UNIVERSITY OF NAIROBI

EXAMINING THE CHARACTERISTICS OF HISTORICAL AND FUTURE RAINFALL OVER THE SUDAN RAINFALL BELT

By

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DECLARATION

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

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DEDICATION

I dedicate this dissertation to my loving family, whose unwavering support and encouragement have been the driving force behind my academic journey. Their belief in my abilities and constant encouragement has fueled my determination to overcome challenges and pursue knowledge. Through their unwavering presence and love, they have provided me with the strength to persevere and reach for my goals. I am forever grateful for their sacrifices, guidance, and unwavering belief in me. This dissertation is a tribute to their love and an expression of my deepest gratitude for their immeasurable impact on my life. With a special dedication to my amazing wife, who has been my constant source of inspiration and motivation.

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ABSTRACT

Global warming significantly affects human activities, especially those reliant on rainfall for agriculture. The IPCC's fifth assessment report predicts that extreme weather events like droughts and floods will become more frequent and severe in the 21st century due to rising greenhouse gas emissions. Therefore, the purpose of this study was to investigate how future rainfall patterns in Sudan Rainfall Belt would be influenced by a changing climate. To do this, the study examined the characteristics of historical and future rainfall over Sudan Rainfall Belt based on observed gridded precipitation datasets, verified three GCMs from CMIP6, selected the model that best replicated the current climate, and then used it to assess the future rainfall pattern under SSP2-4.5 and SSP5-8.5 scenarios. The study used CHIRPs v2.0 and CMIP6 datasets to examine characteristics of historical and future rainfall over Sudan's Rainy Belt. The CHIRPs data period was from 1981 to 2022 and three GCMs from CMIP6 data were from 1981 to 2010 as baseline and from 2030 to 2099 as future projections. The future periods were divided into the near future (2030 – 2059) and the far future (2070 – 2099). The study area was divided into four zones. Mean, Coefficient of Variation, Rainfall Anomaly Index (RAI), and trend analysis were used to determine the spatial and temporal characteristics of observed rainfall. Root Mean Square Error (RMSE), Correlation coefficient, and Bias were used to verify the models. The linear scaling method was used to correct the GCMs output bias, and the projected change in seasonal rainfall was determined across the four zones under SSP2-4.5 and SSP5-8.5. The results showed variations in seasonal rainfall distribution over Sudan, with higher rainfall amounts observed in the southern parts (Zone 4) and portion of central parts (Zone 1, and 3) and decrease as goes northward. All the four zones manifested a significant increasing trend at 95% confidence levels in historical rainfall. The model verification results, MPI-ESM1-2-LR, INM-CM4-8, and BCC-CSM2-MR revealed the lowest RMSE and Bias in the southern parts and higher northward. In terms of correlation coefficients across all zones, the MPI-ESM1-2-LR (MPI) model exhibited superior performance at a 95% confidence level. The overall future changes in seasonal rainfall showed, Under the SSP2-4.5 scenario, a decrease in seasonal rainfall was projected for the near future with an average percentage of change between (-1% and -45%) over the four zones. However, under the more severe SSP5-8.5 scenario, a severe reduction in rainfall was projected across all zones with an average percentage of change between (-51% and -67%) compared to SSP2-4.5. Looking further

into the far future, both scenarios indicated an overall increase in seasonal rainfall with an average percentage of change between (49% and 96 %) for near and far future periods respectively. The study suggests that expected future change is attributed to the influence of climate change that will shift seasonal rainfall patterns. Therefore, this research provides more details on the expected change in seasonal rainfall in each zone of the rainy season and the total rainfall of each year across the four zones. Thereby providing a reasonable basis for agricultural planning, water resource management, and assessing climate change impacts in Sudan particularly in the study area in the future.

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LIST OF ABBREVIATIONS AND ACRONYMS

BCC	Beijing Climate Center Climate
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CMIP	Coupled Model Intercomparison Project
CMIP3	Coupled Model Intercomparison Project Phase 3
CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
CRU	Climatic Research Unit
CV	Coefficient of Variation
DJF	December, January and February
ESGF	Earth System Grid Federation
ENSO	El Niño - Southern Oscillation
FAO	Food and Agriculture Organization of the United Nations
GCAM	Global Change Assessment Model
GCMs	Global Climate Models
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
GPCC	Global precipitation Climatology centre
INM	Institute for Numerical Mathematics
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Intertropical Convergence Zone
JJA	June, July, and August
JJAS	June, July, August, and September

MAE	Mean Absolute Error
MK	Mann- Kendall
MPI	Max Planck Institute for Meteorology
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NSE	Nash–Sutcliffe Efficiency
PBIAS	Percent Bias
r	Pearson Correlation Coefficient
RAI	Rainfall Anomaly Index
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Index
SAI	Standard Anomaly Index
SRA2	SRES A2 Emissions Scenarios
SRES	Special Report on Emission Scenarios
SS	Skill Score
SSPs	Shared Socio-economic Pathways
SST	Sea Surface Temperature
TARCAT	Tropical Applications of Meteorology Using Satellite and Ground-based Observations (TAMSAT) African Rainfall Climatology and Time series
Tmax	Daily Minimum Temperature
Tmin	Daily Maximum Temperature
TEJS	Tropical Easterly Jet Stream
US	United States
WMO	World Meteorological Organization

CHAPTER ONE: INTRODUCTION

1.1 Background Information

Sudan rainfall belt is composed of two main regions. The central part, which includes the east, middle, and west parts of Sudan, is defined by an arid and semi-arid climate *(Alriah et al., (2021)*. The southern part, on the other hand, is marked by a sub-humid climate. The study domain is significant due to its substantial population density, rapid urban expansion, and substantial demand for natural resources. Both rainfed and irrigated crop cultivation, along with intensive pastoralism, are extensively practised in this area *(Trilsbach & Hulme, 1984)*. The rainy season (JJAS) is June, July, August, and September respectively in this region, with the peak rainfall typically observed in August and September *(EL Gamri1 et al., 2009).*

Because of global warming, the frequency, severity, and length of extreme weather occurrences are intensifying *(WMO, 2022).* Climate change influenced crop production across many regions of the globe, especially in Africa *(FAO, 2008).* Rainfall plays a crucial role in the hydrological cycle of the planet and has a substantial influence on the global atmospheric resource balance *(Alriah et al., 2022)*. This is particularly concerning for the African continent due to its high reliance on agriculture and limited potential to adapt and the adverse consequences of rainfall variation and extreme weather events will directly affect crop yields, to address these challenges, adaptation measures are necessary, including changes in production practices, crop selections, and even the relocation of people. Additionally, effective mitigation strategies to combat global warming should involve land-use changes and emissions reductions (*Collier et al., 2008)*.

Alriah et al., (2021) mentioned that due to its arid and semi-arid environment and naturally fragile ecosystems, the Sudan region is facing considerable challenges due to climate change. The region's fluctuating rainfall patterns and rising temperatures make crop production particularly susceptible to global warming. These climate-related issues are projected to impact around 40% of the Gross Domestic Product (GDP). These changes pose significant threats to water resource management and food production, affecting approximately 80% of both rural and urban populations who rely on farming. Desertification and droughts further amplify these challenges. However, *Siddig et al.,* *(2020)* stated that Both rainfed and irrigated agricultural production in Sudan is influenced by a shift in temperature and rainfall trends, which has influenced Sudan's economy.

Franklin & wigge , (2014) indicated Precipitation and temperature play critical roles in determining plant growth. These factors can directly impact plant growth, increase water usage due to heightened evaporative demand, or induce drought responses caused by alterations in precipitation patterns. Consequently, changes in these factors have the potential to cause plant stress. However, Sudan's rainfed agriculture is sensitive to global warming, which is recognized as a significant factor influencing GDP and livelihood. Examining the historical and future rainfall change will assist in understanding the side effects of global warming in Sudan, considering water demand, and to avoid potential economic losses resulting from climate change, Sudan must take immediate action to mitigate its effects.

Based on model simulations, *Siddig et al., (2020)* indicated that Sudan's GDP could decrease by up to 105.5 $ billion between 2018 and 2050 due to the negative impacts of global warming compared to an observed average climate scenario that does not involve climate change. Therefore, urgent measures are required to safeguard Sudan's economy.

The effects of changing precipitation patterns on food security in Sudan have consistently demonstrated negative impacts on cereal crops, inflation, income, and vulnerable households. This underscores the interconnectedness between climate change, food security, and poverty. Nonetheless, deepening our comprehension of the complex links between climate fluctuations, poverty, and food security in Sudan is imperative *(Sassi & Cardaci, 2013)*. In addition, Environmental degradation has caused increased temperatures, decreased rainfall, sunshine duration, and solar radiation in Sudan, with evapotranspiration rates increasing and extreme events increasing *(Elagib & Mansell, 2016)*.

Climate change has impacted Sudan widely in many sectors. However, Sudanese people are more sensitive to global warming due to multiple stresses *(Zakieldeen, 2009)*. The impact of climate factors, particularly temperature and precipitation on agriculture in Sudan has drawn increasing attention from researchers. *Chen et al., (2013*) showed that changing trends in these variables can have a critical influence on agricultural yields. Therefore, it is essential to evaluate the expected influence of changing climate on rainfall patterns and its consequences for agricultural production in the study area because of the high reliance on rainfall. Changing the distribution of atmospheric systems might influence the water resources and food supply in the future around the globe. Thus, monitoring the current and potential conditions of the climate is essential for identifying weaknesses and producing adaptive climate change policies (*Araya-Osses et al., 2020*).

The study highlights the intricate relationship between global warming, rainfall patterns, and their effects on various aspects of Sudan's society and economy. The geographical and temporal features of rainfall play a central role in these dynamics, affecting agriculture, food security, water resources, and overall livelihoods. Understanding and managing these characteristics are essential for developing policies to mitigate the negative impacts of global warming on Sudan's future.

Expanded knowledge of the drivers and implications of warming has recently been considered a most difficult challenge in science, and they are extremely important for society. Apart from the data, Global Climate Models (GCMs) are thought to be among the greatest instruments we have for understanding global climate dynamics. The reliability of GCMs comes from these factors. a) These global models are built on physical laws that quantitatively characterize each component's actions and reactions. b) These models have shown they can reproduce the present and future conditions across a wide range of temporal scales, from now-cast to seasonal prediction, to extremely large geographic and temporal forecasts, in addition to their demonstrated capacity to simulate historical climate *(Hamadalnel et al., 2022)*. GCMs under various emission scenarios are used to analyze potential changes in the climate system as indicated by *Araya-Osses et al., (2020*).

The challenges posed by climate change in Sudan Rainfall Belt, include its impacts on agriculture, water resources, and the economy. It emphasizes the need for more accurate information and immediate action, integrated policy-making, and the use of reliable climate models that simulate the rainy season to understand and mitigate these challenges effectively.

1.2 Statement of the Problem

The effects of global warming on rainfall patterns in Sudan Rainfall Belt pose risks to millions of people dependent on agriculture and related sectors. The management of the region's water resources and agricultural production face challenges as a result of changes in rainfall patterns. To address this issue; a full understanding of the implications of earth warming and extensive investigation is required on future rainfall characteristics in Sudan rainfall belt, and utilize GCMs outputs from Coupled Model Intercomparison Project Phase 6 (CMIP6) under different scenarios to evaluate the rainfall future change to avoid the severe impact of changing climate.

This study aims to support policymakers in developing effective policies to mitigate the risks of global warming on future rainfall changes by obtaining valuable information on the expected change in rainfall, enabling them to formulate strategies that will protect their communities, economies, and environments, particularly over the rainfed agricultural zone.

1.3 Objective of the Study

The primary objective of this study was to analyze the characteristics of historical and future rainfall over Sudan Rainfall Belt. The study's specific objectives are:

1. To investigate the temporal and spatial characteristics of the observed rainfall over Sudan.
2. To verify the skill of GCMs from CMIP6 in simulating the CHIRPs dataset over Sudan Rainfall Belt in JJAS season.
3. To evaluate the potential near-future and far-future change in the rainy characteristics under the SSP2-4.5 and SSP5-8.5 scenarios.

1.4 Justification of the Study

The socioeconomic status of many African countries, including Sudan, is highly dependent on rain-fed crop production and surface fresh water. Approximately 90% of the people in Sudan receive their food from rain-fed farming (*Zhang et al., 2012*). The monsoon season's rainfall is of utmost importance in Sudan's cultivation and water supply management. With global warming causing shifts in precipitation patterns, the potential consequences, including floods and droughts, could have a devastating impact on household individuals, different kinds of farming, livestock, water resources, pastoralism, food security and the environment. Consequently, understanding of future rainfall patterns are essential due to their significant impact on society.

Accordingly, this study focuses on the Sudan Rainfall Belt. The selected region is significant due to its high population, rapid urbanization, and substantial demand for natural resources. The region extensively practices crop cultivation, both rainfed and irrigated, along with intensive pastoralism. These factors have resulted in environmental issues such as desertification *(Trilsbach & Hulme, 1984)*.

Therefore, examining the historical and future rainfall over the study area divided it into four zones will improve our understanding of the impact of shifting rainfall patterns on water supply, and generate meaningful information on rainfall patterns that will aid in mitigating the adverse effects of earth warming on water resources and agriculture production, encourage sustainable management practices in the in each zone, and cover the gap by giving detail information for each zone of Sudan rainfall belt rather than other studies that considered it as one zone.

