutscher Wetterdienst-German Climate Forecast System 2.1 (DWD- GCFS2P1) and Meteo-France-system8. Hindcast data is generated through the process of running a model using historical inputs and comparing the model's outputs to actual observations from the past.

This study was utilized both NMME and C3S models to assess the skill of seasonal temperature and rainfall prediction over Ethiopia. The study utilized monthly hindcast data for rainfall and temperature from 1994 up to 2016. This selection of training period was constrained by data availability from both the observations and the models. The predictor factors are rainfall and two-meter temperature T2m. Table 1 illustrates the models incorporated within C3S and NMME. The initial column contains details regarding the producing institution and the specific model's name. These models encompass diverse ensemble sizes of hindcast, spanning from 4 members to 40 and all models used $1° x 1°$ resolution of data.

Table 1: List of selected nine models, accessible data period, reference information and number of hindcast ensemble members.

No	Model Type	Accessible hindcast data period	Reference information	Hindcast Ensemble size
1	CanSIPS-IC3	1980-2021	(Lin et al., 2020)	20
2	COLA-RSMAS-CCSM4	1982-2023	(Kirtman et al, 2014)	10
3	NCEP-CFSv2	1982-2021	(Saha et al., 2014)	24
4	NASA- GEOSS2S	1981-2017	(Borovikovetal, 2018)	4
5	GFDL-SPEAR	1991-2020	(Delworth et al., 2020)	15
6	ECMWF-SEAS5	1981-2016	(Johnson et al., 2019)	25
7	METEO-FRANCE-SYSTEM8	1993- 2016		25
8	DWD-GCFS2P1	1993-2016	(Fröhlich et al., 2021)	30
9	CMCC-SPS3P5	1993-2016		40

The examination of relevant literature suggests a correlation between Ethiopia's seasonal climate and the influence of SST in the Atlantic and Indian Oceans, as well as the equatorial Pacific, in conjunction with linked atmospheric motion. The primary (JJAS) season's weather is notably impacted by teleconnections with SST anomalies and the ENSO in the Nino-3.4 region of the equatorial Pacific. In contrast, the IOD exhibits a comparatively more pronounced impact on the climates of the Bega season (ONDJ) and the FMAM. Based on this, we have selected the examined predictor domains for this study in Table 2.

Table 2 : List of predictor domains examined in this study.

No:	Names of predictors	Predictor domain
1	Global tropics	180°W to 180°E, 30°S to 30°N
2	Western Indian Ocean	20°W to 70°E, 17°S to 30°N
3	Ethiopia	33°W to 48°E, 3°S to 15°N
4	Atlantic and Indian ocean	60°W to 160°E, 45°S to 45°N

3.3 Methods

In this section discuss the methods employed in the evaluation of the skill of GCMs, the analysis of the effect of the predictor domain, the effect of lead time on the forecast accuracy, and the general description of PyCPT.

This study used a Python-based statistical tool (PyCPT) used to produce the objective seasonal climate forecast (i.e., NextGen) and evaluate the accuracy of individual and MME forecasting techniques in forecasting temperature and precipitation across Ethiopia for various predictor domains and lead-times. The Python script in PyCPT calls the existing Climate Predictability Tool (CPT) to run statistical analyses of the output of one or multiple climate models relative to an observational dataset of the user's choosing (Mason, 2011). As with CPT, the user may examine the raw model output with no model output statistics correction, or make a Model Output Statistics (MOS) based forecast using Principal Component Regression (PCR) or CCA. The ability of the seasonal forecasting models was evaluated using numerous, statistical proven methods, in alignment with the skill assessment verification techniques established by the World Meteorological Organization (WMO) for seasonal prediction (WMO, 2018). The specific approaches used to address each research objective are described as follow: -

3.3.1 Evaluation of the skill of GCMs

The skill of rainfall and temperature prediction from global prediction models depends on the season and areas. Evaluating the performance of seasonal forecasting models across various areas and time frames is crucial for enhance prediction accuracy and improve the effective utilization of forecast information. For the two rainy seasons in Ethiopia, the performance of various worldwide forecasting models to predict rainfall and temperature were examined and compared during the

FMAM and JJAS seasons. The prediction accuracy of C3S and NMME models are evaluated through the utilization of various deterministic and probabilistic skill metrics are Pearson correlation, ROC and Ranked Probability Skill Score (RPSS).

3.3.1.1 Pearson Correlation metrics

Pearson correlation is a statistical measure that quantifies the linear relationship between two continuous variables. It is named after Karl Pearson, who developed the method. The formula for calculating the Pearson correlation coefficient (r) between observed (x) and modeled (y) with n data points formula is refer to equation (2)

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \text{ ……………………………………………..Equation (2)}$$

Where:

x_i and y_i are the individual data points for variables x and y data, respectively

$\bar{x}$ and $\bar{y}$ are the means of the variable x and y data, respectively.

Its value lies within the range of -1 and +1, where -1 signifies a perfect negative correlation (perfect negative linear relationship) , +1 signifies a perfect positive correlation (perfect positive linear relationship), and 0 signifies no linear relationship between the variables(Mason, 1982).

3.3.1.2 Relative Operating Characteristic (ROC)

ROC analysis can be adapted to assess the performance of a seasonal climate prediction model. The primary aim is to evaluate the ability of the model to correctly predict different categories of outcomes, typically related to specific climate conditions or events. The ROC score, determined by calculating area under the ROC curve, is considered a valuable concise metric for assessing prediction proficiency. ROC metrics the skill of a prediction to discriminate between occurrences and non-occurrences, and quantifies the degree of prediction discrimination (Mason, 1982). ROC evaluates the balance between the sensitivity (true positive rate) and the complement of specificity (false positive rate) across various classification thresholds.

For each category, calculate the True Positive Rate (TPR) and False Positive Rate (FPR) based on the model's predictions and actual observations. This mathematical formula is refer to Equation (3) and Equation (4).

$$TPR = \frac{True\ Positives}{True\ Positives + False\ Negative} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots.Equation\ (3)$$

$$FPR = \frac{False\ Positives}{False\ positives + True\ Negatives} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots Equation\ (4)$$

Calculate the Area under the ROC Curve (AUC-ROC) to quantify the overall performance of the seasonal climate forecast model in predicting conditions above normal. A higher AUC-ROC indicates better discrimination between the above normal, normal, and below normal categories. The ROC curve and AUC-ROC in the seasonal forecasting goals. A curve consistently above the diagonal line and a higher AUC-ROC suggest better performance in predicting conditions below normal and above normal.

A ROC value of 0.5 signifies unskillful forecast that means the forecast is no more accurate than climatology. A value exceeding 0.5 indicates a positive discriminatory skill and a value is 1.0 indicating a flawless prediction. Zero value signifies no improvement when compared to a prediction derived from the climatological event frequency (Jolliffe & Stephenson, 2012b). The ROC curve will be positioned above the 45◦ line from the origin when the forecast system is skillful (when the hit rate greater than the false-alarm rate) and the total area under the curve will surpass 0.5 (Mason & Graham, 1999).

3.3.1.3 Ranked Probability Skill Score (RPSS)

The ranked probability score serves as an indicator of the predictive accuracy of probabilistic prediction made for classified events, specifically those derived from terciles. This is calculated by the summing the squared difference between cumulative prediction probabilities and cumulative observed probabilities (Murphy, 1969, 1971).

Rank probability score is an alternative way of skill evaluation, this mathematical formula is refer to equation (5).

$$RPS = \frac{1}{k-1}\left[\sum_{i=1}^{k}\left(CDF_{forc,\ i} - CDF_{obs,\ i}\right)^2\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Equation\ (5)$$

$CDF_{obs,\ i} = \begin{cases} 0 & i < i_{obs} \\ 1 & i >= i_{obs} \end{cases}$ and $CDF_{forc,\ i} = \sum_{j=1}^{i} P_j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Equation\ (6)$

From Equation (1) and (2) the term k represents the total number of groups, k = 3 is tercile forecasts, k = 5 is quintile forecasts, and i and j represent indices of the forecast group. P_j represent a probability of group j. RPSS is a comparison between RPS forecast and RPS reference forecast. For this situation, reference forecast is climatology, it gives a chance of 0.33 terciles and 0.2 quintiles to each of groups.

The RPSS is a performance score derived from RPS, computed as the percentage improvement compared to s climatological value. This mathematical formula is refer to equation (7).

$$RPSS = \left(1 - \frac{RPS_{forc}}{RPS_{clim}}\right) * 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Equation\ (7)$$

RPS_{forc} represent ranked probability score for the actual forecast and RPS_{clim} represents ranked probability score for climatological forecast.

The RPSS values between negative infinity and 1. The value of RPSS less than 0 represent that the prediction is lower skill compared to climatological prediction. RPSS is greater than 0 indicates that prediction is higher performance and 1 indicates a prefect prediction. The score equal to 0 is the forecast ability is similar to the climatology.

The Percent of RPSS is a normalized version of the RPSS and is often used to express the performance of a probabilistic forecast as a percentage. The Percent RPSS is calculated by dividing the RPSS of the forecast by the RPSS of the reference forecast and then multiplying the result by 100 to express the skill as a percentage. The formula for calculating the Percent RPSS is refer to Equation (8)

$Percent\ RPSS = \frac{RPSS}{RPSS_{climo}} * 100$ ………………………………………….…Equation (8)

Where:

RPSS, is the Ranked probability skill score

$RPSS_{climo}$, is the RPSS of climatological forecast

A Percent RPSS of 0% shows no skill. A Percent RPSS of 100% signifies flawless proficiency, meaning the forecast is perfect relative to the reference forecast. The value of percent of RPSS less than 0 % represent that the forecast is less skill than the climatology.

3.3.2 Analysis of the effect of the predictor domain

The rainfall over Ethiopia is impacted by various large-scale circulation features in various parts of the Ocean. For this analysis the forecasting methodology was Canonical Correlation Analysis (CCA), which uses EOF analysis conducted independently on both the model hindcasts (referred to as the X or predictor) and the observations (referred to as the Y or predictand). Subsequently, a portion of the time series derived from the principal components of these EOFs is employed as input for the CCA. While CCA has long been recognized for its ability to identify spatial patterns that account for the highest variance, it is crucial to restrict the number of Principal component Analysis (PCA) and EOF used to prevent the occurrence of spurious or artificial predictions (Barnett & Preisendorfer, 1987). When performing canonical correlation analysis using PyCPT, the input data used are the hindcast data for predictors and the CHIRPS data for predictand. The predictor domain is typically set to be larger than the predictand domain to enable the utilization of pertinent characteristics from the predictand domain, thereby improving the model's calibration. Extensive research has been conducted on the oceanic factors influencing Ethiopia's seasonal rainfall. Notably, the JJAS season exhibits a significant correlation with the ENSO events occurring in the tropical Pacific Ocean (Palmer et al., 2023).

For this study, different Ocean basins that have strong relationship with Ethiopia's seasonal rainfall have been investigated. The analysis of the forecast skill across various predictor domains was assessed using the multimodel ensemble (MME) approach, which is a widely acknowledged method for enhancing forecast ability compared to that of individual GCMs. The predictor domains analyzed for this study include Tropics (180°W to 180°E, 30°S to 30°N), Western Indian Ocean (20°W to 70°E, 17°S to 30°N), Ethiopia (33°W to 48°E, 3°S to 15°N) and Atlantic and Indian Ocean (60°W to 160°E, 45°S to 45°N) predictor domains which have been tested for the two rainfall seasons. These predictor domains are indicated in Figure 5. The predictand domain for the analysis is Ethiopia. Eventually, the study identifies the best predictor domains for the different rainfall seasons.

