

**INVESTIGATING THE PERFORMANCE OF PRECIPITATION
PRODUCTS AND OUTPUTS OF CMIP6 GCMS IN REPRODUCING
PRECIPITATION EXTREMES OBSERVED ACROSS UGANDA**

BY

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DECLARATION

I NAKABUGO JOANITA IRENE hereby declare that this submission is my own work and it contains no material previously published or written by another person nor material which has been accepted for the award of other degree of the university or other institute of higher learning except where due acknowledgment has been made in text and reference list.

Signature

Date.....

APPROVAL

The undersigned approves that he has read and hereby recommends for submission to the Directorate of Research and Graduate Training of Kyambogo University, a dissertation titled “Investigating the Performance of Precipitation Products and Outputs of CMIP6 GCMS in Reproducing Precipitation Extremes Observed across Uganda” in partial fulfilment of the requirements for the award of Masters of Science Water and Sanitation Engineering Degree of Kyambogo University.

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Date.....

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DEDICATION

This report is dedicated to Mr. Charles Biriba and Ms. Solome Biriba.

TABLE OF CONTENTS

DECLARATION.....	i
APPROVAL	ii
ACKNOWLEDGEMENT.....	iii
DEDICATION.....	iv
TABLE OF CONTENTS	v
LIST OF TABLES	viii
LIST OF FIGURES	ix
LIST OF ACRONYMS	xi
ABSTRACT.....	xiii
CHAPTER ONE: INTRODUCTION	1
1.1 Background to the study	1
1.2 Problem Statement	3
1.3 Objectives	5
1.3.1 Main Aim.....	5
1.3.2 Specific Objective.....	5
1.4 Research Question	5
1.5 Significance of Study.....	6
1.6 Study Scope	6
1.6.1 Time study	6
1.6.2 Geographical Coverage.....	6
1.6.3 Content Scope	6
1.7 Conceptual Framework.....	7
2 CHAPTER TWO: LITERATURE REVIEW	8
2.1 Introduction.....	8
2.2 Precipitation Products	8
2.2.1 Climate Forecast System Reanalysis (CFSR).....	8
2.2.2 Japanese 55-year Reanalysis (JRA-55)	10
2.2.3 The Climate Group Hazards group Infrared Precipitation with Stations (CHIRPS).....	11
2.2.4 Princeton Global Forcing (PGF)	11
2.2.5 European Re-Analysis (ERA5-Land)	12
2.3 Historical simulations and scenarios of CMIP 6 GCMs	13

2.3.1	<i>CMIP6 GCMs</i>	14
2.3.2	<i>Historical simulations</i>	15
2.3.3	<i>Scenarios of CMIP6 GCMs</i>	16
2.4	Past studies that used CMIP6 GCMS	17
2.5	Methods of quantifying the mismatch between observed precipitation and outputs of GCMs 18	
2.5.1	<i>Root mean square error (RMSE)</i>	19
2.5.2	<i>Pearsons product-moment correlation coefficient</i>	19
2.5.3	<i>Taylor diagram</i>	19
2.6	Bias Correction	20
2.6.1	<i>Methods of Quantile Mapping</i>	20
2.7	Past studies that used quantile mapping.....	22
2.8	Past studies on the use of satellite products in East Africa	23
2.9	Filling gaps in precipitation data records	23
2.10	Extreme precipitation indices (EPI)	24
2.11	Summary of Research Gap	25
3	CHAPTER THREE: RESEARCH METHODOLOGY	27
3.1	Introduction.....	27
3.1.1	<i>Study area</i>	27
3.2	Data Collection	28
3.2.1	<i>Observed Data</i>	28
3.2.2	<i>Precipitation Products data</i>	29
3.2.3	<i>Outputs of GCMs</i>	30
3.3	Obtaining grid data from precipitation products and GCMs' outputs	30
3.3.1	<i>Suitability of precipitation products data</i>	30
3.3.2	<i>Quantifying the mismatch between observed and GCM precipitation products</i>	31
3.3.3	<i>Implication of precipitation products capabilities for bias correction of GCMs output</i> 32	
3.3.4	<i>Climate change projections</i>	34
3.4	Methodological framework.....	35
3.5	Ethics.....	35
4	CHAPTER FOUR: RESULTS AND DISCUSSION	36
4.1	Introduction.....	36
4.2	Performance of precipitation products.....	36
4.2.1	<i>Performance of precipitation products in reproducing extreme quantiles</i>	36

4.2.2	<i>Performance of precipitation products in terms of model bias</i>	39
4.3	Performance of GCMs in reproducing historical precipitation	43
4.3.1	<i>RMSE, correlation coefficient and Taylor diagram</i>	43
4.4	Implication of the use of precipitation products for bias correction of GCMs' output.....	60
4.4.1	<i>AMS</i>	60
4.4.2	<i>TPREC1</i>	62
4.4.3	<i>MDS1</i>	64
4.4.4	<i>NDD1</i>	66
4.4.5	<i>MWS1</i>	67
4.4.6	<i>NWD1</i>	68
5	CHAPTER FIVE: CONCLUSION AND RECOMMENDATION	76
5.1	Conclusions.....	76
5.2	Recommendations.....	79
5.2.1	<i>To policy makers</i>	79
5.2.2	<i>For future research</i>	79
6	APPENDICES	80
7	REFERENCES	88

LIST OF TABLES

Table 2-1 Some GCM CMIP6 models.....	14
Table 2-2 Extreme precipitation Indices (Onyutha, 2020)	24
Table 3-1 Overview of the precipitation data from rain gauges	28
Table 3-2 Freely available precipitation products	29
Table 4-1 Correlation coefficient and RMSE of models for AMS	48
Table 4-2 Correlation coefficient and RMSE of models for TPREC1	49
Table 4-3 Correlation coefficient and RMSE of models for MDS1	50
Table 4-4 Correlation coefficient and RMSE of models for NDD1	51
Table 4-5 Correlation coefficient and RMSE of models for MWS1	52
Table 4-6 Correlation coefficient and RMSE of models for NWD1	53
Table A-1 Pearson’s significance table.....	86

LIST OF FIGURES

Figure 1-1 Conceptual framework	7
Figure 3-1 Location of selected precipitation stations in Uganda	27
Figure 3-2 Methodological framework	35
Figure 4-1 Performance of the precipitation products in reproducing observed AMS at (a-t) stations 1-20.	38
Figure 4-2 Ratio of precipitation product to observed precipitation indices	42
Figure 4-3 Bias in 10-year AMS quantiles	43
Figure 4-4 Taylor diagram of AMS for stations 1, 2, 5, 9, 13, 16, 17 and 19.	54
Figure 4-5 Taylor diagram of TPREC1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.....	55
Figure 4-6 Taylor diagram of MDS1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.	56
Figure 4-7 Taylor diagram of NDD1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.	57
Figure 4-8 Taylor diagram of MWS1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.	58
Figure 4-9 Taylor diagram of NWD1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.	59
Figure 4-10 Climate change impact on AMS at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20	70
Figure 4-11 Climate change impact on TPREC1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20	71
Figure 4-12 Climate change impact on MDS1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20	72
Figure 4-13 Climate change impact on NDD1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20	73
Figure 4-14 Climate change impact on MWS1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20	74

Figure 4-15 Climate change impact on NWD1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20	75
Figure A-0-1 Climate change impact on AMS based on observations and precipitation data	80
Figure A-0-2 Climate change impact on TPREC1 based on observations and precipitation data.....	81
Figure A-0-3 Climate change impact on MDS1 based on observations and precipitation data.	82
Figure A-0-4 Climate change impact on NDD1 based on observations and precipitation data	83
Figure A-0-5 Climate change impact on MWS1 based on observations and precipitation data	84
Figure A-0-6 Climate change impact on NWD1 based on observations and precipitation data	85

LIST OF ACRONYMS

AMS	Annual Maxima Series
ARC2	African Rainfall Climatology Version 2
ATOVS	Advanced TIROS Operational Vertical Sounder data
CDF	Cumulative Distribution Functions
CFSR	Climate Forecast System Reanalysis
CFS	Climate Forecast System
CFSv2	Climate Forecast System Version 2 Monthly Products.
CORDEX	Coordinated Regional Climate Downscaling Experiment
CMIP6	Coupled Model Intercomparison Project Phase 6
CHIRPS	Climate Hazards Group Infrared Precipitation with Stations
DECK	Diagnostic, Evaluation and Characterization of Klima
DIST	Distribution derived transformations
ERA-5	European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis - fifth generation
GCMs	General Circulation Models
GHGs	Greenhouse Gases
IPCC	Intergovernmental Panel on Climate Change
JMA	Japan Meteorological Agency
JRA-55	Japanese 55- Year Reanalysis
MAM	March to May
MDS1	Maximum Dry Spell with rainfall intensity < 1mm/day
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications, Version 2

MWE	Ministry of Water and Environment
MWS1	Maximum Wet Spell for days with rainfall >1mm/day
NCEP	The National Centers for Environmental Prediction
NDD1	Number of Dry Days with rainfall intensity <1mm/day
NWD1	Number of Wet Days with rainfall intensity >1mm/day
OND	October to December
PGF	Princeton Global Forcing
PET	Potential Evapotranspiration
PERSIANN-CDR	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Climate Data Record
PMP	Precipitation minus PET
QMBC	Quantile Mapping Bias Correction
RCPs	Representative Concentration Pathways
RCA4	Rosby Centre Regional Climate Model
RMSE	Root Mean Square Error
PP	Precipitation Products
SSPs	Shared Socioeconomic Pathways
TARCAT	TAMSAT African Rainfall Climatology and Timeseries
TPREC1	Total Precipitation with rainfall intensity >1mm/day
TRMM3B42	Tropical Rainfall Measuring Mission (daily (3B42)
UN	United Nations
WMZs	Water Management Zones

ABSTRACT

Precipitation products are increasingly being utilized as substitutes for observed precipitation data. This study evaluated the performance of five well-known precipitation products including CFSR, CHIRPS, JRA-55, ERA-5, and PGF and outputs from the CMIP6 General Circulation Models (GCMs) in replicating observed precipitation extremes across Uganda. Annual precipitation extreme events observed at 20 meteorological stations were compared with those from the precipitation products and GCMs outputs over the period 1979-2022. Utilized 6 precipitation extreme indices i.e. total precipitation (TPREC1), annual maxima series (AMS), number of dry days (NDD1), maximum dry spell (MWS1), number of wet days (NWD1), and maximum wet spell (MWS1) using a threshold of 1mm/day. To compare observed data with precipitation products, frequency analysis and bias ratios were applied. Correlation analysis and Taylor diagrams were utilized for comparing observed data with GCMs outputs. The quantile mapping bias correction method, implemented using the qmap package in R Studio, was applied to downscale GCM outputs with both observed data and precipitation products. This approach facilitated the determination of future climate change projections for the SSP2-8.5 and SSP5-8.5 scenarios for the 2050s and 2080s. PGF systematically overestimated observed AMS at all the selected stations. Contrastingly, JRA-55, ERA-5, and CHIRPS datasets consistently underestimated observed AMS quantiles across all stations and return periods. The regression line for AMS when plotted against log-transformed return period exhibited a steeper slope for CFSR than that of the observed data. The null hypothesis (H_0) of no correlation between observed and GCMs-based historical AMS, was rejected in varying proportions of the 20 meteorological stations. For instance, the H_0 was rejected ($p < 0.05$) in 10% of the 20 precipitation stations across Uganda when observed AMS was compared with that of NOR_ESM2. For each of the three GCMs including CESSM_WACCM, INM_CM5, MRI_ESM2, the H_0 was rejected ($p < 0.05$) in 5% of the 20 stations considered. The extent to which GCMs capture precipitation extremes varies due to their coarse spatial resolution. Bias correction of GCM outputs using quantile mapping method yielded different climate change signals in the cases when observations and precipitation products were considered. For instance, climate change impact on the total of precipitation above 1 mm/day intensity were over the ranges 40-170%, 20-61%, 15-41%, 5-36%, 8-67%, and 20-55% when bias correction of GCMs outputs were done using CFSR, PGF, CHIRPS, ERA-5, JRA-55, and observed precipitation, respectively. The choice of precipitation product significantly impacts climate projections. Thus, there is a need for careful selection of which precipitation product should be used for bias correction of GCMs' outputs in absence of observed precipitation when analysis is being done for planning water resource management and climate change impact assessments.

Key words: Precipitation products, CMIP6 GCMs, quantile mapping, climate change, precipitation extremes.

CHAPTER ONE: INTRODUCTION

1.1 Background to the study

Precipitation plays a significant role in the climate system and hydrological processes, as it influences water and energy cycles (Wong et al., 2017). Various aspects of climate change impact studies, including meteorology, climatology, hydrology, and decision-making processes, heavily rely on precise precipitation measurements for multiple purposes which include investigating climate and land-use changes, conducting agricultural and environmental research, and facilitating planning of water resources management (Asadullah et al., 2008). Accurate precipitation data is indispensable for developing reliable adaptation strategies in response to hydrometeorological extremes (Kimani et al., 2017). Additionally, observed data play a crucial role in evaluating the accuracy of General Circulation Models (GCMs) (Maidment et al., 2015).

Ground-based observations, such as precipitation gauges and weather radars, are commonly utilized for collecting precipitation data in developing countries (Behrangi et al., 2011). However, accurately estimating precipitation with adequate spatial distribution remains a challenge due to the limited coverage of rain gauge networks, particularly in regions like the sub-Saharan Africa, where weather stations are sparse and often poorly maintained (Kimani et al., 2017; Onyutha, 2018). Political instability can further exacerbate issues with the operational of weather stations. Problems with precipitation data include missing records, short record periods, and inconsistent entries (Slivinski, 2018).

Continuous and spatially well distributed global precipitation datasets with high resolutions are essential for analysis of climatic conditions and downscaling of GCMs' outputs (Moges et al., 2022). Precipitation products are some of the global datasets that are effective for achieving this goal. Example of some of precipitation products used in this study include Climate Forecast

System Reanalysis (CFSR) (Saha et al., 2014), Japanese 55-Year Reanalysis (JRA-55) (Kobayashi et al., 2015), Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) (Funk et al., 2015), Princeton Global Forcing (PGF) (Sheffield et al., 2006) and European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis Product (ERA-5) (Hersbach et al., 2020). The precipitation product-based approach integrates a data assimilation system to merge field observation data and climate model predictions, enabling accurate estimation of precipitation to fill this data gap, however, rigorous assessment of such estimates is required (Maidment et al., 2013; Moges et al., 2022).

High-resolution precipitation products data is important for evaluating the performance of GCMs in replicating observed climatology despite spatiotemporal variability (Gampe and Ludwig, 2017). GCMs suffer from accuracy issues due to estimation biases and errors stemming from large grid sizes, oversimplified thermodynamic processes and physics, inadequate understanding of the global climate system or stemming from assimilation processes (Smith et al., 2001; Wang and Zeng, 2012; Yin et al., 2021).

GCMs perform fairly well in projecting large-scale circulations and spatially uniform climate variables like temperature and pressure; however, they often struggle with accurately representing spatially non-uniform fields such as precipitation (Meehl et al., 2005). This limitation is attributed to their coarse resolution, typically around 100-250 km (Soriano et al., 2019) necessitating downscaling techniques to achieve more precise results at finer resolutions, typically around 25-50 km, for regional-scale hydrometeorological variables (Misra et al., 2022).

Bias correction, an essential post-processing step is frequently utilized to align climate model outputs with observational records (Soriano et al., 2019). This process involves scaling climate model outputs to account for systematic errors and enhance the model's fit to observations

(Soriano et al., 2019). Bias correction using precipitation products generally has minimal impact on the relative climate change signal, some studies have indicated that it can reduce the projected change compared to raw model simulations in the absence of observed data (Nakkazi et al., 2022; Senatore et al., 2022). Addressing these limitations requires advancing GCMs to better represent interannual rainfall variability alongside spatial patterns. de Padua and Ahn (2024) highlight the need for integrating observed and precipitation products data to offset each other's limitations and enhance climate projections. Bias correction techniques are categorized into three main groups including distribution-derived transformations, parametric transformations, and nonparametric transformations (Gudmundsson et al., 2012). Quantile mapping, a nonparametric transformation, has been employed in many studies that demonstrate the robustness of the downscaling technique for extreme precipitation events (Ayugi et al., 2020; Garibay et al., 2021; Ngoma et al., 2022).

Incorporating precipitation measurements into hydro-meteorological applications requires quantifying their uncertainty, which is especially critical for user groups who lack guidance and confidence in the numerous products used for their specific meteorological problems across different regions (Wong et al., 2017). There have been no studies conducted to investigate the implication of the use of precipitation products (instead of observed precipitation) for downscaling outputs of GCMs in climate change impact investigation.

1.2 Problem Statement

Accurate precipitation data is ideally sourced from a dense network of weather stations, but given their limited availability (Kimani et al., 2017; Onyutha, 2018), precipitation products data is commonly used as an alternative (de Padua & Ahn, 2024). Although precipitation data provides consistent global and temporal coverage, its dependence on data assimilation can introduce biases that may amplify error propagation (de Padua & Ahn, 2024). While

precipitation products data may carry biases, these datasets are often the best available resource for bias-correcting GCMs due to their spatially and temporally continuous climate data over long periods, essential for adjusting GCMs to accurately reflect observed climate variability, calibration with observations, and consistency, which collectively enhance the accuracy of future climate projections (Bodjrenou et al., 2023). Advanced bias correction methods take precipitation products biases into account, resulting in more accurate and usable GCM outputs.

Despite ongoing advancements in GCMs, systematic biases persist due to uncertainties inherent in the parameterization process (de Padua & Ahn, 2024; François et al., 2020; Van de Velde et al., 2022). Additionally, regional projection studies often require higher spatial resolution than GCMs can provide, necessitating downscaling techniques that, while improving resolution, may also introduce further biases (Ahmed et al., 2013). Therefore, an additional correction step, known as bias correction, is essential to reduce biases in GCMs before their application in climate impact studies. Past studies that have used precipitation products to perform bias correction indicate that bias correction can reduce the projected change compared to raw model simulations (Mubialiwo et al., 2021; Nakkazi et al., 2022; Senatore et al., 2022). The correlation coefficient values for CFSR data improved with a range of 0.52–0.61 for raw data to 0.73–0.77 after bias correction. Additionally, PBIAS values, both before and after applying bias corrections, fell within acceptable limits ($PBIAS \pm 25$) (Nakkazi et al., 2022).

Accurate and reliable information on the impacts of climate change is crucial for developing effective policies that support adaptation planning (Gruber and Levizzani, 2008). Achieving Sustainable Development Goal (SDG) 13, which focuses on climate action, depends on precise future climate predictions to enhance resilience. Sustainable development takes a comprehensive approach to growth, aiming to fulfill present needs while ensuring future generations can meet theirs. Thus, minimizing uncertainties in future climate projections is essential (Eyring et al., 2019).

To this end, studies on the analysis of precipitation extremes in Uganda considering observations, precipitation products, and GCMs in a climate change context are lacking. By comparing and contrasting the results obtained based on observed and precipitation products data, this study sought to provide a comprehensive understanding of precipitation extremes in the region, to support decision-making processes related to climate change adaptation and mitigation.

1.3 Objectives

1.3.1 Main Objective

To investigate the performance of precipitation products and outputs of CMIP6 GCMs in reproducing precipitation extremes observed across Uganda.

1.3.2 Specific Objective

The specific objectives were;

- i) To evaluate the suitability of precipitation products for reproducing precipitation extremes.
- ii) To quantify the mismatch between observed precipitation and outputs of GCMs.
- iii) To determine the implication of precipitation products capabilities for bias correction of outputs of GCMs.

1.4 Research Question

- i) How suitable is a precipitation product in reproducing observed precipitation extremes?
- ii) How much is the mismatch between observed precipitation and GCMs' outputs?
- iii) What is the implication of precipitation product capabilities for bias correction of GCMs outputs?

1.5 Significance of Study

Findings of this study can aid in;

- i) Determining the various GCMs' ability to reproduce climate conditions in specific places.
- ii) Quantifying uncertainty on results of climate change impact on precipitation due to the choice of the downscaling data.
- iii) Underscoring the need of improving precipitation products models to perform better in data scarce regions.
- iv) Supporting actionable policy in developing measures for adaptation to the impacts of climate change on precipitation.

1.6 Study Scope

1.6.1 Time study

The study was carried out between October 2022 to May 2024.

1.6.2 Geographical Coverage

The study was limited to Uganda.

1.6.3 Content Scope

This study evaluated the performance of precipitation products and GCMs output for extreme precipitation extremes in Uganda. Further analysis focused on the implications of downscaling using various precipitation products data on climate change projections.

1.7 Conceptual Framework

Fig 1-1 shows conceptual framework for the research study. The dependent variables were the downscaling uncertainty and performance of both precipitation products and GCMs. The capacity to reduce observed climatology was investigated using two independent variables including precipitation products and GCMs' outputs. The intervening variables included the choice of the GCM, uncertainty due to emission scenarios and the type of downscaling.

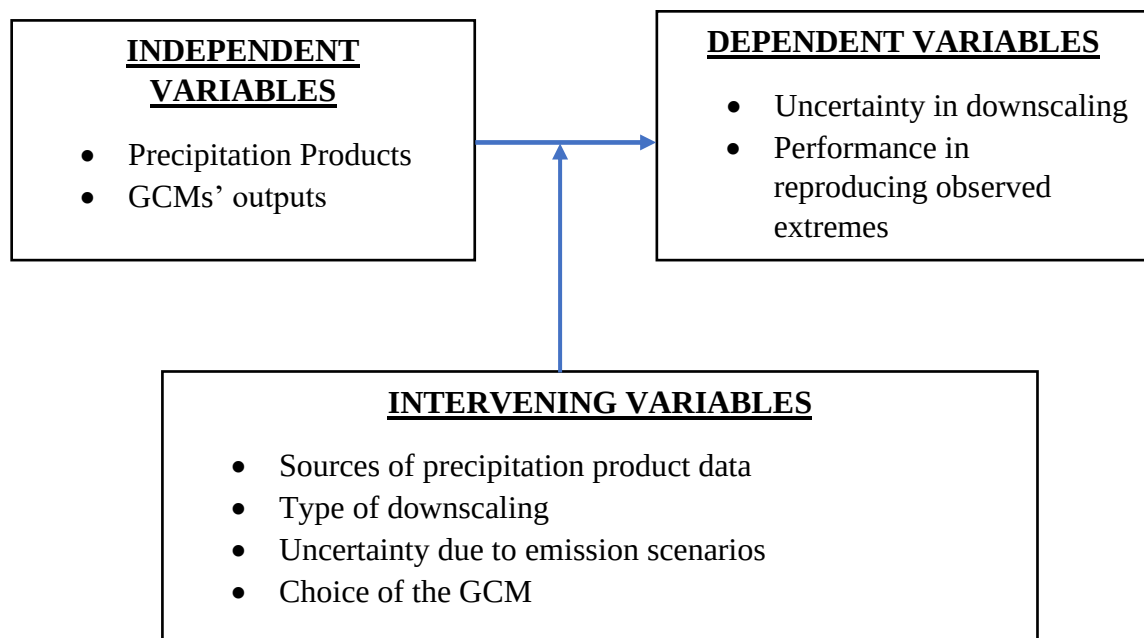


Figure 0-1 Conceptual framework

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

The purpose of a literature review was to provide a comprehensive overview of existing research and knowledge. It serves several key functions in research such as establishing context, identifying gaps, avoiding duplication, and supporting methodology.

2.2 Precipitation Products

Precipitation products entail synergizing observations and models to generate seamless maps of essential climate variables, ensuring consistency and accuracy in depicting key Earth system cycles such as water and energy (Hersbach et al., 2020). They help to evaluate the effects of changes in observing systems, measure advancements in modeling and assimilation techniques, and provide cutting-edge climatological data for assessing forecast inaccuracies (Hersbach et al., 2020). It is important to assess precipitation products against in situ measurements before using them in climate studies, as they may contain uncertainties stemming from assimilation processes (Smith et al., 2001; Wang and Zeng, 2012).

2.2.1 *Climate Forecast System Reanalysis (CFSR)*

The operational implementation of the second version of the NCEP Climate Forecast System (CFSv2) in March 2011 marked a substantial upgrade in climate prediction capabilities (Saha et al., 2014). This upgrade encompassed improvements in data assimilation, forecast models, and comprehensive reanalysis and reforecasting efforts spanning decades (Saha et al., 2014). CFSv2 demonstrates notable advancements such as improved forecasts of the Madden-Julian Oscillation (MJO), seasonal temperatures in the United States, and global sea surface temperatures compared to its predecessor (Wheeler and Hendon, 2004). Additionally, CFSv2 provides various forecast products beneficial for decision-making in sectors like water

management, agriculture, transportation, energy, and hurricane season forecasting. Despite uncertainties in certain regions or phenomena due to complex atmospheric dynamics or limited observational data, ongoing enhancements ensure CFSv2 remains valuable for subseasonal and seasonal forecasting across diverse applications (Saha et al., 2014).

CFSR data was used to identify a significant increase in global mean precipitation around 1998 and this was attributed to the incorporation of Advanced TIROS Operational Vertical Sounder (ATOVS) data (Zhang et al., 2012). Performance of CFSR was compared with that of MERRA-2, and TRMM3B42 datasets in simulating river discharge in data-deficient tropical catchments in Uganda (Nakkazi et al., 2022), CFSR outperformed TRMM, suggesting its potential for accurately simulating river discharge in regions with limited data (Nakkazi et al., 2022). Trends in precipitation, potential evapotranspiration (PET), and precipitation minus PET (PMP) were evaluated across Uganda's water management zones (WMZs) using CFSR data (Onyutha et al., 2021). Observed precipitation trends were satisfactorily reproduced at five out of eight stations (Onyutha et al., 2021). Assessment of bias correction methods for precipitation products data, highlighted notable improvements in the resemblance of bias-corrected CFSR precipitation data to observed data, particularly in metrics like the number of wet days and maximum daily rainfall (Garibay et al., 2021).

Simulations using CFSR data failed to accurately represent the specific regional climate across the three watersheds, with particularly poor performance in regions experiencing two rainy seasons (Roth & Lemann, 2016). China Meteorological Assimilation Driving Datasets (CMADS) demonstrates higher accuracy than CFSR in capturing the spatial distribution of annual average precipitation and maximum/minimum temperatures, showing closer alignment with observed data (Du et al., 2023).

2.2.2 Japanese 55-year Reanalysis (JRA-55)

JRA-55 is the second global atmospheric reanalysis project by the Japan Meteorological Agency, spanning 55 years from 1958 onwards (Kobayashi et al., 2015). This precipitation product consists of significant enhancements over its predecessor, JRA-25, including a new data assimilation and prediction system, higher spatial resolution, and advanced techniques like four-dimensional variational data assimilation with variational bias correction along with the incorporation of GHG with time-varying concentrations. Initial evaluations indicate improvements such as reduced temperature biases in the lower stratosphere and mitigated dry land surface anomalies in the Amazon basin compared to JRA-25 (Kobayashi et al., 2015).

In comparison of the quality of JRA-55 with other precipitation products and observational datasets, JRA-55 generally was found to improve depiction of various phenomena during the satellite era, including equatorial waves and transient eddies within storm track regions, compared to JRA-25 (Harada et al., 2016). Climate change in Uganda's Lake Kyoga Basin was analysed using precipitation and anomaly indices from JRA-55 and CHIRPS, and spatial and temporal increases were revealed in temperature and rainfall, indicative of climate change (Obubu et al., 2021). In contrast, rainfall reliability was evaluated across the Equatorial Africa, and results showed minimal correlation between precipitation products like JRA-55, CHIRPS2, CFSR, ERA-5, and observed rainfall or satellite estimates, particularly over the Congo basin and Lake Victoria regions, due to overestimated or underestimated (Nicholson and Klotter, 2021). In comparison for lower-troposphere winds in the Equatorial Africa, JRA55 outperformed other products like MERRA2 in reproducing intra-annual wind direction frequencies in Western Uganda (Diem et al., 2023).

2.2.3 *The Climate Group Hazards group Infrared Precipitation with Stations (CHIRPS)*

The CHIRPS dataset offers high-resolution of 0.05° and long-term precipitation estimates, leveraging satellite observations, particularly cold cloud duration data, to provide coverage in sparsely gauged regions (Funk et al., 2015). With timely availability and a novel blending procedure considering spatial correlation, CHIRPS facilitates effective hydrological forecasts and trend analyses. However, its reliance on satellite observations and potential biases pose limitations, necessitating careful validation and consideration of regional variations (Funk et al., 2015).

Historical drought occurrences in Central Uganda were analysed using CHIRPS data and Bukomansimbi and Mubende were identified as areas with the highest records of drought severity from 2005 to 2007 (Najjuma et al., 2021). Assessment of current and projected precipitation patterns across Uganda using CHIRPS and CMIP6 showed that future climatic conditions will be wetter from April/May to October than the historical climate condition of the same months (Ngoma et al., 2021). Evaluation of satellite rainfall estimates across the Eastern Africa showed that CHIRP and CHIRPS products were better than ARC2, with varying performance across regions (Dinku et al., 2018).

2.2.4 *Princeton Global Forcing (PGF)*

PGF presents a comprehensive dataset of meteorological forcings spanning 50 years with 3-hourly temporal resolution and a spatial resolution of 1.0° , aimed at driving models of land surface hydrology globally (Sheffield et al., 2006). Statistical downscaling techniques are employed to disaggregate precipitation both spatially and temporally, enhancing the dataset's resolution. While the dataset offers valuable strengths such as long-term global coverage, high temporal resolution, and correction of biases, limitations include reliance on model outputs,

coarse spatial resolution, potential uncertainties in data quality, and a relatively limited evaluation scope (Sheffield et al., 2006).

The studies conducted by Mubialiwo et al. (2021) based on PGF data, highlight the importance of performing bias correction on precipitation and evapotranspiration data prior to its use in hydrological modelling. In the study by Mubialiwo et al. (2021), PGF data set was used to study changes in precipitation and evapotranspiration over two catchments in Uganda. Bias correction was found to be vital to improve the accuracy of hydrological models in reproducing hydrological extremes. By focusing on the historical rainfall and evapotranspiration changes over the Mpologoma catchment in Uganda. Mubialiwo et al. (2023) found that improving the quality of PGF and other precipitation product data was crucial in reproducing observed climatology across various regions, especially in data scarce areas.

PGF datasets provide comprehensive long-term statistics on spatiotemporal drought characteristics in the sub-Saharan Africa, yet they have limitations in accurately estimating drought severity, mapping spatial patterns, and capturing the duration of drought events (Zhan et al., 2016). In a study analyzing geospatial trends and decadal anomalies in extreme rainfall over Uganda, East Africa using PGF data, it was discovered that the null hypothesis (no trend) was collectively rejected at the 5% significance level in the series from 7 out of 168 grid points (Onyutha, 2016).

2.2.5 *European Re-Analysis (ERA5-Land)*

ERA5-Land, a fifth generation of atmospheric reanalysis to be produced developed within the Copernicus Climate Change Service by the European Centre for Medium-Range Weather Forecasts, provides data at global coverage with a 9 km horizontal resolution and hourly temporal resolution, supporting detailed analysis of land surface processes (Muñoz-Sabater et

al., 2021). Its consistency and continuous updates from 1950 to the present make it a valuable resource for hydrological studies and environmental management. While it performs well in describing the hydrological cycle and improving soil moisture representation, challenges remain in accurately depicting snow depth fields and real-time availability (Muñoz-Sabater et al., 2021).