1.5 Study Area

The country of Sudan is situated within the coordinates of 8.2°-23.5°N lat and 21.5°-38.5°E long, in the tropical arid area of northeastern Africa. In the north, it borders Egypt; in the northwest, Libya; in the west, the Central African Republic and Chad; in the east, the Red Sea, Eritrea, and Ethiopia; and in the south, South Sudan. The area of study is part of Sudan, composed the central (Zone 1, 2, and 3) and southern (Zone 4) parts of Sudan as shown in Figure 1. It is divided into four zones according to the distribution of the weather stations in the study domain (i.e. Zones I, II, III, IV) representing the central (east to west), and south of Sudan *(Alriah et al., 2022)*.

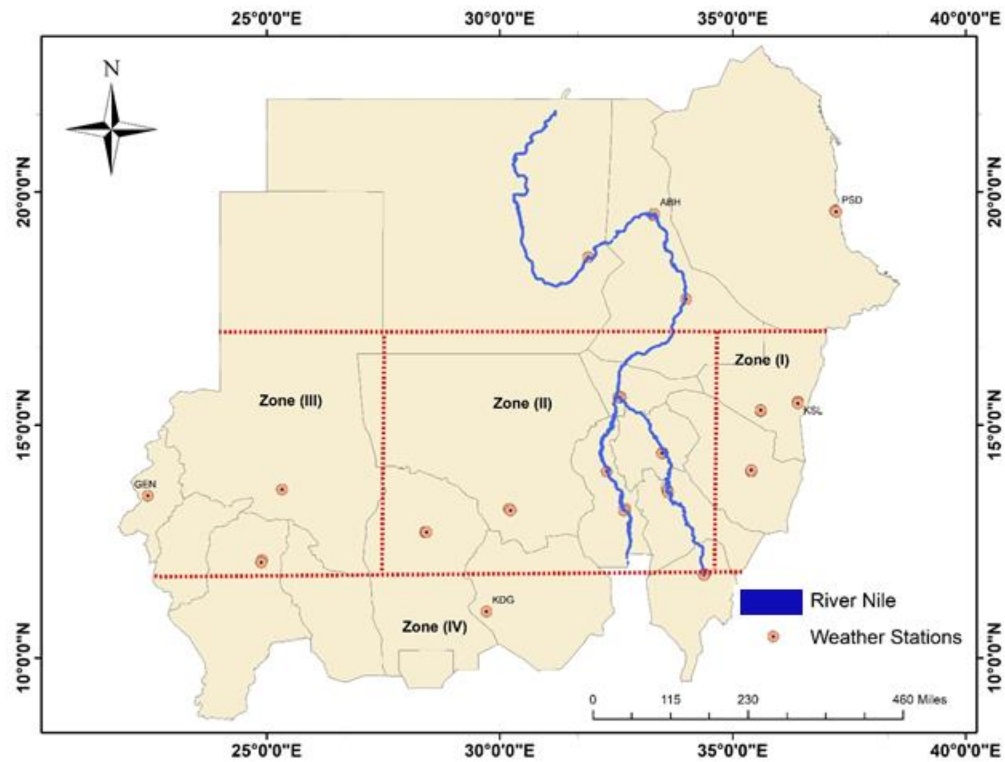

Figure 1: Sudan map the with meteorological stations, the red dotted lines represent the climatological boundaries following the dividing of the meteorological stations into four near-homogeneous rainfall zones, representing the study area which composed of the central (east to west), and south zones—source (Alriah et al., 2021).

1.6 Main Climatic Systems Influenced Sudan's Climate

Since the early 1960s, the annual average rainfall has markedly declined, giving two sections either dry or semi-arid. The amount of rainfall in Sudan exhibits a significant variation northward, with the far southwest receiving as much as 1500 mm. The period from June to September is commonly recognized as the wet season. The main climatic systems that influenced Sudan's climate are the Intertropical Convergence Zone (ITCZ), Tropical Easterly Jet Stream (TEJS), Mesoscale Systems, and El Niño - Southern Oscillation (ENSO) *(EL Gamri1 et al., 2009).*

(Jafari & Lashkari, 2021) their study explained the ITCZ is a thermal low zone in the tropical atmosphere, where trade winds converge to form precipitation as result of convergence that increase the convection processes. *(Waliser & Jiang, 2015)* indicated its position, structure, and

migration impact ocean-atmosphere interactions, circulation, and Earth's climate. *Trilsbach & Hulme, (1984)* found out the maximum rainfall within 400 to 600 Km behind the ITCZ.

The thermal characteristics of the Tibetan Plateau contribute to the formation of the TEJS in central Asia, which extends westward and appears as a weaker jet over West Africa. The TEJS has a great effect on the convection of cumulonimbus clouds, which affects the rainfall distributions. In Sudan, the early presence of the TEJS from May to July leads to low rainfall over the Ethiopian Plateau and high rainfall over Sudan due to advection clouds. Conversely, the delayed development of the TEJS in August is associated with significant rainfall in the Ethiopian Plateau from May through July *(EL Gamri1 et al., 2009).*

El-Tom, (1975) highlighted one influence of mesoscale systems in Sudan's climate. Their study indicated that Sudan's rainfall declines from the southwest to the northeast following the airflow that is causing rain. Mountainous regions including, the Ethiopian Plateau, however, can alter this pattern by shifting isohyets to the north and resulting in rain shadows on the eastern edges of the highlands. Eastern Sudan has moister winds because of the Ethiopian Plateau's deflective influence, which also converts southwesterly to northerly winds.

El Gamri et al., (2007) found out the influences of ENSO events on rainfall patterns in Sudan. Indicating distinct impacts associated with these phenomena. Hence, the below-average rainfalls, closely linked to the ENSO signal, are predictable for early drought warnings, while it observes above rainfall averages during La Nina events *(Ana, 2012)*. Due movement of ITCZ from the south to north of Sudan form March to May in the southern part of the country causing temperature gradient. By June to September the it reaches farthest north resulting wide spread of rainfall in Sudan. By October it starts to retreat to south. The other climatic driver influences the amount of rainfall in the Sudan as well as in the study area.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter is to provide previous studies carried out on the spatio-temporal characteristics of rainfall, verification of GCMs, Projected precipitation under changing climate, Coupled Model Intercomparison Project (CMIP), and climate change scenarios.

2.2 Studies on Spatial and Temporal Characteristics of Rainfall over Sudan

According to *Ghorbani et al., (2021),* the spatio-temporal characteristics of precipitation and temperature was examined Using rainfall datasets from 11 meteorological weather stations and 40 rain gauge over different locations in Ardabil province, Iran for the period from 2009 to 2019. The study involved utilizing descriptive statistics to assess the dataset, with the coefficients of variation highlighting the variability over region. A Pearson linear correlation was conducted to assess the temporal stability. Additionally, spatial interpolation was performed using the Kriging geostatistical estimator in conjunction with a Geographic Information System (GIS) interface. The outcomes of the study revealed that the spatial temperature variation exceeded that of rainfall in the studied region.

Kouman et al., (2022) carried out a study in the Côte d'Ivoire across the Zanzan region for the period 1981 to 2020. The study analyzed extreme precipitation and temperature trends, employing daily precipitation and temperature of 12 meteorological weather stations. The findings indicated a declining trend in total annual precipitations and daily precipitation intensity indices, along with a rising trend in the index for consecutive dry days. Temperature extremes were mostly significant, with cold spells showing decreasing trends and warm spells showing increasing trends. The findings suggest food insecurity and water scarcity may threaten the region, and the findings aim to promote initiatives for climate adaptation and policy interventions.

Ongoma & Chen, (2017) studied the spatio-temporal characteristics of temperature and precipitation within the East Africa region, spanning the time frame of 1951 to 2010. For this analysis, monthly datasets sourced from both the Climate Research Unit (CRU) and the Global Precipitation Climate Centre (GPCC) were employed. The CRU dataset demonstrated superior performance in accurately portraying the annual rainfall cycle compared to the GPCC dataset. The study unveiled notable fluctuations in rainfall and temperature trends, encompassing significant declines and rises. Particularly a significant reduction in rainfall was observed during the March-May period. Notably, the 1960s registered the highest annual rainfall rate, characterized by a reduction of -21.76 mm/year. Temperature-wise, a pronounced escalation occurred from the late 1960s through 1994, with the 1990s marking the pinnacle of warming rates. Geographically, the northern sector exhibited positive anomalies in both rainfall and temperature, contrasting with the opposite conditions in the southern sector.

Omoj et al., (2016) used three types of datasets, monthly rainfall, temperature, and SST. The graphical, statistical, and Spectral analysis techniques were used to evaluate the spatio-temporal characteristics in South Sudan. The findings demonstrate an insignificant increase or reduction in seasonal and annual rainfall across most areas in South Sudan, accompanied by a significant rise in temperature at 0.5 level of confidence across numerous locations within the region.

Trilsbach and Hulme, (1984) investigated spatiotemporal characteristics of rainfall based on statistical and graphical analyses of long-term observations of annual rainfall from 1921 to 1980 across central Sudan highlighting the presence of distinct wet and dry periods. However, there is no long-term trend or regular oscillation evidence. Rainy days with over 10 mm of rainfall consistently mirror wet, while lighter rainfall does not exhibit the same pattern. The heaviest rainfall events exceeding 40 mm closely correspond to annual patterns.

Hulme, (1990) found out that the changing rainfall patterns in Sudan indicated a significant depletion in rainfall supply, particularly in central Sudan, during two distinct periods, specifically between 1921 and 1950 and again from 1956 to 1985, there was a noticeable reduction in yearly precipitation of approximately 15%. This was accompanied by a shortened wet season and a relocation of the rainfall belt towards the southward direction. The reduction in rainfall was primarily attributed to a reduced frequency of rain occurrence, rather than a decrease in the amount of rainfall per occurrence. This has implications for water availability and livelihoods in the region.

In a study conducted in Sudan by *Zhang et al., (2012)*, an assessment of the geographical and temporal characteristics of past and future summer monsoons was conducted. This analysis utilized the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis dataset and station dataset. Linear regression was used and MK to test the significance of the monsoon trend. the result showed a noticeable spatial variation in the annual and monthly mean of monsoonal rainfall in Sudan and a significant negative trend in annual total rainfall over central Sudan from 1984 to 2005.

Ana, 2012) indicated Sudan, a geographically diverse area, has recently witnessed a decrease in its rainfall patterns. By analyzing a large number of rain gauges that exist in the Sahel region of Sudan in conjunction with the Tropical Applications of Meteorology using Satellite and ground-based observations (TAMSAT) African Rainfall Climatology and Time series (TARCAT), the study investigated historical fluctuations and enduring changes. The data indicates a reduction in rainfall between 1960 and 1980, followed by an unprecedented recovery phase from 1980 to 2011.

Hamadalnel et al. (2021) examined The temporal and spatial characteristics of the rainy season in Sudan using a monthly rainfall dataset of 22 stations throughout the country, MK and Sen's slope was used to estimate and test the significance of the trend respectively. The study revealed that there is variation in the trend of monsoon rainfall throughout the country a positive trend during the period (1990 – 2019) and a negative trend during the period (1960 – 1989).

In conclusion, using the graphical, statistical, and Spectral analysis techniques is common in analyzing the spatio-temporal characteristics of rainfall. Moreover, a need for a more recent assessment of the current state of knowledge, aiding in a better understanding of the region's vulnerability to climate variability and informing appropriate adaptation measures.

2.3 Verification of GCMs

The validation of General Climate Models (GCMs) is a subject that has received considerable attention in various research studies worldwide. GCMs have become important tools in climate research, but their accuracy in predicting climate variability is still a topic of debate. In climate prediction utilizing current and high-resolution climate models has become crucial for making informed decisions and developing suitable strategies that can respond to and reduce the influence of changing climate *(Alaminie et al., 2021).*

However, there is a need to assess their performance, whereas, there is no single general circulation climate model that outperforms all others on a global scale. Nevertheless, certain GCMs may provide more accurate projections in specific regions compared to others. To ensure more dependable assessments of climate impacts, it is advisable to prioritize the use of GCMs that demonstrate superior performance *(Amodu & Ejieji, 2017).*

Almazroui et al., (2020), validated 27 GCMs from CMIP6 and compared them to the CRU dataset across Africa for the period 1981 to 2010. The GCMs bias correction was applied for each sub-region and the entire domain. The results ensembles of 27 GCMs were used for further evaluation to assess the future change of precipitation after bias correction.

Shiru et al., (2019), assessed 20 GCMs from Coupled Model Intercomparison Project Phase 5 (CMIP5) based on their ability to replicate historical monthly rainfall from GPCC for the period 1961 – 2005 over the Nigeria domain. Four bias correction methods were compared to identify the most suitable method for downscaling and projection of rainfall. The results showed that only 3 GCMs were the most suitable GCMs for Nigeria's rainfall projections.

In the work conducted by *Kamga, (2000)*, four GCMs were assessed specifically for the region of Cameroon and its surrounding areas for the period 1961 to 1990 to determine their capacity to replicate observed values accurately. Based on the spatial correlation of confidence of the GCMs relative to observed correlated values, two models were selected at more than 90% correlation confidence level for further examination to determine the potential variation in temperature and precipitation.