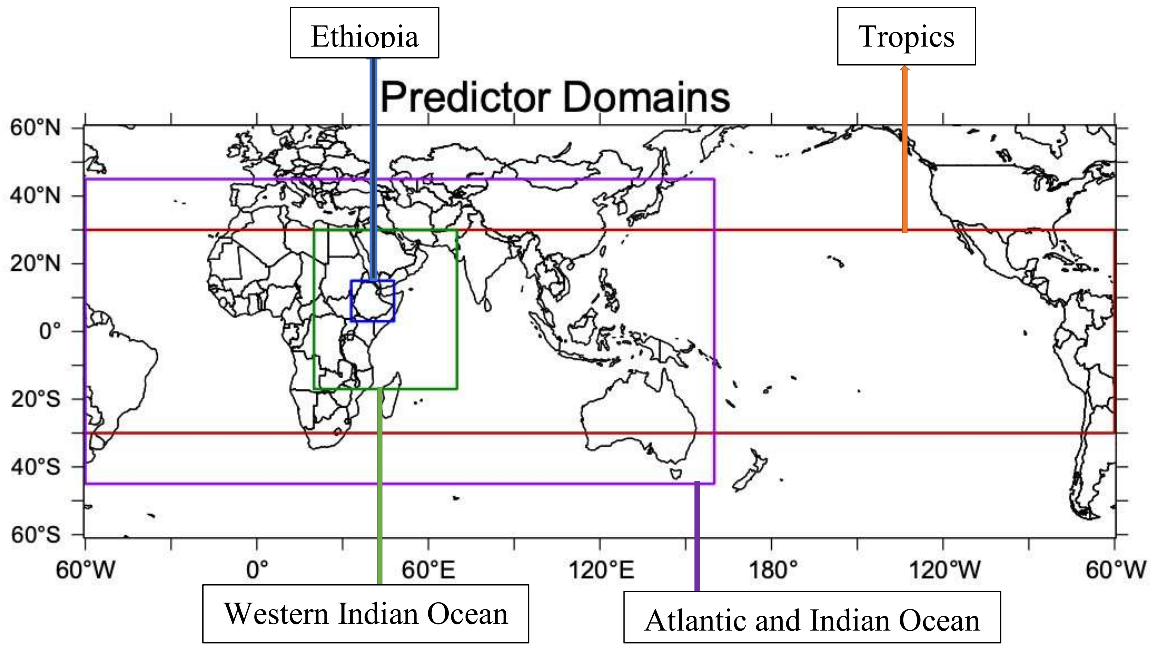

Figure 5: Predictor domains (Tropics, Western Indian Ocean, Ethiopia itself, and Atlantic and Indian Ocean) used to examine the skill of the prediction for the different rainfall seasons.

3.3.3 Analysis of the effect of lead time on the forecast accuracy

It is crucial to note that the lead time has an effect on the skill of the prediction (particularly in weather timescale). This study analyzed and compared the prediction skill of a one month, two-month and zero-month lead reforecasts from global forecasting models over the two rainfall seasons (FMAM and JJAS). For example, for the June-September season, the forecasts initialized in April, May and June were analyzed and compared. Similarly, for the February-May (FMAM) season, the forecast lead time in December, January and February were analyzed and compared.

3.4 Description of Python Climate Predictability Tools Interface

Python climate predictability (PyCPT) tool is a package that offers an application and additional operations to CPT, a popular study and implementation model output forecast toolbox. It is specially made for the massive-production of seasonal and sub-seasonal forecasts, skill evaluation maps, and probabilistic flexible forecasts. It is intended to provide sub seasonal to seasonal climate prediction utilizing MOS adjustments to climate forecast from GCM.

Figure 6, presents a flowchart that depicts the four steps involved in the NextGen seasonal forecast process. NextGen seasonal forecasting system is a systematic approach that facilitates the creation of objective forecasts by utilizing multiple dynamical model output predictors. The first step involves users selecting various models in advance, along with their corresponding hindcast and observational data. In the second step, a statistical calibration method is applied. In this process, the ensemble mean of individual model in the NMME pool is used to rectify biases in the positions and amplitudes of predicted rainfall compared to observations, employing the CCA calibration. Previous performing CCA, standardization is applied to both the predictor and the predictand, followed by orthogonalization through standard EOF analysis. The EOF analysis reduces the dimensionality of the initial data matrices by preserving a restricted number of EOF modes, thereby aiding in the prevention of overfitting. Thirdly, the skill assessment provides forecast skill metrics (ROC, Pearson correlation, RPSS) for both individual models and the MME. Finally, the NextGen forecasting system generates both deterministic and probabilistic forecasts.

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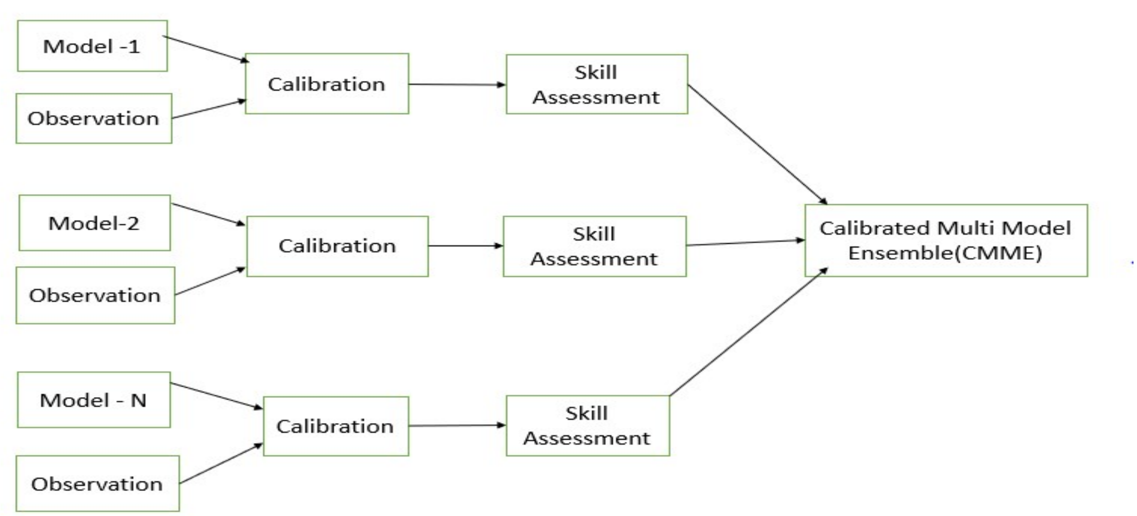


Figure 6: Flow chart illustrating that various steps involved in generating seasonal forecasts using the NextGen approach.
Source (https://www.authorea.com/doi/full/10.1002/essoar.10504989.1)

In Figure 7, the interface of PyCPT is presented in four main steps. The initial step involves configuring the specific case through the name list section. This interface allows users to choose in advance various models along with their corresponding observational data. Users can also specify the predictor variables they are interested in, as well as the domains for both predictor and predictand. Additionally, the interface allows customization of parameters such as the training window period and forecast timing details, including the target season and year, as well as the forecast lead time. The download and CPT execution step involves preparing the necessary input datasets and PyCPT allows users to generate calibrated and bias-corrected forecasts on a per-model basis. The forecasts produced by each individual model are then amalgamated to create a multi-model ensemble forecast. The skill assessment interface provides the forecast skill metrics for both individual models and the MME. The performance measures by Pearson correlation, ROC and RPSS. Lastly, the forecast section focuses on ensemble generation and the production of forecast maps. The resulting forecasts are presented in an objective forecasting format, including the complete probability distribution for each location within the predictand domain.

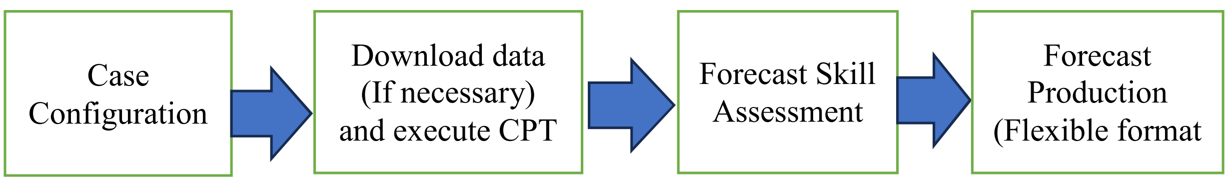


Figure 7: Flow chart illustrating steps of PyCPT forecasting methodology: Source (https://www.authorea.com/doi/full/10.1002/essoar.10504989.1)

CHAPTER FOUR

4. Results and Discussion

This chapter explores the outcomes achieved through various approaches detailed in Chapter three, which were designed to address the research objectives. These outcomes are the result of the performance of global forecasting models in forecasting rainfall and temperature, analysis of the effect of predictor domains on the skill of forecasts, and the influence of lead time on forecast skill.

These goals encompass evaluating the skill of GCM seasonal forecast models (NMME and C3S) in predicting JJAS and FMAM rainfall and temperature over Ethiopia. For this study we have used Pearson correlation, ROC, and RPSS evaluation metrics. To evaluate the performance of a single and MME forecast skill are used to PyCPT NextGen seasonal forecasting tool. The method used to forecasting is CCA technique. The skill of the models was assessed with different predictor domains and lead times, using precipitation as a predictor and CHIRPS as a predictand on rainfall forecast. For the temperature forecast T2m as a predictor and Tmean as a predictand.

4.1 Analysis of the Accuracy of Global Forecasting Models in Predicting Rainfall and Temperature in Ethiopia

In this subsection, we showcase the outcomes derived from evaluating the effectiveness of seasonal forecast models using tropics as predictor domain in predicting temperature and rainfall during JJAS and FMAM over Ethiopia. The ENSO and IOD has play a key role in modulating climate pattern over GHA including Ethiopia. This indicates that tropical region is high influence eastern African rainfall including Ethiopia.

4.1.1 Skill of global prediction models in predicting rainfall during JJAS

The skill of nine models has been assessed using the tropical region (180°W to 180°E, 30°S to 30°N) predictors domain for June-September rainy seasons using observed data from CHIRPs as the predictand , rainfall as the predictor and initialized one month lead (May) forecast. These are currently being used by operational climate-producing centers such as ICPAC and NMA. The results of this skill evaluation based on Pearson correlation, ROC area below normal, ROC area above normal, and the RPSS are shown in Figure 8.