ERA-Interim and ERA-40 tend to overestimate and underestimate precipitation in Uganda, respectively (Maidment et al., 2013). Comparison of ERA5 with ERA-Interim, revealed that ERA-5 exhibited reduced biases and better representation of inter-annual variability, particularly improving the annual precipitation cycle in East Africa (Gleixner et al., 2020). ERA-5 was used and focused on lake and land breezes in the Lake Victoria basin, highlighting temperature contrast and low-level wind patterns as key drivers, with breezes occurring predominantly between 9:00 AM and 3:00 PM (Odongo et al., 2022). ERA5's performance over East Africa in reproducing observed rainfall showed decreasing biases compared to its predecessors this was attributed to improved assimilated observations (Assamnew and Mengistu, 2023).

Bias corrected data of MERRA-2 can be used in simulating river discharge in data-scarce tropical catchments of Uganda. (Nakkazi et al., 2022). MERRA-2 captured precipitation intensity but did not detect extreme precipitation events in some regions (Arshad et al., 2021).

2.3 Historical simulations and scenarios of CMIP 6 GCMs

CMIP6 is the latest or phase 6 iteration of the Coupled Model Intercomparison Project (CMIP), building upon the evolutionary trajectory observed in previous phases administered by the World Climate Research Program (WCRP), CMIP serves as a collaborative effort aimed at advancing and evaluating climate models (Eyring et al., 2016). The outputs from CMIP have found widespread application in numerous climate change studies and in the preparation of

assessment reports by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2012, 2013). This initiative is characterized by a significant expansion in the number of models, future scenarios, and experiments, signifying its ongoing evolution and adaptation.

2.3.1 CMIP6 GCMs

GCMs are complex tools that can simulate the response of the global climate system to rising greenhouse gas (GHG) concentrations. They represent physical processes in the atmosphere, ocean, cryosphere, and land surface, with spatial resolution over the range 100-250 km (IPCC 2012; Soriano et al., 2019). Some of the commonly used models are shown Table 2-1.

Table 0-1 Some GCM CMIP6 models

S/NO	Models	Institution	Resolution	References
1	ACCESS CM2	Australian Community Climate and Earth System Simulator coupled model	$1.25^{\circ} \times 1.875^{\circ}$	(Bi et al., 2020)
2	ACCESS-ESM1.5	The Australian Community Climate and Earth System Simulator, Austrian Earth System Model	$1.875^{\circ} \times 1.25^{\circ}$	(Ziehn et al., 2020)
3	BCC-CSM2-MR	Beijing Climate Center and China Meteorological Administration, China	$1.1^{\circ} \times 1.1^{\circ}$	(Wu et al., 2019)
4	Can-ESM5.0.3	Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada, Victoria, Canada	$2.81^{\circ} \times 2.81^{\circ}$	(Swart et al., 2019)
5	CESM-WACCM	National Centre for Atmospheric Research, USA. Community Earth System Model 1.2.2 – Whole Atmosphere Community Climate Model	$1.25^{\circ} \times 0.94^{\circ}$	(Danabasoglu et al., 2020)
6	INM-CM5-0	Institute for Numerical Mathematics, Russian Academy of Science, Moscow, Russia	$2.00^{\circ} \times 1.50^{\circ}$	Volodin and Gritsun (2018)
7	NorESM2-LM	Norwegian Climate Centre/Norway	$0.9^{\circ} \times 1.3^{\circ}$	(Seland et al., 2020)

8	MRI-ESM2	Meteorological Research Institute (MRI), Japan	$1.1^{\circ} \times 1.1^{\circ}$	(Yukimoto et al., 2019)
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Other CMIP6 GCMs include Model for Interdisciplinary Research on Climate – Earth System Model, 2010 version (MIROC-ESM) (Watanabe et al., 2011), Hadley Centre Global Environmental Model version 1 (HadGEM1) (Johns et al. 2006). MIROC-ESM model aims to simulate the Earth's climate system, integrating interactions among the atmosphere, oceans, land surface, and carbon cycle. It reflects enhancements made up to 2010 and is particularly noted for its advancements in modeling biogeochemical processes and atmospheric dynamics. The development and capabilities of MIROC-ESM are detailed in (Watanabe et al. 2011). HadGEM1 simulates various aspects of climate change and variability, providing insights into potential future climate scenarios (Johns et al. 2006).

Using multiple precipitation products and CMIP6 GCMs, despite their differing results, provides a more comprehensive understanding of the uncertainties and biases in precipitation extreme projections. Each model uses unique algorithms, data assimilation methods, and physical parameterizations, so they may capture different aspects of precipitation dynamics. By comparing these varied models, researchers can better assess their performance, identify consistencies or discrepancies, and ultimately improve the reliability of climate projections.

2.3.2 Historical simulations

Historical simulations within CMIP serve as important tools for evaluating the performance of climate models in replicating observed climate patterns, encompassing both variability and long-term trends (Flato et al., 2013). The key components of these simulations include emissions of short-lived species and long-lived GHGs, global gridded land-use forcing datasets, solar forcing, stratospheric aerosol data sets (volcanic activity), sea surface

temperatures and sea ice concentrations, aerosols, time-varying gridded ozone concentrations and nitrogen deposition (Eyring et al., 2016; Flato et al., 2013).

2.3.3 Scenarios of CMIP6 GCMs

CMIP6 integrates scenarios projecting future climatic outcomes based on consistent datasets encompassing GHG concentrations, aerosols, chemically reactive gases, land use changes, and other influential climate drivers (O'Neill et al., 2016). These projections are harmonized with socioeconomic assumptions introduced through the "Shared Socioeconomic Pathways" (SSPs). CMIP6 introduces updated versions of the four Representative Concentration Pathways (RCPs) initially outlined in IPCC AR5 (IPCC, 2013; van Vuuren et al., 2011) which served as foundational elements in CMIP5 (Taylor et al., 2012). These updated pathways, now labeled as SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, maintain comparable radiative forcing levels to their predecessors from AR5. Additionally, CMIP6 introduces novel scenarios to provide scientists with a more extensive array of potential future trajectories to simulate and enrich the range of possibilities for climate research endeavors (O'Neill et al., 2016).

SSP5-8.5: A high-emission, worst-case scenario projecting up to 8.5°C of warming by 2100, with severe potential impacts on society and the environment if emissions continue to grow unchecked.

SSP3-7.0: A medium-high emissions pathway, bridging the gap in past projections. It represents a forcing level similar to SSP2's baseline, highlighting moderate to high risks.

SSP2-4.5: A moderate scenario predicting approximately 2.7°C of warming, often used as a reference in climate studies. It combines intermediate vulnerability with moderate emissions.

SSP1-2.6: A low-emission pathway aiming to limit global warming well below 2°C by 2100, representing an optimistic future with reduced societal vulnerability and stringent emissions control (O'Neill et al., 2016).

2.4 Past studies that used CMIP6 GCMs

In evaluation of 15 CMIP6 GCMs in simulating rainfall patterns over Uganda from 1981 to 2019, GFDL-ESM4, BCC-CMC-MR, IPSL-CM6A-LR, CanESM5, GDFL-CM4-gr1, and GFDL-CM4-gr2 emerged as the top performers (Ngoma et al., 2020). CNRM-CM6-1 and CNRM-ESM2 underestimated annual and mean rainfall, despite better simulation of the spatial trend during March-April-May (MAM) and September-October-November (SON) seasons. The study underscores the need for further investigation into the model spread within CMIP6 over the study area and advocates for the exploration of robust machine learning approaches to mitigate biases (Ngoma et al., 2020).

In climate change impact assessment using CMIP6 GCMs across Uganda. PET and precipitation were projected to increase across all the WMZs (Onyutha et al., 2021).

Wetter conditions are anticipated during September–October, with maximum wetness in the northwestern parts of Uganda and around Lake Victoria basin. Future research was recommended to focus on examining changes in rainfall extremes under various global warming scenarios while considering model performance and independence (Ngoma et al., 2022).

Analysis of precipitation extremes across the East African region using CMIP6 GCMs by Ayugi et al. (2021) showed increased consecutive dry days (CDD) and a decreased consecutive wet days (CWD) by (2081–2100) compared to the past (1995–2014) in both MAM and SON seasons. The study recommended further research to investigate the underlying physical

mechanisms driving these projected extreme events, with implications for relevant policy considerations (Ayugi et al., 2021).

10 RCMs from the Coordinated Regional Climate Downscaling Experiment (CORDEX) were assessed to simulate rainfall pattern characteristics over Eastern Africa. There were significant biases in individual models depending on the subregion and season (Endris et al., 2013).

Future projections across Uganda indicate a decrease in rainfall during the MAM season, and an increase in the SON with a noticeable shift towards the latter (Ngoma et al., 2021). Higher warming was found in the latest model outputs of CMIP6 compared to its predecessor (CMIP5), despite identical instantaneous radiative forcing (Ayugi et al., 2021).

CMIP5 was found to perform better than CMIP3 in reproducing observed precipitation across East Africa. Results of the analysis were found to depend on the approach of downscaling used (Onyutha et al., 2016). The choice of the statistical downscaling method should depend on the objectives of the climate change impact study (Onyutha et al., 2016).

2.5 Methods of quantifying the mismatch between observed precipitation and outputs of GCMs

It is important to evaluate the reliability of downscaled climate data, particularly when using GCMs and RCMs for future climate change studies (Mirdashtvan et al., 2018). Commonly applied metrics include Pearson correlation coefficient (r), root mean squared error (RMSE) and Taylor diagram.

2.5.1 Root mean square error (RMSE)

RMSE considers squares of the residuals such that;

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (M_i - O_i)^2}{n}} \quad 0-1$$

Where O_i and M_i refer to the i th observed and modelled values, respectively and n is the sample size.

2.5.2 Pearsons product-moment correlation coefficient

The terms r measures the strength of coverability such that

$$r = \frac{\sum_{i=1}^n (o_i - O_1^m)(M_i - M_1^m)}{\sqrt{\sum_{i=1}^n (O_i - O_1^m)^2 \sum_{i=1}^n (M_i - M_1^m)^2}} \quad 0-2$$

2.5.3 Taylor diagram

Taylor diagram provides concise statistical summary of how well patterns match each other in terms of their correlation, their root-mean-square difference, and the ratio of their variances (Taylor, 2001) such that;

$$E'^2 = \sigma_y^2 + \rho_x^2 - 2\sigma_y\sigma_x R \quad 0-3$$

Where R is the correlation coefficient between the model (y) and observed (x) series which are defined at N discrete points in time or space is given by;

$$R = \frac{\frac{1}{N} \sum_{n=1}^N (y_n - y^-)(x_n - x^-)}{\sigma_y \sigma_x} \quad 0-4$$

where y^- and x^- are the mean values and σ_y and σ_x are the standard deviations of y and x , respectively (Taylor, 2001). It is expected that R (Eq. 2-4) should be comparable with r (Eq. 2-2).

2.6 Bias Correction

GCMs tend to overreact to local convective instability, resulting in an overestimation of moderate rainfall events and an underestimation of occurrences of no, minimal, and heavy rainfall events (Daniels et al., 2012; Rosa & Collins, 2013). Consequently, GCMs are not directly suitable for climate studies at the regional scale due to their coarse spatial resolution, particularly in terms of precipitation (Sharma et al., 2019; Wood et al., 2004). To address these limitations, there are two main approaches to downscale climate projections i.e. dynamical and statistical downscaling (Daniels et al., 2012).

Statistical downscaling interpolates regional-scale atmospheric predictor variables such as area averages of precipitation or temperature, and circulation characteristics like mean sea level pressure or vorticity to station-scale meteorological series (Wilby et al., 1998). Dynamical downscaling uses high-resolution regional simulations to extrapolate the effects of large-scale climate processes to the local or regional scale (Maraun et al., 2010).

2.6.1 *Methods of Quantile Mapping*

Quantile mapping statistically attempts to find a transformation of a modeled variable P such that its new distribution equals the distribution of the observed variable as shown in equation 2-5. This method is particularly useful in climate science and hydrology for correcting systematic biases in simulated data, such as temperature or precipitation from climate models.

$$x_o = f(x_m) \quad 0-5$$

x_o = Observed variable

x_m = Modelled variable

$f()$ = Transformation function

Quantile Mapping is an application of the probability integral transform and if the distribution of the variable of interest is known, the transformation h is defined as

$$x_o = F_o^{-1}[F_m(x_m)] \quad 0-6$$

Where; $F_m(x_m) = CDF \text{ of } x_m$

F_o^{-1} = inverse form of the CDF of x_o , which is the quantile function

a) Distribution derived transformations (DIST)

DIST involves matching the cumulative distribution functions (CDFs) of the model and observed data as shown in Equation 2-6. In the DIST method, the theoretical CDF [$F_m()$] is formed by using a mixture of the Bernoulli and the Gamma distributions, where the Bernoulli distribution is used to compute the occurrence probability of the rainfall variable, while the Gamma distribution is used to model the rainfall intensities (Ines and Hansen, 2006) cited by (Enayati et al., 2021).

b) Parametric transformations

In quantile mapping, parametric transformation refers to a method where a specific probability distribution is assumed (e.g., normal, gamma, or exponential) for both the observed and modeled data. The parameters of these distributions are then estimated and used to adjust the modeled data to align with the observed data distribution. This technique is often used when the data is skewed or when there is a need for a simplified transformation based on a theoretical distribution shape shown in Equation 0-5 (Piani et al., 2010b; Gudmundsson et al., 2012).

c) Non-parametric transformations

Nonparametric transformations make minimal assumptions about the functional form of the relationship between the model output and observed data. Instead, they focus on directly adjusting the model output to match the observed data without imposing specific mathematical constraints (Enayati et al., 2021). Empirical quantile (QUANT) commonly used non-

parametric method where the empirical CDFs are approximated using tables of the empirical percentiles. Values in between the quantiles are approximated using linear interpolation (Osuch et al., 2017)

2.7 Past studies that used quantile mapping

An evaluation of CFSR and potential bias correction methods for data-scarce areas was conducted across East Africa. Empirical quantile mapping with a 30-day sliding window length and 1-day timestep demonstrated the best performance by improving the similarity of the number of wet days and maximum daily rainfall between the two datasets (Garibay et al., 2021).

Quantile mapping bias correction (QMBC) was used to adjust the Rossby Centre Regional Climate Model (RCA4) for precipitation over Kenya. QMBC improved the accuracy of the RCA4 model, particularly for the dry season (Ayugi et al., 2020).

Minimal improvement on RCPs resulting from bias correction was observed in a study by Mugume et al. (2020). While bias correction mitigated underestimated rainfall instances, it also led to a reduction in overestimated rainfall events. However, this adjustment did not necessarily enhance the overall skill or reduce error magnitudes (Mugume et al., 2020).

Quantile mapping was utilized to bias-correct the CMIP6 data to examine projected alterations in drought occurrences across East Africa, resulted in overall distribution, closely aligned with observations. Additionally, the multi-model ensemble mean exhibited superior performance compared to individual GCMs (Ayugi et al., 2022).

The QMBC method facilitated the integration of the high-resolution dataset from Kenyan Meteorological Department (KMD) with the superior performance of the GPCC set during examining drought occurrences across East Africa. A new and more accurate bias-corrected

monthly precipitation time series spanning from 1983 to 2014 was generated for each location. This dataset enables a detailed depiction of precipitation distribution throughout the year, offering valuable insights for climate change adaptation strategies and customized territorial planning initiatives (Vigna et al., 2020).

An investigation into how various methods maintain changes in quantiles and extremes while employing quantile mapping bias correction was made by Cannon et al. (2015). Quantile mapping introduces artificial distortions into future model-projected trend. Distortions are significant for changes in long-term return values. (Cannon et al. 2015).

2.8 Past studies on the use of satellite products in East Africa

Past studies have evaluated the accuracy of several high-resolution satellite rainfall products in detecting and retrieving rainfall rates. Satellite products show deviations in high rainfall rates due to systematic and random errors (Maggioni et al., 2016). Satellite data showed good detection of rainfall in Western Uganda but underestimated rainfall in high-altitude areas of Northeastern Tanzania (Diem et al., 2014). Satellite rainfall products could reproduce spatial and seasonal rainfall patterns but have limitations in accurately retrieving rainfall amounts (Asadullah et al., 2008). Performance of different satellite products varied spatially, with weak performances in coastal and mountainous regions (Dinku et al., 2018). Two models were able to capture the spatial pattern of rainfall climatology well in Ethiopia, particularly for the main rainy season Kiremt, despite less accuracy in capturing interannual variability compared to spatial and seasonal variability (Diro et al., 2009).

2.9 Filling gaps in precipitation data records

Various methods such as closest station, simple arithmetic averaging, inverse distance weighting, multiple regression, and normal ratio tend to be employed to estimate missing

precipitation values (Moeletsi et al., 2016). Inverse distance weighting assigns weights to data points based on their distance from a target location, typically giving greater importance to nearby points. In the context of weather stations, this method involves considering data from 2 to 5 neighboring stations, with more emphasis placed on observations from the closest (Moeletsi et al., 2016).

2.10 Extreme precipitation indices (EPI)

EPIs are valuable tools for assessing extreme precipitation events (Zhang et al., 2011). These indices encompass various metrics such as Annual Maxima Series (AMS), Maximum Dry Spell (MDS1), Maximum Wet Spell (MWS1), Number of Dry Days (NDD1), Number of Wet Days (NWD1), and Total precipitation (TPREC1). Table 2-2 shows EPIs based on Onyutha (2020).

Table 0-2 Extreme Rainfall Indices (Onyutha, 2020)

ID	Indicator name	Indicator definition	Unit
AMS	Annual Maxima Series	Series comprising the maximum rainfall intensity in each year	mm/day
MDS1	Severe dry spell	Annual maximum number of consecutive days with rainfall intensity <1 mm/day	days
NDD1	Very dry day	Annual number of days each having rainfall intensity < 1 mm/day	days
NWD1	Wet day	Annual number of days each having rainfall intensity >1 mm/day	days
MWS1	Wet spell	Annual maximum number of consecutive days with rainfall intensity >1 mm/day	days
TPREC1	Rainfall total >1 mm/day	Annual total rainfall from days with rainfall intensity >1 mm/day	mm

The AMS, a useful sub-series in hydrology and water resources management, represents the set of most severe rainfall events that are annually independent from one another. It is relevant for the planning food risk management, guiding infrastructure design to withstand extreme

rainfall, informing urban planning for effective drainage systems. Moreover, during frequency analyses, the AMS helps determine the return intervals relevant for the design of hydraulic structures like sewer systems, culverts, and bridges.

TPREC1 data holds significant importance across multiple domains. In agriculture, it is relevant for crop planning and irrigation schedules. It aids water resource management by guiding reservoir operations and groundwater recharge efforts.

MDS1 and NDD1 comprise important information for planning water resources application that are affected by prolonged dry conditions. The drought can be meteorological or hydrological in nature. On the other hand, MWS1 and NWD1 are relevant for applications such as irrigation and environmental flow monitoring. Details of these indices and their general relevance to water resources management can be found in Onyutha (2020).

All the above metrics were utilized to allow for a detailed understanding of both wet and dry conditions supporting a more accurate and comprehensive assessment.

2.11 Summary of Research Gap

GCMs show limited accuracy in capturing rainfall rates and patterns across varied geographic regions and altitudes, often underestimating rainfall in high-altitude, coastal, and mountainous areas despite their ability to reproduce broad spatial and seasonal trends (Asadullah et al., 2008; Diem et al., 2014; Maggioni et al., 2016). Addressing these limitations requires advancing GCMs to better represent interannual rainfall variability alongside spatial patterns. de Padua and Ahn (2024) highlight the need for integrating observed and precipitation products data to offset each other's limitations and enhance climate projections. Mubialiwo et al. (2021, 2023) similarly emphasize bias correction in precipitation products data, such as PGF, to improve hydrological model accuracy, especially in data-scarce areas like Uganda.

While quantile mapping has shown success in enhancing the accuracy of precipitation products data and GCMs for specific metrics like wet days, seasonal patterns, and drought frequency, it has also introduced potential distortions, especially in the projection of long-term extremes and return values (Cannon et al., 2015). Furthermore, while some studies report improvements in aligning precipitation distributions with observations, others highlight limited gains in overall model skill or accuracy (Mugume et al., 2020).

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

3.1.1 Study area

Uganda is a landlocked country located in East Africa with an approximate geographical area of 236,040 square kilometers. Uganda generally has moderate temperatures, averaging around 22.8°C throughout the year. The temperature ranges from about 20°C in July and 24°C in February. The average annual precipitation is about 1,200 mm, with the highest mean monthly precipitation of about 150 mm in April and the lowest of nearly 40 mm in January.

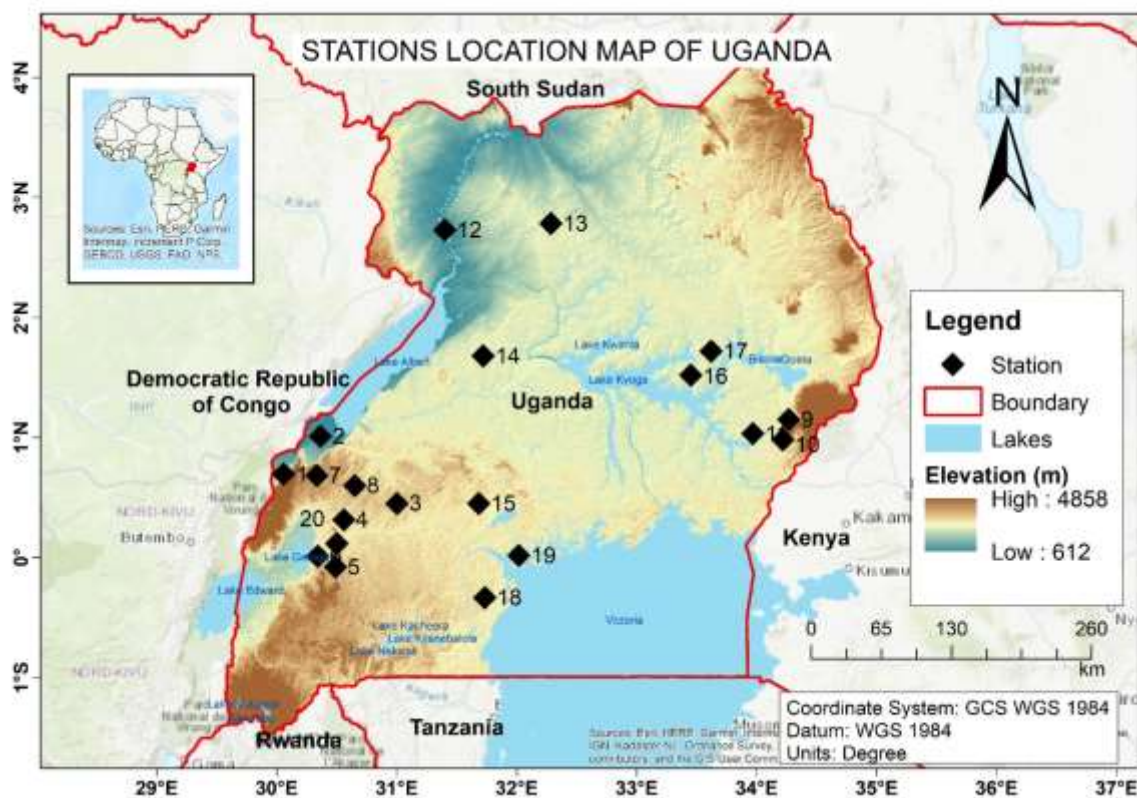


Figure 0-1 Location of selected precipitation stations in Uganda

3.2 Data Collection

3.2.1 Observed Data

Daily precipitation series observed at 20 weather stations were obtained from the Uganda National Meteorological Authority (UNMA). Table 3-1 shows relevant information such as station names and data record periods.

Table 0-1 Overview of the precipitation data from rain gauges

S/NO	Station name	Latitude	Longitude	Data period
1	Bundibugyo Met Station	0.69°N	30.05°E	1991-2020
2	Ntoroko Met Station	1.01°N	30.36°E	1991-2020
3	Kyegegwa Met Station	0.45°N	31.00°E	1991-2020
4	Kamwenge Met Station	0.31°N	30.33°E	1991-2020
5	Ibanda Met Station	-0.07°N	30.48°E	1991-2020
6	Kamwenge Met Station	0.01°N	30.34°E	1991-2020
7	Kabarole Met Station	0.68°N	30.33°E	1991-2020
8	Kyenjojo Met Station	0.60°N	30.65°E	1991-2020
9	Sironko Met Station	1.15°N	34.26°E	1990-2022
10	Mbale Met Station	0.98°N	34.21°	1990-2022
11	Budaka Met Station	1.03°N	33.96°E	1990-2022
12	Wadelai WDD - Gulu	2.73°N	31.40°E	1979-2009
13	Gulu Met Station - Gulu	2.78°N	32.28°E	1979-2009
14	Masindi Met Station	1.68°N	31.72°E	1979-2009
15	Kassanda Met Station - Mubende	0.45°N	31.68°E	1979-2009
16	Serere Agric. Station - Soroti	1.52°N	33.45°E	1979-2009
17	Soroti Met Station	1.72°N	33.62°E	1979-2009
18	Masaka Forest - Masaka	-0.33°N	31.73°E	1979-2009
19	Nkozi Experimental Farm - Mpigi	0.02°N	32.02°E	1979-2009
20	Kamwege Met Station	0.11°N	30.50°E	1979-2009

Data checks for consistency in the observed data were conducted with reference to previous studies by Onyutha et al. (2021) and Onyutha and Kerudong (2022), which utilized these same meteorological stations.

3.2.2 *Precipitation Products data*

The overview of the precipitation datasets used in this study is presented in Table 3-2.

Table 0-2 Freely available precipitation products.

Acronym	Full Name	Resolution	Period	Type	References
JRA-55	Japanese 55-year reanalysis	0.5°×0.5°	1958–2017	Reanalysis	(Kobayashi et al., 2015)
CHIRPS	Climate Hazards Group Infrared Precipitation with Station Data	0.05°×0.05°	1981–2019	Satellite-gauge	(Funk et al., 2015)
CFSR	NCEP climate forecast System version 2	0.25°×0.25°	1979–2013	Reanalysis	(Saha et al., 2014)
PGF	Princeton Global Forcing version	0.25°×0.25°	1948-2010	Reanalysis-gauge	(Sheffield et al., 2006)
ERA-5	ECMWF Re-Analysis	0.1°×0.1°	1950-2022	Reanalysis	(Hersbach et al., 2020)

Daily rainfall totals of CHIRPS were obtained from the Climate Hazards Center, University of California, Santa Barbara, accessed through <https://www.chc.ucsb.edu/data> (accessed on 12 April 2023). Daily rainfall datasets for JRA-55 were obtained from the Japan Meteorological Agency via <https://rda.ucar.edu/datasets/ds628.0> (accessed on 12 April 2023). Daily CFSR series were obtained from <https://swat.tamu.edu/data/cfsr> (accessed on 27 Jan 2021). Three-hourly precipitation datasets of ERA-5 were downloaded via <https://climexp.knmi.nl/selectdailyfield2.cgi?id=someone@somewhere> (accessed on 12 April 2023). Daily global precipitation data of the PGF was acquired via <http://hydrology.priceton.edu/data/pgf/v3/0.25deg/> (accessed on Feb 2021).

3.2.3 *Outputs of GCMs*

This study utilized eight GCMs (those shown in Table 2-1) obtained from the Earth Systems Grid Federation (ESGF); <https://esgf-node.llnl.gov/search/cmip6/> (accessed on April 24, 2023). The historical period considered for analysis was from 1979 to 2014. Daily precipitation data from two scenarios, SSP2–4.5 and SSP5–8.5, were considered in this study. Future projections encompassed two future sub-periods 2041-2070 and 2071-2100 referred to as the 2050s and 2080s, respectively.

3.3 *Obtaining grid data from precipitation products and GCMs' outputs*

The inverse distance weighting method was applied by assigning weights to four data points according to their distance from the target location. The grid point with the highest weight, indicating its proximity to the weather station, was identified and considered in the analysis.

The comparison period was limited to the common periods of the precipitation products and GCMs (1979-2022). However, data availability varied across the different gauge stations as shown in Table 3-1. Therefore, different common periods were used at different stations according to the data availability.

3.3.1 *Suitability of precipitation products data*

For comparison, the various indices in Table 2-2 were extracted from observed data at each station (annual data). Similarly, the indices were extracted from each precipitation product data at the location of the respective weather station. A comparison of indices from observed and precipitation products was done in terms of frequency analysis and model biases.

a) *Frequency analysis*

The frequency of extreme precipitation events from observed and precipitation products-based data was analyzed by calculating their return periods. The AMS was used because it yields

strong independence of the extreme events compared to the approach based on partial duration series. The AMS was sorted from highest to lowest, and the empirical return period of an event was calculated by dividing the data records length (in years) by the corresponding rank. This means that the largest event was given the rank of 1, the second largest event was given the rank of 2, and so on. If h is the data record length in years, then the largest and smallest events will have ranks of $j = 1$ and $j = h$, respectively. Graphically, plots of AMS-based quantiles versus return period were made to consist of both precipitation products data and observed data. For an ideal case, all the precipitation products AMS could have their return periods comparable to those observed extremes.

The 10-year AMS quantile was determined by identifying the AMS quantile values in both the observed data and the precipitation products data that corresponded to the 10-year return period.

b) Performance of precipitation products using model bias

Bias was used to measure the performance of the precipitation products. The bias of the precipitation products was computed as the ratio of the precipitation products data to that of observed data while separately considering each precipitation extreme. A value above 1 indicates that the precipitation data overestimated the observed data value. On the other-hand, a value below 1 indicates that the precipitation products data underestimated the observed value. The best-performing precipitation product would yield a ratio of one. The worst-performing precipitation product would be the one with the largest bias. The bias was calculated for 6 indices including; TPREC1, NDD1, NWD1, MDS1, MWS1, and AMS.

3.3.2 Quantifying the mismatch between observed and GCM precipitation products

Like for precipitation products, the indices in Table 2-2 were extracted from the historical simulations of each GCM. Similarly, the indices were extracted from observed data. The data

was found to be normally distributed, therefore performance of the GCMs was assessed using Pearson's product-moment correlation coefficient, RMSE, and Taylor diagram.

The null hypothesis (H_0) of no correlation was tested at $\alpha = 0.05$. The sample sizes were based on the data record length in years. The critical values for the stations 1-8, 9-11 and 12-20 were 0.404, 0.396 and 0.349, respectively. If the computed absolute value was less than the critical limit of the correlation coefficient, the H_0 (no correlation) was not rejected at the selected α ; otherwise, the H_0 (no correlation) was rejected. Critical values of the correlation were obtained using Table A.1 following Aspelmeier (2005).

The choice of using bias ratios to compare precipitation products data with observed data and using correlation and hypothesis testing for GCMs outputs is based on the nature of the datasets and the objectives of the comparisons. Precipitation products data typically comes from a combination of model outputs and assimilated observational data, aiming to reconstruct the historical state of the atmosphere or climate. Bias was used because the focus is on direct magnitude comparisons. GCM outputs are the results of simulations based on theoretical and physical climate models. These models aim to predict future climate scenarios and evaluate historical climate trends. Correlation analysis and hypothesis testing are used to evaluate patterns, trends, and the statistical significance of model predictions compared to observed data. These methods account for uncertainty and non-linearity in the climate system.