Amodu & Ejieji, (2017) validated 20 GCMs from the Coupled Model Intercomparison Project Phase 3 (CMIP3) across the Sudan-Sahel region of Nigeria relative to four weather stations for the period 1981 to 2000. The primary objective was to validate the GCMs based on specific metrics to determine their skills in replicating the observed values. The study utilized three metrics, namely correlation Coefficient, mean absolute error (MAE), and RMSE. The results found no superiority in performance among the 20 GCMs over the four weather stations. The study has provided valuable insights into selecting suitable GCMs for specific areas and laid the groundwork for potential downscaling methods for applying chosen GCMs in climate change projections.

Hamadalnel et al., (2022) carried out a study evaluating 32 GCMs from CMIP6 and CIMP5 against CRU dataset for the period 1976 to 2005 over the Sudan domain. in simulating the observed rainfall during the rainy season. The study used 4 statistical metrics to validate the skill of 32 models, the metrics are, RMSE, Percentage bias (PBIAS), Correlation coefficient, and Nash–Sutcliffe efficiency (NSE). Based on the metrics values 6 models were selected out of 32. The study selects three models from CMIP6 and CIMP5. The study found improvement in model skills after bias correction.

Moreover, to achieve more reliable results when dealing with simulations of both trends and quantities, it is recommended to consider multiple metrics rather than relying solely on one metric *(Moriasi et al., 2007)*. Validation protocols and quality control standards are important in climate modelling to ensure transparency and reliability. Accurate simulations of current climates are crucial for trustworthy future climate projections and informed decision-making. Therefore, these metrics can be effectively utilized to verify the GCMs against the observed rainfall values.

2.4 Projected Precipitation in Future Under Changing Climate

Many studies have examined future precipitation projections over global and regional dimensions under changing climate. *Almazroui et al., (2021)* investigated the expected changes pattern of temperature and precipitation across Central America, the United States (US), and the Caribbean using data from the CMIP6 dataset based on three SSPs scenarios (low, medium, and high). The study employed a multi-ensemble of 31 GCMs to analyze these changes for three future periods:

2021-2040, 2041-2060, and 2080-2099. These projections were compared to the CRU dataset, serving as a reference period spanning from 1995 to 2014. To calculate the significance of future changes in two variables over each sub-region, the study utilized a two-tailed student t-test. Furthermore, to enhance the analysis, the study repeated the assessment of the nine best-performing models. Their findings revealed that there were no significant changes because of the low bias of the models, indicating that the models' performance did not influence the expected changes in the two variables.

A study by *Araya-Osses et al., (2020*) employed statistical downscaling methods to evaluate the future precipitation changes in Chile, using data from the CMIP5 based on RCP2.6, RCP4.5, and RCP8.5 scenarios for three future periods (2016 to 2035, 2046 to 2065, and 2081 to 2100) and from 1980 to 2015 as the baseline period. By analyzing data from 400 weather stations and employing analogue techniques, the study obtained more accurate and localized projections of potential shifts in precipitation trends within Chile by the year 2020. Additionally, the use of multiple GCMs and global warming scenarios allowed for a more comprehensive assessment of the range of possible outcomes.

A study by *Supharatid et al., (2022)* analyzed 18 GCMs from the latest CMIP6 to project future climate change under SSP2-4.5 and SSP5-8.5 scenarios over the 5 Mainland countries (Cambodia, Laos, Myanmar, Vietnam, and Thailand). The study analyzed Daily Minimum and Maximum Temperature (Tmin) and (Tmax) respectively, and daily precipitation from 1998 to 2014 as a reference and divided the future period into three slices. The Bias was corrected and the ensemble of 18 models was used to project the temperature and precipitation changes by using the Variance Scaling Method. The results showed that southwest and northeast monsoons strong increase in rainfall. While high revealed a more severe change than medium scenarios.

Almazroui et al., (2020) evaluated 27 GCMs from CMIP6 under different climate scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) to project the changes in temperature and precipitation across Africa. The future period was divided into near-future from 2030 to 2059 and long-term from 2070 to 2099. The study utilized temperature from the CRU dataset and precipitation dataset from the GPCC for the period from 1981 to 2010. The model bias was corrected, and then the model ensemble was utilized to determine the expected variations in precipitation and temperature for Africa as a whole and for each sub-region during December, January, and February (DJF) and June, July, and August (JJA). To assess the significance of the trends the study used the two-tailed student t-test. Their findings indicated that the increased temperature is not uniform across Africa, but rather fluctuates depending on the region. Northern and southern regions of Africa exhibit declining precipitation trends, whereas central areas demonstrate an increase. Projections indicate a potential near-term rise in precipitation ranging from 6.2% to 8%, 6.8%, and 15.2%, under different scenarios. Notably, the CMIP6 model ensemble presents more pronounced median warming compared to CMIP5, with mixed precipitation patterns.

Shiru & Park, (2020) in their study used multi-ensemble form CMIP5 under RCP4.5 and RCP8.5 and GPCC rainfall dataset for the period 1961 to 2005). The future change was determined in 323 gird points over Nigeria for the period 2010 to 2099. The study utilized four bias correction techniques to correct the bias and assess the projected change in rainfall and compared between them, they conclude the linear scaling method was the best performing in adjusting the difference between the control and the observed datasets.

Addisu & Regassa, (2021) utilized CMIP6 model data based on all scenarios over the Jimma zone in Ethiopia. Their research aimed to support smallholder farmers who rely on rainfed agriculture in responding to global warming. Mann-Kendall (MK) test was used to determine rainfall change for the period 1980 to 2020. The result showed an insignificant trend in observed rainfall over the Jimma region.

A study by *Chen et al., (2013)*, in their study used daily precipitation and Tmax and Tmin from 9 weather stations in Sudan and South Sudan The projection is based on the SRES A2 Emissions Scenarios (SRA2) from seven GCMs for the periods 2011–2030, 2046–2065, and 2080–2099 using trend analysis and t-test and F-test were used to test the significance of the trend over the study domain. The result revealed a positive trend throughout the future period in JJA over the study area.

Hamadalnel et al.(2021) investigated the projected change in rainfall over Sudan during the rainy season JJAS using 3 GCMs from CMIP6 based on SSP2-4.5 and SSP5-8.5. monthly precipitation of 22 weather stations for the period 1960 to 2019 was used as a reference. The future periods (2030-2089) were divided into 3 slices, the 3 GCMs were verified and the bias was corrected. The trend analysis was used to assess the expected change in summer monsoon. MK and Sen's slope estimator were used to estimate the significance of the trend. The study identified a decline in the period from 1960 to 1989 and a positive trend in the period from 1990 to 2019, with predominantly positive trends in the entire period from 1960 to 2019, with some exceptions at certain stations. When considering future trends under different scenarios, specifically SSP2-4.5, the study indicates a potential continuation of a positive trend. In contrast, under SSP5-8.5, a predominant increasing trend is projected for the period 2030 to 2089.

Hamadalnel et al., (2022) analyzed changes in future rainfall and temperature (2030–2099) during JJAS over the Sudan domain based on ensemble models from CMIP5 based on (RCP4.5 and RCP8.5), and CMIP6 under (SSP2-4.5 and SSP5-8.5) scenarios. Quantile Mapping was used to reduce the model's uncertainty; the improvement was found after the bias correction. Sudan's domain was divided into Zone 1, 2, and 3 (warm desert, warm semi-arid and tropical savanna climate respectively) according to the Koppen-Geiger climate classification. The future period was divided into three slices. To determine the robustness and significance of rainfall future changes, a two-tailed student t-test and F-test were employed. The results showed the far future period manifested severe change, with CMIP6 projections under high with positive change ranging from 60% to over 80% in zone 3. With high bias in the same zone under CMIP5. Notably, future projections are characterized by uncertainty, particularly evident in zone 3 under high emission scenarios for both CMIP6 and CMIP5. The models revealed high agreement in Zone 2 for both CMIP5 and CMIP6 under the emission scenario.

In conclusion, there's a need for more localized and detailed research in Sudan that takes into account its unique climate characteristics, considers model performance and uncertainties, employs appropriate bias correction and downscaling methods, assesses local impacts comprehensively, and establishes standardized approaches for more consistent and reliable climate projections.

2.5 Coupled Model Intercomparison Project (CMIP)

The CMIP was Initiated two decades ago and originally aimed to compare early global coupled climate models. Through five progressive phases, it has evolved into a significant international undertaking, ushering in a new phase of climate science research and establishing itself as a main component of assessments of climate change. The core aim of the project is to provide the climate community and stakeholders with publicly accessible, standardized multi-model output. This extensive dataset is systematically collected, archived, and made available through The Earth System Grid Federation (ESGF) streamlining the process of conducting comprehensive multi-model analyses *(Eyring et al., 2016)*. Over the years, CMIP models have undergone substantial refinement to address these challenges, evolving from CMIP1 to the latest version *(Hamed et al., 2022).*

In the CMIP5, more than 40 models were included, showcasing significant improvements. This phase introduced a new set of climate projection pathways known as Representative Concentration Pathways (RCP), which provided valuable climate insights that proved beneficial for decision-makers and the research community. However, CMIP6 models are exploring a wider range of potential future outcomes than previous models *(Thomson et al., 2011).*

CMIP6 builds upon the progress of CMIP by introducing new global climate modelling experiments aimed at exploring climate responses and mechanisms. The models in CMIP6 incorporate improved dynamical processes and finer resolution and employ Shared Socioeconomic Pathway (SSP) and RCP emission scenarios for future climate simulations *(Chen et al., 2020).*

CMIP6 has significantly improved climate system modelling, with numerous research outputs highlighting its enhanced capabilities and comparative analyses comparing it to CMIP5. *(Nooni et al., 2023).* These models in CMIP6 boast higher resolution and improved dynamical processes, resulting in enhanced accuracy compared to CMIP5 *(Hamed et al., 2022)*.

2.6 Climate Change Scenarios

Burgess et al., (2020) stated in climate change science, scenarios play a vital role in bridging the gap between physical and social studies, enabling the assessment of potential consequences and facilitating discussions on adaptation and mitigation strategies.

Scenarios are typically formed using projections, which illustrate the climate system's response to different emission scenarios involving greenhouse gases and aerosols. Various models are in use for simulating future climate conditions, each with its own set of underlying assumptions. The reliability of long-term projections beyond the 2050s hinges significantly on these models and simulations, as the composition of anthropogenic elements influencing the climate, such as greenhouse gas concentrations, land cover conditions, demographic distributions, socio-economic conditions, and others, will change compared to their current and near-future states *(Santoso et al., 2008).*

The Special Report on Emission Scenarios (SRES), was crafted by the IPCC to define a spectrum of distinct global development trajectories. These scenarios are primarily designed to assess the impact of various development pathways on emissions and the dynamics of climate change *(Parry, 2004)*.

The Representative Concentration Pathways (RCPs) constitute a collection of pathways outlining greenhouse gas concentrations and emissions. These pathways are intentionally crafted to facilitate investigations into the consequences of climate change and potential policy interventions. Collectively, the RCPs encompass the spectrum of forcing levels linked with emission scenarios *(Riahi et al., 2011)*.

The SSPs result from complex calculations dependent on the reduction of greenhouse gas emissions. Nevertheless, these calculations also aim to encompass alterations in socioeconomic factors like population, urban density, education, land usage, and wealth *(Riahi et al., 2016).*

O'Neill et al., (2016) indicated that SSPs depict potential future societal trajectories in projected pathways that do not take into account climate change or climate policy. The study described them in Table 1.

Table 1: Shared Socioeconomic Pathways (SSPs)and their descriptions _ source *(O'Neill et al., (2016)*

Scenario	Description
SSP1-2.6	The scenario envisages achieving net-zero CO2 emissions by 2050, emphasizing shifts towards sustainability while projecting a temperature increase of 1.8°C by the century's end.
SSP2-4.5	The Regional Rivalry scenario represents a medium pathway, where CO2 emissions stay steady, socioeconomic trends remain unchanged, and temperatures rise by 2.7°C by the century's end.
SSP3-7.0	The scenario forecasts a consistent upward trend in emissions, temperatures, and CO2 levels by 2100. This trajectory is expected to result in heightened competition, national security concerns, and challenges to food security.
SSP4-3.4	By the century's end, a strategy is recommended to address gaps through mitigation, targeting minimal radiative forcing. This aligns with a global trajectory shaped by the socioeconomic conditions of SSP4.
SSP5-8.5	The scenario cautions against a doubling of CO2 emissions by 2050, propelled by fossil fuels and energy-intensive lifestyles, leading to a substantial 4.4°C increase in global temperature by 2100.

CHAPTER THREE: DATA AND METHODOLOGY

3.1 Introduction

This part is to provide the data and methodology utilized in a study focused on examining the characteristics of historical and future rainfall over Sudan Rainfall Belt during the summer season.

3.2 Data

To achieve the objective of the study, monthly rainfall data was obtained from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPs), and three Global climate models from CMIP6.