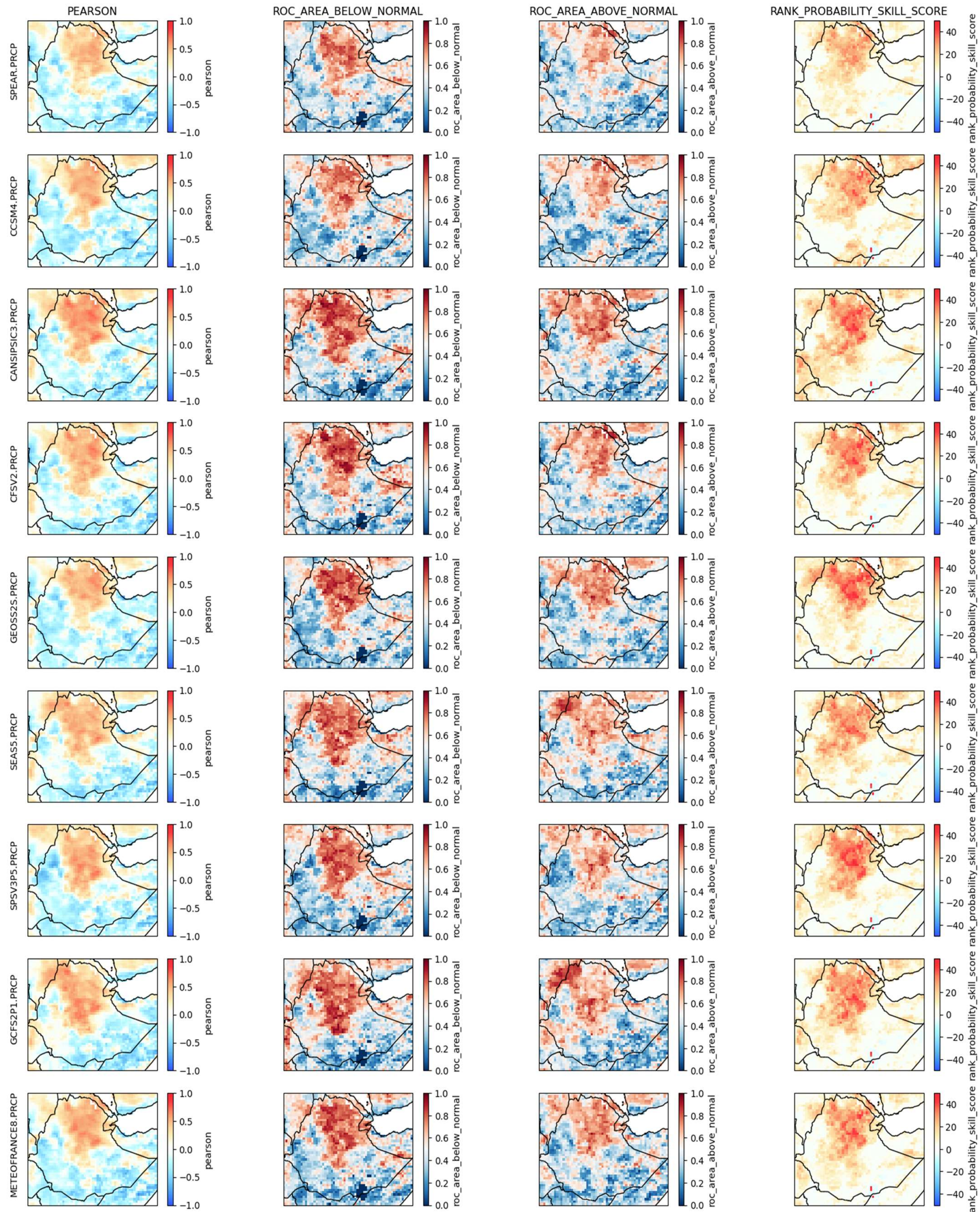

PEARSON
ROC_AREA_BELOW_NORMAL
ROC_AREA_ABOVE_NORMAL
RANK_PROBABILITY_SKILL_SCORE
SPEAR.PRCP
CCSM4.PRCP
CANSIPSIC3.PRCP
CFSV2.PRCP
GEOSS2S.PRCP
SEAS5.PRCP
SPSV3P5.PRCP
GCFS2P1.PRCP
METEOFRANCE8.PRCP
pearson
roc_area_below_normal
roc_area_above_normal
rank_probability_skill_score

Figure 8: Pearson correlation, ROC area below normal, ROC area above normal and RPSS skill of the CCA forecast for JJAS season, initialized in May. The red colors characterize higher skill in predicting JJAS rainfall, while blue areas indicate the opposite.

From Figure (8) first column, the result of Pearson correlation maps indicates that the CANSIPSIC3, CFSV2, SEAS5, GCFS2P1, SPSV3P5, and METEOFRANCE8 models exhibit high skill in the Central, North Western, Northern and Northeastern Ethiopia with the value of Pearson correlation is between 0.5 and 0.8. In addition, the SPEAR, CCSM4, and GEOSS2S models exhibit high skill (Pearson correlation values between 0.5 and 0.8) in the Northern parts of the country, but lower skill (values between 0.0 and 0.4) in the Central parts of the country compared to the other models. The Pearson correlation skill indicates a negative value (less than 0) in the western, southwestern, southern, and southeastern Ethiopia. This indicates that models exhibit very low performance in forecasting the JJAS seasonal rainfall in this region.

To assess the effectiveness of the seasonal forecast systems in terms of other metrics, we have used ROC metrics, Figure 8, the second column, shows the ROC area below normal. The CANSIPSIC3, CFSV2, SEAS5, GCFS2P1, SPSV3P5, METEOFRANCE8 and GEOSS2S models demonstrate high skill (ROC below scores greater than 0.7) in the Northern, Central, Northwestern, and Northeastern areas of the country. In comparison, the SPEAR and CCSM4 models show low performance (values between 0.4 and 0.5) in forecasting JJAS rainfall season over Central parts compared to the other models. The areas where models show higher ROC scores indicating good seasonal prediction skills are consistent with the Pearson correlation map present in the first column of Figure 8. The models present a forecast worse than the climatology in the southern, Western, Southeastern areas of the country, with the ROC area below normal is less than 0.5.

A similar analysis for the ROC area above normal indicates, the CANSIPSIC3, CFSV2, SEAS5, GCFS2P1, GEOSS2S, and METEOFRANCE8 models exhibit high skill (ROC area above normal value between 0.6 and 0.8) across Northern and Northeastern Ethiopia present in the third column of Figure 8. On the other hand, the SPEAR and CCSM4 models show low skill (ROC area above values between 0.4 and 0.5) over Northwestern and Central Ethiopia compared to the other models. However all models exhibit ROC area above normal value of less than 0.5 over southern, Southeastern and Western Ethiopia. This means the prediction skill is worse than the climatology prediction in this areas.

To further elucidate the forecast skill of seasonal forecast systems, we have applied RPSS. The fourth column of Figure 8 displays RPSS maps, and the CANSIPSIC3, CFSV2, GEOSS2S, SEAS5, GCFS2P1, SPSV3P5, and METEOFRANCE8 models exhibit high skill over the Northern, Central and Northeastern Ethiopia with the value of RPSS is between 20 and 40 %. This means the skill of forecast is better than the climatology values. The CCSM4 and SPEAR models show low skill (RPSS values between 0 and 20%) over the central and northern Ethiopia compared to the other examined models. However all models RPSS values less than 0 % over southern, Southeastern and Southwestern areas. This shows the prediction skill is worse than the climatology prediction in this areas.

Overall, in the JJAS season, based on ROC score the ability of the models in forecasting the below normal rainfall are higher than the above normal rainfall. The performance of the models present in Figure 8, the models are low skill in predicting JJAS rainfall season across Southern, Southwestern, Western, Southeastern, and some Central parts of Ethiopia with the Pearson correlation shows negative values, ROC values less the 0.5 and RPSS values less than 0 %. This indicates that the forecast skill is worse than the climatological. The reason for the low skill of the model is that JJAS is not the primary rainy season, especially in the southeastern and southern parts of the country; instead, it is a dry period. The CanSIPS-IC3, SEAS5, GCFS2P1, SPS3P5 and METEOFRANCE8 models show higher skill in predicting JJAS rainfall season across Central, Northwestern, Northeastern, Northern, and pocket areas in the Eastern part of Ethiopia with the values of Pearson correlation > 0.5, ROC area below normal >0.7, ROC area above normal > 0.6 and RPSS >20 % compared to other models. This is because the other models are low skill over the central parts. Additionally, in the Western, West of the Central, and Northwestern parts of Ethiopia, models show very low skill in predicting the JJAS rainy season. This could be due to the low resolution of GCM forecast, that are not able to resolve the effect of topography in these high topography areas. The GCMs lack the ability to resolve well the small-scale processes that are crucial for the local climate.

4.1.2 Skill of global prediction models in predicting rainfall during FMAM

The skill of models initialized in January was examined to predict February to May (FMAM) rainfall using the tropics (180°W to 180°E, 30°S to 30°N) as a predictor domain. Similar to the JJAS season the observed data from CHIRPS served as the basis for predictions, with the hindcast rainfall data from NMME and EU-C3S models. Figure 9 depicts the result of skill analysis metrics, Pearson correlation, ROC area below normal, ROC area above normal, and Rank Probability Skill Score (RPSS).

The result presented in the first column of Figure 9, the Pearson correlation map indicates that the CANSIPSIC3, SEAS5, GCFS2P1, SPSV3P5, and METEOFRANCE8 models have a high spatial skill (values between 0.5 and 0.7) in predicting FMAM rainfall seasons over the Central, Southern, Southeastern, and Eastern portion of Ethiopia. The SPEAR, CCSM4, GEOSS2S and CFSV2 models show high skill (values between 0.5 and 0.7) in the Southern, Central, and Eastern Ethiopia. This models are low skill (Pearson correlation values less than 0) over Southeastern Ethiopia compared to the other models. However, all models over the Western half of Ethiopia have low skill to predicting FMAM rainfall season with the Pearson correlation values less than 0. This means that the forecast skill is worse than the climatological forecast over this region.

To further scrutinize the forecasting skill of the FMAM season, we have used the ROC area below normal, as shown in the second column of Figure 9. The CANSIPSIC3, SEAS5, GCFS2P1, SPSV3P5, and METEOFRANCE8 models show high skill (ROC below value between 0.6 and 0.8) in forecasting FMAM rainfall seasons across Southern, Central, South eastern, Eastern, and Northeastern Ethiopia. Additionally, the SPEAR, CCSM4, CFSV2, and GEOSS2S models exhibit high skill (ROC below score between 0.6 and 0.8) in the Central, Southern, and Northeastern Ethiopia, but they show lower skill (ROC below score between 0.2 and 0.4) over Southeastern and Eastern parts of Ethiopia compared to other models.

The ROC area above normal in the third column of Figure 9, indicates that the CANSIPSIC3, SEAS5, GCFS2P1, SPSV3P5, and METEOFRANCE8 models show high skill (values between 0.6 and 0.7) over the Central, Southern, Southeastern, and Eastern parts. Similarly, the SPEAR, CCSM4, GEOSS2S, and CFSV2 models have a high skill (values between 0.6 and 0.7) in the

Southern, Central, and Northeastern portions of the country but the skill is low (values between 0.2 and 0.4) over the Southeastern and Eastern parts of the country compared to the other models. However, all models over Western half, Southeastern and Northwestern of the country have low ability (values less than 0.5) to predicting FMAM rainfall season. This indicates that the forecast skill is worse than the climatology.

The fourth column of Figure 9 displays the RPSS maps. The result presents the SPEAR, CCSM4, CFSV2, and SEAS5 models exhibit high predictive skill (RPSS values between 20 and 40 %) for the FMAM rainy season within the Central and Eastern regions of Ethiopia. The CANSIPSIC3, GEOSS2S, GCFS2P1, SPSV3P5, and METEOFRANCE8 models show low performance (values between 0 and 20 %) in forecasting FMAM rainfall season over Central and Eastern parts compared to other models. However, all models exhibit very low skill over western half of the country with the RPSS values less than 0% (i.e., the skill of the prediction is worse than the climatological prediction).

Overall, in FMAM season, the result shows all models have very low skill (Pearson correlation <0, ROC < 0.5 and RPSS <0) in predicting FMAM rainfall season over the Western half of Ethiopia (i.e., the performance of the forecast is worse than the climatological forecast). The reason for the low performance of the model in this region is FMAM is not the main rainy season, particularly in the Western Ethiopia, FMAM is a dry season. The models exhibit a higher ability to forecast below-normal rainfall than above-normal rainfall. The CANSIPSIC3, SEAS5, GCFS2P1, SPSV3P5, and METEOFRANCE8 models show higher skill (Pearson correlation between 0.5 and 0.7, ROC area below normal between 0.6 and 0.8, ROC above between 0.6 and 0.7 and RPSS between 20 and 40 %) in forecasting FMAM seasonal rainfall in Southern, Central, Southeastern and Eastern portion of Ethiopia compared to other models (i.e., the prediction performance is better than the climatological skill). During the FMAM season, models demonstrate greater accuracy in forecasting the rainy season in the Southern and Southeastern Ethiopia compared to the Northern and Western regions. This higher skill in prediction can be attributed, in part, to the fact that the Southern parts of the region lack complex topography, which may contribute to the models' improved performance in those areas when compared to the Western parts.