3.3.3 Implication of precipitation products capabilities for bias correction of GCMs output

The procedure involved;

- i) downscaling the GCMs' outputs using observed data,
- ii) downscaling GCMs' outputs using precipitation products data, and
- iii) Quantifying climate change impacts for the case where observed data and precipitation products were used for downscaling GCMs' outputs.

To enhance the reliability of CMIP6 data in forecasting precipitation extremes, this study utilized the "fitQmapQuant" function from the R studio package by Gudmundsson (2022) for bias correction. This non-parametric quantile mapping method using empirical data, was found to have the highest skill in systematically reducing bias to refine the model's accuracy. (Gudmundsson et al., 2012, Bong et al., 2018, Paz and Willems, 2022).

Empirical Quantile Mapping (EQM) is a nonparametric approach that relaxes the assumption of normality commonly made in statistical methods which operates by dividing historical observation and model data into quantile levels and estimating their cumulative distribution functions (CDFs) (Panofsky and Brier, 1968, Qian and Chang, 2021). Linear interpolation is applied to fill in quantile values for unspecified levels. Then, quantile mapping adjusts model projections by mapping model quantiles to corresponding observed quantiles. This ensures alignment between model and observed data, enhancing the accuracy of future projections as shown in equation 0-1 (Panofsky and Brier, 1968, Qian and Chang, 2021).

$$x_{o,p}^{-}(t) = F_{o,h}^{-1}\{F_{m,p}[x_{m,p}(t)]\} \quad 0-1$$

$x_{o,p}^{-}(t)$ is the adjusted future observation at time t during the projection period.

$x_{m,p}(t)$ is climate model data during the projected future period with corresponding CDF

$F_{m,p}(z)$

For a quantile level τ , $0 \leq \tau \leq 1$ the quantile value (also known as the τ -th percentile) is obtained by the inverse CDF: $F_{o,h}^{-1}(\tau)$

The same downscaling technique was applied when downscaling GCMs outputs using both precipitation products and observed precipitation.

3.3.4 *Climate change projections*

Scenarios were partitioned into two distinct time periods i.e. the 2050s (spanning from 2040 to 2070) and the 2080s (spanning from 2071 to 2100). These time periods are commonly used in climate studies to analyze climate projections over different future decades. Additionally, the climate change impact investigations were conducted under two scenarios including SSP 2-4.5 and SSP 5-8.5 for CMIP6 models.

Overall, this processing step allowed for the organization and analysis of downscaled climate data, focusing specifically on precipitation-related indices, time periods, and scenarios.

3.3.4.1 Quantifying the difference in climate change projections especially on extreme quantiles

The downscaled GCM data was averaged to obtain the ensemble mean. This was used because the ensemble mean tends to be better than data from individual climate models (Onyutha, 2020). Historical mean was calculated for both observed data and precipitation products. Climate change impact was obtained using;

$$Change (\Delta) = \frac{A^m - B^m}{B^m} \times 100\% \quad 0-2$$

where

Δ is the percentage change between future downscaled data and historical data,

A^m represents the ensemble mean of downscaled individual future period data, and

B^m represents the historical mean of either observed or precipitation products.

Equation 3-2 was applied to the various indices in Table 2-2 extracted based on observed data, precipitation products series, and downscaled scenarios.

3.4 Methodological framework

Fig 3-2 shows the overview of the methods adopted in this study.

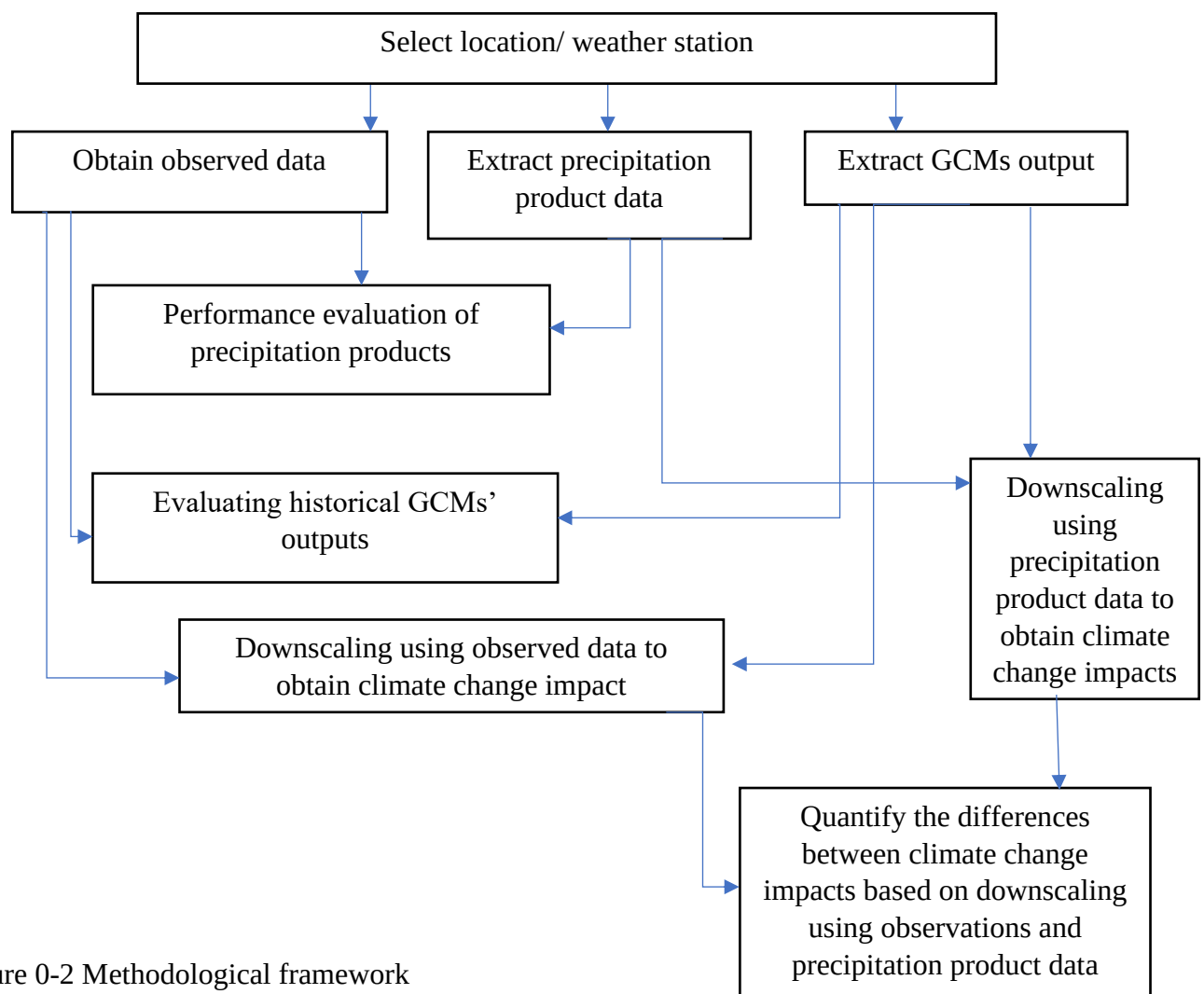


Figure 0-2 Methodological framework

3.5 Ethics

Letter of introduction was used to obtain the secondary data used in this study. Conditions by the data providers were adhered to. Sources of the precipitation products and GCMs' outputs used in this study were also cited.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Introduction

The findings of the research are presented in this chapter according to the study's specific objectives. Additionally, the results are discussed within this section.

4.2 Performance of precipitation products

4.2.1 *Performance of precipitation products in reproducing extreme quantiles*

Figure 4-1 shows performance of precipitation products models in reproducing observed precipitation quantiles. For a given return period, observed quantiles were either over-estimated or under- estimated by the precipitation products models (Fig 4-1 a-t). The PGF model consistently overestimated the observed AMS over the entire range of all return periods at all stations. Conversely, the CHIRPS, JRA, and ERA models underestimated the observed AMS systematically for all considered return periods across many stations. However, ERA-5 overestimated AMS at stations 1, 9, 10 11 (Fig 4-1 a, i, j, k).

Apart from the over-estimations/under-estimations, another notable difference between observed and precipitation products-based quantiles, is the slope of the log-transform return period. This actually corresponds to the scale parameter of the exponential extreme value distribution. Generally, CFSR model exhibited a steep slope of the return periods. There were relatively gradual slopes for JRA, ERA, and CHIRPS models, while the PGF model exhibited a flatter slope (Fig 4-1 b-t). Notably, at stations 7, 15, 18, 19, and 20 (Fig 4-1 g, o, r, s, t), the CFSR model reproduced the slope of observed return periods well. However, it also demonstrated fluctuations showing transition from underestimations to overestimations particularly evident at stations 2-5, 6, 13, 14, and 16 (Fig 4-1 b-f, m, n, p). The CFSR initially

underestimated precipitation at shorter return periods (1-4 years) but switched to overestimations at longer return periods (more than 5 years).

The PGF-based AMS led to systematically higher quantiles than observed series, indicating a persistent bias. Conversely, the JRA, ERA, and CHIRPS quantiles consistently underestimated AMS quantiles across all stations and return periods. These biases could lead to significant overestimation/underestimation of the actual risk associated with extreme precipitation events, impacting infrastructure planning and emergency response strategies in affected areas.

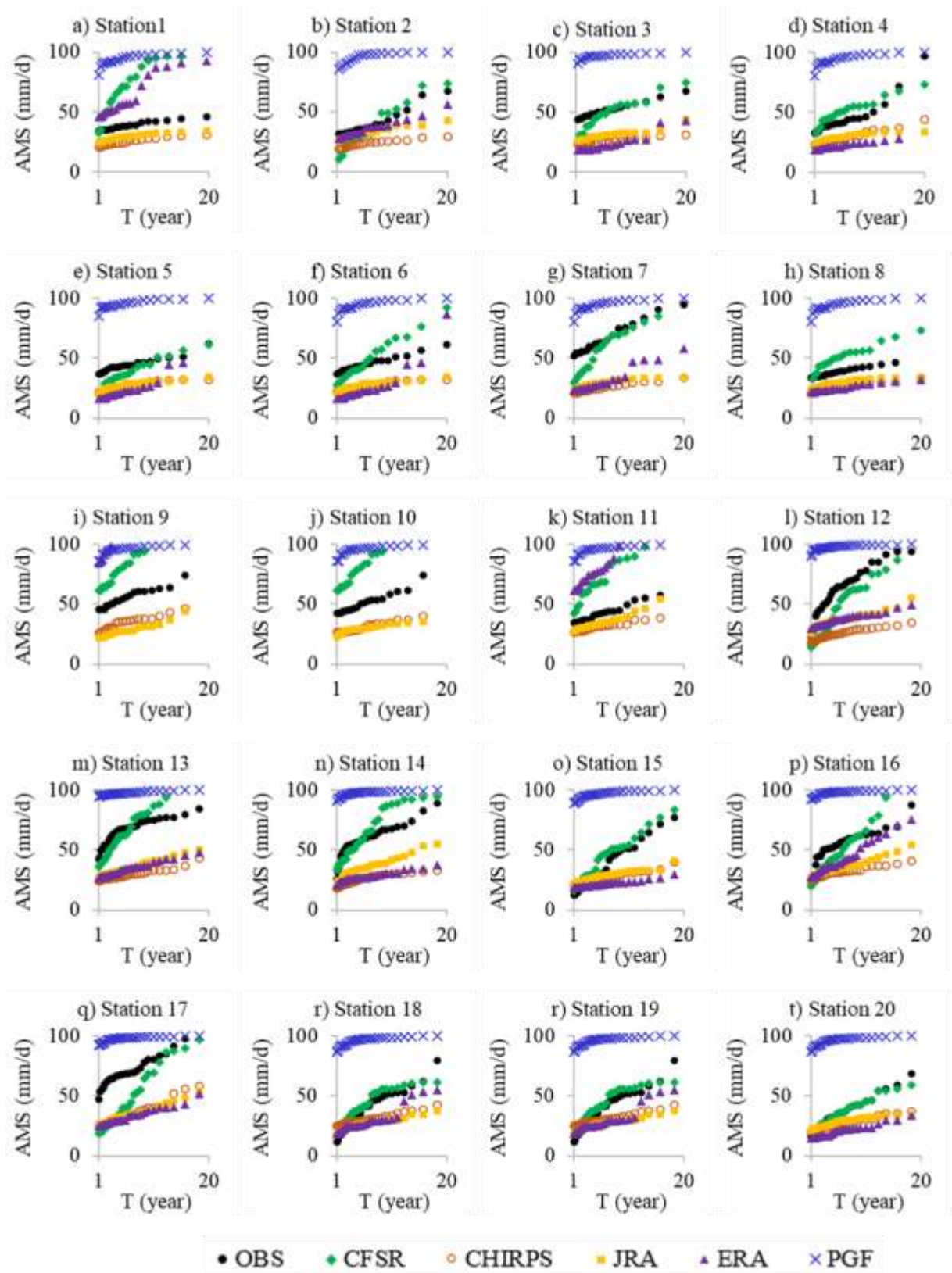


Figure 0-1 Performance of the precipitation products in reproducing observed AMS at (a-t) stations 1-20.

Precipitation products datasets often exhibit biases when reproducing observed extreme events (Ehret et al., 2012). However, the overall accuracy of satellite and precipitation products datasets is poor in detecting heavy and high-intensity precipitation (Mekonnen et al., 2023).

ERA-5 emerged as the top-performing precipitation product dataset when considering annual timescales showing bias of 44.7%, along with lower RMSE (801.75mm) and ME (720.70mm) values compared to JRA-55 and CFSR. In contrast, JRA-55 displays a bias of 171%, RMSE of 2902.21mm, and ME of 2760.63mm. On the other hand, CFSR demonstrated a bias of -85.2%, with a RMSE of 1354.36mm and an ME of -1349.21mm. In a previous study (Wanzala et al., 2022), JRA-55 performs poorly at both annual and seasonal scales, particularly during wet seasons (MAM and OND). Despite JRA-55's better performance in the dry season (JJA), ERA-5 demonstrated better agreement with observations across all three seasons, making it a suitable option for simulating precipitation in Kenyan catchments (Wanzala et al., 2022). While comparing various precipitation products in West Africa, CHIRPS and ERA-5 yielded the best and worst performance respectively (Kouakou et al., 2023).

Results of frequency analysis is vital for planning water resources management. Quantiles of high return periods are associated with increased vulnerability of low-lying areas to flooding events. Analysis of extreme hydrological events is important for planning measures to safeguard against catastrophic events like floods (Onyutha, 2020). This information is crucial for various purposes such as guiding floodplain development, designing hydraulic infrastructure including sewer and river systems, culverts, and bridges.

4.2.2 Performance of precipitation products in terms of model bias

Fig 4-2 shows results of the comparison of observed and precipitation product indices.

A value above one (1) indicates that the observed value was overestimated by the precipitation products data. However, values below one (1) shows an underestimation of the observed value by the precipitation products data. From Fig 4-2, the precipitation products over estimated and underestimated the precipitation extremes. At the various stations, the products exhibited, to varying extents, under-estimations and overestimations of the observed extreme precipitation indices.

The PGF model displayed the most significant overestimation for both TPREC1 and AMS across all stations. Notably, these overestimations for TPREC1 were up to 89% and 35% at stations 18 and 19, respectively. However, the bias for AMS at station 11 was 71%. The underestimation of AMS at station 18 yielded a negative bias by up to -75%. CHIRPS, JRA-55, ERA-5, and CFSR data exhibited underestimations for AMS in 100%, 100%, 80%, and 60% of total rainfall stations, respectively. Specifically, Stations 1, 9, 10, and 11 exhibited overestimations for both CFSR by 66%, 49%, 69% and 94%, respectively. Correspondingly, the overestimations by ERA-5 at stations 1, 9, 10 and 11 were 28%, 91%, 70% and 93%. CFSR and ERA data exhibited a mix of both underestimations and overestimation. With 55% and 45% of total stations showing underestimation for total precipitation, respectively. CHIRPS and JRA reproduced TPREC1 with biases which ranged from 0.8 to 1.1 and covering 65% of total rainfall stations.

Figure 4-3 shows biases in 10-year AMS quantiles. The ranges of ratios of the 10-year AMS quantile from precipitation products to that of observed precipitation were 0.3-2.17, 0.14-0.68, 0.15-0.75, 0.14-2.57 and 0.44-2.21 for CFSR, CHIRPS, JRA-55, ERA-5 and PGF, respectively. Notably, both CFSR and PGF consistently demonstrated overestimation at more than 75% of total stations. The largest overestimation was at station 1 i.e. 17% and 21% for CFSR and PGF, respectively. Conversely, CHIRPS and JRA-55 consistently displayed underestimations across all total stations. ERA-5 indicated underestimation in 75% of total

stations, however at stations 1, 9, 10, and 11, ERA-5 exhibited overestimations. Additionally, all precipitation products exhibited underestimations at specifically station 8. The reanalysis datasets show variability in the 10-year quantile ratios, indicating differing accuracy levels.

In Fig 4-2, CFSR, CHIRPS, JRA-55, and ERA-5 consistently overestimated both NWD1 and MWS1, while PGF underestimated both NWD1 and MWS1 across all stations. The overestimations of both NWD1 and MWS1 by CFSR, CHIRPS, JRA-55 and ERA-5 were in up to 85%, 100%, 85% and 100% of the total stations, respectively. Notably, the highest overestimation biases over 2 for both NWD1 and MWS1 by CHIRPS and ERA were obtained at stations 1, 7-10, and 18-19.

CHIRPS, JRA-55, and ERA-5 consistently underestimated the NDD1, at over 90% of total stations. This underestimation, particularly at station 10 under ERA-5, was by 11%. PGF consistently exhibited an overestimation bias across all stations for NDD1. The largest overestimation was 59% and it was at station 1. However, CFSR performed comparatively well, with biases of NDD1 ranging from 0.85 to 1.14 across 65% of total rainfall stations. CHIRPS and JRA-55 showed consistent overestimation bias for MDS1 in 80% of total stations. CHIRPS and ERA-5 displayed underestimation in 70% of total stations. MDS1 was underestimated by ERA-5 only at stations 1-6. Largest underestimations of MDS1 by ERA-5 were 14% and 17% at stations 18 and 19, respectively.

The precipitation products used showed overestimations/underestimations in mountainous areas (Dinku et al., 2011, Kimani et al., 2017). ERA-5 outperforms the other precipitation products on monthly and seasonal scales, whereas CFSR outperforms ERA-5 on annual and seasonal timescales in Kenya catchment (Wanzala et al., 2022). ERA-5 datasets show good performance in estimating daily precipitation over Africa.

Precipitation products excel in capturing interannual variations in precipitation totals and the frequency of rainy days and their accuracy diminishes when it comes to predicting dry spell duration and average intensity, with the least precision observed in estimating annual maximum 1-day precipitation totals (Harrison et al., 2019).

Station	TPREC					NDD1					NWD1				
	CFSR	CHIRPS	JRA	ERA	PGF	CFSR	CHIRPS	JRA	ERA	PGF	CFSR	CHIRPS	JRA	ERA	PGF
1	1.30	0.76	0.74	1.70	2.35	0.87	0.76	0.98	0.55	1.59	1.14	1.26	1.02	1.49	0.36
2	0.18	0.88	0.91	0.80	4.16	1.54	0.67	0.98	0.89	1.34	0.26	1.45	1.03	1.15	0.54
3	1.01	0.83	0.67	0.59	3.52	0.92	0.69	1.05	0.85	1.34	1.11	1.43	0.93	1.20	0.52
4	1.32	0.95	0.90	0.68	2.87	0.89	0.74	0.92	0.88	1.50	1.13	1.32	1.10	1.15	0.38
5	0.48	0.85	0.56	0.58	3.04	1.19	0.80	1.21	0.92	1.44	0.73	1.29	0.71	1.12	0.38
6	1.20	0.99	0.97	0.50	3.09	0.89	0.68	0.88	1.03	1.43	1.15	1.44	1.16	0.96	0.41
7	0.88	0.91	0.89	1.29	2.83	0.85	0.55	0.71	0.49	1.15	1.38	2.16	1.74	2.31	0.61
8	0.82	0.57	0.56	0.66	1.78	0.66	0.52	0.68	0.48	1.10	2.03	2.44	1.97	2.58	0.69
9	1.83	0.75	0.47	2.43	3.13	0.60	0.73	0.86	0.29	1.13	1.84	1.56	1.29	2.48	0.73
10	1.89	1.07	0.83	4.78	3.24	0.65	0.51	0.64	0.11	1.21	1.60	1.83	1.61	2.52	0.63
11	0.99	0.95	0.79	0.99	3.69	1.01	0.71	0.95	0.72	1.25	0.99	1.45	1.08	1.45	0.60
12	0.23	1.09	1.10	1.35	5.50	1.34	0.66	0.82	0.65	1.04	0.30	1.69	1.36	1.72	0.92
13	0.90	0.96	0.97	1.15	3.97	0.77	0.68	0.75	0.64	1.08	1.45	1.61	1.48	1.69	0.85
14	1.14	0.87	0.88	1.16	3.78	0.75	0.65	0.86	0.54	1.21	1.44	1.57	1.25	1.80	0.64
15	1.00	1.62	1.28	2.08	5.11	1.00	0.64	0.94	0.39	1.27	1.00	1.65	1.11	2.11	0.51
16	0.51	0.98	0.90	0.92	3.99	1.05	0.70	0.87	0.62	1.19	0.92	1.52	1.24	1.66	0.67
17	0.30	0.94	0.90	0.94	4.01	1.14	0.64	0.81	0.64	1.11	0.69	1.78	1.42	1.78	0.77
18	0.97	2.66	0.88	3.06	8.89	1.01	0.60	1.12	0.41	1.09	0.97	2.25	0.63	2.87	0.70
19	1.06	2.68	1.90	2.72	8.35	0.93	0.51	0.81	0.36	1.07	1.21	2.49	1.57	2.94	0.79
20	0.95	1.67	1.64	1.07	5.62	1.00	0.60	0.76	0.76	1.21	0.99	1.81	1.49	1.48	0.57
	MDS1					MWS1					AMS				
	CFSR	CHIRPS	JRA	ERA	PGF	CFSR	CHIRPS	JRA	ERA	PGF	CFSR	CHIRPS	JRA	ERA	PGF
1	1.62	1.01	1.81	1.46	2.05	2.75	2.07	2.99	4.95	0.37	1.66	0.62	0.71	1.28	2.46
2	3.78	0.71	1.36	1.32	1.22	0.35	2.39	1.78	1.53	0.50	0.86	0.58	0.80	0.81	2.49
3	1.81	0.76	2.27	1.17	1.42	2.63	2.00	2.42	1.73	0.53	0.98	0.54	0.66	0.48	2.25
4	1.66	0.82	1.37	1.34	1.55	3.51	2.24	3.04	1.98	0.37	1.13	0.69	0.68	0.49	2.38
5	3.15	1.07	2.28	1.42	1.51	1.51	2.09	1.50	1.92	0.48	0.85	0.62	0.65	0.43	2.43
6	1.79	0.76	1.35	1.59	1.54	3.77	2.42	3.50	1.73	0.43	1.20	0.62	0.70	0.44	2.44
7	1.35	0.57	1.01	0.72	1.15	2.89	3.66	5.28	7.00	0.65	0.94	0.44	0.50	0.44	1.72
8	1.13	0.52	0.93	0.60	1.06	6.13	3.69	5.32	6.53	0.65	0.35	0.19	0.21	0.18	0.75
9	1.19	0.88	1.33	0.43	1.04	5.92	2.08	1.98	7.46	0.63	1.49	0.59	0.50	1.91	1.85
10	1.36	0.69	1.03	0.24	1.19	5.28	3.58	2.99	12.32	0.56	1.69	0.63	0.60	2.70	2.10
11	2.10	0.84	1.46	0.92	1.19	1.94	1.99	1.41	2.23	0.50	1.94	0.79	0.96	1.93	2.71
12	2.63	0.74	1.20	0.76	0.60	0.41	1.75	1.66	2.70	0.63	0.68	0.41	0.58	0.59	1.59
13	0.96	0.66	0.89	0.88	0.57	3.33	2.54	2.73	3.65	0.92	0.90	0.44	0.51	0.49	1.47
14	1.07	0.65	1.23	0.70	0.90	3.18	1.99	2.64	3.83	0.45	0.98	0.42	0.58	0.46	1.65
15	1.00	0.36	1.12	0.26	0.68	1.00	1.23	1.52	2.75	0.34	1.00	0.71	0.74	0.58	2.65
16	1.69	0.71	1.29	0.63	0.93	1.65	2.20	2.08	2.47	0.58	0.77	0.54	0.63	0.70	1.81
17	2.24	0.72	1.18	0.71	0.85	1.40	2.89	2.65	2.90	0.74	0.52	0.45	0.47	0.44	1.37
18	0.98	0.23	1.62	0.14	0.43	0.94	2.12	0.80	4.02	0.57	1.00	0.77	0.63	0.70	2.52
19	0.85	0.24	0.99	0.17	0.53	1.19	2.95	3.08	4.48	0.58	0.98	0.69	0.75	0.76	2.37
20	1.04	0.27	0.50	0.46	0.48	1.05	1.39	1.99	1.18	0.26	0.93	0.73	0.73	0.51	2.64

Figure 0-2 Ratio of precipitation products to observed precipitation indices

Station	10-year AMS quantile				
	CFSR	CHIRPS	JRA	ERA	PGF
1	2.17	0.68	0.75	2.04	2.21
2	1.14	0.44	0.61	0.73	1.57
3	1.13	0.49	0.54	0.66	1.59
4	0.94	0.51	0.47	0.40	1.39
5	1.10	0.62	0.63	0.90	1.95
6	1.35	0.56	0.56	0.81	1.76
7	0.94	0.34	0.37	0.54	1.10
8	0.30	0.14	0.15	0.14	0.44
9	1.69	0.63	0.59	2.00	1.34
10	1.69	0.54	0.47	2.57	1.34
11	1.89	0.67	0.95	2.27	1.73
12	0.92	0.34	0.50	0.50	1.06
13	1.31	0.47	0.60	0.57	1.25
14	1.13	0.39	0.65	0.41	1.20
15	1.07	0.47	0.46	0.37	1.39
16	1.60	0.56	0.71	1.02	1.44
17	0.92	0.57	0.50	0.44	1.02
18	0.98	0.61	0.56	0.86	1.60
19	1.06	0.53	0.65	0.76	1.45
20	0.95	0.59	0.57	0.51	1.69

Figure 0-3 Bias in 10-year AMS quantiles

4.3 Performance of GCMs in reproducing historical precipitation

4.3.1 RMSE, correlation coefficient and Taylor diagram

A model's performance is deemed superior when it demonstrates a small RMSE and a higher positive correlation coefficient. Results of these metrics assessed annually for the precipitation indices over the period 1979-2014 can be seen from Table 4-1 to Table 4-6.

The correlation coefficient for the AMS were over the ranges -0.47-0.52 (Table 4-1). The H_0 (no correlation) was rejected in varying proportions across the 20 precipitation stations. The H_0 was not rejected ($p < 0.05$) at any of the stations when analysis was based on ACCESS_CM2, ACCESS_ESM1.5, BCC_CSM and CAN_ESM5. However, the H_0 was rejected at 5% of the

stations while considering CESSM_WACCM, INM_CM5 and MRI_ESM2. Using NOR_ESM, the H_o was rejected ($p<0.05$) at 10% of the stations. The coefficient of correlation between observed and GCMs' historical series were -0.47, 0.36, 0.52, and 0.49 at stations 7, 16, 17 and 18, respectively and for all these values the H_o was rejected ($p<0.05$). BCC_CSM and NOR_ESM2 had the lowest and highest RMSE values over the ranges 24.26-118.90 and 33.41-129.47, respectively. The order of performance from the best to the worst for AMS was BCC_CSM, INM_CM5, ACCESS_CM2, CESSM_WACCM, MRI_ESM2, CAN_ESM5, ACCESS_ESM1.5, NOR_ESM2.

The correlation coefficient for TPREC1 varied between -0.46 to 0.54 (Table 4-2). The H_o was not rejected ($p<0.05$) at any of the stations when analysis was based on CAN_ESM and CESSM_WACCM. H_o was rejected at 5% of the stations while considering ACCESS_ESM1.5, BCC_CSM and NOR_ESM. H_o was also rejected at 10% of the stations while considering MRI_ESM2. H_o was rejected at 15% of the stations while considering INM_CM5. Using NOR_ESM, the H_o was rejected at 30% of the stations. Stations 3, 5, 6, 9, 10, 11, 12, 13, 16, 17, 18, 20 and their correlation coefficients between observed and GCMs' historical series are 0.45, 0.50, (0.54, -0.46), 0.48, 0.46, 0.46, -0.42, 0.43, 0.42, 0.48, (0.38, 0.40), 0.44, respectively and for all these values the H_o was rejected ($p<0.05$). The RMSE values over the ranges for BCC_CSM are 340-1828 and CAN_ESM5 are 460-2029. BCC_CSM and CAN_ESM5 showed the lowest and highest RMSE values, respectively. Under TPREC1, the performance ranking from best to worst was: BCC_CSM, CESSM_WACCM, INM_CM5, ACCESS_CM2, MRI_ESM2, NOR_ESM2, ACCESS_ESM1.5, and CAN_ESM5.

Under MDS1, Table 4-3 shows that the correlation coefficient spanning from -0.44 to 0.38. When analysis was based on ACCESS_CSM, BCC_CSM, INM_CM5, MRI_ESM2, and

NOR_ESM, the H_o was not rejected ($p < 0.05$) at any of the stations. Yet, when considering ACCESS_ESM1.5, CAN_ESM5, and CESSM_WACCM, H_o was only rejected ($p < 0.05$) by 5% of the stations. The H_o was only rejected at stations 3 and 12 and their correlation coefficients between the observed and GCMs' historical series were (0.44, 0.42) and (0.36), respectively. The RMSE values over the ranges for INM_CM5 and NOR_ESM2 spans from 20.68 to 62.46 and from 110.79 to 235.66, respectively, with INM_CM5 showing the lowest and NOR_ESM2 demonstrating the highest values (Table 4-3). NOR_ESM2, ACCESS_CM2, CAN_ESM5, MRI_ESM2, CESSM_WACCM, ACCESS_ESM1.5, BCC_CSM and INM_CM5, was the order of performance from the worst to the best.

Correlation coefficient for NDD1 varied between -0.3-0.63 (Table 4-4). None of the stations ($p < 0.05$) rejected H_o in the analysis conducted using ACCESS_ESM1.5, BCC_CSM, CAN_ESM, CESSM_WACCM and MRI_ESM2. H_o was rejected at 10%, 15% and 25% of the stations while considering ACCESS_CSM, NOR_ESM2 and INM_CM5, respectively. Stations 15, 16, 18, 19, and 20 and their respective correlation coefficients between the observed and GCMs' historical series were (0.41, 0.48, 0.3), 0.4, (0.47, 0.38), (0.51, 0.38) and (0.37, 0.59). In all these stations, the H_o was rejected ($p < 0.05$). In this case, BCC_CSM and CAN_ESM5 demonstrated the smallest and largest RMSE value ranges, spanning from 32.78 to 103.60 and from 73.37 to 159.35, respectively (Table 4-4). Under NDD1, the performance ranking from best to worst is as follows: BCC_CSM, INM_CM5, CESSM_WACCM, ACCESS_CM2, ACCESS_ESM1.5, MRI_ESM2, NOR_ESM2, and CAN_ESM5.