3.2.1 CHIRPs Dataset

The monthly rainfall dataset from CHIRPs v2.0 with a high resolution of 0.05˚ × 0.05˚lat–long grid was employed in this study. This dataset is obtained from https://iridl.ldeo.columbia.edu and it is recognized for its ability to provide high-quality rainfall data with minimal delay, improved accuracy, and a long record period. CHIRPs dataset involves combining data from gauge stations with precipitation estimates obtained from satellites using interpolation techniques *(Hamadalnel, Monzer & Abdalla, 2021). Alriah et al., (2022)* indicated that the CHIRPs dataset showed high performance across the east, west, north, central, and south parts of Sudan with an average percentage between (85% and 93%) in regional comparison of monthly and seasonal timescale. However, it is recommended to employ where there is a low coverage of observed data, therefore the study used it.

3.2.2 CMIP6 Dataset

CMIP6 models are exploring a wider range of potential future outcomes than previous models *(Thomson et al., 2011)*. In this study, the 3 GCMs model as shown in Table 2, was selected because of their proficiency in simulating summer monsoon rainfall across Sudan as indicated by

(Hamadalnel et al., 2021). Accordingly, further, they were verified across Sudan Rainfall Belt during summer monsoon JJAS to choose the best performance in replicating the summer monsoon across Sudan Rainfall Belt.

Table 2: Details of the three selected CMIP6 utilized in this study along with institution and horizontal resolution

Models	**Institution**	**Horizontal Resolution**
MPI-ESM1-2-LR	Max Planck Institute for Meteorology, Germany	250 km
INM-CM4-8	Institute for Numerical Mathematics, Russia	100 km
BCC-CSM2-MR	Beijing Climate Center Climate, China	100 km

Employing the medium and high emission scenarios in this study, as opposed to SSP1-2.6, provides us with distinct perspectives. SSP8.5 vividly demonstrates the harsh consequences of limited emission cuts and continued fossil fuel usage. In contrast, SSP2-4.5 presents a more measured transition with gradual emission reductions, offering insights into practical shifts and obstacles. These scenarios enable us to examine worst-case possibilities, comprehend achievable transformations, and reveal the obstacles in attaining emission targets.

The CMIP6 dataset is available at https://esgf-node.llnl.gov/seach/cmip6. The 3 GCMs datasets were interpolated to resolution $0.05^\circ \times 0.05^\circ$ lat - long grid, utilizing the bilinear interpolation method as explained by *(Hossain et al., 2021).*

3.3 Methodology

This section presents the methodology used to achieve each specific objective of the study.

3.3.1 Determining Spatial and Temporal Characteristics of Historical Rainfall over Sudan Rainfall Belt

One of the essential tasks in climate change research involves examining past shifts within the climatic system *(Krishan et al., 2018).* To examine the spatio-temporal variation of the observed rainfall over Sudan Rainfall Belt, many statistical methods were used. Mean, Coefficient of

Variation (CV), Rainfall Anomalies Index (RAI), and Trend analysis. The MK test was utilized to test the significance of the trend. These methods are explained in the subsections below.

3.3.1.1 Rainfall Climatology

The arithmetic mean method was used to determine the rainfall climatology over Sudan Rainfall Belt for both the annual and seasonal periods. The arithmetic mean, also known as the average, involves calculating the total amount of rainfall received and dividing by the number of years considered in the study. The average of rainfall was computed as shown in Equation 1:

$$\boldsymbol{\bar{X}} = \frac{1}{N} \sum_{i=1}^{n} X_i \quad \ldots\ldots (1)$$

Where $\boldsymbol{\bar{X}}$ represents the mean, n signifies the sample size, X_i denotes the value assigned to each item within the dataset being averaged.

3.3.1.2 Coefficient of Variation (CV)

The coefficient of variation was employed to determine the spatial characteristics of interannual variability of annual rainfall as indicated by *(Türkes, 1996)* in percentage as Calculated in Equation 2:

$$\mathbf{CV} = (\sigma_s \ / \ \bar{R})100 \quad \ldots\ldots (2)$$

where $\bar{R}$ is the mean rainfall of long-term, and σ_S is the standard deviation of total rainfall.

According to *Addisu et al., (2015)*categorized rainfall variability into three groups based on the CV percentage: low variability (CV < 20%), moderate variability (CV between 20% and 30%), and high variability (CV > 30%).

3.3.1.3 Rainfall Anomaly Index (RAI)

The Rainfall Anomaly Index (RAI) was originally proposed by *(Van Rooy, 1965)*. It is employed to categorize the extent of positive and negative deviations in rainfall. The RAI is computed by subtracting the long-term mean from the observed rainfall value of each zone for a specific period and then dividing it by the standard deviation. This index provides insight into the deviations from the average rainfall patterns. and expressed in Equation 3:

$$\textbf{RAI} = \frac{X_i - \bar{X}}{S_X} \quad \text{..........(3)}$$

Where X_i represent the seasonal rainfall, $\bar{X}$ signified the mean of the entire period, S_X denotes the standard deviation from the mean series, where the Rainfall Anomaly Index (RAI) values range between (4 to -4) indicating extremely humid to dry respectively.

3.3.1.4 Trend Analysis

Trend analysis can be achieved by statistical and graphical techniques *(Ogallo, 1981)*. The Graphical methods are effective tools for providing insights into concentration ranges, distribution shapes, outliers, correlations, and trends. However, their interpretation can be subjective. This study was used to display the outcomes of the trend test. There are two main types of statistical methods commonly employed for trend analysis: parametric and non-parametric methods, linear regression and MK. The study used linear regression and MK represent the parametric and non-parametric respectively *(Costa & Rodrigues, 2017)*.

3.3.1.4.1 Linear Regression

Simple linear regression is a statistical method used to estimate and calculate the relationship between two quantitative variables. It tests the linear trend by analyzing the time (t) and any variables. In this case of study, y represents the rainfall. It can be expressed as in Equation 4:

$$\boldsymbol{Y}^{\wedge} = \alpha_i + b_1(t) \quad \text{..........(4)}$$

Where $Y^{\wedge}$ is the dependent variable, b_1 represent the slope of the line α_i, (t) explanatory and α_i is intercept of the values of $Y^{\wedge}$ and (t). In trend analysis, when the slope is determined to be significantly distinct from zero, the magnitude of the slope denotes the magnitude of the rainfall trend, while the slope's sign establishes the trend's direction.

3.3.1.4.2 Mann Kendall (MK) Test

MK test is a non-parametric statistical test commonly used to detect trends in meteorological variables. MK trend test was used by many studies *(Mann, 1945), (McLeod, 2005), (Hussain & Mahmud, 2019),* and *(Sulaiman et al., 2015).* Accordingly, this study used MK to test the significance of the trends of JJAS rainfall individually. The test involved the calculation of the standardized test statistic S as given by Equation 5:

$$\mathrm{S} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \ldots\ldots (5)$$

Where x_j and x_i represent the data values in a time series of length n. The sign of the functions is denoted as:

$$sgn\left(x_j - x_i\right) = \begin{cases} +1 & if\ \left(x_j - x_i\right) > 0 \\ 0 & if\ \left(x_j - x_i\right) = 0 \\ -1 & if\ \left(x_j - x_i\right) < 0 \end{cases} \ldots\ldots (6)$$

The trend's strength will be assessed through resampling analysis, while the correlation strength will be quantified using Kendall's correlation coefficient (τ), as indicated by Equation 7.

$$\tau = \frac{2S}{(n\,(n-1)} \ldots\ldots (7)$$

Where S represents the standardized test statistic, and n denotes the length of the dataset. When τ is positive, it indicates an increasing trend, while a negative τ suggests a decreasing trend. A τ value of zero signifies no trend as reported by *(Omoj et al., 2016).*

3.3.2 Verification of GCMs Output against the Observations

Climate model verification involves comparing simulations of current climates with observations *(Nooni et al., 2023)*. This study utilized correlation coefficient, RMSE and Bias metrics as indicated by *(Gunavathi S, 2021)*The CHIRPs dataset was used to verify the model simulation for the period 1981 to 2014 matching the model history which spans to 2014.

For this study, O_i is representing rainfall observations (CHIRPs); O^{-} represents an average of the observations; S_i represents model simulation; n represents the number of data samples. Then correlation coefficient (r), Bias and RMSE were computed using formulas in Equations (8) to (10).

$$r_{OS} = \frac{\frac{1}{n}\sum_{i=1}^{n}(O_i - \overline{O})(S_i - \overline{S})}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\{(O_i - \overline{O})^2 . \frac{1}{n}\sum_{i=1}^{n}(S_i - \overline{S})^2\}}} \qquad (8)$$

The bias is computed using the formula in Equation (9)

$$Bias = \frac{1}{N}\sum_{i=1}^{N}(S_i - O_i) \qquad (9)$$

The mean differences between each of the 3 models' output simulations and CHIRPs as reference. Observed data computed employing RMSE using the formula in Equation (10)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - S_i)^2}{n}} \qquad (10)$$

These formulas were employed to assess the skill of CMIP6 to simulate CHIRPs in the study area. Their value is to evaluate the models' skill score (SS) as explained by *(Hamadalnel et al., 2021)*. In this study, based on the values of these metrics the best model for replicating CHIRPs is the higher Correlation Coefficient, which becomes a key metric of concern especially when the primary interest lies in accurately representing trends as indicated by *(Amodu & Ejieji, 2017)*, and then smallest RMSE and Bias. The correlation coefficient signifies either a positive or negative relationship varied between 1 to -1, with the best correlation value at 1 and a value close to zero indicating a weak relationship. Whereas the RMSE ranges from 0 to infinity, where lower values are indicative of better skill of the model. the low Bias value is close to zero, the negative values indicate the model underestimated, while the positive values indicate the model overestimated the observed values.

3.3.3 Evaluating the Potential Future Change in Rainy Season Under Medium and High Emission Scenarios

After verification, the best model simulation was selected and used to evaluate the potential future change of rainfall from CMIP6 simulation under medium and high scenarios. Using in this study SSP5-8.5 and SSP2-4.5 scenarios, rather than SSP1-2.6, gives us unique insights. SSP8.5 illustrates the severe impacts of minimal emission reductions and ongoing fossil fuel use. On the other hand, SSP2-4.5 portrays a moderate transition with gradual emission reduction, shedding light on realistic changes and challenges. These scenarios allow us to analyze worst-case scenarios, understand feasible transitions, and uncover the hurdles in reaching emission goals. After selecting the best model that simulated the historical data, the bias of the model was corrected.

Jaiswal et al., (2022) indicated the high uncertainty in projection is due to the bias in the GCMs, it is essential to correct the GCMs bias, and then use it in further assessment. Accordingly, the study used linear scaling techniques to reduce the model bias and evaluated the future change of JJAS in the Sudan's Rainy Belt. The linear scaling simply employs a multiplicative term to adapt the biases within the model. This adjustment is accomplished by comparing the monthly mean rainfall values of the corrected data with those observed *(Shrestha et al., 2017).* linear scaling technique, firstly, modified the GCMs rainfall mean value to align with the observed data. Secondly, the rainfall values for both the control and scenario are adjusted using the ratio between the long-term monthly mean observed data and the control/scenario data as explained by *(Gunavathi S, 2021).* The study period is divided into baseline periods (1981-2010) and future periods (near future from 2030 to 2059, and far future from 2070 to 2099). The potential changes in seasonal rainfall were analyzed for both future periods relative to the baseline (1981-2010) over the four zones for the best-selected model simulation under SSP2-4.5 and SSP5-8.5 for both future periods. The percentage of change for seasonal rainfall over the four zones for the two future periods were calculated across each month of the rainy season, and it calculated as the current model simulation minus the observed values divided by 100.

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter obtains the analysis and the discussion of the results based on the specific objectives.

4.2 Spatial and Temporal Characteristics of Historical Rainfall Over Sudan Rainfall Belt

This section discussed the results of analyzing spatio-temporal characteristics of historical rainfall over Sudan Rainfall Belt.

4.2.1 Rainfall Climatology

Figure 2 reveals the distribution of seasonal and total annual rainfall between 1981 and 2010. Rainfall levels exhibit an increase from north to south. The data indicates that seasonal rainfall ranges from (300 to 1100) mm within the study area during this period, providing suitable conditions for various types of plant growth throughout the season.

Figure 2 (a) illustrates the distribution of total annual rainfall for the period from 1981 to 2010, which exhibits significant variation from south to north. The southern region receives more than 1000 mm of annual rainfall, while the central (east to west) region experiences rainfall ranging from 300 to 1000 mm per year. The central part of Sudan corresponds to Zones 1, 2, and 3, while the southern region is designated as Zone 4, as indicated in Figure 1.

Figure 2 (b) shows the seasonal rainfall over Sudan in JJAS from 1981 to 2010. Sudan lies within many climatic zones. The Sahel (Central), the northern, and, southern parts lie within semi-arid and semi-humid climates *(Girma et al., 2016)*. The results showed the central received between 300 to 1000 mm and the southern part received between 500 to 1000 mm per year. Zone 1, Zone 3, and Zone 4 received high amounts of seasonal rainfall between 500 to 1000.