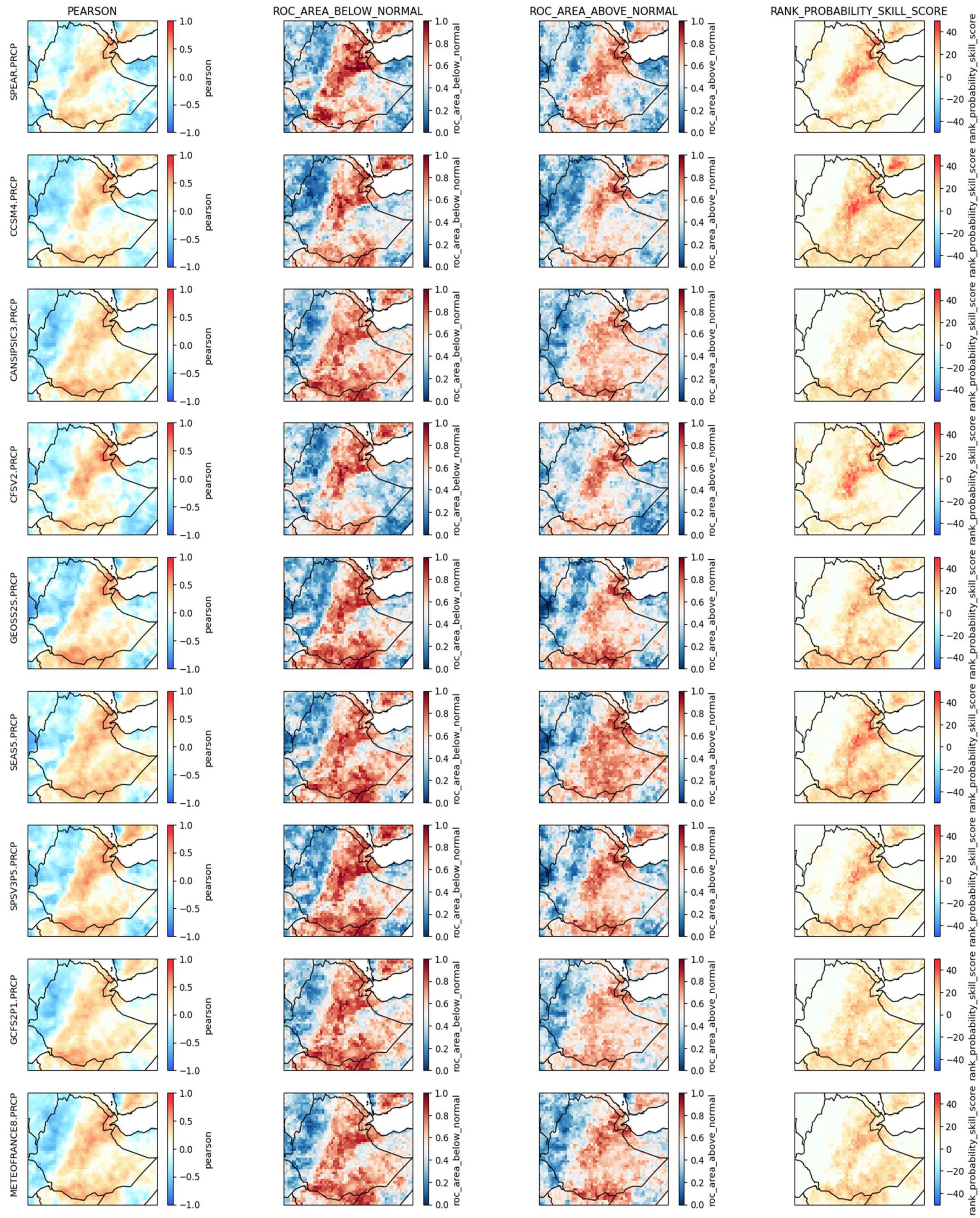

PEARSON
ROC_AREA_BELOW_NORMAL
ROC_AREA_ABOVE_NORMAL
RANK_PROBABILITY_SKILL_SCORE
SPEAR.PRCP
CCSM4.PRCP
CANSIPSIC3.PRCP
CFSV2.PRCP
GEOSS2S.PRCP
SEAS5.PRCP
SPSV3P5.PRCP
GCFS2P1.PRCP
METEOFRANCE8.PRCP
pearson
roc_area_below_normal
roc_area_above_normal
rank_probability_skill_score

Figure 9: Pearson correlation, ROC area below normal, ROC area above normal and RPSS of the CCA forecast for FMAM season, initialized in January. The Red colour indicate higher skill, while blue parts represent the lower skill.

4.1.3 Skill of global prediction models in predicting temperature during JJAS

The skill of the models has been assessed using the tropics (180°W to 180°E, 30°S to 30°N) predictor domain for the temperature season spanning June to September. The predictions were built upon the observed data obtained from CRU, as well as the hindcast temperature data from both NMME and C3S models. The results, illustrated in Figure (10), show the skill evaluation metrics of Pearson correlation, ROC area below normal, ROC area above normal, and Rank Probability Skill Score (RPSS) and using initialized in one month lead (May) with in a predictor is two-meter temperature.

The Pearson correlation in the first column of Figure 10, indicates that the SPEAR, CCSM4, CFSV2, GEOSS2S, GCFS2P1, and SPSV3P5 models show a higher spatial skill (values between 0.6 and 1.0) in predicting the JJAS seasonal mean temperature across the entire country, except for certain localized areas in the Northwestern and Southern regions. This shows that the skill of the forecast is better than the climatological forecast over the region. Nevertheless, the CANSIPSIC3, SEAS5, and METEOFRANCE8 models show low spatial skill (Pearson correlation values between 0 and 0.2) specifically in the Southwestern and North Western Ethiopia.

The ROC area below and ROC area above normal metrics shown in the second and third column of Figure 10, indicates that the SPEAR, CCSM4, CFSV2, GEOSS2S, GCFS2P1, and SPSV3P5 models show a higher spatial skill (ROC values between 0.8 and 1.0) in predicting and capturing the JJAS seasonal mean temperature across the entire country, except for some pocket areas in the Northwestern and Southern Ethiopia. However, the CANSIPSIC3, SEAS5, and METEOFRANCE8 models show a low spatial skill (ROC values between 0.2 and 0.4) specifically in the Southern and Western half of the country.

The RPSS shown in the fourth column of Figure 10, indicates that the SPEAR, CCSM4, CANSIPSIC3, CFSV2, GEOSS2S, SEAS5, GCFS2P1, and SPSV3P5 models show higher spatial positive skill (RPSS values between 40 and 100 %) in predicting and capturing the JJAS seasonal mean temperature across the entire country, except for some pocket areas in the Northwestern and Southern Ethiopia. However, the METEOFRANCE8 models depicts a lower spatial skill (values between 0 and 20 %) specifically in the Southern and Western half of the country compared to other models.

In general during the JJAS season, most models display low performance (Pearson correlation < 0, ROC values < 0.4 and RPSS values < 0 %) in forecasting the seasonal temperature in the pocket areas of Southern and Northwestern parts of Ethiopia. However, the SPEAR, CCSM4, CFSV2, GEOSS2S, GCFS2P1, and SPSV3P5 models demonstrate higher spatial skill (Pearson correlation values between 0.6 and 1.0, ROC values between 0.8 and 1.0 and RPSS values between 40 and 100 %) in predicting the JJAS seasonal temperature across the entire country, except for certain localized areas in the Northwestern and Southern Ethiopia.

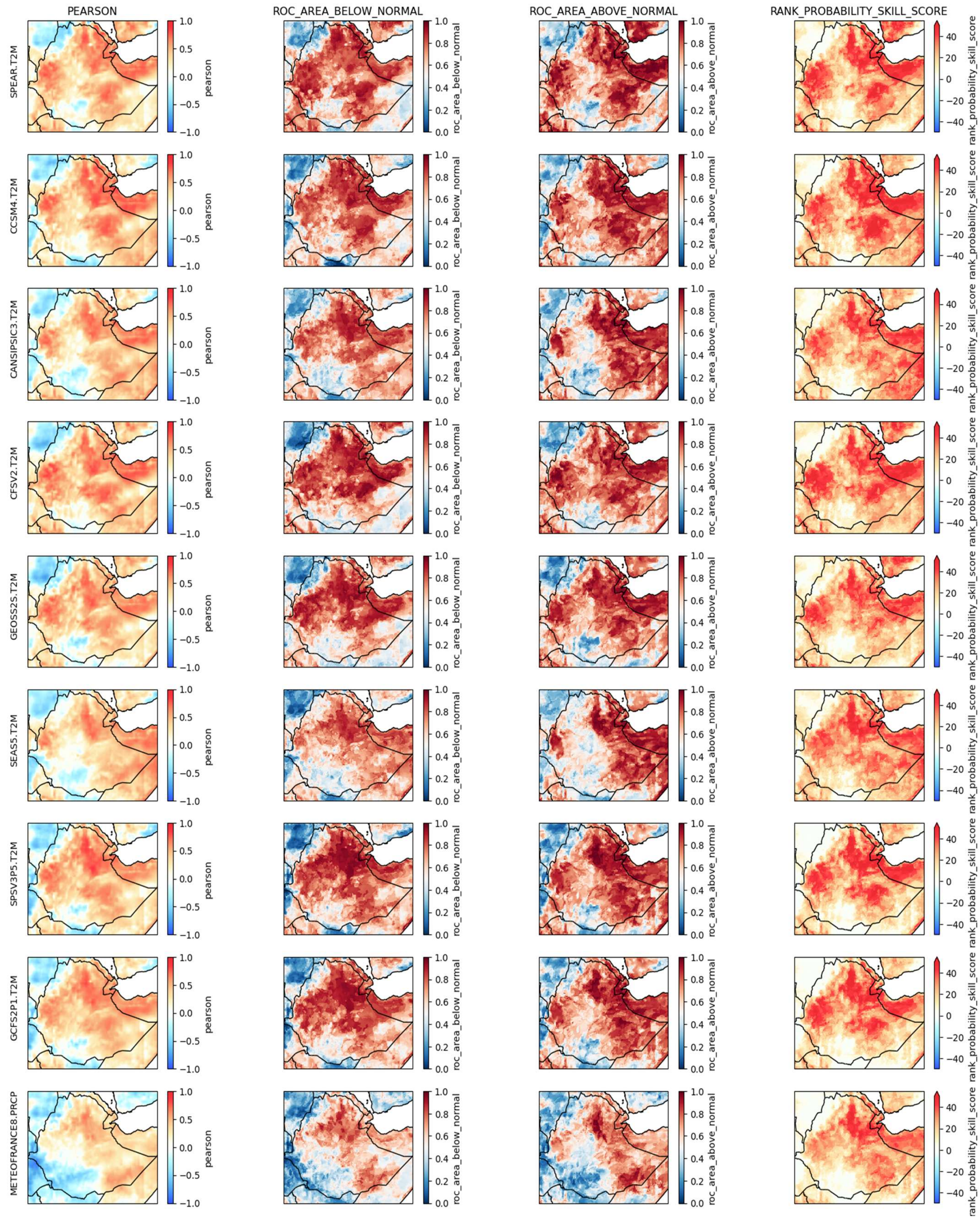

PEARSON
ROC_AREA_BELOW_NORMAL
ROC_AREA_ABOVE_NORMAL
RANK_PROBABILITY_SKILL_SCORE
SPEAR.T2M
CCSM4.T2M
CANSIPSIC3.T2M
CFSV2.T2M
GEOSS2S.T2M
SEAS5.T2M
SPSV3P5.T2M
GCFS2P1.T2M
METEOFRANCE8.PRCP
pearson
roc_area_below_normal
roc_area_above_normal
rank_probability_skill_score

Figure 10: Pearson correlation, ROC area below normal, ROC area above normal and RPSS of the CCA forecast for JJAS temperature season, initialized in May. The red regions indicate higher skill, whereas blue areas indicate the opposite.

4.1.4 Skill of global prediction models in predicting temperature during FMAM

The skill of individual models was investigated using tropics predictor domains for the temperature season spanning from February to May, using the observed data for two- meter temperature as the predictor and the mean temperature as a predictand. The forecast is initialized with a one-month lead time (January). The results, illustrated in Figure (11), used skill evaluation metrics are Pearson correlation, ROC area below normal, ROC area above normal and RPSS.