Under MWS1, the correlation coefficients ranged from -0.47 to 0.54 (Table 4-5). ACCESS_ESM1.5 and MRI_ESM2 are the models where H_o was not rejected ($p < 0.05$) at any of the stations. At 5% of the stations, H_o was rejected when considering ACCESS_CSM,

BCC_CSM, CESSM_WACCM, and MRI_ESM2. Conversely, when utilizing INM_CM5 and NOR_ESM, H_o was rejected at 15% of the stations. The coefficient of correlation between observed and GCMs' historical series were 0.54, 0.42, -0.47, 0.43, 0.4, (0.38, 0.4), 0.37, 0.46 and 90.48 at stations 3, 5, 7, 9, 13, 17, 18, 19 and 20, respectively, and for all these values, the H_o was rejected ($p < 0.05$). INM_CM5 and MRI_ESM2 had the lowest and highest RMSE value over the ranges of 3.31-13.99 and 14.49-27.19, respectively (Table 4-5). MRI_ESM2, CESSM_WACCM, NOR_ESM2, ACCESS_CM2, CAN_ESM5, ACCESS_ESM1.5, BCC_CSM and INM_CM5, was the order of performance from worst to best.

Correlation coefficient for NWD1 spanned from -0.41 to 0.59 and -0.41 (Table 4-6). The H_o of no correlation was rejected in varying proportions across 20 rainfall stations. When analysis was based on ACCESS_ESM15, BCC_CSM, CAN_ESM, CESSM_WACCM and MRI_ESM2, the H_o was not rejected ($p < 0.05$) at any of the stations. H_o was rejected at 10% of the stations while considering ACCESS_CSM and NOR_ESM. Using INM_CM5, the H_o was rejected at 25% of the stations. Stations 15, 16, 18, 19, and 20 and their correlation coefficients between observed and GCMs' historical series were (0.41, 0.48), 0.40, (0.47, 0.38), (0.51, 0.38) and (-0.38, 0.59), respectively ($p < 0.05$) rejected the H_o . Just like MDS1, INM_CM5 and MRI_ESM2 exhibited the smallest and largest RMSE value ranges, spanning from 38.09 to 136.09 and from 63.95 to 197.95 for NWD1 (Table 4-6). BCC_CSM, CESSM_WACCM, INM_CM5, ACCESS_CM2, ACCESS_ESM1.5, MRI_ESM2, NOR_ESM2 and CAN_ESM5, was the order of performance from the best to the worst under NDD1.

The CMIP5 models showed a low positive correlation (0.01 to 0.24) in simulating East African rainfall, indicating a generally low overall performance across the region (Ongoma et al., 2019). However, the individual performance of these models varies widely (Ongoma et al., 2019). Models exhibit poor performance specifically when reproducing observed annual

rainfall patterns compared to seasonal patterns (Ngoma et al., 2020). CAN_ESM5 showed the best performance in reproducing MAM rainfall patterns over East Africa, yet it exhibited poor performance while considering annual precipitation patterns (Ongoma et al., 2019). This suggests that the performance of climate models can vary depending on the temporal scale being examined (seasonal versus annual precipitation patterns).

Figure 4-4 to Fig 4-9 showed performance of the GCMs' in correlating with the observed precipitation and the ability of the models to reproduce the variability in precipitation quantified by the standard deviation. Across the annual scale and extreme precipitation indices metrics, the order of performance from the best to the worst is BCC_CSM, INM_CM5, CESSM_WACCM, ACCESS_CM2, ACCESS_ESM1.5, MRI_ESM2, CAN_ESM5 and NOR_ESM2. Despite the improvement of GCMS compared to those of CMIP5, the GCMS of CMIP6 still generally perform poorly in reproducing precipitation extremes especially across the East African region (Endris et al., 2013; Ngoma et al., 2020; Onyutha, 2020).

Table 0-1 Correlation coefficient and RMSE of models for AMS

	Correlation coefficient																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	↑ 0.33	↑ 0.32	↑ 0.20	↑ 0.37	↓ -0.16	↑ 0.23	↑ 0.40	↓ -0.29	↓ -0.24	↔ -0.04	↔ -0.04	↑ 0.24	↓ -0.18	↓ -0.34	↔ -0.11	↔ 0.06	↔ 0.01	↓ -0.09	↓ -0.17	↓ -0.21
ACCESS_ESM15	↔ 0.04	↓ -0.01	↔ -0.25	↔ -0.08	↔ -0.07	↔ -0.08	↔ 0.03	↔ -0.08	↑ 0.05	↓ -0.20	↓ -0.20	↔ 0.01	↔ -0.04	↔ -0.06	↔ -0.04	↔ 0.01	↓ -0.21	↔ 0.13	↔ 0.20	↔ 0.00
BCC_CSM	↔ -0.06	↓ -0.05	↓ -0.38	↔ -0.02	↑ 0.27	↔ -0.22	↔ -0.18	↔ -0.05	↔ -0.04	↔ -0.02	↔ -0.02	↔ 0.15	↑ 0.31	↔ 0.01	↓ -0.20	↓ -0.09	↓ -0.08	↔ 0.07	↑ 0.34	↓ -0.17
CAN_ESM	↓ -0.18	↓ -0.09	↑ 0.16	↓ -0.25	↓ -0.21	↓ -0.35	↔ 0.10	↑ 0.05	↓ -0.24	↔ -0.04	↔ -0.04	↓ -0.12	↔ -0.08	↑ 0.25	↔ -0.19	↓ -0.18	↔ 0.07	↓ -0.14	↔ -0.04	↓ -0.15
CESSM_WACCM	↔ -0.07	↓ -0.06	↓ -0.35	↔ -0.02	↔ 0.02	↔ 0.01	↔ 0.03	↔ -0.02	↓ -0.21	↔ 0.09	↔ 0.09	↓ -0.06	↑ 0.30	↔ 0.11	↓ -0.26	↑ 0.36	↔ 0.09	↔ 0.07	↓ -0.15	↔ -0.09
INM_CM5	↔ -0.04	↔ 0.02	↑ 0.15	↔ 0.04	↓ -0.16	↔ -0.15	↓ -0.47	↑ 0.07	↔ -0.05	↔ 0.00	↔ 0.00	↔ -0.02	↔ -0.05	↔ 0.10	↑ 0.06	↓ -0.10	↓ -0.12	↔ 0.02	↓ -0.12	↑ 0.11
MRI_ESM2	↓ -0.14	↓ -0.09	↑ 0.15	↔ 0.14	↓ -0.15	↔ -0.17	↔ 0.12	↔ -0.14	↑ 0.09	↑ 0.26	↑ 0.26	↓ -0.12	↔ 0.18	↔ -0.16	↔ -0.19	↓ -0.20	↑ 0.52	↔ 0.03	↓ -0.15	↔ -0.08
NOR_ESM	↓ -0.11	↓ -0.04	↑ 0.12	↔ 0.05	↔ 0.10	↔ -0.02	↔ -0.22	↑ 0.09	↔ -0.05	↑ 0.26	↑ 0.26	↔ -0.03	↔ 0.08	↔ -0.01	↔ -0.03	↔ 0.03	↑ 0.43	↑ 0.49	↔ 0.12	↑ 0.10
	RMSE																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	31.39	34.50	33.78	30.43	36.56	30.90	46.24	129.28	46.86	38.96	38.96	28.34	28.72	36.87	35.31	32.35	46.25	35.62	37.49	33.17
ACCESS_ESM15	34.00	38.09	39.95	38.06	36.38	36.79	50.37	135.59	45.93	38.99	38.99	46.53	48.56	52.51	37.89	48.47	65.03	38.54	40.92	37.16
BCC_CSM	28.50	33.43	27.31	26.02	27.52	24.46	40.68	118.90	36.35	28.54	28.54	43.80	44.95	40.36	28.86	36.53	51.33	31.05	25.61	24.85
CAN_ESM	35.26	38.78	33.75	34.18	36.66	32.26	48.83	128.21	46.86	38.96	38.96	53.90	58.72	48.30	34.23	48.18	63.69	38.99	35.68	30.79
CESSM_WACCM	34.53	36.67	35.54	33.13	31.84	31.44	49.86	129.74	45.43	36.76	36.76	47.67	47.87	47.10	35.63	42.62	59.65	37.16	38.40	30.93
INM_CM5	32.97	36.83	32.38	31.48	29.69	30.21	49.70	128.32	42.98	35.40	35.40	45.17	46.71	40.21	32.29	39.88	52.88	33.52	36.41	29.00
MRI_ESM2	36.91	40.59	35.46	33.44	33.08	33.59	49.41	129.60	43.03	38.45	38.45	45.65	46.71	48.29	36.44	44.98	57.37	35.35	38.71	32.60
NOR_ESM	37.50	40.73	36.60	35.22	35.07	34.15	52.61	129.47	48.38	40.36	40.36	51.43	52.97	54.72	37.11	50.19	65.19	35.87	39.17	33.41

Table 0-2 Correlation coefficient and RMSE of models for TPREC1

	Correlation coefficient																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	→ -0.03	→ -0.05	↑ 0.45	↑ 0.26	↑ 0.50	↑ 0.54	↓ -0.23	↓ -0.36	↑ 0.48	↑ 0.46	↑ 0.46	↑ 0.24	↑ 0.26	↓ -0.23	↓ -0.29	→ 0.04	→ 0.15	→ -0.14	↓ -0.28	↓ -0.22
ACCESS_ESM15	→ 0.03	→ 0.04	↓ -0.21	→ -0.04	→ 0.05	→ 0.07	→ 0.13	↑ 0.11	↓ -0.18	↓ -0.22	↓ -0.22	↑ 0.19	↓ -0.42	→ 0.02	→ 0.04	→ 0.08	↓ -0.12	→ 0.08	↑ 0.18	→ 0.04
BCC_CSM	↓ -0.33	↓ -0.34	↓ -0.34	↓ -0.21	→ 0.19	→ 0.21	↓ -0.18	→ 0.04	→ -0.04	↓ -0.10	↓ -0.10	→ -0.03	→ 0.07	→ 0.05	↓ -0.17	↑ 0.42	→ 0.26	↓ -0.30	↑ 0.17	↓ -0.10
CAN_ESM	→ -0.14	→ -0.05	→ -0.06	→ -0.10	↓ -0.25	→ -0.13	→ 0.03	↑ 0.19	→ 0.01	→ -0.07	→ -0.07	↑ 0.15	↑ 0.21	↑ 0.22	↓ -0.16	→ -0.02	→ 0.19	↓ -0.29	→ -0.06	↓ -0.19
CESSM_WACCM	→ -0.15	→ -0.19	→ 0.02	→ -0.07	→ 0.04	→ -0.09	→ -0.09	→ -0.22	→ 0.08	→ -0.01	→ -0.01	→ 0.07	↑ 0.22	↑ 0.27	→ 0.01	→ 0.13	→ 0.10	→ 0.22	→ -0.10	→ 0.07
INM_CM5	→ -0.08	→ -0.02	→ 0.04	↓ -0.16	↓ -0.33	↓ -0.46	↓ -0.19	↓ -0.34	↓ -0.10	→ -0.02	→ -0.02	→ -0.18	→ -0.28	→ 0.11	↑ 0.40	↓ -0.14	↓ -0.11	↑ 0.38	↑ 0.15	↑ 0.44
MRI_ESM2	→ 0.13	→ 0.17	→ -0.05	→ 0.10	→ 0.00	→ -0.08	→ 0.16	→ -0.08	→ 0.23	→ 0.18	→ 0.18	↓ -0.43	→ -0.06	→ -0.12	→ -0.02	↓ -0.13	↑ 0.48	→ 0.14	→ -0.03	→ 0.02
NOR_ESM	↑ 0.31	↑ 0.37	↑ 0.31	↑ 0.31	→ 0.23	→ 0.09	↑ 0.35	↑ 0.10	→ 0.26	→ 0.24	→ 0.24	→ -0.10	→ -0.02	→ 0.02	→ 0.23	→ 0.10	→ 0.32	↑ 0.40	↑ 0.19	→ 0.24
	RMSE																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	1398	1125	1262	1146	1073	1059	1226	2008	1554	1496	1496	494	603	925	718	968	949	420	500	699
ACCESS_ESM15	1389	1114	1349	1227	1155	1143	1202	2061	1555	1498	1498	639	1010	1206	763	1244	1235	445	521	747
BCC_CSM	1232	966	1106	985	1003	893	1062	1828	1402	1345	1345	801	1194	1034	583	1085	1077	371	340	565
CAN_ESM	1445	1169	1318	1198	1171	1115	1256	2029	1602	1545	1545	1000	1384	1238	740	1282	1269	460	499	726
CESSM_WACCM	1350	1017	1222	1105	1049	1022	1174	1956	1430	1377	1377	732	1017	1028	669	1077	1069	434	490	647
INM_CM5	1386	1110	1255	1141	1066	1059	1206	1989	1533	1475	1475	762	1133	988	664	1021	1007	345	440	654
MRI_ESM2	1355	1094	1259	1130	1084	1067	1173	1954	1463	1463	1463	819	1094	1110	739	1160	1099	483	568	723
NOR_ESM2	1386	1105	1262	1143	1123	1072	1185	1974	1572	1514	1514	855	1205	1238	723	1268	1251	428	497	696

Table 0-3 Correlation coefficient and RMSE of models for MDS1

	Correlation coefficient																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	→ -0.02	↑ 0.27	↓ -0.35	↘ -0.16	→ -0.02	↓ -0.17	↓ -0.32	↘ -0.17	↓ -0.11	↓ -0.06	↓ -0.06	↘ 0.03	↗ 0.01	↘ -0.02	↓ -0.33	↓ -0.18	↓ -0.15	↓ -0.16	↓ -0.12	↓ -0.21
ACCESS_ESM15	↘ -0.05	→ 0.04	↓ -0.44	→ -0.02	↘ -0.15	↘ -0.04	↘ -0.14	↑ 0.08	↓ -0.12	↘ 0.01	↘ 0.01	↓ -0.15	↓ -0.32	↘ -0.04	→ -0.10	→ -0.01	↑ 0.17	↘ -0.10	↑ 0.11	↘ 0.17
BCC_CSM	↑ 0.38	↑ 0.35	↘ 0.06	↘ 0.03	↓ -0.33	↘ -0.05	↑ 0.27	↑ 0.16	↑ 0.25	↑ 0.35	↑ 0.35	→ 0.08	↑ 0.17	↑ 0.26	↘ 0.08	↑ 0.25	↑ 0.21	↘ 0.06	→ 0.02	↘ 0.18
CAN_ESM	→ 0.07	↘ 0.15	↘ -0.18	→ -0.05	↑ 0.17	→ 0.02	↘ -0.20	↓ -0.25	→ 0.07	↘ -0.02	↘ -0.02	↑ 0.36	↘ 0.00	↘ 0.17	↑ 0.16	↘ 0.08	↘ 0.11	↘ 0.12	↘ 0.04	↑ 0.28
CESSM_WACCM	↘ 0.10	↑ 0.36	↓ -0.42	→ -0.02	↑ 0.25	↑ 0.26	↘ 0.07	↑ 0.12	↓ -0.05	↓ -0.15	↓ -0.15	↘ -0.01	↘ 0.02	↓ -0.14	↘ -0.10	↓ -0.22	↓ -0.15	→ -0.03	↘ -0.07	↓ -0.20
INM_CM5	↓ -0.33	↓ -0.32	↑ 0.22	↘ 0.02	↘ -0.13	↑ 0.24	↘ 0.04	↘ 0.01	→ 0.06	↘ -0.01	↘ -0.01	→ 0.05	→ -0.09	↘ -0.03	↘ 0.06	→ 0.00	↓ -0.15	↓ -0.23	↓ -0.09	↓ -0.20
MRI_ESM2	↘ -0.16	↓ -0.19	→ -0.15	↓ -0.26	↓ -0.24	↓ -0.22	↓ -0.36	↓ -0.27	↓ -0.05	↘ 0.04	↘ 0.04	↓ -0.07	↘ 0.01	↑ 0.29	↑ 0.24	↑ 0.16	↘ -0.06	↓ -0.14	↑ 0.08	↑ 0.24
NOR_ESM	↓ -0.24	↘ 0.10	↘ 0.06	↑ 0.20	→ 0.01	→ 0.04	↓ -0.34	↘ -0.16	↘ 0.00	↘ -0.03	↘ -0.03	↘ -0.03	↘ -0.14	↘ -0.04	↘ 0.12	↑ 0.16	→ 0.00	↑ 0.24	↘ -0.04	↘ -0.07
	RMSE																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	146.25	140.39	143.55	142.86	133.70	142.33	136.38	134.31	138.28	141.50	141.50	47.93	47.50	80.42	129.79	85.14	82.55	101.65	123.96	117.97
ACCESS_ESM15	95.66	90.75	122.73	141.79	141.14	141.25	86.31	133.00	91.00	93.58	93.58	27.87	25.08	87.22	114.11	82.58	79.19	95.04	101.19	103.81
BCC_CSM	109.71	105.10	107.55	107.67	85.00	107.59	100.10	99.66	106.08	108.69	108.69	105.05	103.44	107.52	97.95	109.56	107.87	61.41	91.72	86.98
CAN_ESM	125.81	120.53	122.81	122.32	144.36	121.49	115.80	114.41	141.94	145.41	145.41	119.65	128.60	125.10	111.80	135.68	133.23	98.37	102.32	97.91
CESSM_WACCM	129.70	116.00	126.13	126.05	117.12	124.65	118.47	116.94	107.12	110.73	110.73	96.81	89.78	118.85	115.66	114.35	111.54	85.87	99.47	100.55
INM_CM5	62.46	57.89	58.30	57.95	55.78	56.68	51.03	49.65	46.29	49.79	49.79	23.74	20.68	24.55	43.69	22.31	21.18	60.82	44.98	47.84
MRI_ESM2	27.89	29.49	22.88	29.42	29.83	30.12	33.37	32.51	230.62	266.23	266.23	145.01	147.77	213.36	238.78	216.00	214.18	221.09	226.14	219.28
NOR_ESM	193.69	187.84	189.12	188.69	235.66	188.55	183.94	181.71	203.82	207.15	207.15	113.07	110.79	197.23	183.14	196.39	194.98	197.32	173.80	176.78

Table 0-4 Correlation coefficient and RMSE of models for NDD1

	Correlation coefficient																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	→ 0.02	→ -0.07	→ 0.08	→ 0.09	→ 0.25	→ 0.23	↓ -0.16	↓ -0.18	→ 0.10	→ 0.11	→ 0.11	→ 0.04	→ 0.26	→ 0.05	↓ -0.41	→ 0.02	→ 0.16	↓ -0.25	↓ -0.30	↓ -0.37
ACCESS_ESM15	→ -0.02	→ -0.03	↓ -0.19	→ 0.00	→ 0.27	→ 0.19	→ 0.06	→ 0.07	→ 0.05	→ -0.03	→ -0.03	→ -0.03	→ -0.08	↓ -0.22	→ 0.12	↓ -0.33	→ -0.01	→ 0.15	→ 0.21	→ 0.01
BCC_CSM	↓ -0.23	↓ -0.30	↓ -0.09	→ -0.04	→ 0.22	→ 0.19	↓ -0.15	→ -0.02	→ 0.02	↓ -0.14	↓ -0.14	→ -0.12	↓ -0.14	→ -0.10	→ -0.20	→ -0.03	↓ -0.22	↓ -0.25	↓ -0.18	→ -0.12
CAN_ESM	→ -0.05	→ 0.03	↓ -0.11	→ -0.03	→ 0.06	→ 0.16	→ 0.03	→ 0.10	→ 0.19	→ 0.22	→ 0.22	→ 0.18	→ 0.17	→ -0.12	→ -0.08	→ 0.11	→ 0.14	↓ -0.22	→ -0.08	→ -0.07
CESSM_WACCM	↓ -0.17	→ -0.16	→ 0.07	↓ -0.13	→ 0.30	→ -0.02	→ -0.09	↓ -0.21	→ 0.19	→ 0.10	→ 0.10	→ -0.14	→ 0.08	→ -0.10	→ -0.03	→ 0.06	→ 0.02	→ 0.30	→ -0.07	→ 0.04
INM_CM5	→ 0.22	→ 0.29	→ 0.40	→ 0.19	↓ -0.21	↓ -0.15	→ 0.16	↓ -0.23	→ -0.14	↓ -0.09	↓ -0.09	→ 0.18	→ 0.16	→ 0.14	→ 0.48	→ 0.40	→ -0.04	→ 0.47	→ 0.51	→ 0.59
MRI_ESM2	→ -0.03	→ 0.04	→ 0.03	→ 0.07	→ 0.04	→ 0.08	→ 0.17	→ 0.09	↓ -0.27	↓ -0.16	↓ -0.16	→ -0.05	↓ -0.18	→ 0.01	→ 0.04	→ 0.33	→ 0.18	→ 0.03	→ 0.06	→ 0.09
NOR_ESM	→ -0.04	→ -0.03	→ 0.23	→ 0.01	→ 0.21	→ 0.07	→ 0.14	→ 0.01	→ 0.18	→ 0.21	→ 0.21	↓ -0.34	→ -0.06	→ 0.01	→ 0.34	→ 0.21	→ 0.19	→ 0.38	→ 0.38	→ 0.32
	RMSE																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	148.23	127.94	127.61	135.76	125.95	125.30	79.81	65.99	95.19	112.05	112.05	63.56	48.33	57.45	113.73	68.97	45.19	78.29	77.30	107.48
ACCESS_ESM15	134.62	114.18	140.73	148.24	134.93	137.74	65.62	74.69	83.85	100.74	100.74	61.57	55.66	99.88	122.43	107.28	81.68	82.69	82.87	115.23
BCC_CSM	103.60	85.48	83.78	91.07	99.75	79.36	46.85	32.78	56.82	73.22	73.22	63.34	65.03	67.70	79.30	78.79	56.39	65.86	53.00	74.32
CAN_ESM	159.35	138.12	138.80	146.91	145.64	136.35	87.20	73.37	105.46	122.57	122.57	106.68	110.78	117.83	121.81	122.52	100.39	92.16	83.07	114.83
CESSM_WACCM	134.61	101.81	112.81	122.75	107.84	111.68	70.24	58.59	70.35	85.48	85.48	72.12	61.44	83.47	98.88	86.36	68.02	56.76	70.89	92.95
INM_CM5	136.09	114.87	114.92	123.82	114.15	113.98	65.72	53.58	80.87	97.74	97.74	51.02	48.79	56.74	96.86	60.28	38.96	61.55	58.46	89.43
MRI_ESM2	153.30	132.65	134.21	140.75	132.01	130.92	83.76	72.93	91.36	119.26	119.26	64.71	63.95	92.28	112.51	94.36	76.70	81.12	77.13	103.86
NOR_ESM	151.61	131.11	130.04	139.27	138.44	128.95	81.28	69.91	102.00	118.70	118.70	81.64	73.74	116.35	117.10	118.67	97.54	87.76	78.10	107.23

Table 0-5 Correlation coefficient and RMSE of models for MWS1

	Correlation coefficient																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	↑ 0.21	↓ -0.17	↓ -0.07	↓ -0.11	↓ -0.20	↗ 0.07	↗ -0.09	↘ -0.09	↑ 0.43	↑ 0.39	↑ 0.39	↗ 0.11	↓ -0.25	↗ -0.03	↓ -0.21	↓ -0.22	↗ 0.02	↓ -0.22	↗ 0.03	↗ 0.19
ACCESS_ESM15	↘ -0.15	↘ -0.11	↓ -0.10	↓ -0.13	↓ -0.10	↗ 0.15	↗ 0.02	↘ -0.08	↓ -0.38	↗ 0.01	↗ 0.01	↓ -0.11	↗ 0.25	↗ -0.01	↗ 0.18	↗ 0.05	↓ -0.13	↘ -0.05	↗ 0.13	↘ -0.04
BCC_CSM	↓ -0.27	↓ -0.28	↓ -0.15	↘ -0.05	↗ 0.08	↗ 0.03	↓ -0.47	↓ -0.19	↘ -0.09	↘ -0.04	↘ -0.04	↗ 0.17	↓ -0.23	↓ -0.33	↓ -0.20	↓ -0.30	↓ -0.19	↓ -0.34	↗ 0.02	↓ -0.21
CAN_ESM	↑ 0.23	↑ 0.11	↗ 0.11	↑ 0.16	↗ 0.06	↑ 0.29	↘ -0.01	↑ 0.30	↘ -0.10	↗ 0.20	↗ 0.20	↑ 0.26	↘ -0.03	↓ -0.24	↘ -0.04	↗ 0.15	↓ -0.14	↘ -0.13	↓ -0.12	↓ -0.11
CESSM_WACCM	↓ -0.25	↗ 0.08	↓ -0.18	↓ -0.12	↗ 0.08	↓ -0.27	↘ -0.21	↓ -0.12	↗ 0.16	↑ 0.35	↑ 0.35	↗ 0.15	↓ -0.29	↘ -0.21	↗ 0.05	↓ -0.19	↗ 0.18	↑ 0.28	↑ 0.46	↘ -0.03
INM_CM5	↗ 0.09	↑ 0.21	↗ 0.38	↑ 0.16	↓ -0.08	↗ 0.09	↑ 0.12	↗ 0.03	↗ 0.02	↓ -0.17	↓ -0.17	↓ -0.08	↑ 0.40	↑ 0.19	↗ 0.19	↗ 0.12	↓ -0.08	↑ 0.37	↗ 0.20	↑ 0.48
MRI_ESM2	↗ 0.09	↘ -0.09	↗ 0.29	↗ 0.02	↓ -0.18	↗ 0.09	↑ 0.24	↗ 0.18	↘ -0.01	↓ -0.18	↓ -0.18	↓ -0.13	↓ -0.26	↑ 0.21	↓ -0.12	↑ 0.33	↑ 0.38	↗ 0.02	↓ -0.01	↘ -0.02
NOR_ESM	↗ 0.00	↘ -0.04	↑ 0.54	↑ 0.19	↑ 0.42	↑ 0.26	↑ 0.11	↘ -0.04	↗ 0.03	↗ 0.20	↗ 0.20	↓ -0.10	↓ -0.24	↗ 0.10	↑ 0.34	↑ 0.26	↑ 0.40	↑ 0.39	↗ 0.16	↗ 0.20
	RMSE																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	7.11	7.42	7.73	7.09	7.28	5.53	4.07	4.26	5.41	6.42	6.42	12.15	16.66	9.88	15.73	9.14	8.88	8.10	7.06	13.55
ACCESS_ESM15	7.00	6.87	8.35	7.30	5.22	5.63	5.53	3.52	5.46	5.47	5.47	19.97	19.72	7.60	16.31	7.00	6.37	6.11	6.43	15.00
BCC_CSM	7.35	7.68	7.35	6.38	4.40	5.79	7.78	7.68	5.40	5.23	5.23	7.33	4.57	6.98	12.96	6.32	5.77	5.59	4.73	11.87
CAN_ESM	7.79	7.33	7.95	7.25	6.92	5.78	3.40	3.12	6.47	7.35	7.35	9.89	5.60	8.70	16.32	8.20	6.54	7.01	6.48	15.30
CESSM_WACCM	9.61	16.85	11.11	8.81	6.73	8.38	8.43	8.47	18.18	17.29	17.29	32.95	30.65	27.85	17.10	28.30	27.80	17.50	16.87	16.98
INM_CM5	6.65	5.99	6.27	5.92	3.88	4.76	3.31	3.66	4.92	6.01	6.01	8.32	4.87	5.99	13.99	5.92	6.73	4.01	4.68	12.35
MRI_ESM2	26.26	27.18	17.42	26.52	25.77	26.50	27.11	27.19	14.49	17.90	17.90	23.79	24.67	18.80	21.99	15.62	16.44	17.22	19.78	26.29
NOR_ESM	9.59	9.43	7.70	8.63	6.47	7.83	7.36	7.73	9.37	9.47	9.47	11.90	10.26	9.74	15.09	9.11	7.45	6.86	8.31	14.47

Table 0-6 Correlation coefficient and RMSE of models for NWD1

	Correlation coefficient																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	→ 0.02	→ -0.07	→ 0.08	→ 0.09	↑ 0.24	↑ 0.22	↓ -0.16	↓ -0.19	→ 0.10	→ 0.10	→ 0.10	→ 0.04	↑ 0.26	→ 0.05	↓ -0.41	→ 0.02	↑ 0.16	↓ -0.25	↓ -0.30	↓ -0.38
ACCESS_ESM15	→ -0.02	→ -0.03	↓ -0.18	→ 0.01	↑ 0.28	↑ 0.19	→ 0.06	↑ 0.07	→ 0.05	→ -0.02	→ -0.02	→ -0.03	→ -0.07	↓ -0.22	→ 0.12	↓ -0.32	→ 0.00	→ 0.14	→ 0.20	→ 0.01
BCC_CSM	↓ -0.22	↓ -0.29	↓ -0.09	→ -0.03	↑ 0.24	↑ 0.20	↓ -0.15	→ -0.01	→ 0.02	↓ -0.14	↓ -0.14	→ -0.12	↓ -0.13	→ -0.10	→ -0.20	→ -0.02	↓ -0.21	↓ -0.25	↓ -0.18	→ -0.12
CAN_ESM	→ -0.05	→ 0.03	↓ -0.10	→ -0.02	→ 0.06	↑ 0.16	→ 0.03	↑ 0.10	↑ 0.20	↑ 0.22	↑ 0.22	↑ 0.18	↑ 0.18	→ -0.12	→ -0.08	→ 0.11	↑ 0.14	↓ -0.22	→ -0.08	→ -0.07
CESSM_WACCM	↓ -0.17	→ -0.15	→ 0.07	↓ -0.12	↑ 0.30	→ -0.01	→ -0.08	↓ -0.20	↑ 0.20	→ 0.11	→ 0.11	→ -0.13	→ 0.09	→ -0.09	→ -0.03	→ 0.07	→ 0.03	→ 0.29	→ -0.06	→ 0.04
INM_CM5	↑ 0.22	↑ 0.29	↑ 0.40	↑ 0.19	↓ -0.20	↓ -0.15	↑ 0.16	↓ -0.23	→ -0.14	↓ -0.11	↓ -0.11	↑ 0.18	→ 0.16	↑ 0.13	↑ 0.48	↑ 0.40	→ -0.04	↑ 0.47	↑ 0.51	↑ 0.59
MRI_ESM2	→ 0.09	→ 0.05	↓ -0.16	→ 0.03	→ 0.05	→ 0.10	↓ -0.10	↑ 0.13	↓ -0.27	↓ -0.17	↓ -0.17	→ -0.06	↓ -0.19	→ 0.00	→ 0.04	↑ 0.32	↑ 0.18	→ 0.02	→ 0.06	→ 0.09
NOR_ESM	→ -0.04	→ -0.02	→ 0.24	→ 0.02	↑ 0.22	→ 0.08	↑ 0.14	→ 0.01	↑ 0.18	↑ 0.21	↑ 0.21	↓ -0.34	→ -0.05	→ 0.01	↑ 0.34	→ 0.21	↑ 0.19	↑ 0.38	↑ 0.38	→ 0.32
	RMSE																			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ACCESS_CM2	148.23	127.86	127.61	135.76	125.88	125.30	79.81	65.99	95.19	112.05	112.05	63.56	48.33	57.45	113.73	68.97	45.19	78.29	77.30	107.48
ACCESS_ESM15	134.62	114.11	140.73	148.24	134.85	137.74	65.62	74.69	83.85	100.74	100.74	61.57	55.66	99.88	122.43	107.28	81.68	82.69	82.87	115.23
BCC_CSM	103.60	85.39	83.78	91.07	99.66	79.36	46.85	32.78	56.82	73.22	73.22	63.34	65.03	67.70	79.30	78.79	56.39	65.86	53.00	74.32
CAN_ESM	159.35	138.05	138.80	146.91	145.56	136.35	87.20	73.37	105.46	122.57	122.57	106.68	110.78	117.83	121.81	122.52	100.39	92.16	83.07	114.83
CESSM_WACCM	134.61	101.72	112.81	122.75	107.75	111.68	70.24	58.59	70.35	85.48	85.48	72.12	61.44	83.47	98.88	86.36	68.02	56.76	70.89	92.95
INM_CM5	136.09	114.81	114.92	123.82	114.07	113.98	65.72	53.58	80.87	97.74	97.74	51.02	48.79	56.74	96.86	60.28	38.96	61.55	58.46	89.43
MRI_ESM2	119.28	139.78	145.89	131.35	166.81	137.59	190.76	197.95	91.36	119.26	119.26	64.71	63.95	92.28	112.51	94.36	76.70	81.12	77.13	103.86
NOR_ESM	151.61	131.04	130.04	139.27	138.35	128.95	81.28	69.91	102.00	118.70	118.70	81.64	73.74	116.35	117.10	118.67	97.54	87.76	78.10	107.23