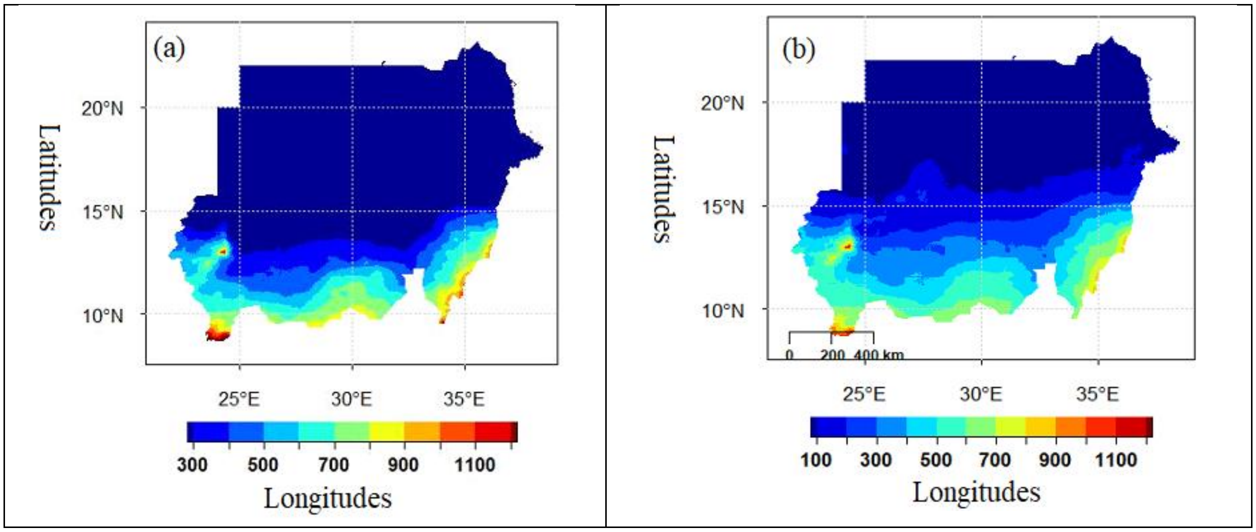

Figure 2: Climatology maps of Rainfall, with maps (a) Total Annual Rainfall and (b) Seasonal Rainfall for JJAS Season for the period 1981 to 2010 over Sudan

4.2.2 Coefficient of Variation (CV)

Figure 3 shows CV that describes the variability of rainfall during the rainy season JJAS over Sudan Rainfall Belt, the results manifested moderate to high variability of rainfall over the central (Zone 1, Zone 2, and Zone 3). The southern part revealed the moderate to low rainfall variability.

To sum up, the spatial maps of mean and coefficient of variation revealed the spatial characteristics of rainfall in the Sudan Rainfall Belt. Most of the study proves with no doubt that the area of study is the only region in Sudan appropriate for rainfall agriculture and suitable for plant growth properly in the rainy season JJAS. The results depict the outcome of *El Gamri et al., (2009)* in their study indicated that most of the region is characterized by low rainfall variability in Sudan and the rainy season lasts for four months and this part of Sudan is mainly suitable for rainfed agriculture.

In general, the variability is higher northward, the results revealed and emphasize total rainfall seasonal between 300 – 1100 mm lies within the study area. All results indicated the central is characterized by moderate to higher variability (20% to > 30), more investigations are needed in this area, due to its sensitivity to the influence of climate change. South of the study area (Zone 4) is characterized by low to moderate (10% to 30%) variability making it suitable for different kinds of farming and crops as seen clearly in Figures 2 (b) and 3.

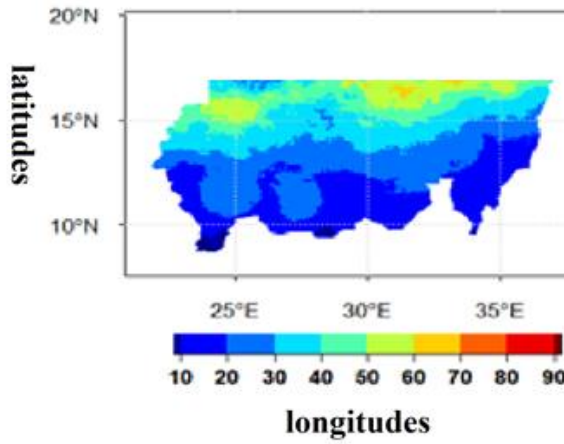

Figure 3: Coefficient of Variation of Seasonal Rainfall over Sudan Rainfall Belt for the period 1981 to 2010

4.2.3 Rainfall Anomaly Index (RAI)

Figure 4 displays the RAI for each zone. The time series graphs highlight the wettest years in all zones, which include 1988, 1989, 1996, 2007, 2012, 2017, and 2019, while the driest years encompass 1982, 1983, 1984, 1985, 1986, 1987, 1991, 2002, 2009, 2015, and 2021. The wettest years are associated with the presence of the La Niña phase, whereas the driest years are linked to the El Niño phase. as reported by *(El Gamri et al., 2007).* All four zones exhibited comparable patterns, albeit with variations in the intensity and variability of rainfall from 1981 to 2022. Notably, Zone 2 and Zone 4 displayed higher variability and intensity of wet and dry years compared to the other zones. Zone 4, in particular, witnessed a higher frequency of dry years in the last four years, with driest years 1991 last for tow year and 1984 last for one year in zone 2.

In general, results reveal variation between the four zones in dry and wet years (1981-2022). Zone 2 and 4 witnessed severe droughts. These outcomes are in line with the study done by *(Salih et al., 2018),* in which the study indicated that Sudan has experienced dry conditions in the past four decades. All these changes stated the influence of climate change across the study area, and these changes have negatively impacted many fields, especially rain-fed agriculture as shown by *(Mahmoud et al., 2014).*

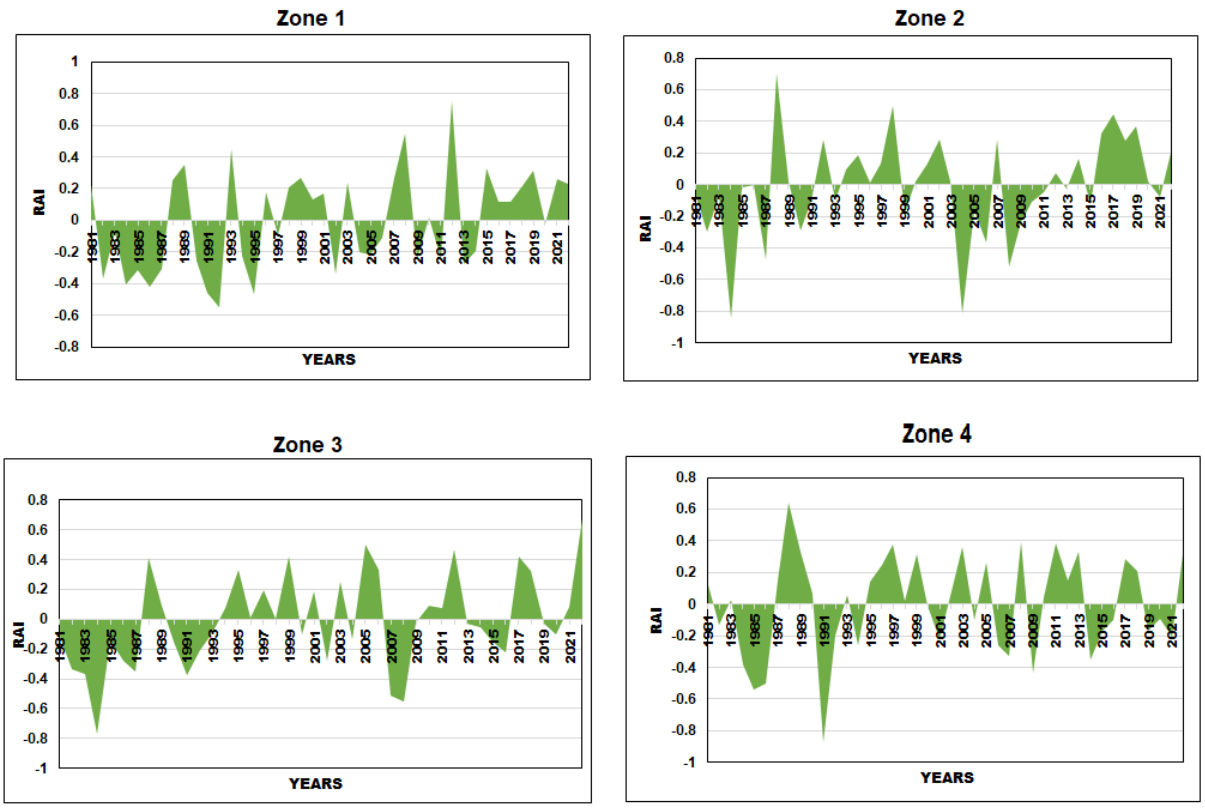

Figure 4: Rainfall Anomaly Index (RAI) for representative zones: (a) Zone1, (b) Zone2, (c) Zone3, and Zone4, respectively, for the years for the period 1981 to 2022

4.2.4 Trend Analysis

Figure 5 shows the Linear Regression trend across the four zones covering the period between (1981 and 2022). The outcomes revealed all four zones had positive values of the slope indicating the increasing trend of rainfall with time and a positive linear relationship.

The Mann-Kendall test was employed, with corresponding p-values of (0.008), (0.067), (0.027), and (0.0001) for Zone 1, 2, 3, and 4 respectively as shown in Table 3. These p-values are much smaller than the significance level of (0.05), leading to the rejection of the null hypotheses. Accordingly, the results revealed a significant trend over the four zones. The positive value of τ indicates an increasing trend in all four zones.

Table 3: Mann-Kendall test with corresponding p-values for each Zone.

	Zone 1	Zone 2	Zone 3	Zone 4
P-value	0.008	0.067	0.027	0.0001

The outcomes are consistent with *Alriah et al., (2022)* study that found a positive trend over the Central (east to west), and south of Sudan. This is consistent with *Hamadalnel et al. (2021)* their study revealed the trend of monsoon rainfall throughout the country and an increasing trend from (1990 – 2019). *Onyutha, (2018)* indicated the turning point from the monsoon rainfall time series was 1990.

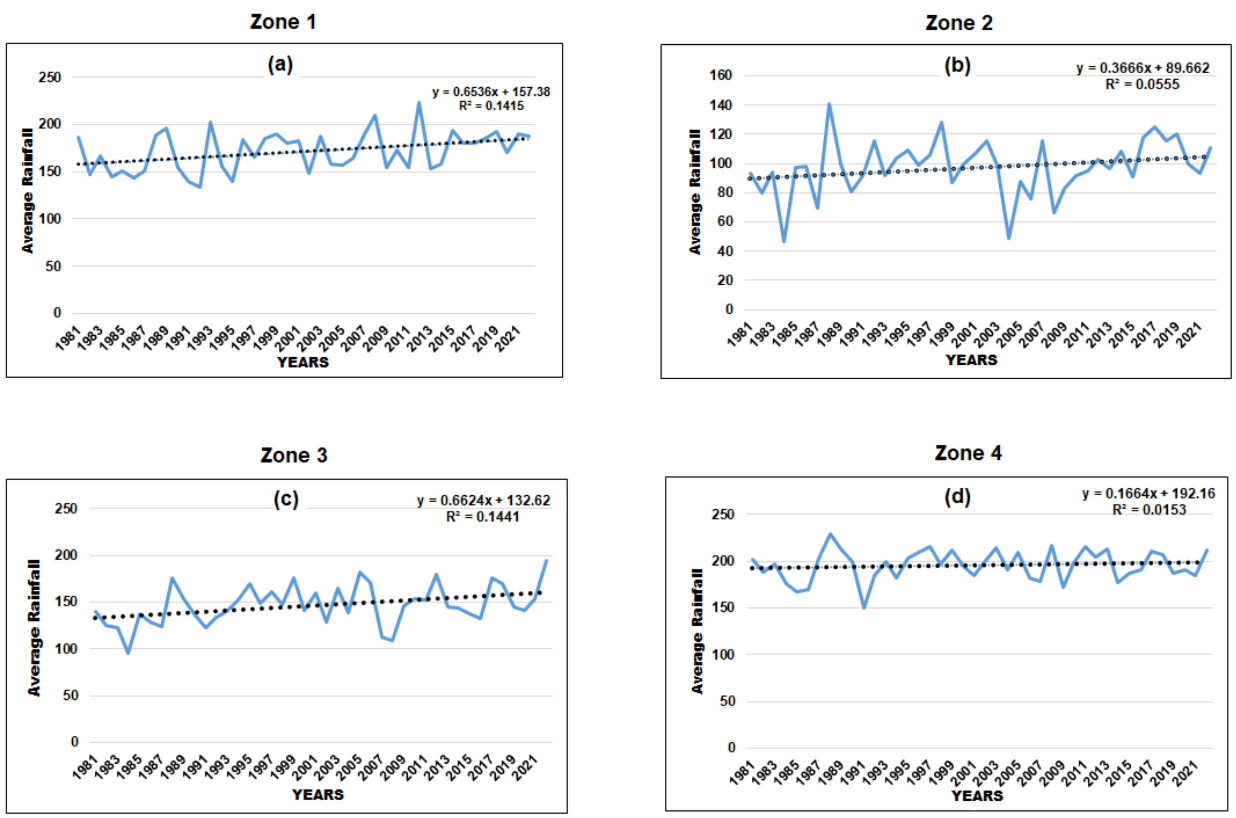

Figure 5: Linear regression trend results for seasonal rainfall for the period 1981 to 2022 for representative stations: (a) Zone1, (b) Zone2, (c) Zone3, and (d) Zone4 over Sudan.