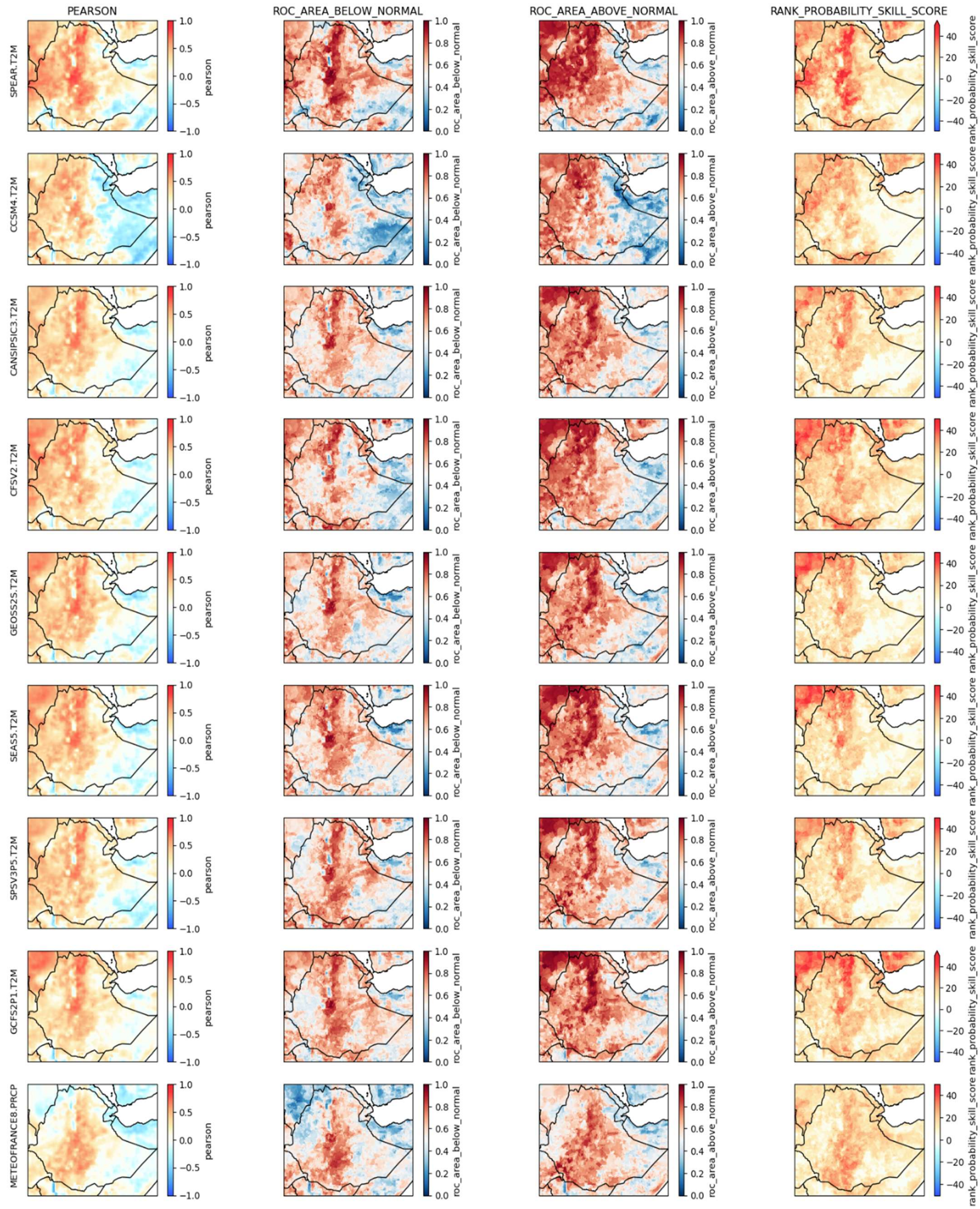
The Pearson correlation shown in the first column of Figure11, indicates that the SPEAR, CCSM4, CANSIPSIC3, CFSV2, GEOSS2S, SEAS5, GCFS2P1, and SPSV3P5 models show a high spatial skill (values between 0.5 and 0.8) in predicting and capturing the FMAM seasonal mean temperature across the entire country, except for Southwestern, Eastern and Northeastern parts of Ethiopia. The METEOFRANCE8 model show lower spatial skill (values between 0 and 0.2) in forecasting the seasonal mean temperature in the Western half, Southeastern and Northern Ethiopia compared to other models. However, all models exhibit lower spatial skill in predicting the FMAM seasonal mean temperature over the eastern half of the country (Pearson correlation values between 0 and 0.2).

The ROC area below normal metrics shown in the second column of Figure 11, indicates that the SPEAR, SEAS5, GCFS2P1, and SPSV3P5 models show high spatial skill (ROC area below normal values between 0.6 and 0.8) in predicting and capturing the FMAM seasonal mean temperature over Southern, Central and Northern portion of Ethiopia. In this case, the SPEAR model has shown a higher spatial skill (ROC area below normal values between 0.8 and 1.0) over southern, central and Northern parts compared to the other examined model. However, all models have shown a low skill (ROC below normal values between 0.2 and 0.4) in the Western half and Eastern parts except SPEAR model.

The ROC area above normal skill metrics shown in the third column of Figure 11, indicates that the SPEAR, CANSIPSIC3, CCSM4, CFSV2, GEOSS2S, SEAS5, GCFS2P1, and SPSV3P5 models shows high spatial skill (ROC area above normal values between 0.7 and 1.0) in predicting and capturing the FMAM seasonal mean temperature across the entire country, except for Southeastern and Eastern parts of Ethiopia.

The RPSS shown in the fourth column of Figure 11, indicates that the SPEAR, SEAS5, GCFS2P1, and SPSV3P5 models show high spatial skill (RPSS values between 20 and 40 %) in predicting the FMAM seasonal mean temperature over Southern, Central and Northern portion of Ethiopia. In this case, the SPEAR model has displayed a higher spatial skill (RPSS values between 40 and 100 %) in predicting seasonal mean temperature over Central, Southern, and Northern parts compared to the other examined models. However, all models have shown low skill (RPSS values between 0.0 and 20%) in forecasting the FMAM seasonal temperature in the Western half and Eastern parts except SPEAR model.

Overall, during the FMAM season, all models shown lower skill (Pearson correlation values between 0 and 0.2, ROC values between 0.2 and 0.4 and RPSS values between 0 and 20%) in forecasting and capturing FMAM seasonal mean temperature in the Southeastern and Eastern parts of Ethiopia. However, the SPEAR, CANSIPSIC3, CFSV2, GEOSS2S, SEAS5, GCFS2P1, and SPSV3P5 models exhibit high spatial skill (Pearson correlation between 0.5 and 0.8, ROC below normal value between 0.6 and 0.8, ROC above normal values 0.7 and 1.0 and RPSS values between 20 and 40 %) in predicting the FMAM seasonal mean temperature over the entire country, except for Southeastern and Eastern Ethiopia. The SPEAR model is higher spatial skill compared to the other models.



PEARSON
ROC_AREA_BELOW_NORMAL
ROC_AREA_ABOVE_NORMAL
RANK_PROBABILITY_SKILL_SCORE
SPEAR.T2M
CCSM4.T2M
CANSIPSIC3.T2M
CFSV2.T2M
GEOSS2S.T2M
SEAS5.T2M
SPSV3P5.T2M
GCFS2P1.T2M
METEOFRANCE8.PRCP
pearson
roc_area_below_normal
roc_area_above_normal
rank_probability_skill_score

Figure 10: Pearson correlation, ROC area below normal, ROC area above normal and RPSS skill of the CCA forecast for FMAM temperature season, initialized in January.

4.2. Analysis of the Effect of Different Predictor Domains on the Skill of Forecasts

In this subsection discussed the results of the effects of the examined predictor domains in the skill of prediction during JJAS and FMAM seasons.

The analysis of the forecast skill across various predictor domains was assessed using the multimodel ensemble (MME) approach, which is a widely acknowledged method for enhancing forecast ability compared to that of individual GCMs. For seasonal forecasting, such an approach could involve using historical climate data and Canonical Correlation Analysis (CCA) to identify patterns that are relevant to the JJAS season. Consequently, several predictor domains that are linked to the rainfall over Ethiopia have been examined for the JJAS and FMAM rainfall seasons. The examined predictor domains are Tropics, Western Indian Ocean, Ethiopia, Atlantic and Indian Oceans.

4.2.1 Analysis of forecast skill for different predictor domains during JJAS

The skill of the forecast has been evaluated across various predictor domains using the MME of nine models. A one-month lead forecast initialized in May has been employed for the evaluation during the JJAS season. The skill evaluation metrics Pearson correlation, ROC below normal, ROC above normal, and RPSS have been utilized in the analysis.

4.2.1.1 Tropical predictor domain (180°W to 180°E, 30°S to 30°N)

Figure 11 shows the multimodel ensemble forecast skill during JJAS rainfall season. The result presents the MME forecast exhibit higher skill (Pearson correlation values between 0.6 and 0.8, ROC below values between 0.7 and 1.0, Roc above values between 0.6 and 0.9 and RPSS values between 30 and 100 %) in predicting and capturing JJAS seasonal rainfall forecast in the Northern, Central, Northwestern, and Northeastern and Eastern portions of the country. This indicates that, when using the tropics predictor domain, the forecast skill in this region is better than that of climatology. However, the result of MME forecast shows very low skill (Pearson correlation values < 0, ROC values between 0 and 0.5 and RPSS values between 0 and 10 %) in the predicting

JJAS seasonal rainfall in the Southern, Southeastern, Western and Southwestern portions. It is worth noting that these parts of the areas except the Western part are dry during JJAS season.

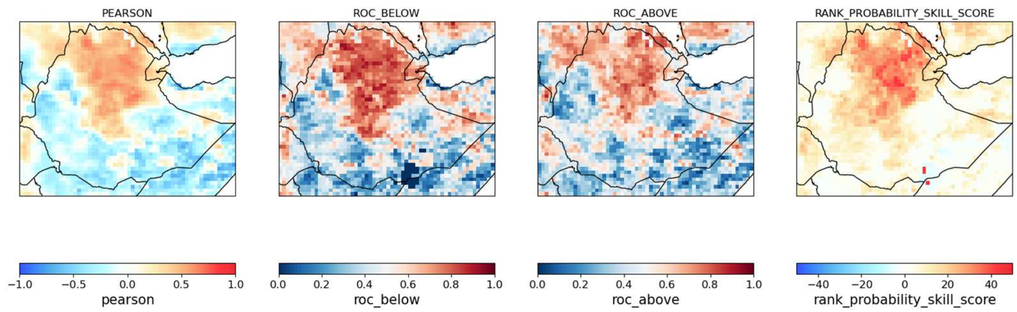


Figure 11: CCA multimodel ensemble forecast skill during JJAS season using tropical predictor domain and May initialized 1-month lead forecast.

4.2.1.2 Western Indian Ocean predictor domain (20°W to70°E and 17°S to 30°N)

In Figure 12, the evaluation of the multimodel ensemble seasonal forecast skill results show, the higher skill (Pearson correlation values between 0.6 and 0.8, ROC below values between 0.7 and 1.0, Roc above values between 0.6 and 0.9 and RPSS values between 30 and 100 %) for predicting the JJAS seasonal rainfall forecast in the Northern, Northeastern, Northwestern and Eastern portion. However, the Western Indian Ocean predictor domains are low skill (Pearson correlation values between 0.3 and 0.5, ROC below values between 0.5 and 0.6, Roc above values between 0.4 and 0.5 and RPSS values between 0 and 20 %) over the central parts of the country compared to tropical region. This indicates that when using the western Indian Ocean predictor domain, the forecast performance over central Ethiopia is lower than that of climatology compared to the tropics.

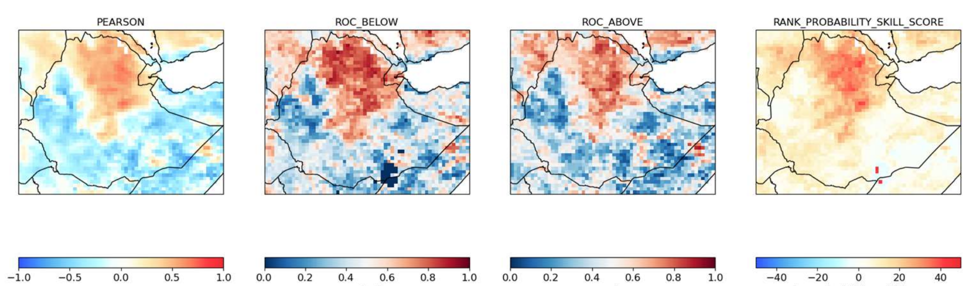


Figure 12: CCA multimodel ensemble forecast skill during JJAS season using Western Indian Ocean predictor domain and May initialized 1-month lead forecast.