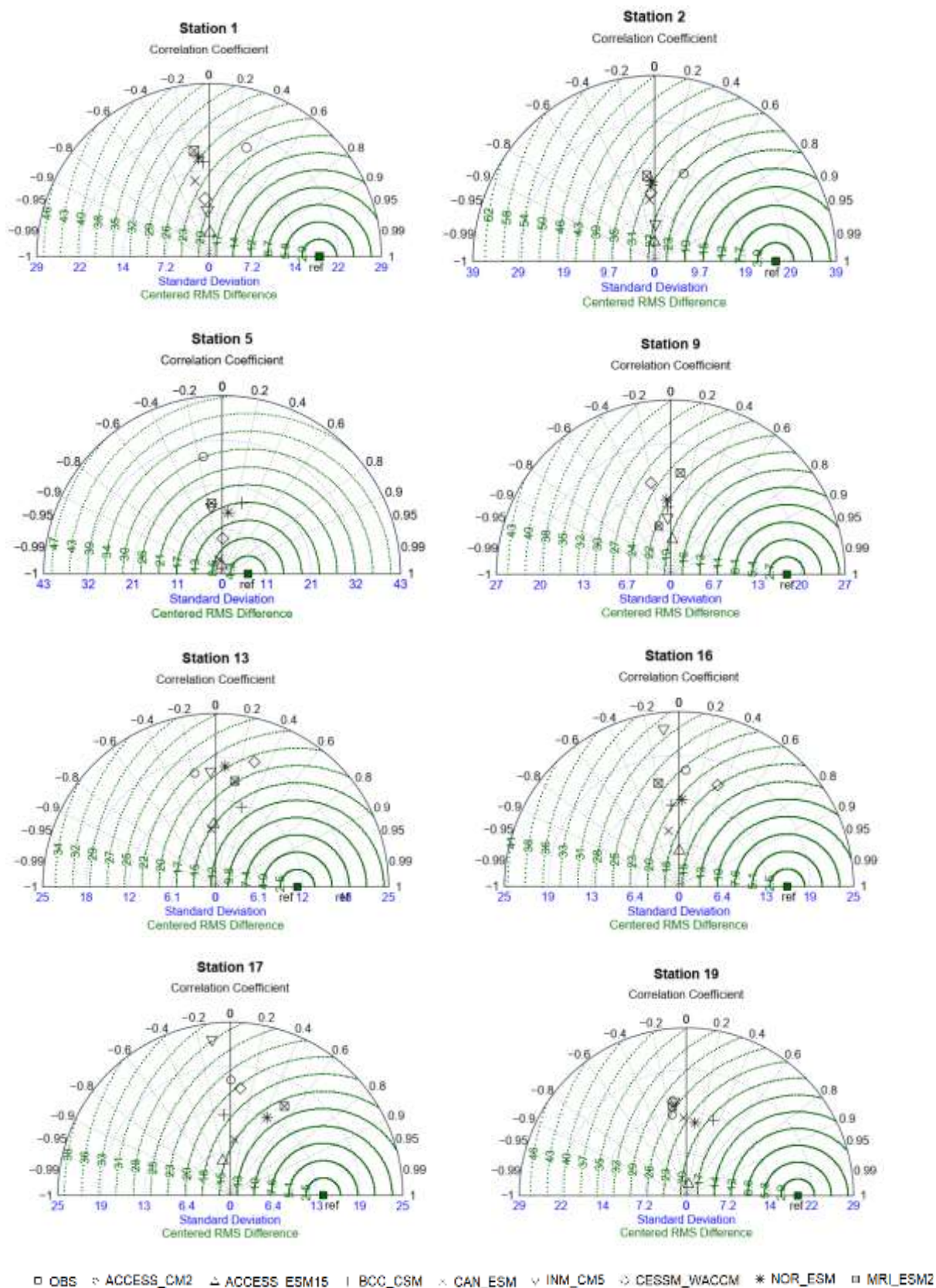


Figure 0-4 Taylor diagram of AMS for stations 1, 2, 5, 9, 13, 16, 17 and 19.

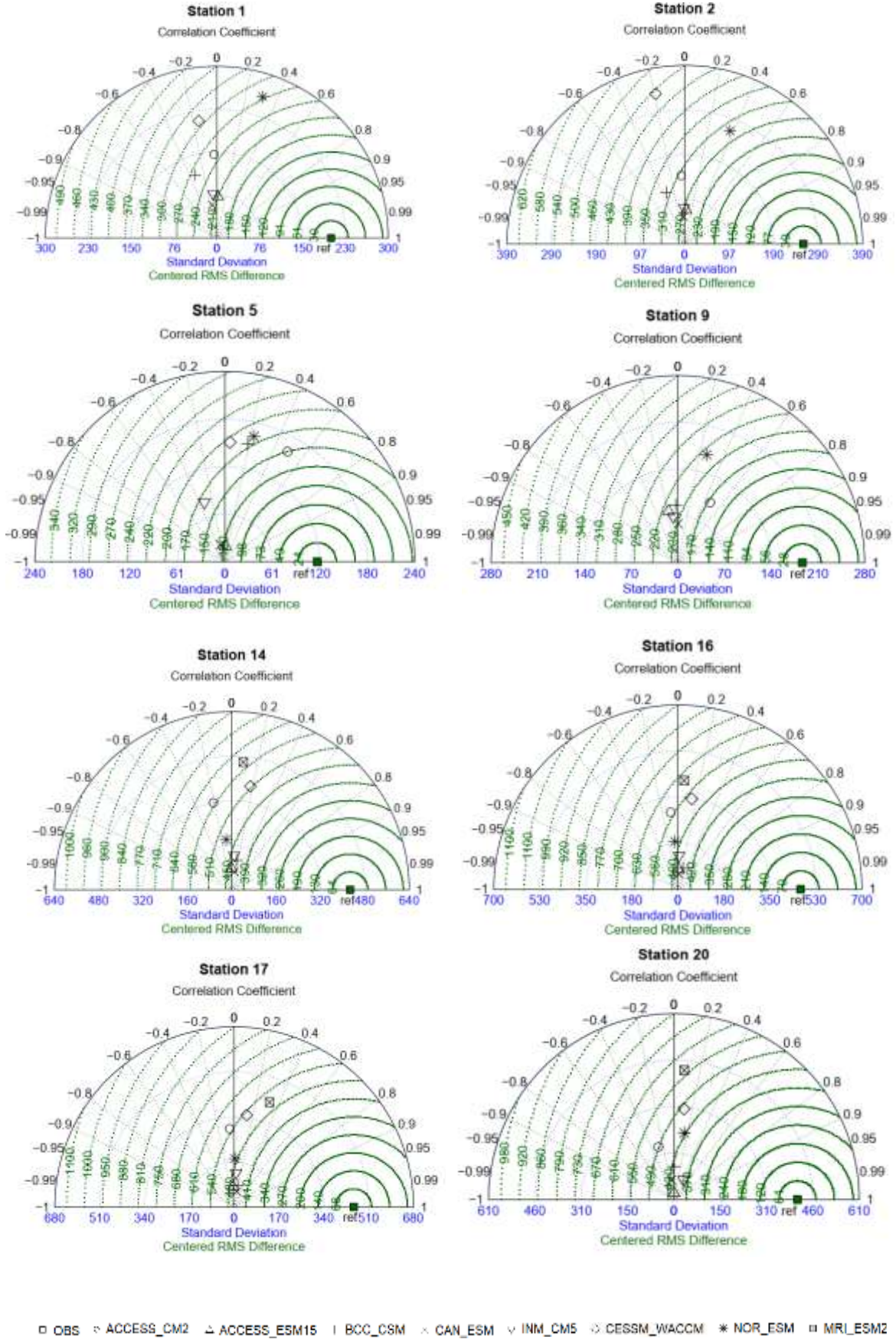


Figure 0-5 Taylor diagram of TPRED1 for stations 1, 2, 5, 9, 13, 16, 17 and 20

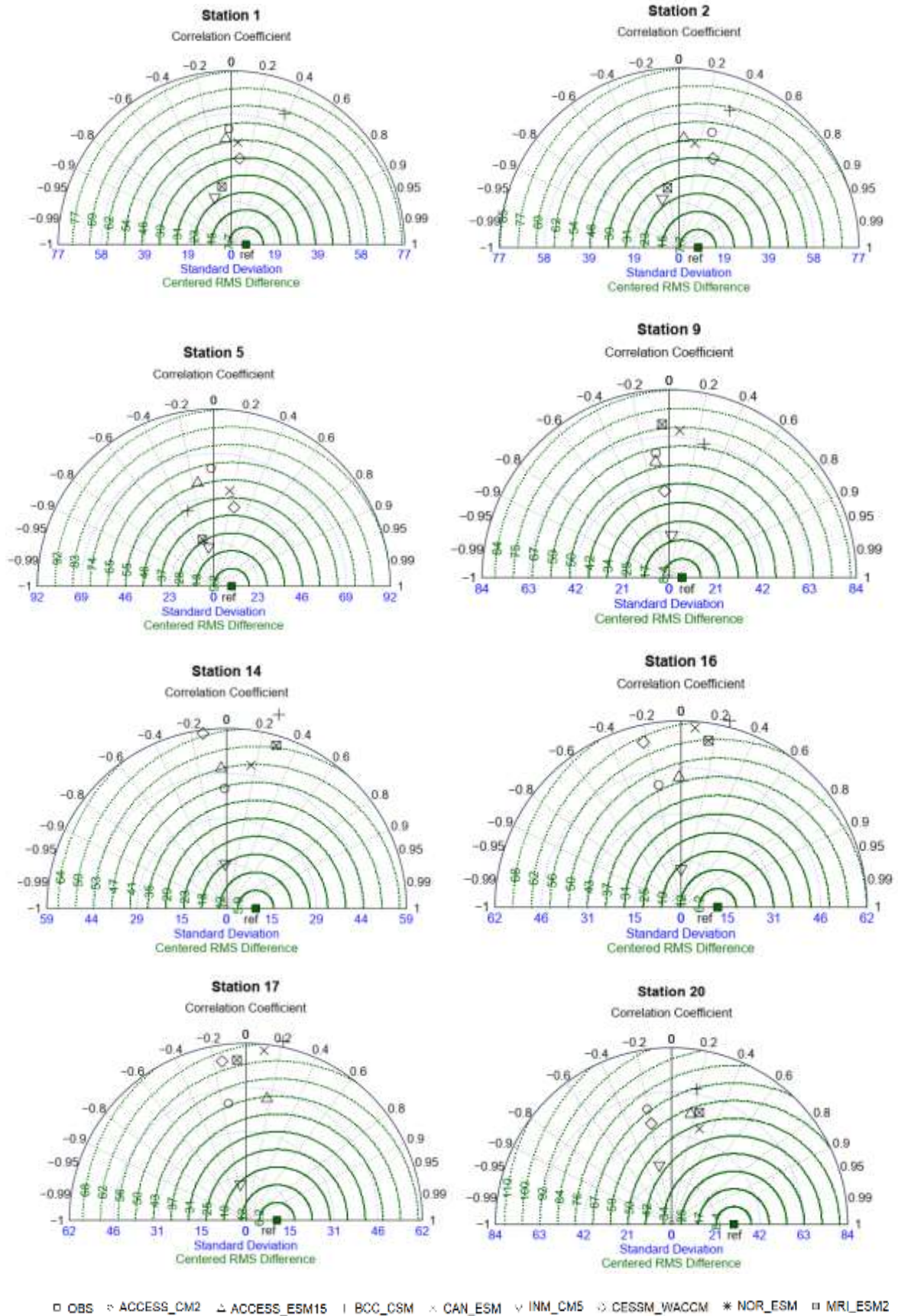


Figure 0-6 Taylor diagram of MDS1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.

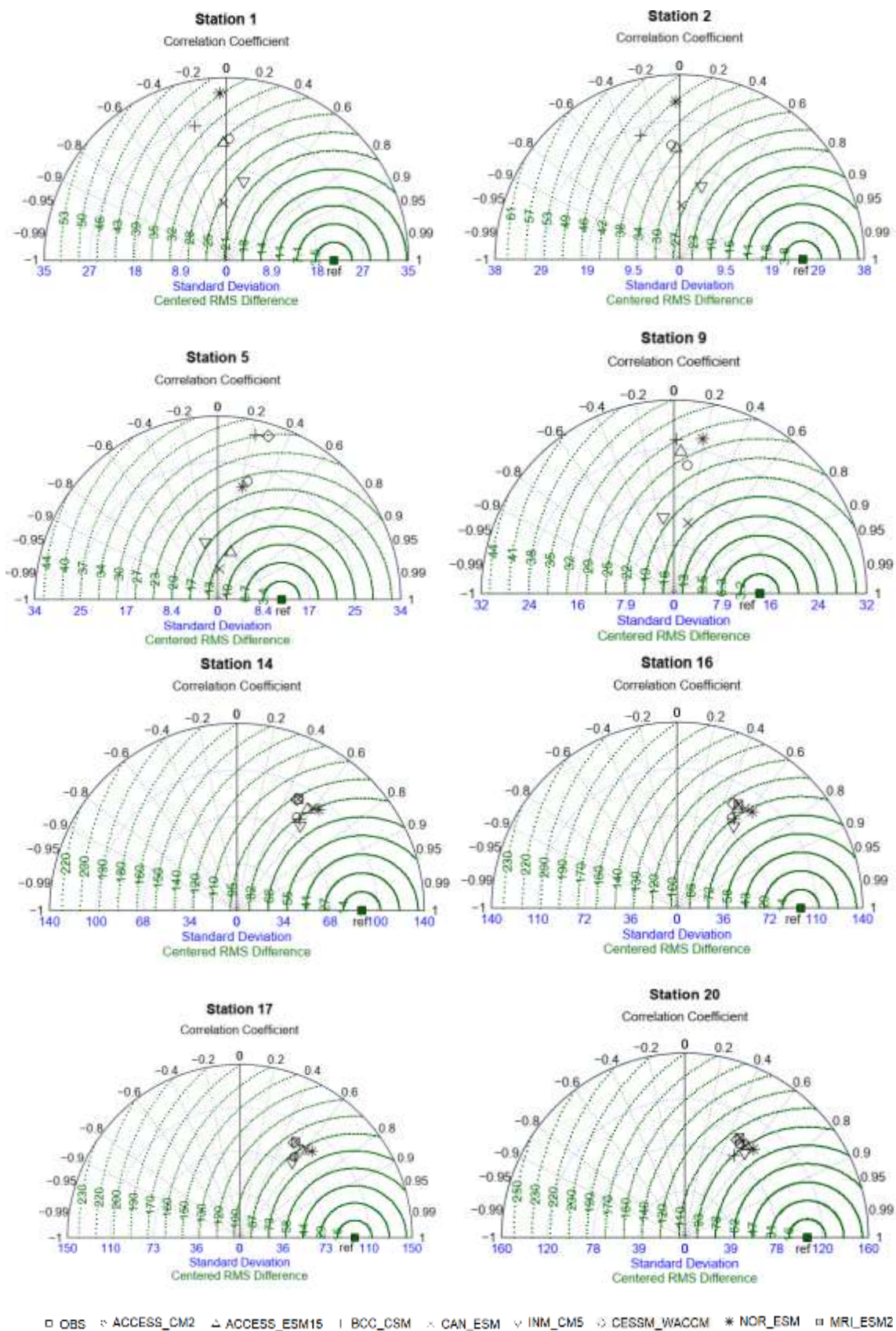


Figure 0-7 Taylor diagram of NDD1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.

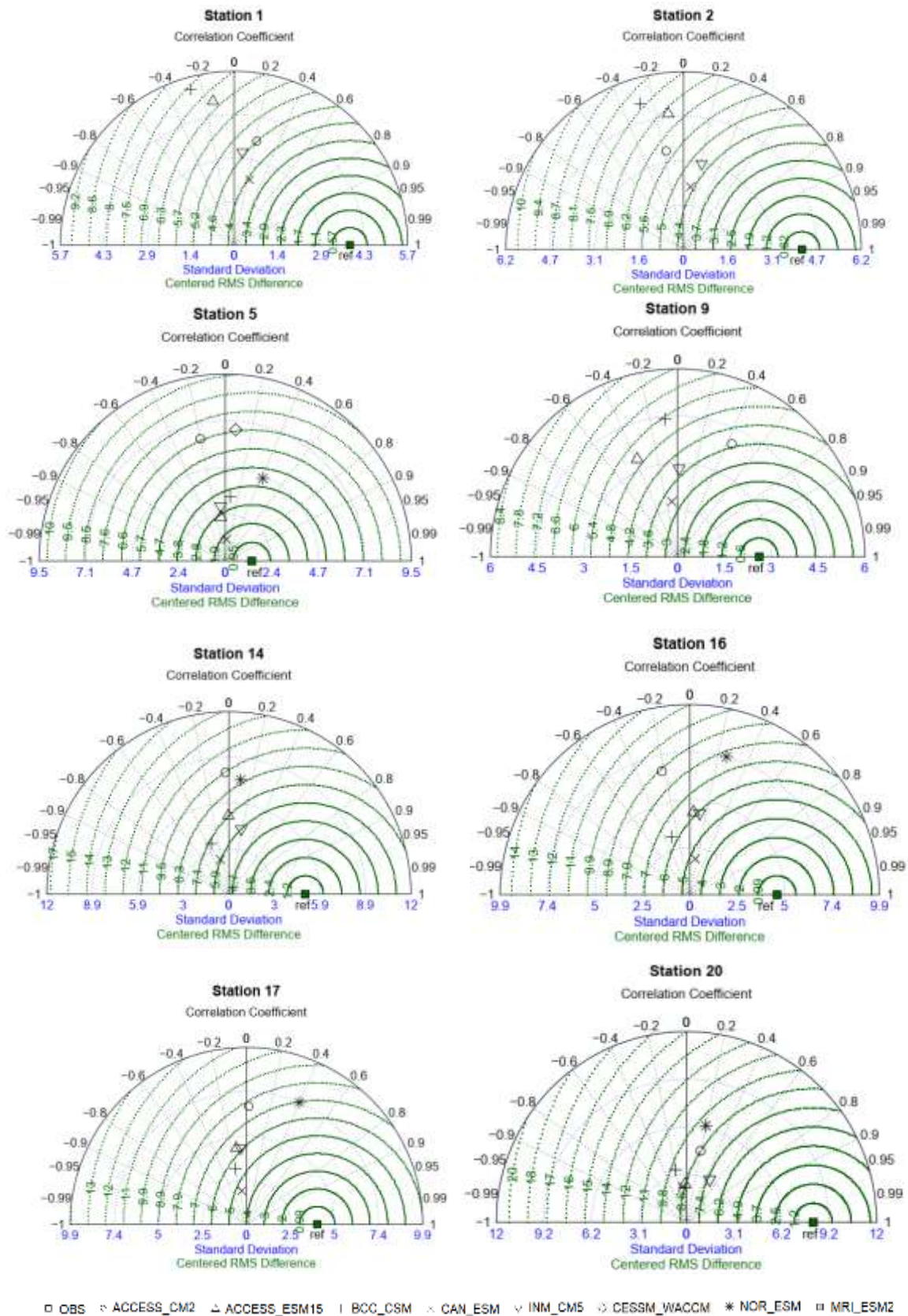


Figure 0-8 Taylor diagram of MWS1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.

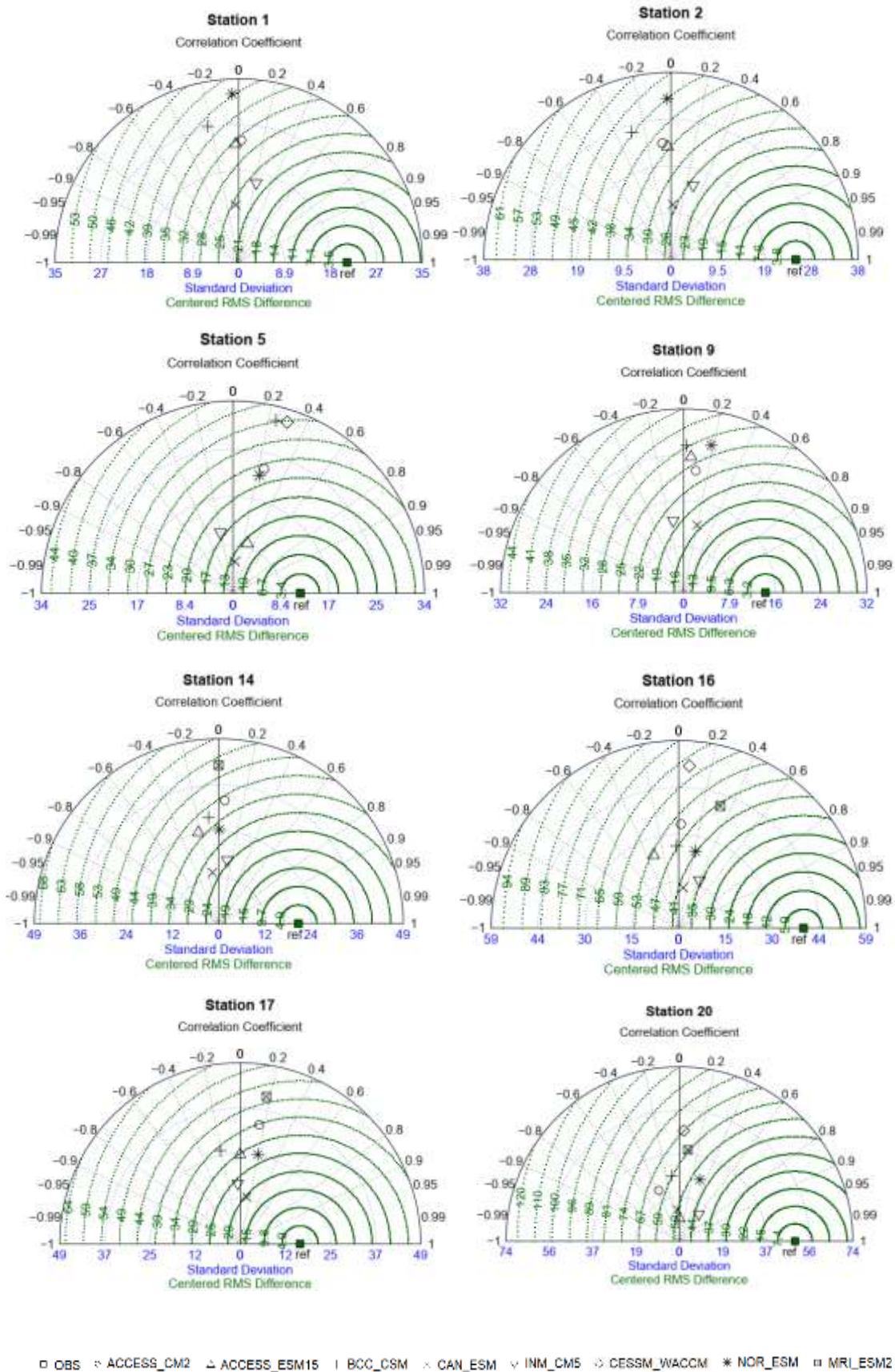


Figure 0-9 Taylor diagram of NWD1 for stations 1, 2, 5, 9, 13, 16, 17 and 20.

4.4 Implication of the use of precipitation products for bias correction of GCMs' output

Fig 4-10 to Fig 4-15 show the impact of climate change on the extreme precipitation indices for selected stations namely stations 1, 2, 4, 5, 9, 13, 14, 16, 17, and 20 for scenarios SSP 2-4.5 and SSP 5-8.5 in the 2050s and 2080s. Fig A-0-1 to Fig A-0-6 show detailed performance of impact of climate change on precipitation indices of each station after performing bias correction using quantile mapping.

4.4.1 AMS

Figure 4-10 shows the impact of climate change on AMS. It is noticeable that future AMS is projected to decrease at nearly all stations especially when using observed precipitation. Results based on precipitation products also exhibited decreases in future AMS. The most significant decrease was observed at station 5, up to 21.21% from SSP 2-4.5 under 2050s. Other stations exhibited smaller decreases. Across all stations, the smallest decrease was observed under the SSP 2-4.5 compared to the SSP 5-8.5 for the 2080s.

Comparisons across precipitation products, such as CFSR, CHIRPS, and JRA-55, show similar results at stations 4, 5, and 14. The PGF dataset exhibited the smallest decrease in AMS among the precipitation products datasets.

The results are different across all stations, indicating the influence of spatial precipitation variability across the country. Precipitation across the various subregions of the study area are different in terms of variability and seasonality to some extent. For instance, observed data at stations 2 showed a positive increase in AMS of up to 20% across all the scenarios in both 2050s and 2080s. Some precipitation products also indicated positive increases in AMS projections compared to decrease obtained when using observed data. For example, the ERA-5 dataset showed increases of less than 50.08% at stations 4, 5, 14, 16, and 20 from SSP5-8.5

in 2080s. At stations 16 and 17, increases of less than 33.99% were obtained when using the CFSR dataset from SSP 5-8.5 in the 2080s.

The most significant increases in PRCPTOT (Wet-day precipitation amount), R95p (extremely wet days), and SDII (wet day intensity) were observed in eastern and northern Kenya. Under the SSP5-8.5 scenario, projected changes in PRCPTOT (R95p) were estimated to be 2% (10%) and 4% (20%) at 1.5 °C and 2.0 °C of global warming levels, respectively (Ayugi et al., 2022).

Precipitation products tend to depict more occurrences of light and moderate precipitation events compared to satellite and gauge-based products, while displaying fewer instances of intense and extreme events (Dosio et al., 2021; Sun et al., 2018). The AMS for RCP 2.6 will decrease in 2050s and 2080s with the future AMS being lower than the past not exceeding 80mm/day (Onyutha, 2020). There are minimal to no notable alterations in annual maximum values under RCP 4.5, and substantial decrease in annual maximum values in the future under RCP8.5 (Aarnes et al., 2017). This pattern is observed consistently across CFSR, CHIRPS, and JRA-55, with changes remaining under -35% while PGF not surpassing -8.38%. The divergence in the performance of ERA-5, showing an increase at stations 4, 5, 14, 16, and 20, suggests the importance of considering localized conditions in climate assessments and projections.

Results of this study can be different from other, due to differences in scale, spatial size of the study area, chosen time horizons, precipitation indices, and the number of GCMs used.

In this study, climate change impacts tended to depend on the chosen precipitation product. Furthermore, results based on observed precipitation were different from those based on precipitation products. Thus, there is a need for caution when selecting precipitation products for downscaling in climate change analysis.

4.4.2 *TPREC1*

Figure 4-11 shows projected climate change signals on TPREC1. Generally, TPREC1, was projected to increase at all stations, regardless of whether the downscaling was based on observed data or the precipitation products. This contrasts with the overall projected decrease in AMS. The only exception is station 1, which showed a projected decrease in TPREC1 from the precipitation products. The magnitude of increase in TPREC1 was to varying extents with the highest under the SSP 5-8.5 scenario compared to the SSP 4-8.5 scenario. Additionally, the projected increase under the SSP 5-8.5 in the 2080s was slightly higher than that of the SSP 2-4.5 for a selected time horizon.

The used CFSR dataset showed the highest projected increase in TPREC1. Downscaling based on other precipitation products datasets, including CHIRPS, JRA-55, ERA-5, and PGF, led to comparable increases that aligned closely with observed data. The ranges of projections were as follows: 40% to 170% for CFSR, 20% to 61% for PGF, 15% to 41% for CHIRPS, 5% to 36% for ERA-5, and 8% to 67% for JRA-55. Reassuringly, these precipitation products closely reproduced the observed changes, which ranged from 20% to 55%. The direction and magnitude of changes agreed better under TPREC1 than AMS.

Worth noting is the fact that stations 1, 2, 4, and 5 are located in the western region of Uganda. However, results from station 1 showed an opposite direction in the projected TPREC1, indicating that the effects of climate variability are highly localized.

Past studies across East Africa have also showed increase in the total precipitation. There will be increase in SDII (Simple Daily Intensity Index) and 99p–90p (width of the right tail of the precipitation distribution) implying a possibility of occurrence of heavy and extreme precipitation incidences by the end of the twenty-first century in East Africa (Ogega et al., 2020).

There is projected increase in total precipitation across Uganda from 2040 to 2100, with a notable emphasis on the 2090s (Ngoma et al., 2021; Onyutha et al., 2021). Projected increase in total precipitation by less than 30% across the WMZ in Uganda was also obtained in a previous study (Onyutha et al., 2021). This research involved downscaling GCMs using quantile mapping for datasets, including observations, CFSR, CHIRPS, JRA, ERA, and PGF, resulting in varied magnitudes of increased changes exceeding 30%. Therefore, users must consider several factors influencing the accuracy of the products and consequently affecting the outcomes of their applications, such as gauge density, orography, and the rainfall regime (Le Coz and van de Giesen, 2020). The heightened precipitation changes were especially notable during the October-November-December (OND) and January-February (JF) seasons (Onyutha et al., 2021) and this could be attributed to the increased moisture convergence, thereby enhancing the local monsoon during the boreal autumn over East Africa (Blau and Ha, 2020). Analysis of data at Station 1 showed consistently negative changes in TPREC1 by less than 20% across all precipitation products.

In a past study (Diem et al., 2019), CHIRPS was found to be the more accurate product in estimating seasonal rainfall totals in Western Uganda compared to African Rainfall Climatology Version 2 (ARC2), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR), and TAMSAT African Rainfall Climatology And Timeseries (TARCAT).

In another study (Onyutha et al., 2021), CFSR data satisfactorily replicated the observed precipitation trend direction at five out of eight stations in the WMZs of Uganda. The null hypothesis (no correlation between CFSR and observed precipitation) was rejected ($p < 0.05$) in approximately 60% of the validation cases across various time scales.

Challenges exist in assessing interannual variability and its causes in Congo and Lake Victoria basin due to low correlations among different products; CHIRPS (0.7-0.9), CFSR (0.18-0.75), ERA-5 (0.38-0.65), and JRA-55 (0.15-0.75), therefore validation of products must be done before use (Nicholson and Klotter, 2021).

It is advisable to evaluate gauge-corrected rainfall products using dependent validation datasets (Mekonnen et al., 2023). This recommendation stems from the observed variability in results at an annual scale. The selection of rainfall datasets should be contingent upon the nature of the application study, the performance metrics employed, and the validation datasets utilized (Mekonnen et al., 2023).