In conclusion, the analysis of rainfall patterns in Sudan Rainfall Belt for the period (1981-2010) revealed a southward increase in rainfall, with central regions (Zones 1-3) receiving 300-1000 mm and in the south (Zone 4) receiving 500-1000 mm per season, fostering suitable plant growth. Variability is higher northward in the central and lower in the south of Sudan. Wet and dry years are attributed to La Niña and El Niño phases, with Zones 3 and 4 experiencing more intensity and variability. Rainfall exhibited a significant trend across all zones from 1981 to 2022. These results revealed the climatology of Sudan including the study.

4.3 Verification of CMIP6 GCMs

Figure 6 (a) shows a significant correlation of the MPI model a high correlation in southern, and central compared to other INM and BCC. Figure 6 (b) reveals a high correlation of the INM model in the central (east to west), with a small portion in the western and the eastern parts showing low correlation. Figure 6 (c) manifests a high correlation of the BCC model in the Khartoum state with a relatively high portion of the southern (Zone 4) region and part of the east (Zone 1). The MPI model showed larger areas with correlation coefficients in the study domain than the INM and BCC models.

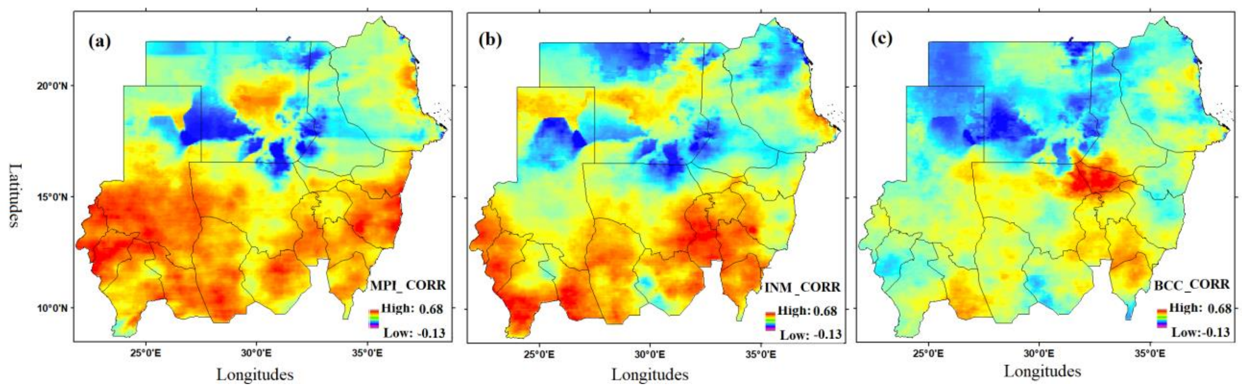

Figure 6: Correlation Coefficient between the JJAS seasonal rainfall amounts from CHIRPs and (a) MPI-ESM1-2-LR, (b) INM-CM4-8, and (c) BCC-CSM2-MR models for the period 1981 to 2014 over Sudan

Table 4 shows variations in correlation values for MPI, BCC, and INM across the four zones. The MPI model showed a significant correlation at 95% over the four Zones, while INM only in Zone 4, the BCC revealed no significant correlation in the four zones. Notably, the average MPI correlation across the four zones showed the best correlation among the other models. Whereas the average correlations of the three models in each zone are almost the same value. Suggests that the average of the models perform equally in each zone. In conclusion, the MPI model is the best performance with better correlation in the four zones compared to INM and BCC, indicating its superiority in replicating the rainy season in all zones. The outcomes revealed the MPI model perform better than the average of all three models in each zone and across the four zones. The BCC model showed the lowest correlation among the two models.

Table 4: Results of Correlation Coefficient for CHIRPs and the various CMIP6 GCMs comparison of simulating summer monsoon over the Four zones for the period 1981-2014. The symbols and bold values indicate significance at a 95% confidence level

Models	Zone 1	Zone 2	Zone 3	Zone 4	Model average
MPI	**0.48***	**0.38***	**0.52***	**0.42***	**0.45***
INM	0.31	0.34	0.32	**0.39***	0.34
BCC	0.24	0.29	0.22	0.22	0.25
Spatial average	0.34	0.34	0.35	0.34	

Figure 7 illustrates RMSE for the three model across Sudan's entire domain. Notably, RMSE values are the lowest in the southern region (Zone 4) and parts of the (eastern and western) central regions, Zone 2 shows high values of RMSE. Notably, the MPI, INM and BCC models depict a similar spatial pattern. This suggests that the three models demonstrate a similar pattern in simulating the study domain. The results manifested variation in RMSE values across all zones. Zone 1, Zone 3, and Zone 4 revealed the smallest RMSE for the three models compared to Zone 2. The study suggested Zone 1, 3, and 4 are mountainous regions the models are not good at replicating the hills and mountainous regions.

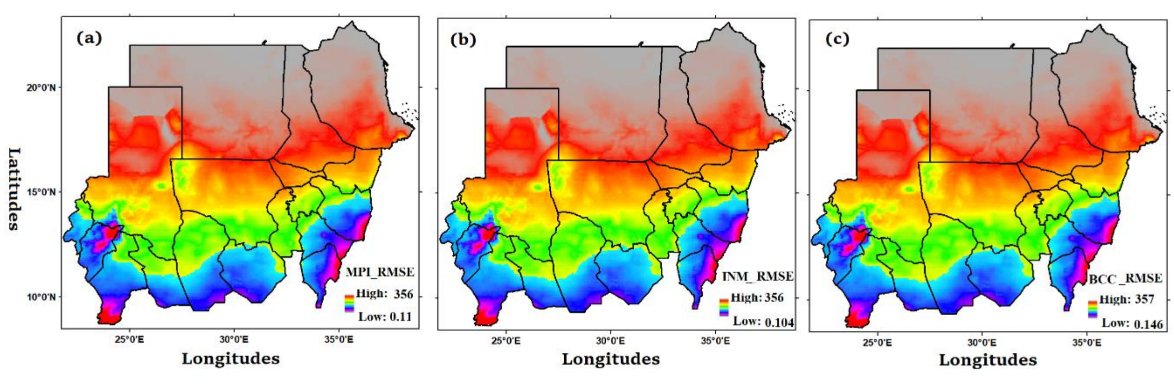

Figure 7: Root Mean Square Error between the CHIRPs and MPI-ESM1-2-LR model for the period 1981 to 2014 over Sudan

Figure 8 shows the Bias for the three model across Sudan's domain and reveals distinct patterns. The three models exhibit the lowest Bias in the southern (Zone 4) part of the country, followed by relatively low Bias in the central (east and west). However, the Bias becomes very high as goes northward in all zones, as seen from the map key, the yellow color the low bias the purple color the higher bias. The MPI, INM and BCC models revealed similar patterns. The results revealed Variation in Bias values for MPI, INM, and BCC among the four zones, with the lowest bias in central (east (Zone 1), west (Zone 3), and south (Zone 4). Zone 2 manifested high bias compared to other zones. Notably, the three models have negative Bias values indicating the models underestimate the observed values of rainfall.

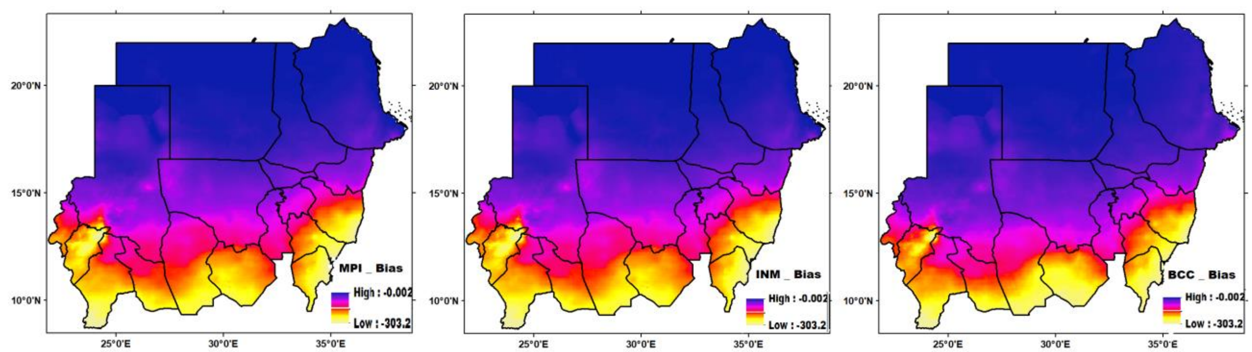

Figure 8: Bias between the CHIRPs and MPI-ESM1-2-LR model for the period 1981 to 2014 over Sudan

In conclusion, these results highlight variations in the three model's performance across different regions of Sudan. The outcomes match with the study done by *(Hamadalnel et al., 2022)* their study indicated all three models showed good skill in replicating the summer monsoon over Sudan. The MPI model is better at replicating summer monsoon in terms of correlation than other models over Sudan’s domain, whereas all three models all mostly the same Bias and RMSE.

The selection of metrics should be consistent with the specific goals and requirements of the research to obtain meaningful and relevant results, For instance, when the primary interest lies in accurately representing trends, the correlation coefficient becomes a key metric of concern as indicated by *(Amodu & Ejieji, 2017)*. Based on that, in this study, the choice of the best-skill model relies on the values of the correlations across each zone. A higher correlation across all zones is a metrics concern in this study, and then the lower bias and smaller value of RSME are indicative of better performance. Across all four Zones, the MPI model demonstrated the highest correlation, and similar pattern RMSE across all zones. MPI relative to INM and BCC models is more accurate. Therefore, the study used MPI model output to examine the future impact of changing climate in the study area.

4.4 Future Change of Rainfall under Different Scenarios Over Sudan Rainfall Belt.

This section provides results of possible future changes in seasonal rainfall JJAS over Sudan Rainfall Belt in each zone under different pathway scenarios, using the MPI model because of Its higher correlation values in all zones indicated its accuracy and reliability relative to the other models.

4.4.1 Projected Rainfall for the Near Future (2030 – 2059) under SSP2-4.5 and SSP5-8.5

Figure 9 presents the projected seasonal rainfall average for the near future (2030 – 2059) relative to the baseline period (1981-2010) under both SSP2-4.5 and SSP5-8.5 for the four selected zones. However, in Zone 4, the peak shifts to August and September for SSP2-4.5. Across all four zones, the average seasonal peak for the near future is projected to be between (150 – 250 mm per month). The outcomes manifested a decrease in the expected seasonal rainfall average for the near future for SSP2-4.5 scenarios, in Zone 1 and Zone 2 as shown in Figure 9 (a) and (b). Notably, Zone 3 and Zone 4 stand out as exceptions, where the future seasonal rainfall average is expected to increase in June and September during this period as shown in Figure 9 (c) and (d). SSP5-5.8 revealed a severe reduction in seasonal average rainfall during the near future period in Zones 2, 3 and 4. The finding aligns with the outcomes reported by *Hamadalnel et al., (2021)* indicated that the lowest seasonal rainfall average occurs in June and September, while the peak is observed in July and August under medium and high scenarios.