4.2.1.3 Ethiopia predictor domain (33°W to 48°E and 3°S to 15°N)

Used to the predictor domain was Ethiopia itself the skill of the ensemble models showcased in Figure 13. The result reveals a higher skill (Pearson correlation values between 0.6 and 0.8, ROC below values between 0.7 and 1.0, Roc above values between 0.6 and 0.9 and RPSS values between 30 and 100 %) in predicting and capturing JJAS rainfall forecast over the Northern, Northeastern and Northwestern parts of Ethiopia. However, the multimodel ensemble forecast, utilizing the Ethiopian predictor domain, shows lower skill (Pearson correlation values between 0.3 and 0.5, ROC below values between 0.5 and 0.6, ROC above values between 0.4 and 0.5, and RPSS values between 0 and 20%) in forecasting the JJAS season in the central and eastern parts of the country compared to the tropical predictor domain.

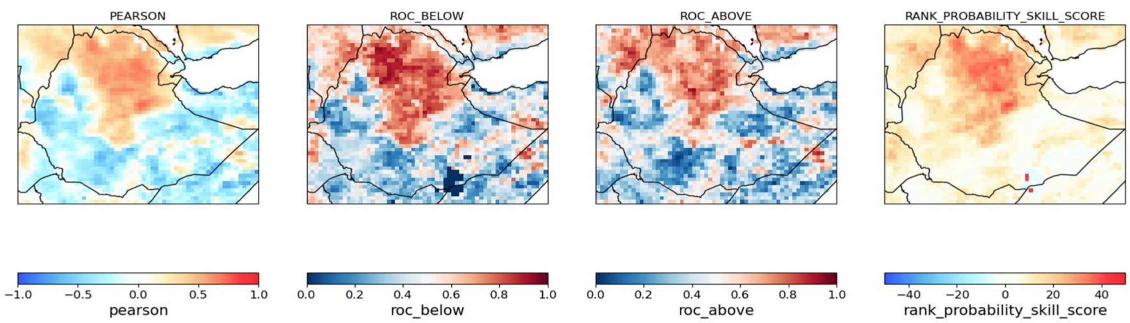


Figure 13: CCA multimodel ensemble forecast skill during JJAS season using Ethiopia predictor domain and May initialized 1-month lead forecast.

4.2.1.4 Atlantic and Indian Ocean predictor domain (60°W-160°E & 45°S-45°N)

The multimodel ensemble forecast skill was assessed using the Atlantic and Indian Ocean predictor domain, as shown in Figure 14. The multimodel ensemble forecast, utilizing the Atlantic and Indian Ocean predictor domain, shows similar predicting skill to the Ethiopian predictor domain in forecasting the JJAS season. However, the multimodel ensemble forecast, utilizing the Atlantic and Indian Ocean predictor domain, demonstrates lower performance in forecasting JJAS rainfall seasons in the central and eastern part compared to the tropical predictor domain.

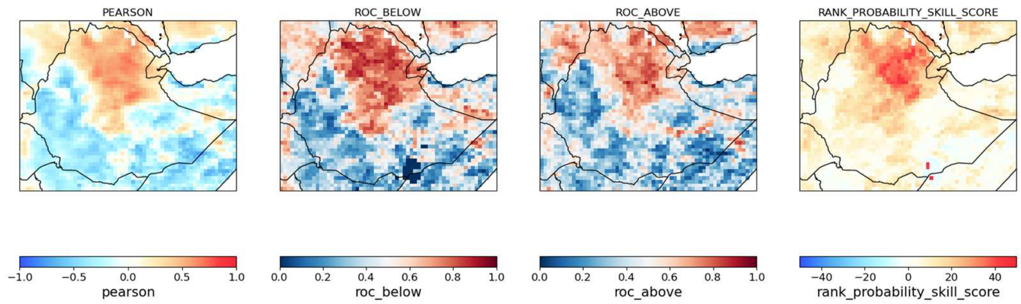


Figure 14: CCA multimodel ensemble forecast skill during JJAS season using Atlantic and Indian Ocean predictor domain and May initialized 1-month lead forecast.

In general, the evaluation of the effects of various predictor domains on forecast skill shows that the global tropics (180°W to 180°E, 30°S to 30°N) exhibit superior performance in the JJAS seasonal rainfall forecast for Ethiopia when compared to other examined domains. This is due to the tropical ocean particularly the Pacific has high association with rainfall over the central parts of Ethiopia, which outperforms the predictions of other domains. This indicates that the ENSO has a significant impact on the JJAS (June to September) rainfall season over Ethiopia. Furthermore, assessment based on ROC indicated that the multimodel ensemble exhibits stronger predictive skill for below-normal rainfall compared to above-normal rainfall during the JJAS rainy seasons. This suggests that the multimodel ensemble forecast demonstrates greater skill in forecasting dry conditions rather than wet conditions over Ethiopia.

4.2.2 Analysis of forecast skill at different predictor domains during FMAM

This section discusses the CCA ensemble model forecasting skill from February to May (FMAM) rainfall forecasts using similar methods as for the June to September season. During FMAM, a one month initialized prediction is utilized (January).

4.2.2.1 Tropics predictor domain (180°W to 180°E, 30°S to 30°N)

Regarding the Tropics predictor domain, the Pearson, ROC below, ROC above, and RPSS skill metrics for the ensemble models are depicted in Figure 15. The outcome shows a spatially high ability (Pearson correlation values between 0.6 and 0.7, ROC below values between 0.7 and 0.9, Roc above values between 0.6 and 0.8 and RPSS values between 20 and 30 %) in forecasting the FMAM rainfall season in the Southern, Central, Southeastern, some areas of Northeastern, and Eastern Ethiopia. However, the results show very low accuracy (Pearson < 0.0, ROC < 0.4, and

RPSS < 0%) in forecasting the FMAM (February to May) rainfall season in the western half of the country. This indicates that the prediction skill is worse than the climatological forecast over this region. Climatologically, this region experiences low rainfall during the Belg season.

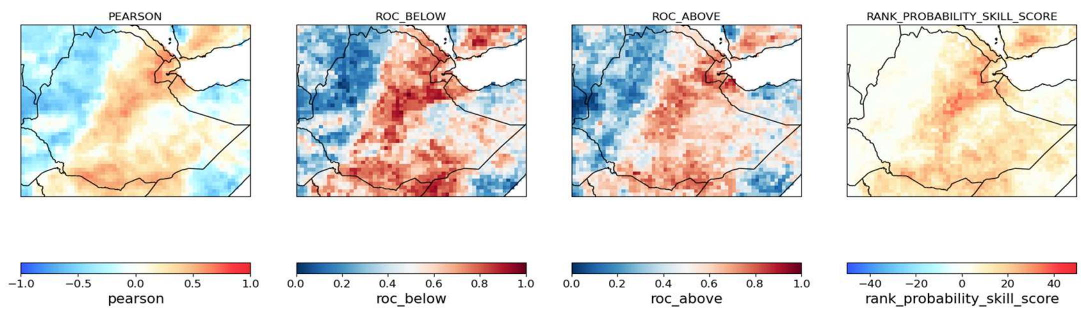


Figure 15: CCA multimodel ensemble forecast skill during FMAM season using tropical predictor domain and January initialized 1-month lead forecast

4.2.2.2 Western Indian Ocean predictor domain (20°W-70°E to -17°S-30°N)

Used to the Western Indian Ocean predictor domain for the ensemble models forecast during FMAM are depicted in Figure 16. The result shows high skill (Pearson correlation values between 0.4 and 0.6, ROC below values between 0.6 and 0.8, Roc above values between 0.6 and 0.7 and RPSS values between 10 and 30 %) in predicting the FMAM rainfall season in the Southern, Central, and Eastern parts of the country. Nevertheless, the result show very low skill (Pearson <0, ROC< 0.5 and RPSS values between o and 10 %) in forecasting the FMAM seasonal rainfall in the Southeastern, Northern and Western half of Ethiopia. Utilized the Western Indian Ocean predictor domain is low skill predicting FMAM rainfall seasons over Southeastern, and some areas of Northeastern parts of the country compared to Tropical predictor domain.

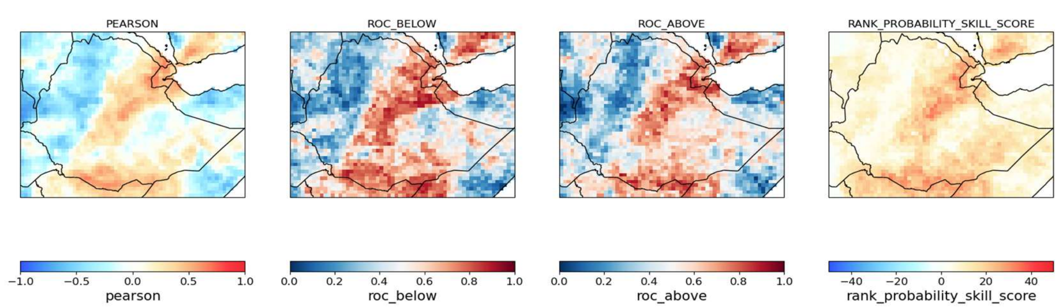


Figure 16: CCA multimodel ensemble forecast skill during FMAM season using Western Indian Ocean predictor domain and January initialized 1-month lead forecast

4.2.2.3 Ethiopia predictor domain (33°W to 48°E and 3°S to 15°N)

The ensemble models shown in Figure 17 demonstrate skill when Ethiopia itself is used as the predictor domain. The results, as depicted, exhibit a high skill (Pearson correlation values between 0.4 and 0.5, ROC below values between 0.6 and 0.7, Roc above values between 0.5 and 0.7 and RPSS values between 10 and 20 %) in forecasting the FMAM seasonal rainfall over Central, and Eastern portion of Ethiopia. However, the outcomes show lower in forecasting the FMAM seasonal rainfall compared to tropics and Western Indian Ocean predictor domain. Utilized the Ethiopian predictor domain is very low skill in predicting FMAM rainfall seasons over western half of the country.

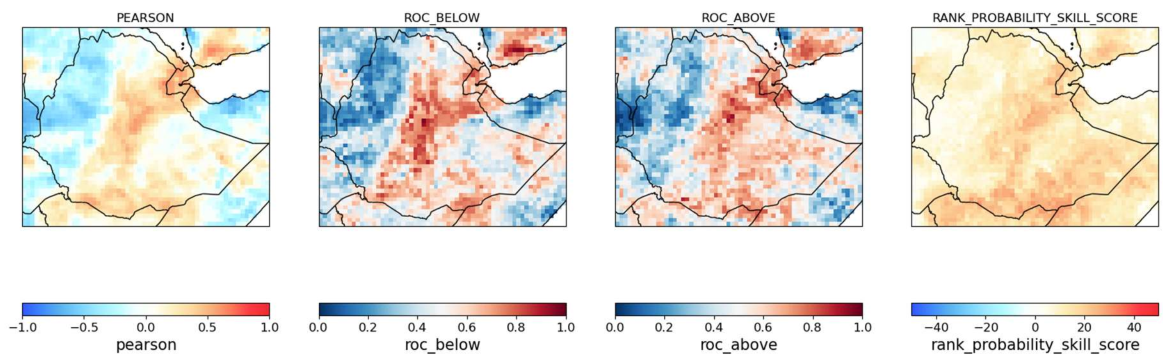


Figure 17: CCA multimodel ensemble forecast skill during FMAM season using Ethiopia predictor domain and January initialized 1-month lead forecast

4.2.2.4 Atlantic and Indian Ocean predictor domain (60°W-160°E & 45°S -45°N)

Figure 18 illustrates the spatial skill of the ensemble models using the Atlantic and Indian Ocean predictor domain. The result indicates that the Atlantic and Indian Ocean predictor domain has similar predicting skills for the tropics predictor domain, but lower skills (Pearson correlation values between 0 and 0.4, ROC values between 0.4 and 0.5, and RPSS values between 0 and 20%) over the southeastern and some areas of northeastern parts of the country compared to the tropical predictor domain.