Total precipitation in agriculture plays a crucial role in crop planning and irrigation scheduling, guiding the selection of suitable crops based on rainfall totals during a rainy season. Regions experiencing lower-than-normal rainfall totals necessitate the planting of drought-resistant crops to mitigate potential water shortages. The diverse changes observed across different precipitation products emphasize the importance of careful consideration before utilizing them for decision-making purposes.

4.4.3 MDS1

Figure 4-12 shows projected climate change signals on MDS1. It revealed varied patterns among different precipitation products. Notably, PGF stood out by projecting the highest increase, surpassing 150% for both SSP 2-4.5 and SSP 5-8.5 in the 2050s and 2080s. Increase in PGF aligns with projections from observed data, which also showed an increase, although not exceeding 130.83% under SSP 5-8.5 in 2050s. In contrast, the use of the other precipitation products (CFSR, CHIRPS, JRA, and ERA) for downscaling generally led to a decrease in MDS1 for SSP 2-4.5 and SSP 5-8.5 during the same periods not exceeding 60%, hence they

are comparable. PGF showed the prolonged dry spells while other precipitation products showed reduced projections indicating wetter conditions in the future. However, there is an exception at station 2, where CFSR indicates a notable increase of less than 65%.

This analysis points out to a significant disparity in the forecasted consequences of climate change on dry spells between PGF and other precipitation products. While PGF indicates a notable intensification, most other datasets depict towards decreased intensity, highlighting a consensus projection across other products (CFSR, CHIRPS, JRA-55 and ERA-5). Notably, the discrepancy observed at station 2, where CFSR shows a substantial increase (less than 64.77%), underscores the necessity of accounting for regional nuances in climate projections.

In East Africa and certain areas of the Sahel and East Asia, there are shorter dry spells during the dry season accompanied by increased precipitation and more rainy days during this period (Wainwright et al., 2021). Northeast Africa (NEAF) shows shorter dry spells (decrease of 12 days) under CMIP6 SSP5-8.5 (Wainwright et al., 2021). There will be an increase in the duration of dry spells, extent of this increase varies from one location to another. Stations 2 and 6, the dry spell duration under RCP4.5 in the 2050s is expected to increase by 25.7% and 14.4%, respectively (Onyutha, 2020). Global Precipitation Climatology Project (GPCP) shows high number of dry spells in the tropics but fewer in the subtropics. In contrast, Canadian Regional Climate Model, version 5 (CRCM5_ERA_Interim) underestimates dry spell occurrences in the Kalahari Desert and the tropics but overestimates them along the eastern coast of Africa and the Guinean coast. (Bouagila and Sushama, 2013).

In agriculture, dry spell is used to inform irrigation schedules and crop planning, while in water resource management, helps assess water availability and drought risk. These disparities underscore the inherent uncertainty in climate modeling, with some models predicting substantial changes in dry spell severity while others suggest more moderate shifts or even

decreases. Consequently, careful consideration is warranted when formulating strategies to address the potential impacts of climate change, particularly in sectors such as water resources, agriculture, and ecosystems.

4.4.4 NDD1

Figure 4-13 shows projected climate change signals on NDD1. Generally, the NDD1 is projected to decrease from the observed data and precipitation products. The changes obtained do not exceed 20% under both SSP 2-4.5 and SSP 5-8.5 in both time horizons. SSP 5-8.5 showed slightly higher decrease than the SSP 2-4.5 in the 2080s.

Just as CFSR showed the highest projected increase under TPREC1 while the other precipitation products were comparable, CFSR again also exhibited the highest decrease under NDD1. CHIRPS, JRA-55, and ERA-5 and PGF showed comparable results in this context as well.

The precipitation products results show greater agreement for NDD1 than for MDS1. Therefore, analyzing dry conditions requires considering multiple statistics such as severity, duration, and intensity. Relying on a single statistic to analyze drought is insufficient; different dimensions of water-related catastrophes should be included in the analysis. The count of dry days is a critical metric for characterizing instances of dry conditions. Water resource managers rely on it to evaluate drought severity and gauge water availability.

Many locations across East Africa are expected to encounter wetter conditions in the future relative to the reference period of 1970–2023 (Onyutha, 2020). Additionally, this decrease is further supported by the increase in NWD1 shown in Fig 4-15. However, the magnitude of the decrease in dry days varies among different scenarios and precipitation products datasets. The anomaly at station 9, located in a mountainous area where ERA-5 shows a positive change,

underscores the importance of considering localized variations in climate projections. Some products have been shown to perform relatively better while some are inadequate for mountainous areas (Le Coz and van de Giesen, 2020). Significant changes in dry season precipitation patterns, including both increased overall rainfall and changes in the frequency and intensity of rainy days within what is typically considered a dry period (Wainwright et al., 2021).

4.4.5 MWS1

Fig 4-14 shows projected climate change signals on MWS1. Generally, there is projected increase is notable across all stations from both the observed data and the precipitation products.

Projections from observed data and PGF are comparable, showing an increase exceeding 100% MWS1 across all scenarios and time horizons, similar to MDS1 in terms of magnitude. Other precipitation products (CFSR, CHIRPS, JRA-55, and ERA-5) are also comparable but show lower values than PGF (not exceeding 100%) at stations 5, 13, 16, and 17. CHIRPS projections exceed those of CFSR, JRA-55, and ERA-5 at stations 1, 4, 9, 14, and 20. Projections from SSP5-8.5 are slightly higher than those from SSP2-4.5 for both time horizons.

Uganda's future climate is anticipated to be wetter compared to historical data, evidenced by higher MWS1 (more than 10 days) and MWS5 (more than 5 days) values for future climatic conditions (Onyutha, 2020). For the mean length of dry spells in the wet season, the changes are generally very small (multimodel median is generally less than half a day) and not statistically significant (Wainwright et al., 2021). Additionally, at the interannual scale, there is a positive correlation between intraseasonal statistics of wet spells and seasonal rainfall totals across East Africa, while a negative correlation exists for dry spells. The relationship with wet spells was notably significant (at a 95% confidence level), whereas correlations with dry spells

were generally not statistically significant (Gitau, 2011). The previous studies discussion aligns with results from this research as discussed above which all show an increase in the MWS1 for both observed data and the precipitation products. With exception of few stations that indicated a decrease in the MWS1.

In agriculture, wet spells play a crucial role in guiding irrigation schedules and crop planning, whereas in water resource management, they aid in evaluating water availability and assessing drought risk. Given the disparities in predictions by different models, careful consideration should be exercised before their utilization.

4.4.6 NWD1

Figure 4-15 showed the projected climate change signals on NWD1. Generally, NWD1 is projected to increase. Both the observed data and precipitation products showed increase. The precipitation products showed varied performances eg PGF demonstrates the highest increase at stations 1 and 4 ranging (4%-42%). In contrast, JRA shows the highest increase at stations 2, 9, 13, 14, 16, 17, and 20 ranging (0%-114%). Additionally, CFSR exhibits the highest increase at stations 2 and 17, ranging (0%-103%). Notably, ERA and CHIRPS shows the least increase not greater than 17% and 14% respectively. All precipitation products reproduced the observed values which also showed an increase ranging (3%-36%).

Very wet and extremely very wet days will increase, under future climatic conditions, especially over Uganda and western Kenya (Ongoma et al., 2018). There is observed increase in both parameters with time, especially in Uganda and western Kenya where the trend exceeds 2.4 mm/year (Ongoma et al., 2018). South and East Asia, eastern Africa, and eastern North America showed projected increase in wet season rainfall due to a combination of increasing rainfall intensity in the wet season and either limited change or a slight increase in the number

of wet days in the wet season (Wainwright et al., 2021). However a number of studies have identified an increasing contrast between wet and dry seasons, with wet seasons getting wetter and dry seasons getting drier (Chou et al., 2013; Kumar et al., 2015; Haile et al., 2020; Wainwright, Black and Allan, 2021). The number of wet days were decreasing although insignificantly ($p > 0.05$) in the Mpologoma catchment in Uganda (Mubialiwo et al., 2023). This analysis highlights the diversity in the projected impacts of climate change on wet days across different precipitation products and stations. The variability underscores the complexity of climate modeling and emphasizes the importance of considering multiple sources of data when assessing the effects of climate change on precipitation patterns.

A general overview is that there are areas where individual datasets may diverge significantly from others. ERA-5 and PGF show tendencies to overestimate specific metrics (AMS and MDS1, respectively), while CFSR similarly overestimates in TPREC1 and NDD1. However, the general consistency among CHIRPS, JRA-55, ERA-5, and PGF in metrics such as TPREC1, NDD1, and MDS1 suggests a degree of reliability and stability in their projections for Uganda. These insights underscore the importance of considering multiple precipitation products to provide a more robust understanding of potential climate trends in Uganda. For future-focused applications, these findings emphasize that ERA-5 and PGF should be applied with caution in areas with complex topography or unique microclimates, while CFSR may require validation checks in total precipitation estimates. In practice, these insights can inform water resource planning, agricultural scheduling, and climate risk assessments across Uganda, helping to build resilience against potential climatic changes.

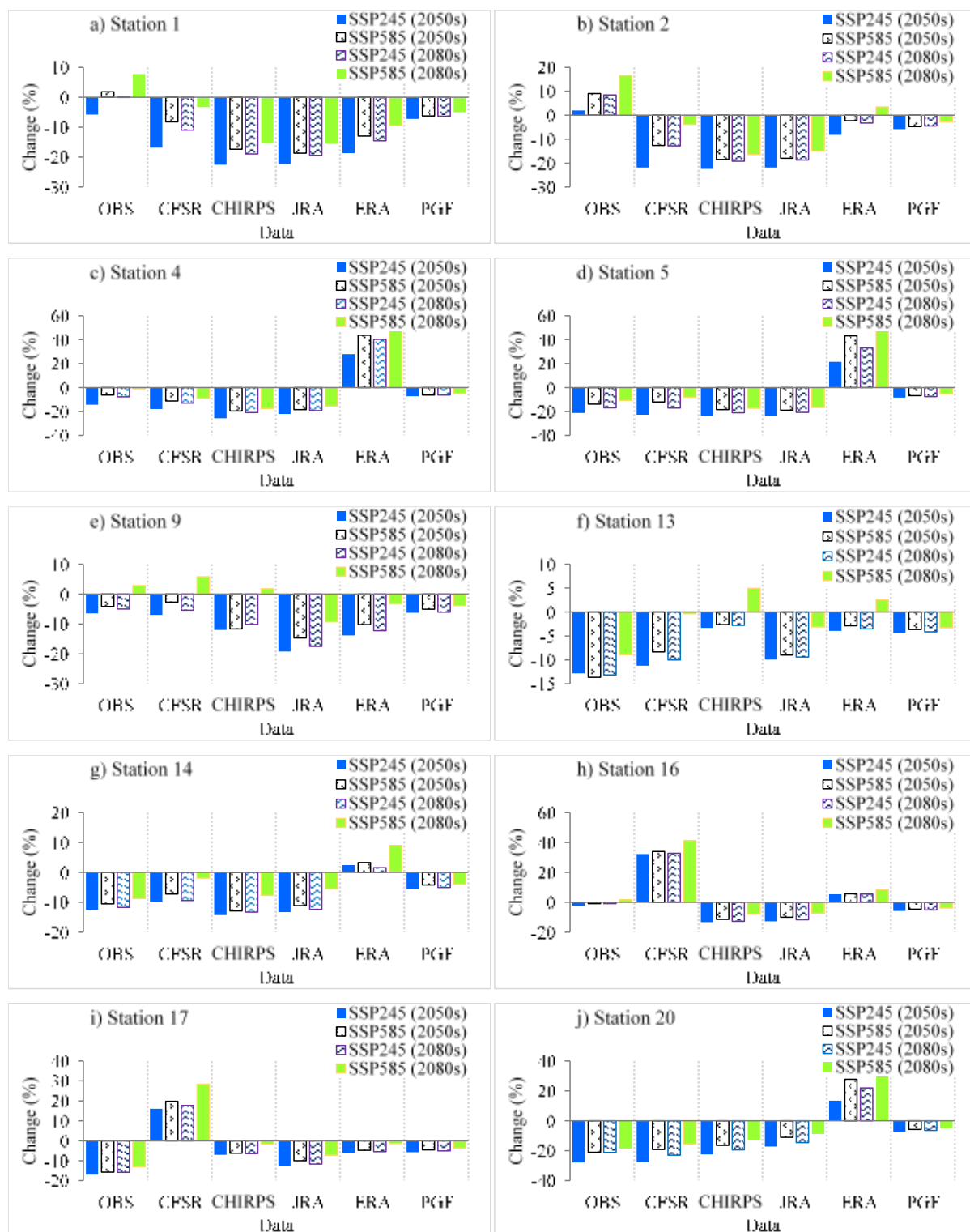


Figure 0-10 Climate change impact on AMS at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20

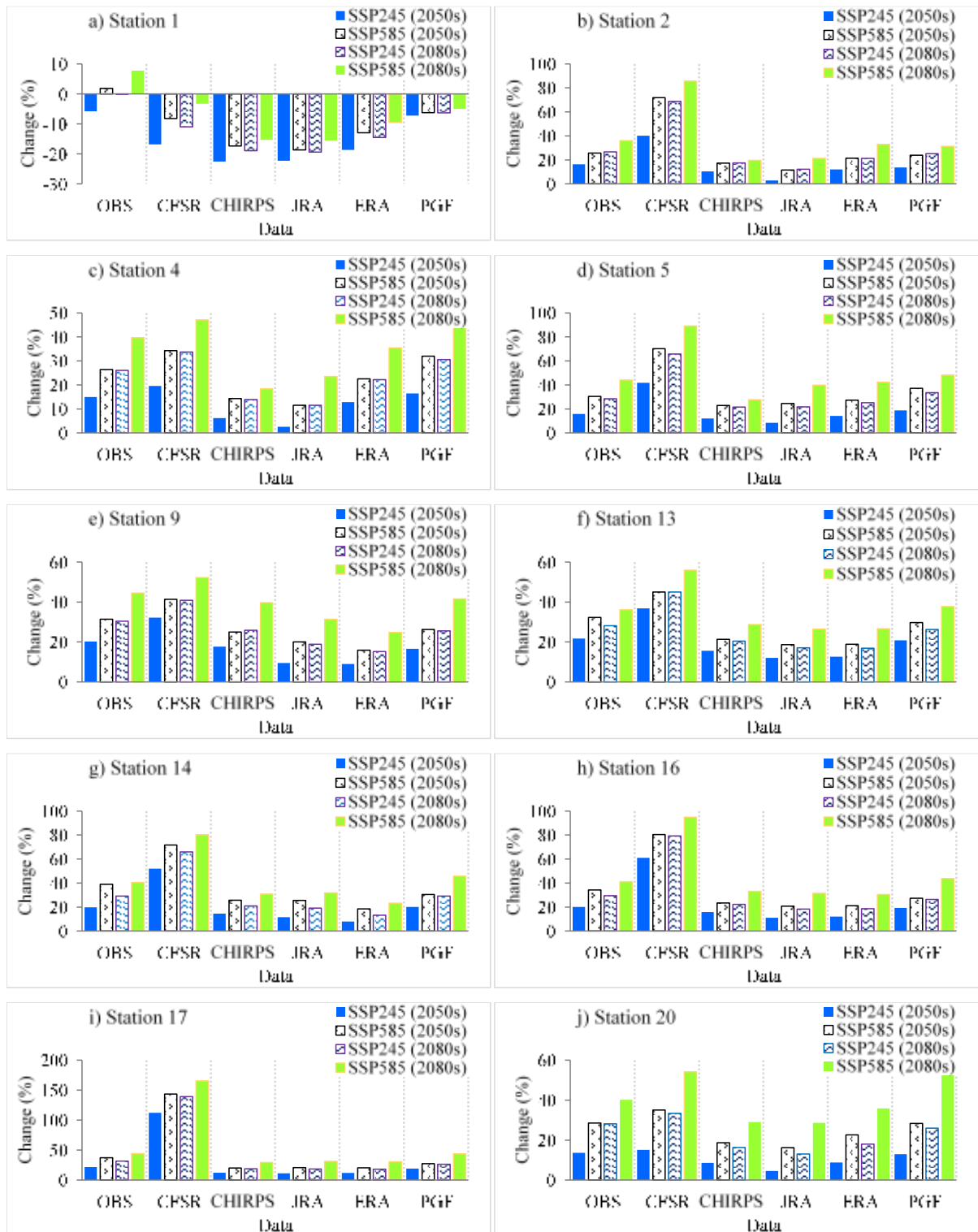


Figure 0-11 Climate change impact on TPREC1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20

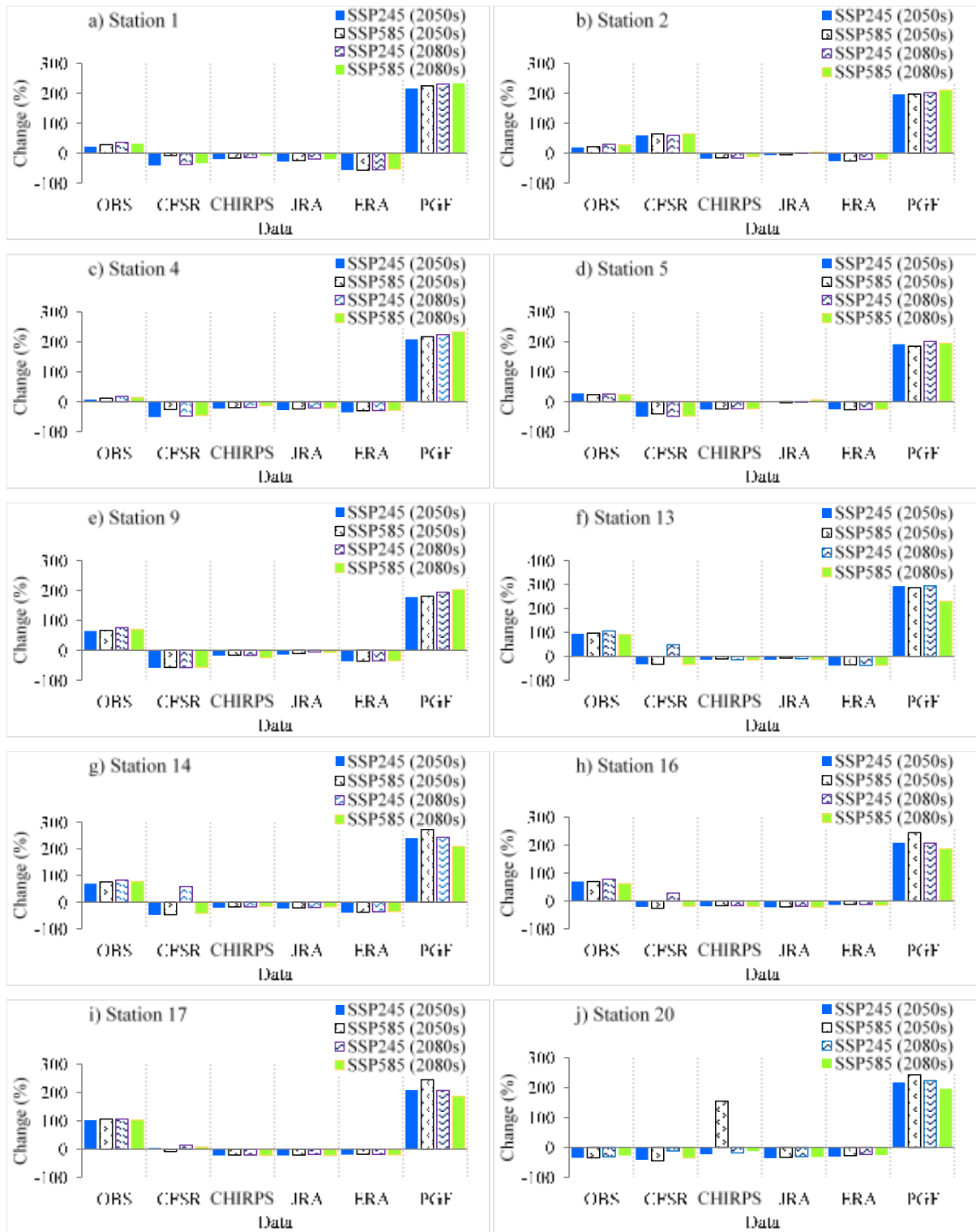


Figure 0-12 Climate change impact on MDS1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20

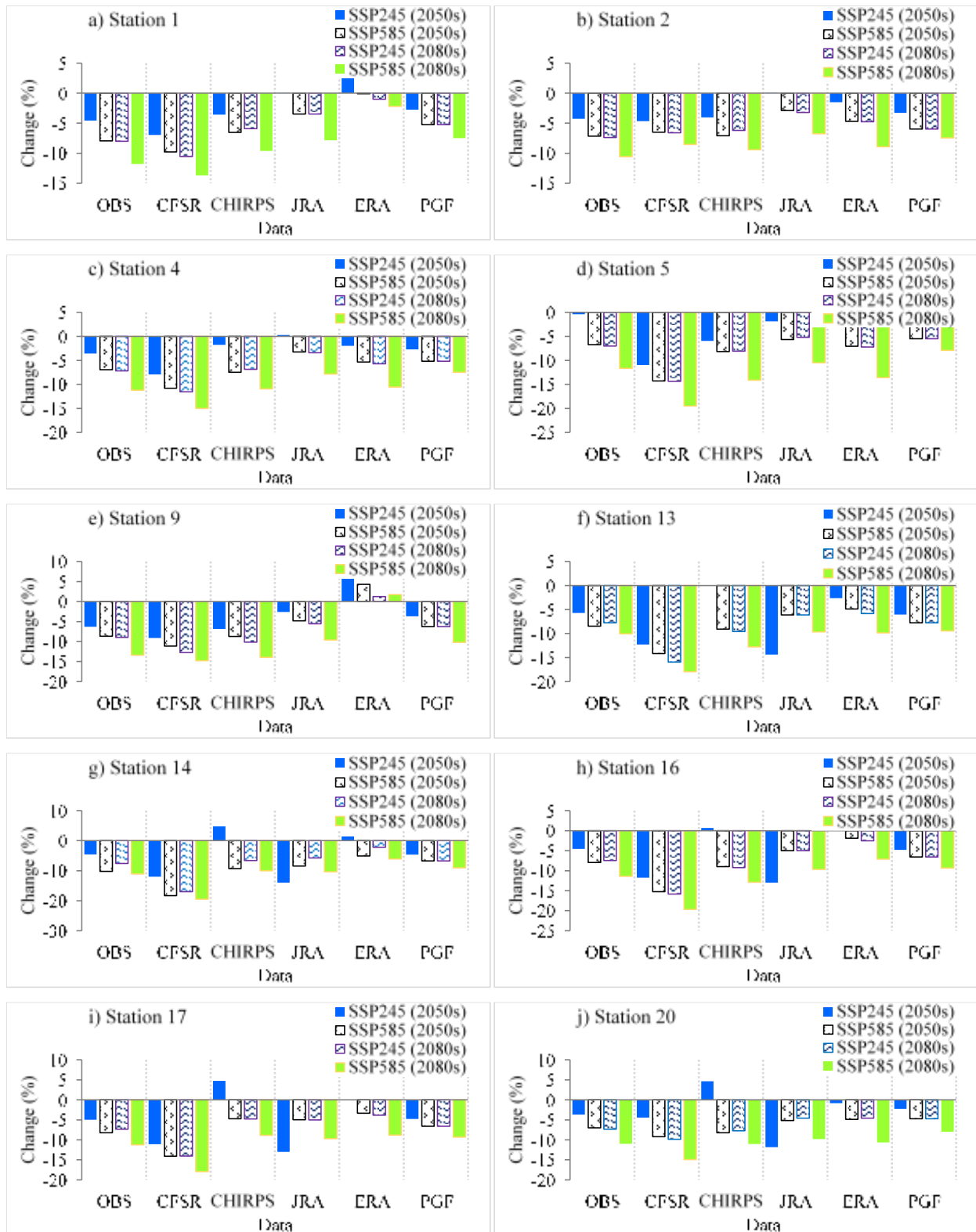


Figure 0-13 Climate change impact on NDD1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20

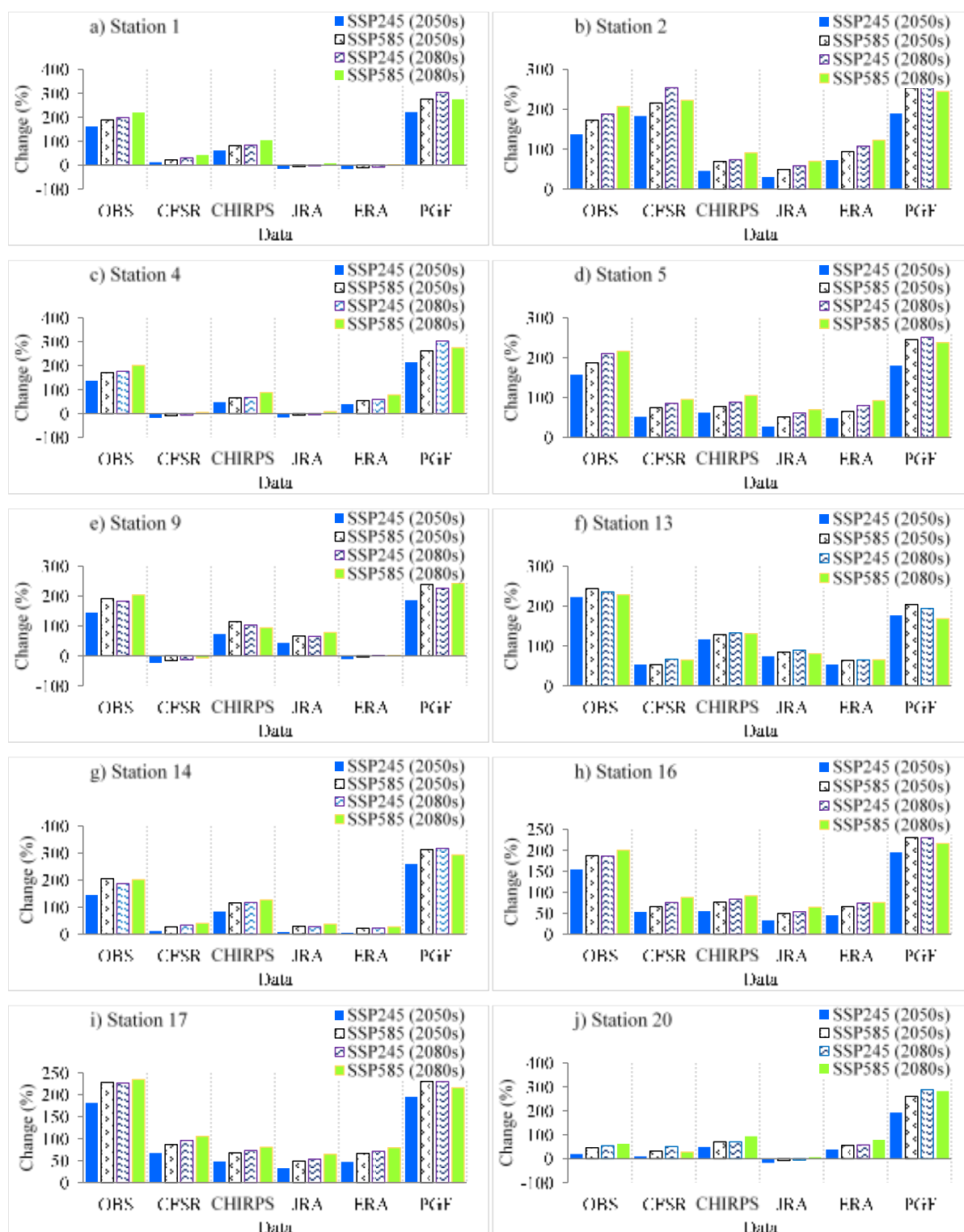


Figure 0-14 Climate change impact on MWS1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g)

14, h) 16, i) 17, j) 20

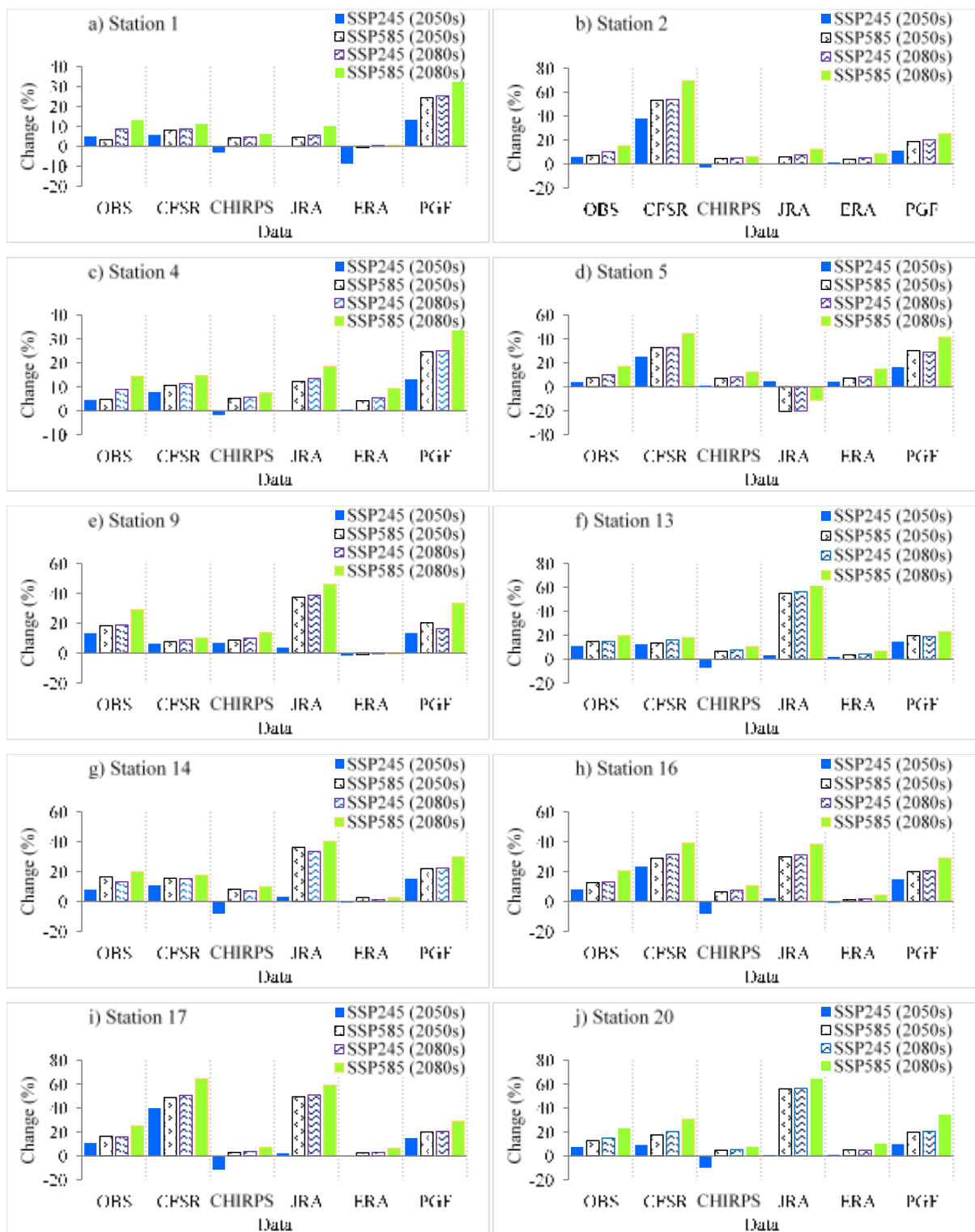


Figure 0-15 Climate change impact on NWD1 at Stations a) 1, b) 2, c) 4, d) 5, e) 9, f) 13, g) 14, h) 16, i) 17, j) 20

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1 Conclusions

This study focused solely on precipitation extreme indices, including AMS, TPREC1, MDS1, NDD1, MWS1, and NWD1 which considered 1mm threshold.