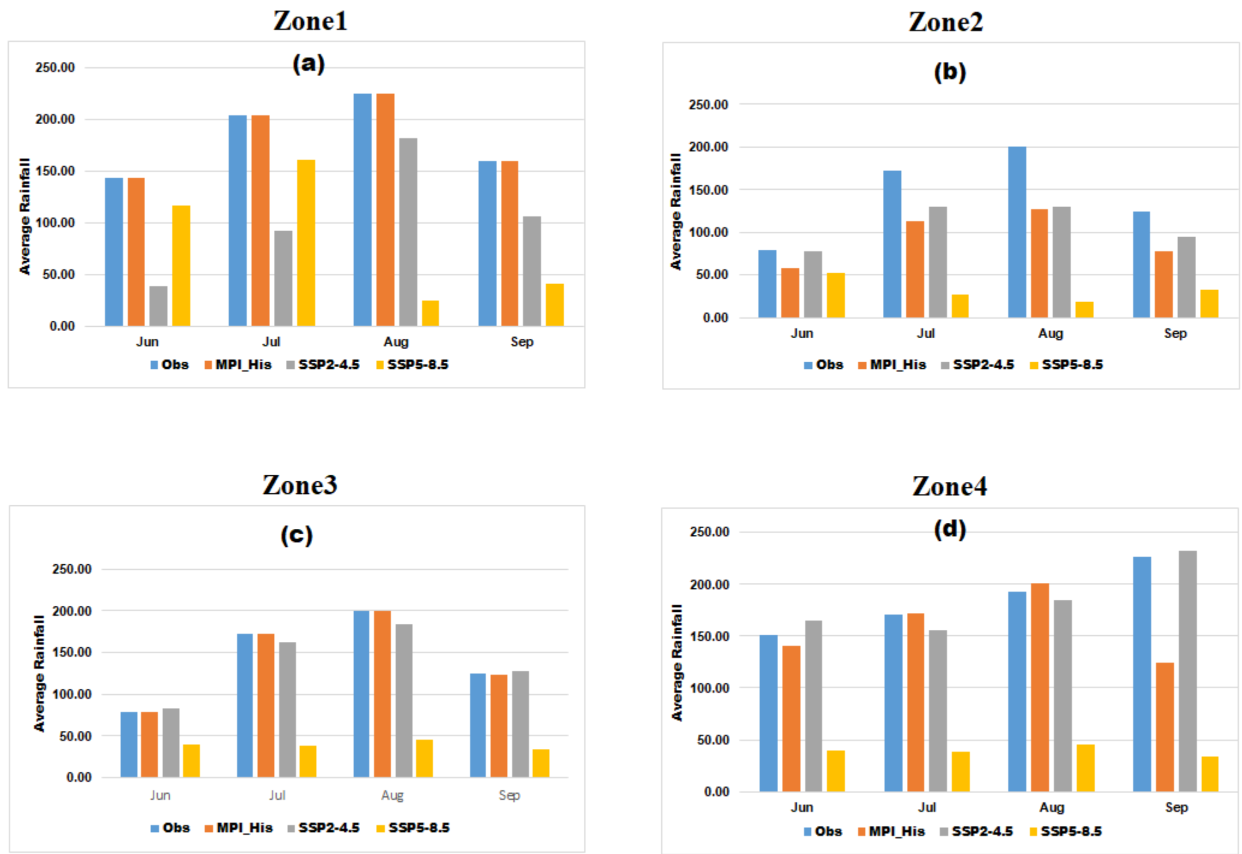

Figure 9: Future Seasonal Rainfall Average for JJAS from MPI Model under SSP2-4.5 and SSP5-8.5 for the Near Future (2030-2059) for: (a) Zone 1, (b) Zone 2, (c) Zone 3, and (d) Zone 4

Table 5 shows variation in the percentage of expected average seasonal rainfall change for the near future based on SSP2-4.5 and SSP5-8.5, varied between severe and slight reduction with average percentage of change (1% and 91%) in the near future period. For SSP2-4.5 results revealed a reduction in rainfall average from the average observed baseline rainfall values in the four months across all zones. The average percentage of change revealed a severe reduction in Zone 1, and Zone 2, with a slight decrease in Zone 3 and 4. On the other hand, the SSP5-8.5 manifested a severe negative change in projected seasonal rainfall in all four zones during the near future, with an average percentage of change varied from -51% to - 70% from the observed values of seasonal rainfall.

Overall, both scenarios showed a negative average percentage of change in seasonal rainfall from observed values. SSP5-85 revealed a severe reduction compared to the SSP2-4.5 scenario during the near future period.

Table 5: Percentage of change of seasonal Rainfall average during the near future (2030-2059) under SSP2-4.5 and SSP5-8.5 scenarios for JJAS from the MPI model against the baseline observed values for the period 1981 to 2010 over the four zones

Zone/Month	Jun		Jul		Aug		Sep		Average	
SSPs Scenarios	**SSP2-4.5**	**SSP5-8.5**	**SSP2-4.5**	**SSP5-8.5**	**SSP2-4.5**	**SSP5-8.5**	**SSP2-4.5**	**SSP5-8.5**	**SSP2-4.5**	**SSP5-5.8**
Zone 1	-73%	-19%	-55%	-21%	-19%	-89%	-33%	-74%	-45%	-51%
Zone 2	-1%	-33%	- 25 %	-85%	-35%	-91%	-24%	-74%	-21%	-58%
Zone 3	6%	-50%	-5%	-78%	-8%	-77%	3%	-73%	-1%	-70%
Zone 4	9%	-52%	-9%	-76%	-4%	-77%	3%	-64%	0%	-67%
Average	**-15%**	**-39%**	**-24%**	**-65%**	**-17%**	**-84%**	**-13%**	**-71%**		

Figure 10 displays the outcomes of future seasonal rainfall over the four zones during the near period under SSP2-4.5 and SSP5-8.5 scenarios. The result showed the expected JJAS rainfall varied between 0 to 1000 mm per season under SSP2-4.5, while SSP5.85 varied between 90 and 600 mm per season. In comparison between the two scenarios in projected seasonal rainfall, the results manifested in Zone1 small difference as shown in Figure 10 (a) than Zone 2, 3, and 4, the difference is between 100 and 500 mm per season as shown in Figure 10 (b), (c), and (d). Overall, the high emission path indicated a severe reduction in the projected seasonal rainfall compared to SSP2.4.5 scenarios. The results are in line with the results of Figure 10 and Table 5.

In conclusion, Results showed a reduction in the future seasonal average during the near future (2030-2059) for both scenarios, this reduction is observed in all four zones, indicating a potential decrease in overall seasonal rainfall during the near future period which will has great implications to Sudan economy and food security during this period, proactive measures are needed to enhance climate resilience.

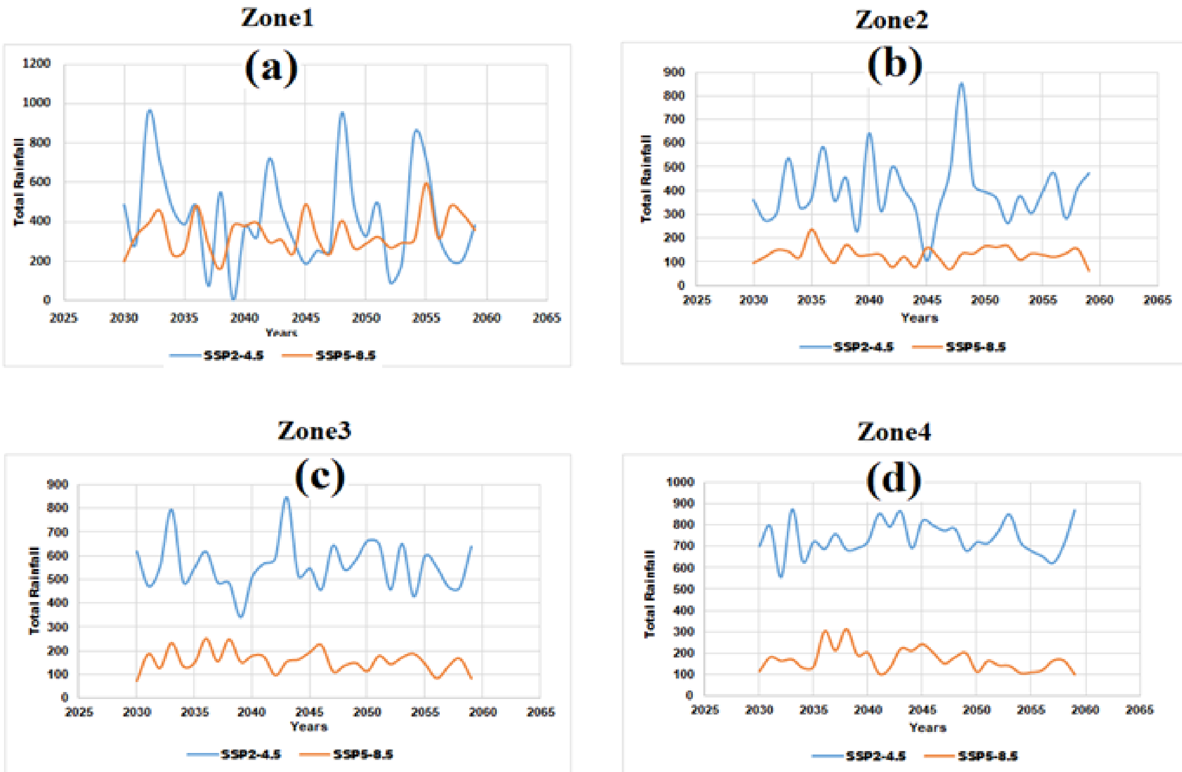

Figure 10: Time Series of Seasonal Rainfall for the near future (2030-2059) from the MPI model under SSP2-4.5 and SSP5-8.5 for: (a) Zone1, (b) Zone2, (c) Zone3, and (d) Zone4

4.4.2 Projected Rainfall for the Far Future (2070 – 2099) under SSP2-4.5 and SSP5-8.5

Figure 11 illustrates the outcomes of the projected rainfall for the far future period based on SSP2-4.5 and SSP5-8.5 scenarios for the four zones. Under SSP2-45 the outcomes revealed the projected change in seasonal average rainfall is to increase with an increasing percentage of change in rainfall from the observed baseline period as shown in Table 6. The change is expected to be positive in Zone 1 during the four months as shown in Figure 11 (a), while Zone 2 showed a slight reduction in July as indicated by Figure 11 (b), whereas Zone 3 and Zone 4 revealed a positive slight change in all months during the far period as depicted in Figure 11 (c) and (d). While under the high emission pathway, the future seasonal rainfall average changes over the Sudan's Rainy Belt, showed a positive change in the future seasonal rainfall average over the four zones in the far future. Notably, Zone 4 reveals a slight reduction in July and August as shown in Figure 11 (d).

Generally, the projected seasonal rainfall is to increase in the far future period under the SSP2-4.5 and SSP5-8.5 scenarios across the four zones. However, there is an exception in Zone 4, where a reduction in rainfall is observed for July and August.

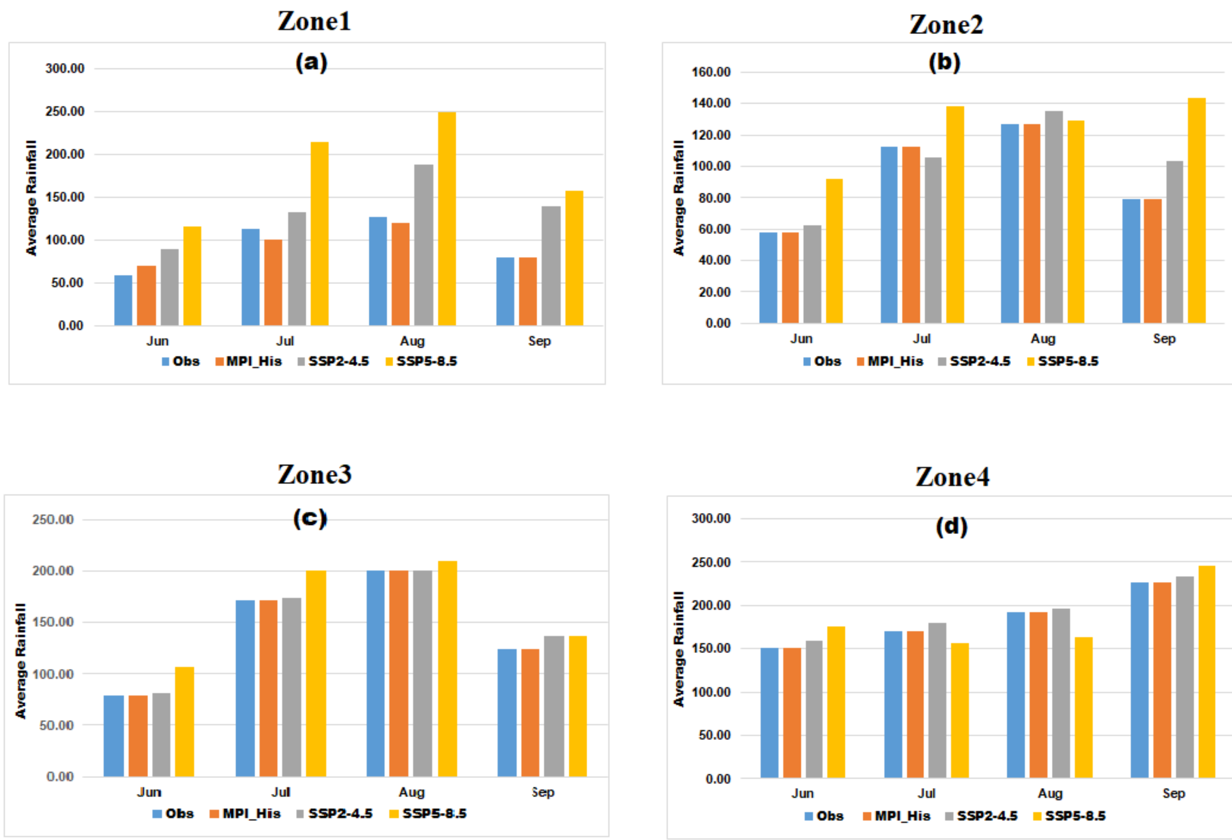

Figure 11: Projected Seasonal Rainfall Average for the far future (2070-2099) from the MPI model under SSP2-4.5 and SSP5-8.5 for: (a) Zone1, (b) Zone2, (c) Zone3, and (d) Zone4

Table 6 shows variation in the percentage of change for expected JJAS rainfall during the far future across the four zones of both scenarios. Based on SSP2-4.5 the outcomes of the average percentage of change manifested positive change in Zone 1 with an average percentage of change of 49 % for the rainy season, and Zone 2 showed a slight negative change in July with a percentage of change of -6 %. Whereas Zone 3, and 4, showed slight positive changes of 17% and 1% respectively in monsoon rainfall. Whereas under SSP5-8.5 the result showed positive changes in projected seasonal rainfall in all four zones during the far future based on the high emission scenarios. With a slight average change in Zone 4 with an average percentage of 1%.