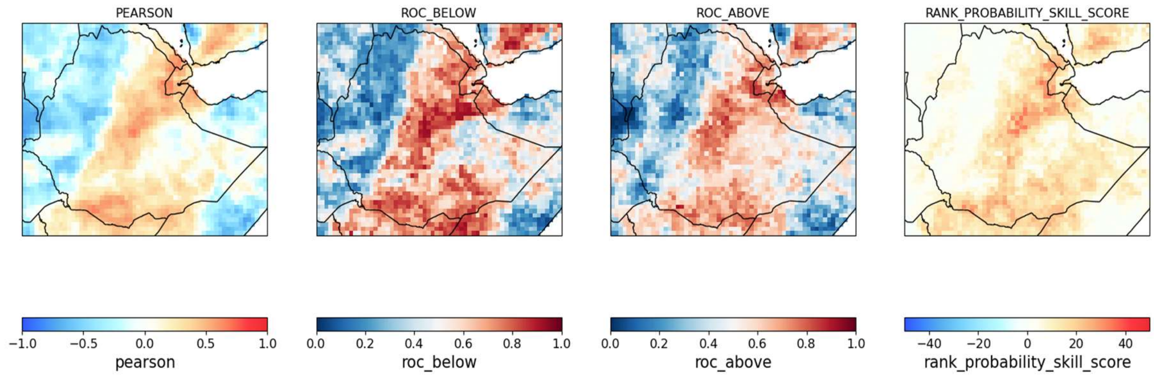


Figure 18: CCA multimodel ensemble forecast skill during FMAM season using Atlantic and Indian Ocean predictor domain and January initialized 1-month lead forecast

Furthermore, when comparing the tested predictor domains, the forecast exhibits higher skill levels when utilizing the tropical ocean domain (-180W-180E, -30S-30N) compared to others examined predictor domains. This is due to the tropics predictor domain high ability to predict the Northeastern, Southwestern and Southeastern parts of Ethiopia, which compared to other examined predictor domains. It has been noted that the performance of the models in forecasting the below normal rainfall are higher than the above normal rainfall for FMAM rainfall seasons. The performance of the multimodal ensemble (MME) is relatively weaker during the Belg season over Western parts of Ethiopia due to its weaker association with ENSO.

4.3 Examination of the Influence of Lead Time on the Forecast Skill

In this subsection discussed the results of the influence of lead time for both JJAS and FMAM seasons during 0-month, 1-month, and 2-month initialized forecast. The skill of the prediction is based on MME forecast. We used the Tropics region (180W to 180E and 30S to 30N) as the predictor domains for this analysis as it is the domain currently used by operational centers in the region and is supported by its demonstrated superior skill, as highlighted in Section 4.2.

4.3.1 Examination of the influence of lead time on the forecast accuracy during JJAS

During April initialized two-month lead forecast, the skill of the ensemble model as depicted in Figure 19. The outcomes indicate that MME shown substantial skill (Pearson correlation values between 0.5 and 0.8, ROC below values between 0.7 and 0.9, Roc above values between 0.6 and 0.8 and RPSS values between 30 and 40 %) in effectively predicting and capturing JJAS seasonal rainfall forecasts across the Northern, Northeastern, and Northwestern regions of Ethiopia. Utilized the two-month initialized forecast is lower skill (Pearson correlation values between 0.4 and 0.5, ROC below values between 0.5 and 0.6, Roc above values between 0.4 and 0.6 and RPSS values between 10 and 20 %) in forecasting JJAS rainfall seasons in the Central parts compared to one month and zero month initialized time forecast.

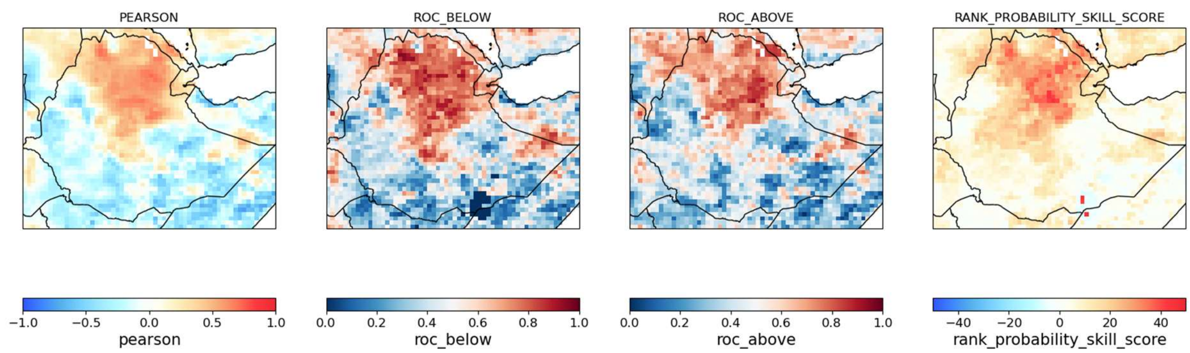


Figure 19: April initialized 2-month lead JJAS CCA multimodel ensemble forecast skill using tropical predictor domain.

During the 1-month lead forecast initialized on May illustrate in Figure 20. The outcomes reveal that the MME forecast demonstrates remarkable proficiency in effectively predicting JJAS rainfall season (Pearson correlation values between 0.6 and 0.9, ROC below values between 0.8 and 1.0, Roc above values between 0.6 and 0.8 and RPSS values between 30 and 100 %) over the Central, Northern, Northeastern, and Northwestern regions. Utilized the one-month initialized forecast is higher skill for predicting JJAS rainfall seasons over Central parts of the country compared to two month initialized forecast.

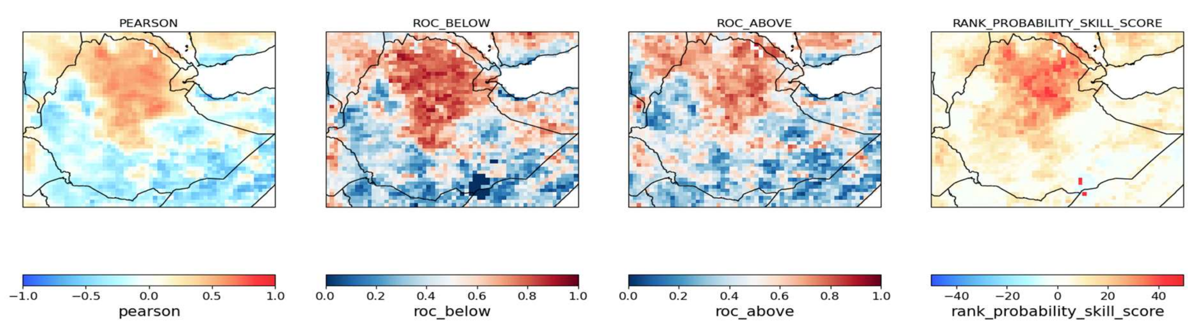


Figure 20: May initialized 1-month lead JJAS CCA multimodel ensemble forecast skill using tropical predictor domain.

Likewise, Figure 21 illustrates the June-initialized forecast skill. The results indicate that the skill of the MME forecast is similar to the 1-month lead time (May) forecast skill. The zero-initialized forecast does not provide sufficient planning time due to its proximity to the target season, hindering effective agricultural and water management planning.

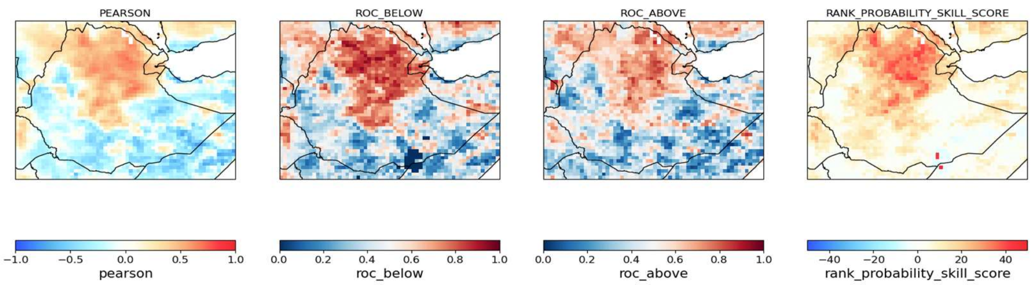


Figure 21: June initialized 0-month lead JJAS CCA multimodel ensemble forecast skill using tropical predictor domain.

Generally, it has been observed in the MME forecast that models demonstrate greater proficiency in predicting below-normal rainfall compared to above-normal rainfall during the JJAS season. It has also been indicated that one-month lead time (May) and zero-month lead time (June) forecasts show a better skill compared to April initialed forecast during JJAS season particularly over Central, Northern, Northeastern, Northwestern, and Eastern portion of Ethiopia. The one-month and zero-month initialized forecast are higher skill to predict the Central parts of Ethiopia compared to 2-month initialized forecast. The zero-lead time forecast does not provide sufficient planning time due to its proximity to the target season. For effective agricultural and water management planning, the preferred choice is the May-initialized forecast. However, MME forecast is low skill (Pearson correlation value <0, ROC values < 0.4 and RPSS values between 0 and 10 %) over Southern, Southeastern, Southwestern and Western parts of the country (i.e., the skill of the forecast is worse than the climatological forecast).

4.3.2 Examination of the influence of lead time on the forecast accuracy during FMAM

During FMAM season, the influence of lead time on the forecast skill evaluation using similar method used in JJAS season.

During FMAM the December initialized MME forecast is presented in Figure 22. The outcomes indicate that substantial skill (Pearson correlation values between 0.5 and 0.7, ROC below values between 0.6 and 0.8, Roc above values between 0.6 and 0.7 and RPSS values between 10 and 30 %) in effectively predicting and capturing FMAM seasonal rainfall forecasts across the Southern, Central, and Eastern regions of Ethiopia. The two-month lead time forecast skill is relatively low skill predicting FMAM rainfall seasons over Northeastern parts of the country compared to one month and zero-month lead time forecast.

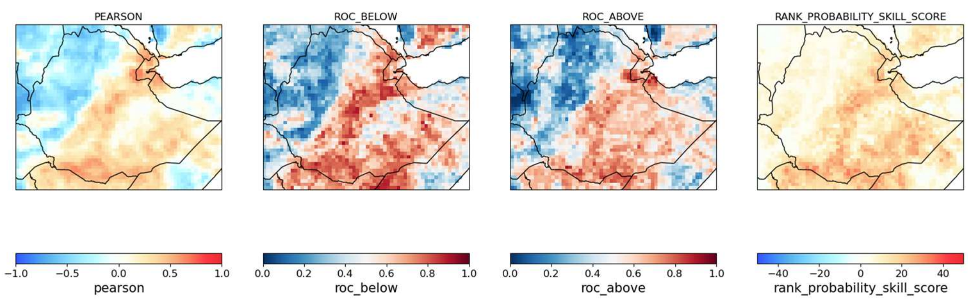


Figure 22: December initialized 2-month lead FMAM CCA multimodel ensemble forecast skill using tropical predictor domain.

In the 1-month lead forecast initialized in January, presented in Figure 23. The outcomes reveal that the MME forecast demonstrates remarkable proficiency (Pearson correlation values between 0.5 and 0.7, ROC below values between 0.7 and 0.9, Roc above values between 0.6 and 0.8 and RPSS values between 20 and 30%) in effectively predicting JJAS rainfall season over the Southern, Central, Northeastern, and Eastern portions of Ethiopia. The one-month initialized forecast is higher skill in predicting FMAM rainfall seasons over Northeastern parts of the country compared to two month and zero month initialized forecast.

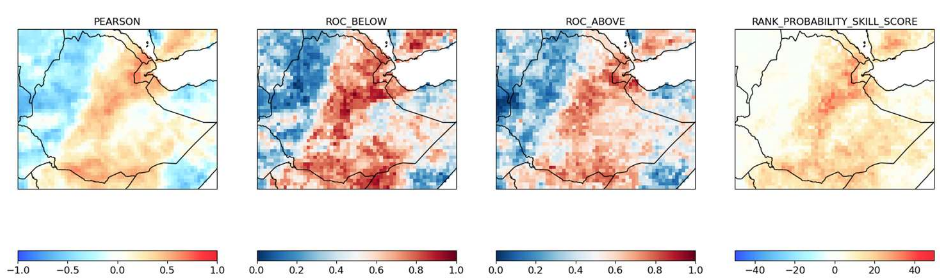


Figure 23: January initialized 1-month lead FMAM CCA multimodel ensemble forecast skill using tropical predictor domain.