How suitable is a precipitation product dataset in reproducing observed precipitation extremes?

The CFSR model performed well in reproducing the slopes of observed return periods at especially at stations 7, 15, 18, 19, and 20. PGF model consistently overestimates observed AMS at all stations while CHIRPS, JRA-55, and ERA-5 frequently underestimated observed AMS. CHIRPS, JRA-55 and ERA-5 exhibited relatively flatter slopes, indicating a more gradual increase in the probability of extreme events concerning precipitation magnitude. Overall, understanding these biases is crucial for ensuring accurate risk assessments and informed decision-making in managing extreme precipitation events.

While considering the model bias, CFSR, CHIRPS, JRA-55, ERA-5 and PGF models either underestimate or overestimate the extreme precipitation indices AMS, TPREC1, MDS1, NDD1, MWS1 and NWD1. The ranges of the ratio of 10-year AMS quantile from precipitation products to that of the observed precipitation were 0.3-2.17, 0.14-0.68, 0.15-0.75, 0.14-2.57 and 0.44-2.21 for CFSR, CHIRPS, JRA-55, ERA-5 and PGF, respectively.

The assessment of precipitation products focused on their ability to replicate AMS precipitation quantile and illustrating model bias. CFSR, CHIRPS, JRA-55, ERA-5, and PGF exhibited varying degrees of success in reproducing annual maximum series, displaying both steep and gradual/flatter slopes of return periods compared to that of the observed data. However, these precipitation products also demonstrated instances of overestimation and underestimation of

the precipitation quantiles relative to those based on observed data especially for the 10-year return period. Regarding model bias, the precipitation products displayed tendencies toward both overestimations and underestimations of precipitation extremes quantiles (AMS, TPREC1, MDS1, NDD1, MWS1 and NWD1).

In summary, the analysis underscores the importance of identifying and rectifying biases in climate datasets to enhance their accuracy for various applications. It emphasizes the need for continual advancements in observational data collection, assimilation techniques, and modeling methodologies. Understanding the strengths and limitations of each model is crucial for effective risk assessment and management. Overall, addressing biases and improving modeling capabilities are essential steps toward addressing climate change challenges.

How much is the mismatch between observed and GCM precipitation products?

At the annual scale, the correlation coefficient between observed and GCMs outputs data varies across all extreme precipitation indices, ranged from (-4.47 to 0.52), (-0.46 to 0.54), (-0.44 to 0.38), (-0.3 to 0.63), (-0.47 to 0.54) and (-0.41 to 0.59) for AMS, TPREC1, MDS1, NDD1, MWS1 and NWD1, respectively indicating both positive and negative correlations.

The correlation coefficient for annual total precipitation ranged from 0.01 to 0.54 for positive correlation and -0.46 to 0 for negative correlation. The null hypothesis of ($p < 0.05$) no correlation between observed and GCMs-based historical TPREC1, was rejected in varying proportions across 20 meteorological stations. The H_0 was not rejected at any of the stations when analysis was based on CAN_ESM and CESSM_WACCM. The H_0 was rejected at 5% of the stations while considering ACCESS_ESM1.5, BCC_CSM and NOR_ESM. The H_0 was rejected at 10% of the stations while considering MRI_ESM2. H_0 was rejected at 15% of the stations while considering INM_CM5. Using NOR_ESM, the H_0 was rejected at 30% of the

stations. The positive and negative correlations imply that GCMs capture variability in observed precipitation to varying extents.

Across the annual scale, the order of performance from the best to the worst model is BCC_CSM, INM_CM5, CESSM_WACCM, ACCESS_CM2, ACCESS_ESM1.5, MRI_ESM2, CAN_ESM5 and NOR_ESM2. Overall, the findings underscore the challenges and limitations associated with GCMs in accurately reproducing observed precipitation patterns, highlighting the need for continued improvements in model development and validation techniques to enhance their reliability for various applications, such as climate impact assessments and forecasting.

What is the implication of precipitation products capabilities for bias correction of GCMs output?

In the 2080s, as per SSP 5-8.5, observed data showed increase in TPREC1, ranged from 32.79% to 53.58%. Precipitation products similarly indicated increase in TPREC1 across different datasets: 34.66% to 165.27% for CFSR, 21.30% to 66.44% for JRA-55, 31.22% to 60.38% for PGF, 14.75% to 43.70% for ERA-5 and 18.39% to 40.48% for CHIRPS. These results indicate that the use of precipitation products instead of the observed precipitation can lead to underestimation or overestimation of climate change impacts.

A general conclusion is that precipitation products underestimate/overestimate the observed precipitation extremes. The extent to which GCMs capture precipitation extremes varies mainly due to their coarse spatial resolution. The extent to which GCMs capture precipitation extremes varies due to their coarse spatial resolution. Bias correction of GCM outputs using quantile mapping method yielded different climate change signals in the cases when observations and precipitation products were considered. The choice of precipitation product

significantly impacts climate projections. Thus, there is a need for careful selection of which precipitation product should be used for bias correction of GCMs' outputs in absence of observed precipitation when analysis is being done for planning water resource management and climate change impact assessments.

5.2 Recommendations

5.2.1 *To policy makers*

Decision making regarding climate change impacts on precipitation should be made while considering the uncertainty in data. For improved climate change analysis, there is a need for the government to invest in weather stations to improve on the required availability of observed climatic data to support scientific research.

5.2.2 *For future research*

It is crucial to carefully consider factors such as selecting precipitation products, scenarios, and downscaling methods to maintain the integrity of climate model simulations. The variations observed in changes across different precipitation products and scenarios highlight areas requiring further research and improvement. This might involve refining data assimilation techniques, enhancing model parameterizations, or improving the representation of specific physical processes within GCMs. Recognizing these research gaps contributes to continuous endeavors aimed at improving the accuracy and reliability of climate projections.

APPENDICES

No	SSP245 (2050s)						SSP585 (2050s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	👉 -5.79	👉 -16.81	👇 -22.54	👇 -22.29	👇 -18.66	👉 -7.22	👉 1.83	👉 -8.25	👇 -17.35	👇 -18.69	👉 -12.94	👉 -6.28
2	👉 1.96	👇 -21.81	👇 -22.44	👇 -21.84	👉 -8.21	👉 -5.86	👉 9.08	👉 -12.62	👇 -18.49	👇 -18.02	👉 -2.32	👉 -4.75
3	👉 -15.38	👉 -13.36	👇 -17.29	👇 -22.15	👉 -14.36	👉 -6.90	👉 -11.34	👉 -8.15	👉 -13.68	👇 -18.17	👉 -10.36	👉 -6.22
4	👉 -14.27	👇 -17.99	👇 -25.63	👇 -22.01	👉 27.93	👉 -7.29	👉 -6.20	👉 -11.19	👇 -19.52	👇 -18.35	👉 43.66	👉 -6.33
5	👇 -21.21	👇 -22.64	👇 -24.08	👇 -23.96	👉 21.58	👉 -8.38	👉 -13.81	👉 -11.95	👇 -18.42	👇 -18.92	👉 43.19	👉 -6.79
6	👉 -16.16	👇 -23.58	👇 -22.42	👇 -22.01	👉 19.93	👉 -7.29	👉 -9.22	👉 -15.91	👉 -16.86	👇 -18.35	👉 34.42	👉 -6.33
7	👉 -17.01	👇 -24.85	👇 -23.50	👇 -23.33	👉 -0.34	👉 -7.71	👉 -9.30	👉 -15.58	👇 -17.61	👇 -19.06	👉 6.77	👉 -6.54
8	👇 -17.95	👉 -17.14	👇 -21.76	👇 -21.61	👉 -14.57	👉 -6.92	👉 -9.63	👉 -11.18	👉 -16.86	👇 -18.35	👉 -10.46	👉 -6.33
9	👉 -6.45	👉 -7.00	👉 -11.98	👇 -19.19	👉 -13.82	👉 -6.24	👉 -4.14	👉 -2.73	👉 -11.62	👉 -14.65	👉 -10.18	👉 -5.10
10	👇 -17.69	👉 -7.36	👉 -11.64	👉 -14.92	👉 -13.32	👉 -6.43	👉 -13.68	👉 -3.51	👉 -11.50	👉 -11.48	👉 -8.91	👉 -5.38
11	👉 -11.53	👇 -24.57	👉 -14.76	👉 -17.13	👇 -18.58	👉 -6.43	👉 -8.29	👇 -20.74	👉 -15.08	👉 -13.60	👉 -15.01	👉 -5.52
12	👉 -13.87	👉 -0.54	👉 -15.39	👉 -16.49	👉 -14.11	👉 -4.09	👉 -12.51	👉 5.10	👉 -13.64	👉 -14.97	👉 -12.11	👉 -2.91
13	👉 -12.81	👉 -11.22	👉 -3.32	👉 -9.95	👉 -3.93	👉 -4.39	👉 -13.61	👉 -8.32	👉 -2.62	👉 -8.98	👉 -2.88	👉 -3.64
14	👉 -12.50	👉 -10.01	👉 -14.23	👉 -13.27	👉 2.42	👉 -5.59	👉 -10.50	👉 -7.23	👉 -12.88	👉 -11.14	👉 3.31	👉 -4.20
15	👇 -23.68	👇 -19.68	👉 -17.02	👇 -18.58	👉 -15.09	👉 -7.96	👇 -18.08	👉 -13.25	👉 -12.99	👉 -14.44	👉 -11.09	👉 -7.21
16	👉 -2.31	👉 32.22	👉 -13.31	👉 -12.75	👉 5.38	👉 -5.81	👉 -0.88	👉 33.99	👉 -11.39	👉 -9.99	👉 5.66	👉 -4.60
17	👉 -17.04	👉 15.98	👉 -7.04	👉 -12.75	👉 -6.12	👉 -5.81	👉 -15.76	👉 19.74	👉 -6.29	👉 -9.99	👉 -4.74	👉 -4.60
18	👇 -32.45	👇 -32.33	👉 -18.97	👇 -17.72	👉 -8.72	👉 -8.36	👇 -23.00	👇 -24.26	👉 -12.96	👉 -11.14	👉 1.55	👉 -6.49
19	👇 -24.58	👇 -23.32	👉 -13.67	👇 -17.65	👇 -24.69	👉 -6.87	👇 -18.06	👉 -14.80	👉 -8.90	👉 -12.32	👇 -19.50	👉 -5.89
20	👇 -27.87	👇 -27.58	👇 -22.51	👇 -17.26	👉 13.47	👉 -7.31	👇 -21.03	👇 -19.18	👉 -16.44	👉 -10.98	👉 27.76	👉 -5.76
No	SSP245 (2080s)						SSP585 (2080s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	👉 -0.04	👇 -10.96	👇 -18.92	👇 -19.42	👇 -14.55	👉 -6.29	👉 7.73	👉 -3.33	👇 -15.33	👇 -15.54	👉 -9.54	👉 -4.99
2	👉 8.48	👇 -12.83	👇 -19.21	👇 -18.73	👉 -3.30	👉 -4.51	👉 16.49	👉 -3.81	👇 -16.39	👇 -14.93	👉 3.50	👉 -2.82
3	👉 -10.54	👉 -8.21	👇 -13.96	👇 -18.21	👉 -9.11	👉 -5.81	👉 -6.02	👉 -3.71	👇 -10.85	👇 -13.96	👉 -5.28	👉 -4.13
4	👉 -7.76	👇 -12.96	👇 -20.97	👇 -19.26	👉 40.28	👉 -6.22	👉 -1.01	👉 -8.91	👇 -17.44	👇 -15.54	👉 50.08	👉 -4.99
5	👇 -16.93	👇 -17.08	👇 -21.02	👇 -20.78	👉 33.12	👉 -7.57	👉 -10.65	👉 -8.10	👇 -17.32	👇 -16.58	👉 49.84	👉 -5.28
6	👇 -11.04	👇 -17.91	👇 -18.28	👇 -19.26	👉 31.31	👉 -6.22	👉 -5.42	👇 -12.90	👇 -15.33	👇 -15.54	👉 41.05	👉 -4.99
7	👉 -10.16	👇 -17.50	👇 -18.82	👇 -19.93	👉 5.70	👉 -6.36	👉 -4.98	👉 -10.20	👇 -15.33	👇 -15.54	👉 11.42	👉 -4.99
8	👇 -10.84	👇 -12.74	👇 -18.18	👇 -19.26	👇 -11.26	👉 -6.08	👉 -4.29	👉 -8.91	👇 -15.33	👇 -15.54	👉 -8.74	👉 -4.99
9	👉 -4.97	👉 -5.38	👉 -10.16	👇 -17.46	👇 -12.21	👉 -6.07	👉 2.83	👉 5.80	👉 1.76	👉 -9.27	👉 -3.27	👉 -3.89
10	👇 -14.13	👉 -4.15	👉 -9.21	👇 -12.35	👉 -10.12	👉 -5.86	👉 -7.21	👉 6.15	👉 0.55	👉 -6.95	👉 -3.21	👉 -3.97
11	👉 -7.95	👇 -20.46	👇 -12.32	👇 -14.11	👇 -14.09	👉 -5.86	👉 -2.29	👉 -8.78	👉 -2.99	👉 -8.26	👉 -5.76	👉 -4.26
12	👉 -9.86	👉 6.95	👇 -13.22	👇 -13.95	👇 -11.97	👉 -3.34	👉 -7.99	👉 16.10	👉 -7.57	👉 -8.63	👉 -7.62	👉 -2.88
13	👇 -13.15	👉 -10.01	👉 -2.80	👉 -9.41	👉 -3.54	👉 -4.13	👉 -8.91	👉 -0.36	👉 4.92	👉 -3.11	👉 2.54	👉 -3.26
14	👇 -11.72	👉 -9.40	👇 -13.30	👇 -12.35	👉 1.61	👉 -5.07	👉 -8.74	👉 -1.91	👉 -7.69	👉 -5.50	👉 9.01	👉 -3.92
15	👇 -16.59	👇 -12.86	👇 -12.57	👇 -14.19	👇 -11.16	👉 -6.87	👇 -13.89	👉 -7.20	👉 -8.01	👉 -10.31	👉 -8.32	👉 -5.44
16	👉 -0.91	👉 32.77	👇 -12.72	👇 -11.71	👉 5.49	👉 -5.08	👉 1.80	👉 41.30	👉 -7.81	👉 -7.27	👉 8.46	👉 -3.73
17	👇 -15.85	👉 17.74	👉 -6.49	👇 -11.70	👉 -5.50	👉 -5.08	👇 -13.06	👉 28.34	👉 -1.76	👉 -7.29	👉 -1.38	👉 -3.73
18	👇 -23.55	👇 -26.03	👇 -15.17	👇 -13.24	👉 -0.82	👉 -7.01	👇 -13.84	👇 -17.63	👉 -8.51	👉 -6.34	👉 4.85	👉 -4.98
19	👇 -17.44	👇 -18.99	👉 -10.49	👇 -14.86	👇 -20.80	👉 -6.36	👇 -11.12	👉 -7.53	👉 -2.16	👉 -7.65	👇 -13.35	👉 -4.36
20	👇 -21.11	👇 -22.97	👇 -19.39	👇 -14.56	👉 21.92	👉 -6.46	👇 -18.48	👇 -15.46	👇 -12.93	👉 -8.77	👉 34.01	👉 -4.92

Figure A-0-1 Climate change impact on AMS based on observations and precipitation products data

No	SSP245 (2050s)						SSP585 (2050s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	↓ 11.85	↓ 17.61	↓ 9.81	↓ 2.83	↓ 5.65	↓ 16.77	↓ 20.86	↓ 27.97	↓ 17.39	↓ 11.44	↓ 11.87	↓ 31.37
2	↓ 16.28	↓ 40.16	↓ 10.36	↓ 2.89	↓ 11.97	↓ 13.61	↓ 25.76	↓ 71.80	↓ 17.29	↓ 11.63	↓ 21.39	↓ 23.89
3	↓ 16.75	↓ 32.57	↓ 9.46	↓ 3.77	↓ 6.11	↓ 13.05	↓ 29.01	↓ 49.42	↓ 17.79	↓ 14.78	↓ 15.38	↓ 25.71
4	↓ 15.01	↓ 19.56	↓ 6.17	↓ 2.54	↓ 12.87	↓ 16.43	↓ 26.40	↓ 34.24	↓ 14.29	↓ 11.52	↓ 22.53	↓ 31.96
5	↓ 15.87	↓ 41.75	↓ 11.98	↓ 8.40	↓ 14.24	↓ 18.81	↓ 30.48	↓ 70.21	↓ 22.94	↓ 24.48	↓ 27.27	↓ 37.14
6	↓ 15.91	↓ 9.29	↓ 9.53	↓ 2.54	↓ 15.68	↓ 16.43	↓ 28.42	↓ 24.33	↓ 17.47	↓ 11.52	↓ 28.01	↓ 31.96
7	↓ 13.63	↓ 13.13	↓ 7.92	↓ 0.57	↓ 5.80	↓ 13.38	↓ 29.69	↓ 32.02	↓ 15.74	↓ 9.54	↓ 12.33	↓ 28.74
8	↓ 13.10	↓ 19.53	↓ 9.45	↓ 2.44	↓ 6.44	↓ 16.26	↓ 31.77	↓ 34.25	↓ 17.47	↓ 11.52	↓ 13.31	↓ 31.96
9	↓ 20.24	↓ 32.15	↓ 17.66	↓ 9.50	↓ 9.05	↓ 16.60	↓ 31.34	↓ 41.31	↓ 25.00	↓ 20.04	↓ 15.88	↓ 26.21
10	↓ 16.91	↓ 30.39	↓ 11.18	↓ 3.93	↓ 2.74	↓ 14.01	↓ 27.72	↓ 39.97	↓ 16.55	↓ 11.37	↓ 7.83	↓ 24.72
11	↓ 16.73	↓ 8.29	↓ 12.10	↓ 7.19	↓ 10.74	↓ 14.01	↓ 26.68	↓ 20.64	↓ 18.10	↓ 17.17	↓ 22.37	↓ 23.81
12	↓ 20.53	↓ 92.27	↓ 13.92	↓ 10.55	↓ 9.76	↓ 18.07	↓ 33.44	↓ 120.70	↓ 21.12	↓ 19.52	↓ 18.66	↓ 29.12
13	↓ 21.76	↓ 36.78	↓ 15.64	↓ 12.06	↓ 12.64	↓ 20.81	↓ 32.28	↓ 44.99	↓ 21.37	↓ 18.64	↓ 18.86	↓ 29.67
14	↓ 19.80	↓ 51.93	↓ 14.46	↓ 11.49	↓ 7.98	↓ 20.03	↓ 38.96	↓ 71.70	↓ 25.65	↓ 25.45	↓ 18.44	↓ 30.46
15	↓ 12.27	↓ 36.45	↓ 10.26	↓ 8.33	↓ 2.91	↓ 18.32	↓ 26.38	↓ 57.74	↓ 18.77	↓ 19.92	↓ 8.94	↓ 30.21
16	↓ 20.12	↓ 60.97	↓ 15.81	↓ 11.14	↓ 12.10	↓ 19.29	↓ 34.23	↓ 80.37	↓ 23.43	↓ 20.70	↓ 21.05	↓ 27.26
17	↓ 21.68	↓ 112.19	↓ 12.16	↓ 11.14	↓ 12.00	↓ 19.29	↓ 37.36	↓ 143.37	↓ 20.10	↓ 20.70	↓ 20.66	↓ 27.26
18	↓ 14.89	↓ 37.61	↓ 14.21	↓ 18.59	↓ 5.95	↓ 18.57	↓ 35.98	↓ 67.38	↓ 25.29	↓ 42.84	↓ 14.60	↓ 30.76
19	↓ 16.03	↓ 38.33	↓ 9.15	↓ 4.91	↓ 1.79	↓ 13.37	↓ 36.95	↓ 65.67	↓ 19.50	↓ 20.88	↓ 10.70	↓ 27.52
20	↓ 13.63	↓ 15.08	↓ 8.59	↓ 4.57	↓ 8.80	↓ 12.91	↓ 28.52	↓ 35.00	↓ 18.68	↓ 16.22	↓ 22.59	↓ 28.37
No	SSP245 (2080s)						SSP585 (2080s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	↓ 21.01	↓ 27.24	↓ 17.06	↓ 11.42	↓ 11.80	↓ 30.63	↓ 32.79	↓ 39.97	↓ 21.53	↓ 23.50	↓ 21.79	↓ 44.50
2	↓ 26.58	↓ 68.73	↓ 17.47	↓ 12.27	↓ 21.30	↓ 25.26	↓ 36.03	↓ 85.67	↓ 19.67	↓ 21.30	↓ 32.95	↓ 31.22
3	↓ 28.59	↓ 48.79	↓ 17.43	↓ 14.42	↓ 15.14	↓ 25.03	↓ 43.11	↓ 64.05	↓ 22.13	↓ 28.38	↓ 28.58	↓ 36.89
4	↓ 26.10	↓ 33.68	↓ 13.91	↓ 11.53	↓ 22.24	↓ 30.58	↓ 39.72	↓ 47.08	↓ 18.39	↓ 23.51	↓ 35.43	↓ 44.49
5	↓ 28.43	↓ 65.84	↓ 21.64	↓ 21.73	↓ 25.27	↓ 33.54	↓ 44.09	↓ 89.10	↓ 27.67	↓ 39.89	↓ 42.35	↓ 48.24
6	↓ 27.76	↓ 23.47	↓ 17.15	↓ 11.53	↓ 27.10	↓ 30.58	↓ 42.55	↓ 36.59	↓ 21.55	↓ 23.51	↓ 43.70	↓ 44.49
7	↓ 28.88	↓ 31.42	↓ 15.94	↓ 10.04	↓ 12.91	↓ 28.34	↓ 46.82	↓ 49.99	↓ 21.55	↓ 23.51	↓ 24.35	↓ 44.49
8	↓ 29.43	↓ 33.65	↓ 17.11	↓ 11.49	↓ 13.28	↓ 30.46	↓ 48.20	↓ 47.08	↓ 21.55	↓ 23.52	↓ 23.86	↓ 44.49
9	↓ 30.42	↓ 40.80	↓ 25.82	↓ 18.86	↓ 15.26	↓ 25.60	↓ 44.49	↓ 52.21	↓ 39.71	↓ 31.36	↓ 24.76	↓ 41.49
10	↓ 27.02	↓ 39.71	↓ 17.56	↓ 11.06	↓ 7.67	↓ 23.67	↓ 41.10	↓ 52.21	↓ 26.81	↓ 21.36	↓ 14.75	↓ 41.72
11	↓ 26.62	↓ 19.79	↓ 19.73	↓ 16.67	↓ 21.53	↓ 23.67	↓ 39.94	↓ 34.66	↓ 31.83	↓ 30.61	↓ 36.17	↓ 41.17
12	↓ 27.03	↓ 110.13	↓ 19.22	↓ 16.47	↓ 15.00	↓ 24.37	↓ 36.66	↓ 139.93	↓ 28.36	↓ 27.79	↓ 26.93	↓ 36.86
13	↓ 28.09	↓ 45.01	↓ 20.48	↓ 17.08	↓ 16.88	↓ 26.21	↓ 36.15	↓ 55.94	↓ 28.77	↓ 26.48	↓ 26.68	↓ 37.67
14	↓ 29.18	↓ 65.91	↓ 20.94	↓ 19.05	↓ 13.13	↓ 29.13	↓ 40.45	↓ 80.25	↓ 30.84	↓ 31.71	↓ 23.22	↓ 45.70
15	↓ 26.56	↓ 58.27	↓ 18.74	↓ 19.11	↓ 8.47	↓ 32.25	↓ 36.95	↓ 74.21	↓ 29.42	↓ 34.10	↓ 16.51	↓ 55.15
16	↓ 29.52	↓ 79.28	↓ 22.16	↓ 18.38	↓ 18.71	↓ 26.40	↓ 41.05	↓ 94.87	↓ 33.06	↓ 31.44	↓ 30.45	↓ 43.77
17	↓ 31.79	↓ 139.18	↓ 18.78	↓ 18.38	↓ 18.28	↓ 26.40	↓ 44.06	↓ 165.27	↓ 29.51	↓ 31.44	↓ 30.81	↓ 43.77
18	↓ 34.98	↓ 65.98	↓ 24.47	↓ 37.42	↓ 13.35	↓ 33.18	↓ 53.58	↓ 90.61	↓ 40.48	↓ 66.44	↓ 25.53	↓ 60.38
19	↓ 35.68	↓ 62.66	↓ 17.16	↓ 15.77	↓ 8.07	↓ 25.78	↓ 48.15	↓ 87.98	↓ 30.33	↓ 35.73	↓ 19.59	↓ 52.67
20	↓ 28.13	↓ 33.35	↓ 16.26	↓ 13.09	↓ 18.01	↓ 25.96	↓ 40.16	↓ 54.11	↓ 29.06	↓ 28.64	↓ 35.85	↓ 52.71

Figure A-0-2 Climate change impact on TPREC1 based on observations and precipitation products data.

No	SSP245 (2050s)						SSP585 (2050s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	22.06	-41.41	-19.44	-28.41	-56.13	215.90	28.26	-7.75	-16.08	-24.87	-57.14	225.13
2	19.08	59.10	-18.28	-6.24	-26.81	196.48	21.61	64.77	-15.42	-5.29	-26.52	196.94
3	22.14	-51.08	-13.76	-31.74	-15.52	168.38	19.39	-29.11	-9.12	-29.95	-15.90	169.51
4	7.21	-50.88	-22.99	-28.39	-35.17	208.44	11.65	-26.30	-19.75	-24.12	-30.24	216.98
5	27.52	-49.69	-26.29	-0.85	-25.45	192.12	23.77	-40.38	-24.46	-2.93	-26.81	185.25
6	25.27	-51.73	-20.16	-28.39	-19.28	208.44	24.47	-27.81	-16.94	-24.12	-18.92	216.98
7	86.31	-28.63	-19.52	-28.02	-41.30	211.32	88.63	-8.03	-15.71	-23.92	-40.32	221.20
8	108.13	-50.27	-17.77	-26.15	-32.30	211.40	112.70	-26.30	-16.94	-24.12	-33.33	216.98
9	64.77	-58.61	-17.31	-14.23	-36.66	177.74	66.36	-56.88	-16.44	-10.78	-36.86	180.88
10	36.74	-59.01	-35.05	-38.07	-29.84	152.11	39.11	-57.04	-31.87	-35.75	-31.59	163.99
11	27.53	-35.64	-21.60	-13.93	-20.91	152.11	27.07	-35.53	-20.01	-12.36	-21.42	161.40
12	137.85	54.55	-17.61	2.35	-14.82	296.46	130.83	31.86	-15.15	7.38	-10.94	291.05
13	93.90	-33.06	-14.48	-14.60	-38.93	293.10	96.93	-33.47	-10.67	-7.42	-35.40	286.50
14	69.35	-47.91	-20.89	-23.64	-39.53	240.08	75.64	-47.45	-17.83	-21.31	-37.53	272.28
15	-21.09	-37.37	-13.79	-41.43	-22.98	216.18	-21.64	-40.92	-14.94	-40.55	-23.95	242.10
16	69.64	-21.52	-19.02	-22.88	-14.57	208.59	69.62	-26.44	-17.45	-21.30	-12.34	244.85
17	102.24	4.17	-22.46	-22.88	-20.06	208.59	106.39	-8.51	-21.27	-21.30	-18.50	244.85
18	-19.03	-29.60	-8.82	-17.94	0.06	171.64	-21.30	-33.96	-10.44	-19.23	-3.32	187.69
19	16.06	-26.78	-14.79	-48.26	-5.07	175.97	14.39	-31.42	-12.96	-47.35	-5.98	198.26
20	-34.42	-41.32	-22.90	-36.03	-30.70	217.07	-34.65	-44.56	154.49	-33.06	-27.31	242.82
No	SSP245 (2080s)						SSP585 (2080s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	36.35	-37.98	-15.34	-19.32	-55.88	230.86	31.52	-33.57	-8.88	-20.39	-52.89	233.31
2	29.53	59.50	-16.38	1.07	-20.35	202.04	27.98	64.55	-11.70	3.57	-20.14	210.62
3	25.11	-47.88	-9.87	-27.78	-10.97	167.44	23.98	-47.04	-4.51	-24.35	-10.73	185.45
4	17.94	-47.69	-18.75	-21.03	-29.43	223.92	14.04	-46.14	-12.90	-20.69	-28.93	233.31
5	25.50	-48.65	-23.69	-0.21	-26.37	201.44	23.69	-48.20	-23.42	6.74	-25.72	195.25
6	30.80	-47.25	-15.89	-21.03	-14.33	223.92	28.27	-47.18	-8.88	-20.69	-14.44	233.31
7	81.75	-24.20	-15.39	-20.17	-39.05	229.60	88.72	-25.05	-8.88	-20.69	-33.13	233.31
8	103.63	-47.96	-14.92	-22.35	-30.28	221.39	117.17	-46.14	-8.88	-20.69	-24.22	233.31
9	75.98	-57.54	-16.99	-6.06	-35.51	193.98	69.80	-56.58	-24.72	-6.86	-34.77	202.40
10	44.99	-59.53	-36.12	-36.84	-30.94	157.18	44.53	-56.21	-35.62	-35.84	-28.57	181.63
11	34.85	-31.39	-20.03	-6.00	-20.31	157.18	40.78	-32.90	-24.72	-7.89	-20.62	173.32
12	131.34	36.50	-14.63	2.84	-10.97	288.40	124.93	44.53	-13.56	6.75	-11.54	231.32
13	105.96	48.21	-14.11	-10.13	-38.07	293.74	91.05	-34.03	-15.73	-13.47	-38.48	229.79
14	82.43	59.23	-18.05	-19.95	-36.22	242.84	77.75	-42.28	-15.81	-17.85	-35.21	208.77
15	-17.04	13.77	-11.58	-38.89	-22.65	224.30	-13.58	-32.11	-6.73	-38.22	-19.61	196.64
16	78.34	28.30	-17.28	-19.22	-12.96	206.82	62.14	-19.13	-19.37	-22.63	-15.74	187.00
17	106.06	13.62	-21.12	-19.22	-19.35	206.82	102.60	7.20	-22.65	-22.63	-20.62	187.00
18	-21.05	-12.25	-2.60	-16.81	-0.53	175.69	-14.50	-27.20	-5.01	-15.08	8.89	152.86
19	12.66	10.41	-11.75	-46.38	-5.57	178.23	20.96	-19.37	-9.83	-45.36	0.20	156.89
20	-31.64	-11.47	-18.09	-30.67	-23.68	222.81	-26.72	-35.33	-12.48	-31.77	-25.62	196.27

Figure A-0-3 Climate change impact on MDS1 based on observations and precipitation products data.