Table 6: Percentage of change of seasonal Rainfall average during the far future (2070-2099) under SSP2-4.5 and SSP5-8.5 scenarios for JJAS from the MPI model against the baseline observed values for the period 1981 to 2010 over the four zones

Month	**Jun**		**Jul**		**Aug**		**Sep**		**Average**	
SSPs scenarios	**SSP2-4.5**	**SSP5-8.5**	**SSP2-4.5**	**SSP5-8.5**	**SSP2-4.5**	**SSP5-8.5**	**SSP2-4.5**	**SSP5-8.5**	**SSP2-4.5**	**SSP5-5.8**
Zone 1	53%	98%	18%	91%	48%	97%	78%	99%	**49%**	**96%**
Zone 2	7%	59%	- 6 %	23%	7%	2%	31%	82%	**10%**	**42%**
Zone 3	4%	36%	1%	16%	0%	5%	10%	10%	**4%**	**17%**
Zone 4	5%	16%	5%	-8%	2%	-15%	3%	9%	**4%**	**1%**
Average	**17%**	**52%**	**5%**	**31%**	**14%**	**22%**	**31%**	**50%**		

Figure 12 presents the seasonal rainfall during the far future period for both scenarios. The results revealed the seasonal rainfall for both scenarios varied between (200 and 1400) in four zones. The SSP2-4.5 showed a slight reduction compared to SSP5-8.5 along with the years, as depicted by Figure 12 (b), (c), (d). The result is in line with the outcome in Table 6 the average percentage of change based on the SSP5-8.5 scenario showed a severe positive change in future rainfall compared to the SSP2-4.5 scenario.

In conclusion, the model history demonstrates a good agreement with observed values across all zones. The results revealed that both scenarios project a reduction in seasonal rainfall average and total seasonal rainfall for the near future period (2030 – 2059), with a slight increase observed in June and September for Zone 3 and Zone 4 under SSP2-4.5. Notably, the SSP5-8.5 showed more severe reductions in all four zones compared to SSP2-4.5.

In contrast, for the far future period (2070 - 2099) under both scenarios, the outcomes revealed a positive percentage of change in rainfall across all four zones throughout the four months under

SSP5-8.5, while Zone 4 showed slight reductions in July and August based on the SSP5-8.5 and Zone 2 manifested a slight reduction in July under the SSP2-4.5.

These outcomes are in line with the findings by *Hamadalnel et al., (2022)*, which projected severe changes with a percentage of change between 60% and 80% over central and Southern Sudan. However, the finding is not match a study done by *(Chen et al., 2013)* their study based on the ensemble of seven GCMs from the SRA2 scenario, indicated that the expected rainfall revealed a negative trend throughout the future period in Sudan from 2011 to 2099, the study suggested that because of using GCMs under SRA2 scenario instead of using CMIP6 under SSP2-4.5 and 8.5 which are exploring a wider range of potential future outcomes than previous models *(Thomson et al., 2011)*.

Overall, these outcomes provide valuable insights into the expected changes in rainfall patterns for each zone individually, presenting projected seasonal average rainfall patterns for each month and the total seasonal rainfall for each zone. This unique approach distinguishes the study from others, improving our comprehension of how climate change may affect rainfall patterns in the study area.

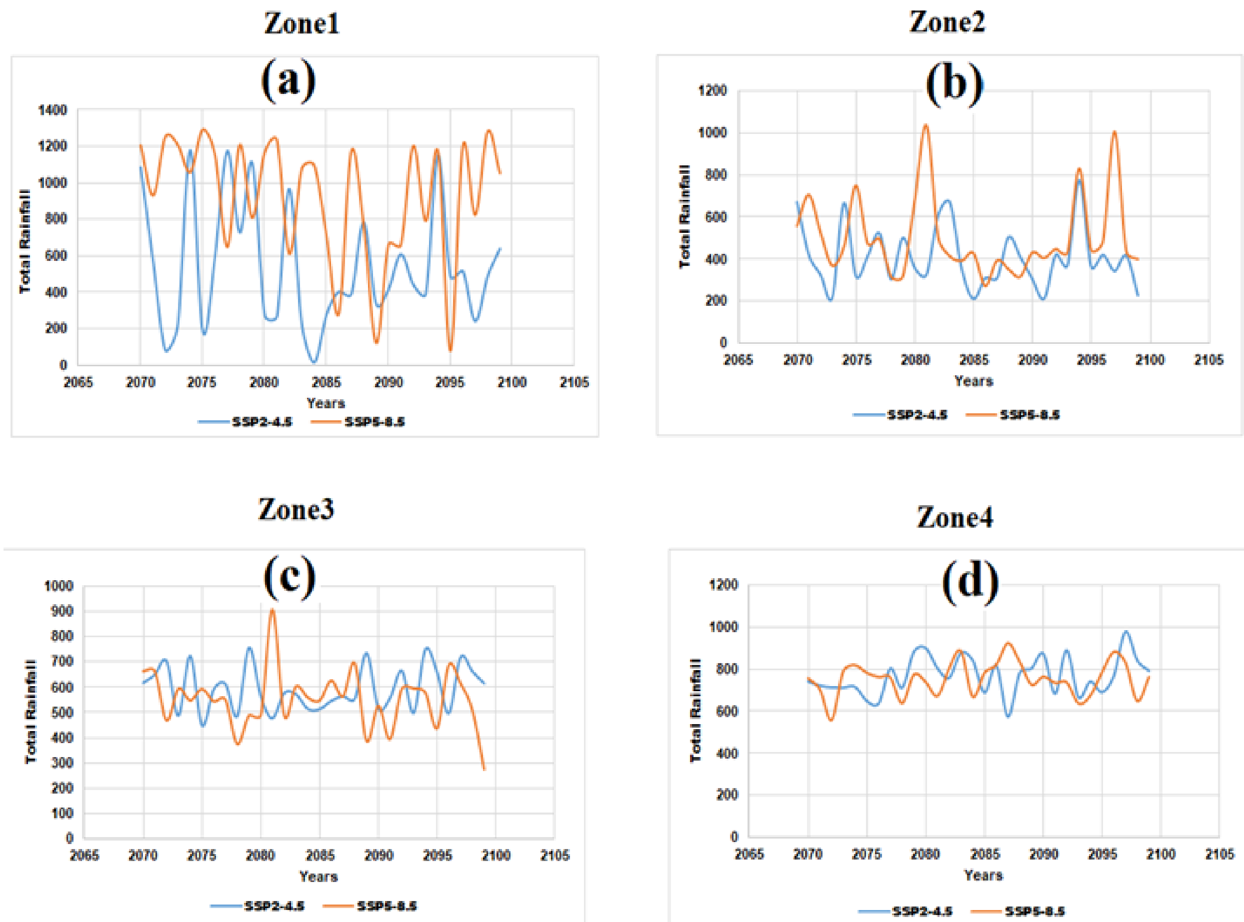

Figure 12: Time Series of Seasonal Rainfall for the Far future (2070-2099) from the MPI model under SSP2-4.5 and SSP5-8.5 for: (a) Zone1, (b) Zone2, (c) Zone3, and (d) Zone4

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter provides the conclusions and recommendations from the achieved outcomes of the three specific objectives of the study.

5.2 Conclusions

The analysis of spatial and temporal characteristics of historical rainfall in Sudan rainfall Belt during the JJAS from 1981 - 2010 revealed the distribution of seasonal and total annual rainfall, and variability of rainfall across different regions. The study confirmed that the southern parts of Sudan receive higher rainfall amounts compared to central regions during these 30 years. The analysis of the coefficient of variation showed low to moderate variability in the southern parts the central parts moderate to high variability in seasonal rainfall between 1981 and 2010. The study also identified the observed wet and dry years across different zones, with Zone 2 and Zone 4 exhibiting higher variability. Trend analysis revealed a significant increasing trend in historical rainfall for all four zones.

In another hand, this study aimed to select the best skill GCMs for simulating the summer monsoon over Sudan. The verification process involved using metrics such as Correlation Coefficients, RMSE, and Bias. The results consistently showed that all three models (MPI, INM, and BCC) performed well in simulating the summer monsoon. However, only the MPI model gave significant correlation coefficients across all zones, with relatively the same bias, and RMSE values in most zones compared to the other models across different zones. Based on the consistent results across the four zones, the MPI model as the best performer to simulate the summer monsoon over Sudan Rainfall Belt was selected. Its higher correlation values in most zones indicated its accuracy and reliability relative to the other models. Consequently, the MPI model was chosen for further analysis to evaluate the potential future of rainfall change in the study area. Its consistent performance across different zones provided confidence in its ability to provide reliable simulations for studying the effects of changing climate conditions in Sudan.

The study also investigated the future changes in seasonal rainfall over the Sudan Rainfall Belt using the MPI model and different climate scenarios. For the near future, a decrease in seasonal rainfall average is projected under SSP2-4.5, except for Zone 3, which showed a slight increase in June and September. However, under the more severe SSP5-8.5 scenario, there is a severe reduction in rainfall across zones 2, 3, and 4 compared to SSP2-4.5. For the far future period, both SSP2-4.5 and SSP5-8.5 scenarios indicate an overall increase in seasonal rainfall average. Zone 4 showed slight reductions in July and August under SSP5-8.5. while Zone 2 revealed a slight reduction in July under SSP2-4.5. In comparison between the two scenarios, the SSP5-8.5 showed a severe change in seasonal rainfall over Sudan Rainfall Belt for the near and far future periods. These changes for both scenarios indicate potential challenges for water resources and agriculture. However, in the far future (2070-2099), there are contrasting patterns: Zone 1 and 2 show an increase in average rainfall, and Zone 3 and Zone 4 exhibit fluctuations between increasing and decreasing across JJAS. The results underscore the complexity of predicting future rainfall patterns. Additionally, under SSP5-8.5 scenarios, there is a severe reduction in future seasonal rainfall for the near period across most zones. These findings highlight the potential impacts of climate change on rainfall patterns in the Sudan Rainfall Belt and provide valuable information for future planning and adaptation strategies in the region.

5.3 Recommendations

Based on the findings of this study, several recommendations are made for different sectors that rely on seasonal rainfall.

5.3.1 Recommendation to Scientists and Climate Research Institutions

Following the study outcomes, climate scientists should further their efforts by considering the utilization of additional CMIP6 models when assessing the impacts of evolving climate on forthcoming seasonal rainfall. Incorporating a broader range of GCMs that accurately replicate historical climate conditions would provide valuable insights into the performance of CMIP6 models within Sudan Rainfall Belt and the broader Sudanese region.

MPI model best simulates summer monsoon over the mountainous regions than flat areas over the study area, therefore, the scientist should consider a good representation of the initial conditions of GCMs to replicate the mesoscale features that impact the local climate scale.

5.3.2 Recommendation to User of Climate Information

Utilizing MPI model output as input for sector-specific models in agriculture and hydrology is a crucial recommendation for gaining a thorough understanding of and effectively addressing the expected consequences of climate change on these critical sectors.

For the agriculture sector, the severe changes in seasonal rainfall patterns, particularly under the high emission scenario, emphasize the need for proactive measures to enhance climate resilience. In the future where average rainfall is projected to increase strategies should focus on optimizing crop selection and irrigation practices to capitalize on these favorable conditions. Conversely, in Zone 3 and Zone 4 with fluctuating JJAS rainfall patterns, diversification of crops and water management strategies that can adapt to varying rainfall should be prioritized. In the near future period projecting a decrease in seasonal rainfall, innovative drought-resistant crop varieties, efficient water harvesting, and sustainable farming practices are essential to reduce the adverse influences of changing rainfall patterns on agriculture.

For the hydrology sector, the future change in seasonal rainfall over all zones for future periods under different scenarios underscores the importance of integrated water resource management. Periods that expect increases in seasonal rainfall, should focus on sustainable water storage and distribution systems to harness excess water during wet seasons for use during dry spells, benefiting both agriculture and domestic needs. In periods that project a reduction in seasonal rainfall, proactive measures such as efficient water recycling, demand management, and the development of alternative water sources like desalination should be considered to ensure water availability for various purposes, including industry and urban centers.

5.3.3 Recommendation to Policy Maker:

Policymakers and agricultural planners in Sudan should take into account the observed rainfall patterns and variability across the study area. The higher rainfall amounts in the southern parts of Sudan indicate the need for appropriate irrigation and water management strategies in the drier areas of central regions. Additionally, the identification of wet and dry years can guide farmers in their crop selection and planting decisions.

The expected future changes in seasonal rainfall under different climate scenarios provide valuable information for future planning and adaptation strategies. The expected decrease in seasonal rainfall for the near future and the significant reduction under more severe climate scenarios call for proactive measures to ensure water availability and sustainable agricultural practices. Additionally, the projected increase in seasonal rainfall for the far future highlights the need to consider long-term planning and infrastructure development to manage potential flood risks and utilize the additional water resources effectively.

Overall, these recommendations emphasize the importance of incorporating the study's findings into policy formulation, decision-making processes, and adaptation strategies to enhance Sudan's resilience to climate change and ensure sustainable development in the face of expected changing rainfall patterns across the four zones.

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