Similarly, Figure 24 illustrates the zero-month (February) initialized forecast. The results indicate that similar skill with one- month (January) initialized forecast but zero lead time forecast is lower skill for predicting FMAM rainfall seasons over Northeastern parts of the country compared to one month lead time forecast**.**

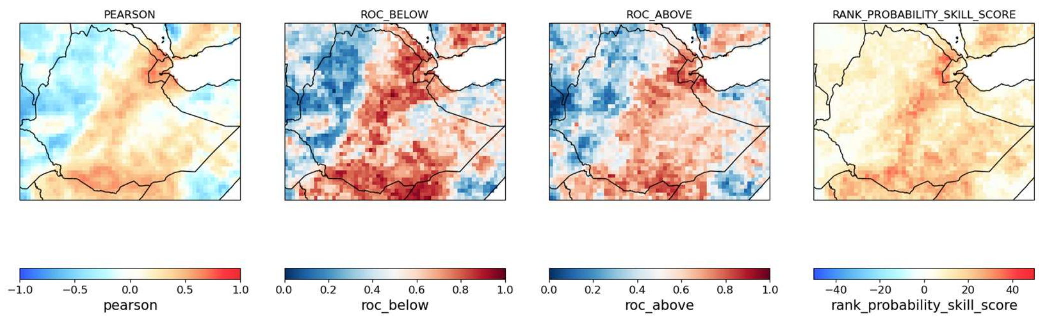


Figure 24: February initialized 0-month lead FMAM CCA multimodel ensemble forecast skill using tropical predictor domain.

Overall, one-month lead time forecast demonstrates higher predictive skill (Pearson correlation values between 0.5 and 0.7, ROC below values between 0.7 and 0.9, Roc above values between 0.6 and 0.8 and RPSS values between 20 and 30%) in forecasting the FMAM seasonal rainfall over the Northeastern parts of Ethiopia compared to a two-month and zero-month initialized forecast. This is because the two-month and zero-month initialized forecasts show low performance in the Northern parts of the country. However, the MME shows low performance (Pearson correlation <0, ROC values < 0.4 and RPSS values between 0 and 10 %) on predicting FMAM season over the Western half of Ethiopia. Multimodal ensemble (MME) Forecast has been noted that the performance of the models in predicting the below normal rainfall are higher than the above normal rainfall during FMAM seasons.

CHAPTER FIVE

5. Summary, Conclusion and Recommendation

This chapter summarizes the findings derived from various analyses, outlines the key conclusions drawn from these findings, and offers recommendations are also given future extensions of this research.

5.1 Summary

This research evaluated the performance of nine operational global seasonal prediction models over Ethiopia focusing on their ability to predict seasonal rainfall and temperature during the JJAS and FMAM seasons. Additionally, the study evaluated the effect of lead time and predictor domain on the forecast accuracy. The performance of NMME and C3S models was evaluated using hindcast data by employing the prediction at initialized of two-month, one-month, and zero month in the period from 1994 to 2016. The CHIRPS data has been used as a reference for rainfall, while the Climatic Research Unit (CRU) used as reference for temperature. These evaluations were conducted for the tropics, the Western Indian Ocean, Ethiopia, and the Atlantic Ocean and the Indian Ocean predictor domains.

The evaluation of seasonal forecast performance utilized a Python-based statistical tool called PyCPT to generate objective seasonal climate forecast (i.e., NextGen) and evaluate the accuracy of individual forecasting techniques in predicting temperature and precipitation over Ethiopia. This evaluation was conducted across various predictor domains and forecast lead times. The effectiveness of the models was measured by employing various skill evaluation metrics such as Pearson correlation, ROC, and RPSS.

During the JJAS and FMAM season, the models exhibit various levels of skill in predicting seasonal rainfall and temperature. The CanSIPS-IC3, ECMWF-SEAS5, DWD-GCFS2P1, CMCC-SPS3P5, and METEOFRANCE8 models shown higher skill (Pearson correlation between 0.5 and 0.7, ROC area below normal between 0.7 and 1.0, ROC area above normal between 0.6 and 0.8 and RPSS between 30 and 100 %) in predicting JJAS rainfall season over Central, Northwestern, Northeastern, Northern, and pocket areas in the Eastern part of Ethiopia compared to other models like GFDL-SPEAR, CCSM4, NASA-GEOSS2S, and NCEP-CFSv2. However, all models show robust low performance in predict JJAS rainfall season over the Southern, southeastern, Southwestern, and Western half of Ethiopia (i.e., the forecast skill is worse than climatological forecast). During FMAM season, the CanSIPS-IC3, ECMWF-SEAS5, DWD-GCFS2P1, CMCC-SPS3P5 and METEOFRANCE8 models shown higher spatial skill (Pearson correlation between 0.5 and 0.7, ROC area below normal between 0.6 and 0.8, ROC above between 0.6 and 0.7 and RPSS between 20 and 40 %) in forecasting the seasonal rainfall in the Southern, Southeastern, Central, and Eastern parts compared to other models. However, all models have very low skill (Pearson correlation <0, ROC < 0.5 and RPSS <0) in predicting FMAM rainfall season over Western half of Ethiopia.

The models SPEAR, CCSM4, CFSV2, GEOSS2S, GCFS2P1, and SPSV3P5 exhibit higher spatial skill (Pearson correlation values between 0.6 and 1.0, ROC values between 0.8 and 1.0 and RPSS values between 40 and 100 %) in predicting the JJAS seasonal mean temperature across entire regions of the country, with the exceptions being pocket areas in the Southern and Northwestern Ethiopia (i.e., the skill of the forecast is better than the climatological forecast). The SPEAR, CANSIPSIC3, SEAS5, CFSV2, GEOSS2S, GCFS2P1, and SPSV3P5 models exhibit higher spatial skill (Pearson correlation between 0.5 and 0.8, ROC below normal value between 0.6 and 0.8, ROC above normal values 0.7 and 1.0 and RPSS values between 20 and 40 %) in predicting the FMAM seasonal mean temperature over the Central and Western half of the country. The SPEAR model is higher spatial performance compared to the other models. However, the CCSM4 and METEOFRANCE8 models shown a low spatial skill over the Western half of Ethiopia.

The evaluation of the effect of various predictor domains on the forecast performance the tropics region (180W to 180E and 30S to 30N) exhibit superior performance during JJAS and FMAM seasons for Ethiopia when compared to other examined domains. This indicates that the ENSO has a significant impact on the JJAS (June to September) rainfall season over Ethiopia. During the FMAM season, the tropics predictor domain higher ability to predict the Northeastern, Southwestern and Southeastern parts of Ethiopia, which compared to other examined predictor domains.

The influence of lead time on the forecast accuracy for JJAS season, the one-month initialized (May) and zero-month initialized (June) forecasts showed a better skill compared to the forecast initialized in April. The June-initialized forecast does not provide sufficient planning time due to its proximity to the target season. For effective agricultural and water management planning, the preferred choice is the May-initialized forecast. During the FMAM season, the January initialized forecast is better skill for predicting FMAM rainfall season compared to the two month and zero month initialized forecast. This is due to the fact that a one-month lead forecast leads to higher predictive skill over the northeastern parts of Ethiopia.

5.2 Conclusion

Among the 9 prediction models, CanSIPS-IC3, ECMWF-SEAS5, DWD-GCFS2P1, CMCC-SPS3P5, and METEOFRANCE8 demonstrate noticeably better performance in predicting JJAS and FMAM rainfall than the other models, like GFDL-SPEAR, CCSM4, NASA-GEOSS2S, and NCEP-CFSv2. However, the skill of rainfall forecasts from the C3S and NMME models is very low over the southern, southeastern, southwestern, and western half of Ethiopia (i.e., the forecast skill is worse than climatology) during JJAS. Additionally, during FMAM, the forecast skill is particularly low over the western half of Ethiopia. This finding is consistent with other published literature and a significant portion of our skill assessment outcomes closely align with pertinent previous studies (Acharya et al., 2021; Teshome et al., 2022) .The performance of the models in predicting temperature is higher than that in predicting rainfall. The performance of the models in forecasting the below normal rainfall are higher than the above normal rainfall during JJAS and FMAM season. This indicates that the models demonstrates greater skill in forecasting dry conditions rather than wet conditions over Ethiopia. The MME forecast skill is better than the individual model forecasting skill. The Tropical region exhibit higher skill in the JJAS and FMAM seasonal rainfall forecasts for Ethiopia when compared to other examined domains. The influence of lead time on the forecast accuracy for JJAS and FMAM season, the 1-month lead forecast exhibits a better skill compared to the 2-month and 0-month lead time forecast. The findings of this study help to inform how a set of models could be chosen to generate an objectively consolidated MME of seasonal prediction, with the aim of producing operational objective seasonal forecasts and improving the accuracy of forecasting for Ethiopia, as recommended by the WMO.

5.3 Recommendations

The study's recommendations cover various stakeholders, including climate research scientists, the seasonal forecasting community, policymakers, service providers, infrastructure stakeholders in need of precise forecast information, and the overall public relying on seasonal rainfall outlook.

5.3.1 Recommendations to scientists

The evaluation of the ability of the model in forecasting rainfall in this research used precipitation as the predictand and predictor variable. For temperature, the two-meter temperature (T2m) serves as a predictor, and mean temperature (Tmean) is the predictand. We advise further studies could explore the inclusion of SST as a predictor variable for rainfall forecasting. The models consistently exhibit very limited skill in predicting rainfall over the Western half of Ethiopia. We recommend pursuing further research and implementations aimed at enhancing accuracy and skill in these challenging regions. In addition, further diagnostic examination of alternative potential drivers is necessary to gain a deeper comprehension of the sources of seasonal predictability and the connection between the accuracy of rainfall forecasts and the depiction of crucial mechanisms. We only examined the precipitation and temperature prediction, whereas many of the models showcased here generate several additional variables that may exhibit variations in performance. It should be noted that assessing some of these variables on a global scale is challenging because of the absence of climatological observations. Hence, forthcoming researchers could explore diverse components of the forecast variables.

5.3.2 Recommendations to users of climate prediction products

It is important to consider these findings when developing and refining seasonal rainfall forecasting models for Ethiopia, as they can contribute to improved decision-making in various sectors such as agriculture, water resource management, and disaster preparedness. The models consistently demonstrate better performance in forecasting JJAS and FMAM rainfall season at 1-month lead times compared to other lead times. Therefore, it is advisable to prioritize and rely on forecasts generated closer to the target period for more accurate predictions. Instead of relying on a single model, consider using an ensemble or combination of models to improve prediction accuracy. Identify the models that demonstrate promising skill in different regions or lead times and integrate their forecasts to leverage their strengths and compensate for their weaknesses. The performance of the models varies across different predictor domains. While some models show promising skill in certain regions, they may have limited ability to predict rainfall patterns in other areas. Consider the specific predictor domain relevant to the target region in Ethiopia when selecting models for prediction. Effective partnership between end-users and climate researchers is vital in appraising the economic importance of the particular forecasts provided by Ethiopian Meteorology Institutes and diverse climate centers.

The results obtained would be useful for various socioeconomic sectors. Farmers optimize yields and mitigate losses through crop and irrigation planning. Energy industries ensure efficient operations by predicting demand and managing resources. Tourism based on forecasts, enhancing customer experiences. Construction minimizes delays and costs by scheduling work and designing climate-resilient structures. Water management, disaster preparedness, public health, insurance, and trade decisions all benefit.

5.3.3 Recommendations to policy makers

Policy formulation and decision-making greatly benefit from accurate and actionable climate information. Initialization stands as a crucial aspect of numerical weather prediction, hinging on the quality of observational data. Given the region's challenging topography, the current station network across the country remains insufficient. Thus, a plan must be devised to augment the number of stations and also expand automatic weather stations strategically. Policymakers should actively collaborate to expand and strategically position these stations, encourage the collection and sharing of high-quality observational data to validate and improve climate models. Robust data from various regions and time frames are essential for model evaluation and verification. Policymakers should allocate resources to support research and development of climate models. This includes refining existing models, integrating new data and scientific understanding, and exploring novel modeling approaches. The results obtained would be useful for formulating actionable insights that can guide policy decisions across various sectors, helping to enhance resilience to climate variability, mitigate risks, and promote sustainable development.

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