No	SSP245 (2050s)						SSP585 (2050s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	→ -4.54	→ -6.95	→ -3.59	→ 0.06	→ 3.37	→ -2.75	→ -7.96	→ -9.78	→ -6.53	→ -3.48	→ -0.10	→ -5.24
2	→ -4.25	→ -4.65	→ -4.05	→ 0.10	→ -1.50	→ -3.28	→ -7.16	→ -6.51	→ -7.08	→ -2.87	→ -4.68	→ -5.97
3	→ -4.29	→ -10.35	→ -1.69	→ 0.05	→ 1.52	→ -2.96	→ -7.50	→ -13.26	→ -4.87	→ -3.13	→ -2.26	→ -5.65
4	→ -3.58	→ -7.95	→ -1.76	→ 0.30	→ -1.97	→ -2.70	→ -6.97	→ -10.81	→ -7.46	→ -3.24	→ -5.34	→ -5.19
5	→ -0.42	→ -10.94	→ -5.94	→ -1.87	→ -2.81	→ -3.10	→ -6.75	→ -14.28	→ -8.16	→ -5.65	→ -7.07	→ -5.50
6	→ 0.42	→ -6.73	→ -3.40	→ 0.30	→ -3.32	→ -2.70	→ -5.29	→ -9.49	→ -6.53	→ -3.24	→ -6.65	→ -5.19
7	→ -4.07	→ -5.94	→ -2.67	→ 0.95	→ 1.08	→ -2.22	→ -7.20	→ -8.72	→ -5.68	→ -2.55	→ -2.40	→ -4.86
8	→ -4.03	→ -7.89	→ -3.20	→ 0.33	→ 1.07	→ -2.67	→ -7.22	→ -10.81	→ -6.53	→ -3.24	→ -2.78	→ -5.16
9	→ -6.32	→ -9.13	→ -6.86	→ -2.59	→ 6.67	→ -3.69	→ -8.67	→ -11.13	→ -8.73	→ -4.80	→ 4.31	→ -6.26
10	→ -5.68	→ -8.44	→ -4.33	→ 1.30	→ 8.14	→ -2.81	→ -8.63	→ -10.23	→ -5.35	→ -0.65	→ 9.05	→ -5.58
11	→ -5.10	→ -3.76	→ -3.35	→ -0.77	→ 1.36	→ -2.81	→ -7.72	→ -6.18	→ -5.13	→ -2.80	→ -1.11	→ -5.58
12	→ -4.89	→ -7.35	→ 0.61	→ -13.50	→ -1.14	→ -5.03	→ -8.52	→ -9.37	→ -9.93	→ -6.32	→ -4.80	→ -7.26
13	→ -5.71	→ -12.28	→ 0.06	→ -14.38	→ -2.63	→ -6.03	→ -8.48	→ -14.18	→ -9.07	→ -6.13	→ -4.87	→ -7.79
14	→ -4.57	→ -12.03	→ 4.77	→ -13.97	→ 1.40	→ -4.62	→ -10.19	→ -18.28	→ -9.33	→ -8.45	→ -5.11	→ -6.77
15	→ -3.71	→ -9.06	→ 4.29	→ -13.41	→ 5.83	→ -2.92	→ -6.84	→ -13.99	→ -7.12	→ -5.06	→ 2.55	→ -5.50
16	→ -4.56	→ -11.73	→ 0.65	→ -13.00	→ 1.45	→ -4.78	→ -7.94	→ -15.23	→ -9.00	→ -4.98	→ -1.89	→ -6.57
17	→ -4.97	→ -11.07	→ 4.73	→ -13.00	→ -0.09	→ -4.78	→ -8.21	→ -14.11	→ -4.75	→ -4.98	→ -3.37	→ -6.57
18	→ -3.22	→ -7.75	→ 0.02	→ -14.72	→ 1.49	→ -3.05	→ -6.54	→ -12.37	→ -9.95	→ -5.66	→ -2.97	→ -5.67
19	→ -3.23	→ -7.87	→ 6.33	→ -11.87	→ 6.70	→ -2.37	→ -6.20	→ -12.57	→ -8.22	→ -4.16	→ 3.20	→ -4.90
20	→ -3.67	→ -4.41	→ 4.65	→ -11.81	→ -0.85	→ -2.25	→ -6.98	→ -9.23	→ -8.24	→ -5.19	→ -4.86	→ -4.75
No	SSP245 (2080s)						SSP585 (2080s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	→ -8.01	→ -10.55	→ -5.89	→ -3.49	→ -1.01	→ -5.24	→ -11.78	→ -13.68	→ -9.63	→ -7.85	→ -2.18	→ -7.47
2	→ -7.39	→ -6.60	→ -6.20	→ -3.20	→ -4.75	→ -5.97	→ -10.57	→ -8.52	→ -9.41	→ -6.76	→ -8.93	→ -7.44
3	→ -7.87	→ -14.04	→ -4.47	→ -3.32	→ -2.52	→ -5.65	→ -11.90	→ -17.85	→ -8.69	→ -8.39	→ -7.77	→ -7.33
4	→ -7.18	→ -11.53	→ -6.86	→ -3.43	→ -5.72	→ -5.19	→ -11.20	→ -15.01	→ -10.92	→ -7.85	→ -10.54	→ -7.47
5	→ -7.02	→ -14.36	→ -8.09	→ -5.21	→ -7.22	→ -5.50	→ -11.64	→ -19.49	→ -14.11	→ -10.51	→ -13.57	→ -7.91
6	→ -5.57	→ -10.25	→ -6.01	→ -3.43	→ -6.90	→ -5.19	→ -9.80	→ -14.14	→ -9.65	→ -7.85	→ -12.17	→ -7.47
7	→ -7.32	→ -9.59	→ -4.86	→ -2.95	→ -2.89	→ -4.86	→ -11.63	→ -14.45	→ -9.65	→ -7.85	→ -6.56	→ -7.47
8	→ -7.03	→ -11.45	→ -5.99	→ -3.28	→ -3.14	→ -5.16	→ -11.08	→ -15.01	→ -9.65	→ -7.85	→ -6.22	→ -7.47
9	→ -8.99	→ -12.77	→ -10.17	→ -5.57	→ 1.22	→ -6.26	→ -13.42	→ -14.77	→ -13.93	→ -9.60	→ 1.75	→ -10.19
10	→ -8.97	→ -12.41	→ -8.56	→ -2.37	→ 3.10	→ -5.58	→ -13.59	→ -14.25	→ -9.00	→ -5.51	→ 9.03	→ -10.19
11	→ -8.40	→ -6.82	→ -7.31	→ -3.48	→ -2.68	→ -5.58	→ -12.85	→ -11.36	→ -9.90	→ -8.20	→ -6.85	→ -10.06
12	→ -6.89	→ -8.67	→ -9.42	→ -5.06	→ -4.65	→ -7.26	→ -9.65	→ -10.98	→ -13.18	→ -9.50	→ -9.33	→ -9.51
13	→ -7.75	→ -15.95	→ -9.58	→ -6.11	→ -5.85	→ -7.79	→ -10.06	→ -17.95	→ -12.76	→ -9.64	→ -9.88	→ -9.46
14	→ -7.60	→ -17.02	→ -6.63	→ -5.78	→ -2.24	→ -6.77	→ -11.05	→ -19.52	→ -10.02	→ -10.37	→ -6.10	→ -9.04
15	→ -7.26	→ -14.62	→ -7.58	→ -5.06	→ 0.70	→ -5.50	→ -11.01	→ -18.74	→ -10.59	→ -10.20	→ 0.11	→ -7.76
16	→ -7.47	→ -15.84	→ -9.22	→ -5.01	→ -2.53	→ -6.57	→ -11.41	→ -19.67	→ -12.86	→ -9.69	→ -7.12	→ -9.32
17	→ -7.32	→ -14.04	→ -4.79	→ -5.01	→ -3.81	→ -6.57	→ -11.22	→ -17.94	→ -8.88	→ -9.69	→ -8.81	→ -9.32
18	→ -6.63	→ -12.63	→ -10.07	→ -4.95	→ -3.17	→ -5.67	→ -10.87	→ -17.64	→ -15.44	→ -9.44	→ -8.08	→ -9.01
19	→ -6.21	→ -12.97	→ -8.27	→ -3.52	→ 1.40	→ -4.90	→ -9.89	→ -18.19	→ -11.38	→ -9.67	→ 0.07	→ -8.20
20	→ -7.35	→ -9.87	→ -7.74	→ -4.59	→ -4.58	→ -4.75	→ -10.98	→ -14.90	→ -11.02	→ -9.81	→ -10.63	→ -7.96

Figure A-0-4 Climate change impact on NDD1 based on observations and precipitation products data

	MWS1											
	SSP245 (2050s)						SSP585 (2050s)					
No	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	⇒161.71	↓12.01	⇒61.26	↓-15.77	↓-16.38	⇒221.67	⇒188.38	↓21.62	⇒80.86	↓-6.26	↓-11.15	↑275.42
2	⇒137.37	⇒182.97	⇒45.61	↓30.09	⇒72.74	⇒189.48	⇒172.63	⇒215.34	⇒68.95	⇒48.91	⇒93.60	↑253.59
3	⇒123.08	↓0.36	⇒61.05	↓-17.04	⇒44.57	⇒144.42	⇒167.51	↓16.29	⇒84.04	↓-2.85	⇒70.63	⇒204.53
4	⇒136.98	↓-18.31	⇒47.03	↓-16.99	⇒38.79	⇒213.89	⇒170.18	↓-9.46	⇒65.75	↓-6.89	⇒53.86	↑261.96
5	⇒157.53	⇒51.74	⇒62.15	↓27.06	⇒48.34	⇒180.17	⇒186.97	⇒74.53	⇒77.42	⇒51.50	⇒65.17	↑244.98
6	⇒147.14	↓-16.55	⇒59.32	↓-16.99	⇒40.84	⇒213.89	⇒194.53	↓-8.78	⇒80.18	↓-6.89	⇒66.40	↑261.96
7	⇒189.94	↓26.54	⇒58.47	↓-17.31	↓-12.46	⇒210.44	↑246.89	⇒49.08	⇒78.08	↓-7.17	↓-1.08	↑260.16
8	⇒159.71	↓-20.02	⇒58.65	↓-18.40	↓-6.91	⇒202.78	⇒215.99	↓-9.46	⇒80.18	↓-6.89	⇒5.39	↑261.96
9	⇒144.47	↓-23.78	⇒73.13	⇒43.45	↓-11.33	⇒185.83	⇒191.21	↓-15.81	⇒114.44	⇒66.28	↓-3.80	⇒238.78
10	⇒124.07	↓-31.05	↓18.11	↓9.91	↓-17.94	⇒170.48	⇒177.36	↓-19.63	⇒32.85	⇒31.44	↓-13.53	⇒236.17
11	⇒104.00	↓2.86	⇒43.37	⇒44.75	↓22.40	⇒170.48	⇒144.69	↓22.51	⇒68.27	⇒72.70	⇒42.78	⇒229.80
12	⇒118.04	⇒107.23	⇒119.66	⇒72.45	⇒39.31	⇒198.18	⇒131.98	⇒127.27	⇒137.17	⇒87.43	⇒49.86	⇒228.40
13	⇒222.23	⇒53.64	⇒116.42	⇒74.31	⇒53.35	⇒176.57	⇒243.62	⇒53.05	⇒128.11	⇒84.22	⇒63.59	⇒203.77
14	⇒144.86	↓11.94	⇒83.98	↓8.29	↓5.57	↑259.56	⇒205.60	↓26.90	⇒116.05	↓29.47	↓22.02	↑312.57
15	↓24.54	↓28.64	⇒58.79	↓-16.58	↓-1.94	⇒105.72	⇒46.00	⇒55.47	⇒80.99	↓-1.46	↓10.98	⇒143.17
16	⇒154.52	⇒52.99	⇒55.14	↓33.04	⇒44.97	⇒195.20	⇒187.32	⇒65.84	⇒76.62	⇒49.14	⇒65.84	⇒230.39
17	⇒181.55	⇒67.42	⇒48.23	↓33.04	⇒47.01	⇒195.20	⇒227.83	⇒86.70	⇒67.67	⇒49.14	⇒66.51	⇒230.39
18	⇒92.41	⇒112.98	⇒81.41	⇒66.60	↓32.77	⇒156.96	⇒141.71	⇒162.66	⇒105.74	⇒118.41	⇒53.31	⇒222.82
19	⇒86.69	⇒88.70	⇒41.16	↓-21.74	↓9.97	⇒150.96	⇒123.33	⇒125.53	⇒63.30	↓-4.48	↓25.42	⇒204.28
20	↓19.07	↓9.40	⇒49.10	↓-17.67	⇒38.53	⇒192.61	⇒46.04	↓32.12	⇒70.13	↓-7.36	⇒55.80	↑259.94
	SSP245 (2080s)						SSP585 (2080s)					
1	⇒198.13	↓30.04	⇒83.20	↓-2.90	↓-8.61	↑303.78	⇒220.08	↓42.65	⇒103.93	↓7.80	↓0.04	↑274.78
2	⇒187.96	↑254.11	⇒73.73	⇒58.55	⇒107.54	↑262.37	⇒207.11	⇒222.57	⇒90.60	⇒69.75	⇒122.32	⇒244.87
3	⇒176.92	↓18.62	⇒87.75	↓3.26	⇒74.01	⇒217.58	⇒180.80	↓30.58	⇒100.82	↓8.48	⇒88.26	⇒205.89
4	⇒176.24	↓-6.65	⇒67.33	↓-5.28	⇒58.98	↑302.67	⇒201.29	↓4.34	⇒87.52	↓7.80	⇒77.38	↑274.78
5	⇒210.20	⇒85.24	⇒88.29	⇒61.23	⇒80.02	↑251.16	⇒216.21	⇒95.37	⇒105.33	⇒69.77	⇒92.22	⇒237.66
6	⇒199.81	↓-6.27	⇒80.48	↓-5.28	⇒72.54	↑302.67	⇒225.43	↓6.18	⇒103.93	↓7.80	⇒92.68	↑274.78
7	↑273.28	⇒55.67	⇒79.93	↓-5.56	↓-0.65	↑299.56	↑278.52	⇒75.29	⇒103.93	↓7.80	↓13.92	↑274.78
8	↑250.80	↓-6.88	⇒81.84	↓-3.59	⇒6.99	↑306.89	⇒240.43	↓4.34	⇒103.93	↓7.80	↓21.63	↑274.78
9	⇒182.79	↓-13.32	⇒103.26	⇒65.33	↓0.09	⇒226.21	⇒204.07	↓-7.43	⇒93.83	⇒78.17	↓1.35	⇒242.89
10	⇒166.96	↓-21.21	↓33.44	↓30.27	↓-14.35	⇒220.53	⇒191.42	↓-10.29	↓35.02	↓45.85	↓-12.06	⇒243.07
11	⇒147.33	↓22.38	⇒71.77	⇒72.60	↓45.67	⇒220.53	⇒156.51	↓40.46	⇒73.31	⇒80.96	⇒55.26	⇒244.39
12	⇒132.27	⇒121.64	⇒140.78	⇒85.97	⇒51.48	⇒225.84	⇒122.75	⇒125.40	⇒141.97	⇒85.27	⇒54.64	⇒193.64
13	⇒235.31	⇒66.90	⇒132.97	⇒89.56	⇒64.67	⇒193.65	⇒228.26	⇒64.50	⇒130.92	⇒80.54	⇒65.30	⇒168.20
14	⇒187.29	↓33.40	⇒117.52	↓27.97	↓22.66	↑317.45	⇒201.30	↓40.31	⇒126.73	↓37.26	↓27.27	↑293.21
15	⇒56.62	⇒71.58	⇒84.54	↓2.56	↓10.34	⇒161.89	⇒61.84	⇒79.05	⇒97.70	↓9.16	↓18.73	⇒164.06
16	⇒185.97	⇒75.51	⇒83.69	⇒53.43	⇒74.03	⇒229.81	⇒200.32	⇒87.88	⇒91.37	⇒64.50	⇒75.44	⇒215.97
17	⇒226.60	⇒95.74	⇒72.95	⇒53.43	⇒71.26	⇒229.81	⇒234.70	⇒105.24	⇒80.83	⇒64.50	⇒79.37	⇒215.97
18	⇒142.52	⇒175.96	⇒108.82	⇒109.03	⇒48.72	⇒222.43	⇒164.89	⇒215.03	⇒139.23	⇒135.79	⇒68.34	⇒245.90
19	⇒141.41	⇒154.56	⇒64.82	↓-1.44	⇒26.38	⇒228.03	⇒146.78	⇒169.83	⇒80.71	↓4.97	↓40.88	⇒229.42
20	⇒53.95	⇒50.56	⇒70.01	↓-5.98	⇒57.33	↑287.81	⇒61.78	↓27.46	⇒93.56	↓6.55	⇒78.36	↑281.95

Figure A-0-5 Climate change impact on MWS1 based on observations and precipitation products data

No	SSP245 (2050s)						SSP585 (2050s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	4.94	5.76	-3.14	-0.03	-8.78	13.36	3.32	8.10	4.24	4.59	-0.60	24.42
2	5.90	38.02	-3.01	-0.09	1.22	11.19	7.29	53.15	4.54	5.93	3.99	18.79
3	5.96	11.84	-3.60	-0.03	-1.61	10.57	7.45	15.16	3.26	-3.47	1.30	19.17
4	4.47	7.81	-1.85	-0.28	0.47	13.13	4.73	10.60	5.17	12.18	4.13	24.59
5	3.94	25.04	1.01	4.53	4.21	16.40	7.61	32.66	7.12	-20.57	7.16	30.20
6	2.72	7.13	-2.97	-0.28	9.07	13.13	5.05	10.04	4.24	18.69	8.57	24.59
7	10.48	9.41	-2.49	-0.96	-5.53	10.79	25.58	13.79	3.70	77.22	0.59	22.15
8	12.25	7.75	-3.10	-0.31	-6.21	12.98	33.22	10.60	4.24	101.65	0.83	24.59
9	13.29	6.31	6.81	3.67	-1.65	13.39	18.24	7.69	8.66	37.36	-1.06	20.33
10	9.74	5.83	2.07	-0.88	-0.61	10.85	14.77	7.07	2.56	61.57	-0.68	18.95
11	8.08	6.07	2.61	1.09	-1.05	10.85	12.23	9.95	4.00	11.85	0.88	17.83
12	10.07	68.65	-7.78	2.68	0.91	11.79	16.09	82.47	7.14	45.45	3.76	18.90
13	10.90	12.38	-7.30	3.23	1.91	14.62	14.78	13.33	6.44	55.02	3.53	19.59
14	7.97	10.85	-8.14	3.22	-0.72	15.33	16.44	15.57	8.21	36.13	2.70	22.00
15	6.73	16.41	-10.03	2.46	-1.93	13.33	11.06	23.98	4.18	17.96	-0.84	21.21
16	8.02	23.45	-8.26	2.30	-0.93	14.93	12.64	28.98	6.44	29.88	1.26	20.06
17	10.81	39.91	-11.53	2.30	0.09	14.93	16.30	48.67	2.87	49.35	2.64	20.06
18	10.19	25.39	-8.06	14.36	-0.65	15.02	18.65	38.44	7.51	-18.87	1.34	23.38
19	9.84	18.48	-10.05	-0.10	-2.47	9.88	16.93	27.92	4.32	65.40	-1.17	19.10
20	7.46	9.08	-9.86	0.81	0.91	9.78	12.70	17.51	4.75	56.01	5.08	19.87
No	SSP245 (2080s)						SSP585 (2080s)					
	OBS	CFSR	CHIRPS	JRA	ERA	PGF	OBS	CFSR	CHIRPS	JRA	ERA	PGF
1	8.67	8.72	4.64	5.57	0.42	25.27	13.17	11.30	6.23	10.20	0.50	36.01
2	10.17	53.84	4.84	7.48	5.04	20.26	15.14	69.46	6.01	12.25	8.58	25.25
3	10.89	16.03	3.87	-2.08	2.48	20.05	17.01	20.38	5.77	5.28	6.91	29.54
4	8.90	11.29	5.63	13.45	5.40	25.05	14.42	14.69	7.53	18.51	9.23	36.01
5	9.94	32.82	8.14	-20.18	8.35	28.92	17.13	44.51	12.26	-11.20	14.75	41.57
6	7.63	10.82	4.70	20.03	10.09	25.05	13.98	14.93	6.24	25.38	16.80	36.01
7	18.76	15.12	4.33	79.62	1.58	23.47	30.78	22.78	6.24	88.52	3.07	36.01
8	21.28	11.22	4.64	103.63	1.76	24.88	34.64	14.69	6.24	113.01	2.96	36.01
9	18.87	8.80	10.07	38.72	-0.31	16.28	29.02	10.18	13.79	46.02	-0.69	33.34
10	15.33	8.55	4.08	63.43	-0.24	14.07	23.86	9.82	4.29	66.88	-0.77	33.34
11	13.02	10.96	5.67	12.85	2.09	14.07	20.92	18.26	7.68	19.96	4.77	32.92
12	14.17	80.84	7.60	44.76	3.63	16.98	20.48	102.35	10.85	52.28	6.73	22.23
13	14.75	16.05	7.71	56.34	4.22	18.84	19.70	18.07	10.46	61.39	6.63	22.88
14	13.22	15.32	7.10	33.44	1.18	22.43	19.89	17.58	9.82	40.28	2.68	29.92
15	13.13	26.46	5.33	19.28	-0.23	25.03	20.64	33.91	7.70	28.03	-0.37	35.33
16	13.10	31.61	7.49	31.22	1.67	20.49	20.55	39.24	10.67	38.33	4.19	29.04
17	15.86	50.58	3.76	50.89	2.97	20.49	25.03	64.59	7.20	59.06	6.29	29.04
18	20.89	41.31	8.50	-19.41	1.42	27.85	35.50	57.67	13.39	-3.60	3.13	44.24
19	18.86	30.43	5.13	65.72	-0.52	20.30	31.33	42.66	7.25	80.87	-0.35	33.94
20	14.86	20.26	5.22	56.51	4.78	20.52	23.08	30.60	7.70	64.49	10.27	34.37

Figure A-0-6 Climate change impact on NWD1 based on observations and precipitation products data

Table A-1 Pearson's significance table

Pearson's Significance Table

df \ α	0.2	0.1	0.05	0.02	0.01	0.001
1	0.951057	0.987688	0.996917	0.999507	0.999877	0.999999
2	0.800000	0.900000	0.950000	0.980000	0.990000	0.999000
3	0.687049	0.805384	0.878339	0.934333	0.958735	0.991139
4	0.608400	0.729299	0.811401	0.882194	0.917200	0.974068
5	0.550863	0.669439	0.754492	0.832874	0.874526	0.950883
6	0.506727	0.621489	0.706734	0.788720	0.834342	0.924904
7	0.471589	0.582206	0.666384	0.749776	0.797681	0.898260
8	0.442796	0.549357	0.631897	0.715459	0.764592	0.872115
9	0.418662	0.521404	0.602069	0.685095	0.734786	0.847047
10	0.398062	0.497265	0.575983	0.658070	0.707888	0.823305
11	0.380216	0.476156	0.552943	0.633863	0.683528	0.800962
12	0.364562	0.457500	0.532413	0.612047	0.661376	0.779998
13	0.350688	0.440861	0.513977	0.592270	0.641145	0.760351
14	0.338282	0.425902	0.497309	0.574245	0.622591	0.741934
15	0.327101	0.412360	0.482146	0.557737	0.605506	0.724657
16	0.316958	0.400027	0.468277	0.542548	0.589714	0.708429
17	0.307702	0.388733	0.455531	0.528517	0.575067	0.693163
18	0.299210	0.378341	0.443763	0.515505	0.561435	0.678781
19	0.291384	0.368737	0.432858	0.503397	0.548711	0.665208
20	0.284140	0.359827	0.422714	0.492094	0.536800	0.652378
21	0.277411	0.351531	0.413247	0.481512	0.525620	0.640230
22	0.271137	0.343783	0.404386	0.471579	0.515101	0.628710
23	0.265270	0.336524	0.396070	0.462231	0.505182	0.617768
24	0.259768	0.329705	0.388244	0.453413	0.495808	0.607360
25	0.254594	0.323283	0.380863	0.445078	0.486932	0.597446
26	0.249717	0.317223	0.373886	0.437184	0.478511	0.587988
27	0.245110	0.311490	0.367278	0.429693	0.470509	0.578956
28	0.240749	0.306057	0.361007	0.422572	0.462892	0.570317
29	0.236612	0.300898	0.355046	0.415792	0.455631	0.562047
30	0.232681	0.295991	0.349370	0.409327	0.448699	0.554119
35	0.215598	0.274611	0.324573	0.380976	0.418211	0.518898
40	0.201796	0.257278	0.304396	0.357787	0.393174	0.489570
45	0.190345	0.242859	0.287563	0.338367	0.372142	0.464673
50	0.180644	0.230620	0.273243	0.321796	0.354153	0.443201
60	0.164997	0.210832	0.250035	0.294846	0.324818	0.407865
70	0.152818	0.195394	0.231883	0.273695	0.301734	0.379799
80	0.142990	0.182916	0.217185	0.256525	0.282958	0.356816
90	0.134844	0.172558	0.204968	0.242227	0.267298	0.337549
100	0.127947	0.163782	0.194604	0.230079	0.253979	0.321095
125	0.114477	0.146617	0.174308	0.206245	0.227807	0.288602
150	0.104525	0.133919	0.159273	0.188552	0.208349	0.264316
175	0.096787	0.124036	0.147558	0.174749	0.193153	0.245280
200	0.090546	0.116060	0.138098	0.163592	0.180860	0.229840

250	0.081000	0.103852	0.123607	0.146483	0.161994	0.206079
300	0.073951	0.094831	0.112891	0.133819	0.148019	0.188431
350	0.068470	0.087814	0.104552	0.123957	0.137131	0.174657
400	0.064052	0.082155	0.097824	0.115997	0.128339	0.163520
450	0.060391	0.077466	0.092248	0.109397	0.121046	0.154273
500	0.057294	0.073497	0.087528	0.103808	0.114870	0.146436
600	0.052305	0.067103	0.079920	0.094798	0.104911	0.133787
700	0.048427	0.062132	0.074004	0.087789	0.097161	0.123935
800	0.045301	0.058123	0.069234	0.082135	0.090909	0.115981
900	0.042711	0.054802	0.065281	0.077450	0.085727	0.109385
1000	0.040520	0.051993	0.061935	0.073484	0.081340	0.103800
1500	0.033086	0.042458	0.050582	0.060022	0.066445	0.084822
2000	0.028654	0.036772	0.043811	0.051990	0.057557	0.073488
3000	0.023397	0.030027	0.035775	0.042457	0.047006	0.060027
4000	0.020262	0.026005	0.030984	0.036773	0.040713	0.051996
5000	0.018123	0.023260	0.027714	0.032892	0.036417	0.046512

REFERENCES

- AARNES, O. J., REISTAD, M., BREIVIK, Ø., BITNER-GREGERSEN, E., INGOLF EIDE, L., GRAMSTAD, O., MAGNUSSON, A. K., NATVIG, B. and VANEM, E. (2017) Projected changes in significant wave height toward the end of the 21st century: Northeast Atlantic. *Journal of Geophysical Research: Oceans*, 122(4), 3394–3403.
- AHMED, K. F., WANG, G., SILANDER, J., WILSON, A. M., ALLEN, J. M., HORTON, R. and ANYAH, R. (2013) Statistical downscaling and bias correction of climate model outputs for climate change impact assessment in the U.S. northeast. *Global and Planetary Change*, 100, 320–332.
- ARSHAD, M., MA, X., YIN, J., ULLAH, W., LIU, M. and ULLAH, I. (2021) Performance evaluation of ERA-5, JRA-55, MERRA-2, and CFS-2 reanalysis datasets, over diverse climate regions of Pakistan. *Weather and Climate Extremes*, 33, 100373.
- ASADULLAH, A., McINTYRE, N., and KIGOBE, M. (2008) Evaluation of five satellite products for estimation of rainfall over Uganda / Evaluation de cinq produits satellitaires pour l'estimation des précipitations en Ouganda. *Hydrological Sciences Journal*, 53(6), 1137–1150.
- ASPELMEIER, J. (2005). *Table of critical values for Pearson's r*.
- ASSAMNEW, A. D., and MENGISTU TSIDU, G. (2023). Assessing improvement in the fifth-generation atmospheric reanalysis precipitation over East Africa. *International Journal of Climatology*, 43(1), 17–37.
- AYUGI, B., DIKE, V., NGOMA, H., BABAOUSMAIL, H., MUMO, R. and ONGOMA, V. (2021). Future Changes in Precipitation Extremes over East Africa Based on CMIP6 Models. *Water*, 13(17), 2358.

- AYUGI, B., NGOMA, H., BABAOUSMAIL, H., KARIM, R., IYAKAREMYE, V., LIM KAM SIAN, K. T. C. and ONGOMA, V. (2021). Evaluation and projection of mean surface temperature using CMIP6 models over East Africa. *Journal of African Earth Sciences*, 181, 104226.
- AYUGI, B., SHILENJE, Z. W., BABAOUSMAIL, H., LIM KAM SIAN, K. T. C., MUMO, R., DIKE, V. N., IYAKAREMYE, V., CHEHBOUNI, A. and ONGOMA, V. (2022). Projected changes in meteorological drought over East Africa inferred from bias-adjusted CMIP6 models. *Natural Hazards*, 113(2), 1151–1176.
- AYUGI, B., TAN, G., RUOYUN, N., BABAOUSMAIL, H., OJARA, M., WIDO, H., MUMO, L., NGOMA, N. H., NOONI, I. K. and ONGOMA, V. (2020). Quantile Mapping Bias Correction on Rossby Centre Regional Climate Models for Precipitation Analysis over Kenya, East Africa. *Water*, 12(3), 801.
- BEHRANGI, A., KHAKBAZ, B., JAW, T. C., AGHAKOUCHAK, A., HSU, K., and SOROOSHIAN, S. (2011). Hydrologic evaluation of satellite precipitation products over a mid-size basin. *Journal of Hydrology*, 397(3–4), 225–237.
- BI, D., DIX, M., MARSLAND, S., O’FARRELL, S., SULLIVAN, A., BODMAN, R., LAW, R., HARMAN, I., SRBINOVSKY, J., RASHID, H. A., DOBROHOTOFF, P., MACKALLAH, C., YAN, H., HIRST, A., SAVITA, A., DIAS, F. B., WOODHOUSE, M., FIEDLER, R. and HEERDEGEN, A. (2020) Configuration and spin-up of ACCESS-CM2, the new generation Australian Community Climate and Earth System Simulator Coupled Model. *Journal of Southern Hemisphere Earth Systems Science*, 70(1), 225–251.
- BLAU, M. T. and HA, K. -J. (2020). The Indian Ocean Dipole and its Impact on East African Short Rains in Two CMIP5 Historical Scenarios With and Without Anthropogenic Influence. *Journal of Geophysical Research: Atmospheres*, 125(16).

- BODJRENOU, R., COHARD, J.-M., HECTOR, B., LAWIN, E. A., CHAGNAUD, G., DANSO, D. K., N'TCHA M'PO, Y., BADOU, F. and AHAMIDE, B. (2023) Evaluation of Reanalysis Estimates of Precipitation, Radiation, and Temperature over Benin (West Africa). *Journal of Applied Meteorology and Climatology*, 62(8), 1005–1022.
- BONG, T., SON, Y.-H., YOO, S.-H. and HWANG, S.-W. (2018) Nonparametric quantile mapping using the response surface method – bias correction of daily precipitation. *Journal of Water and Climate Change*, 9(3), 525–539.
- BOUAGILA, B. and SUSHAMA, L. (2013). On the Current and Future Dry Spell Characteristics over Africa. *Atmosphere*, 4(3), 272–298.
- CHOU, C., CHIANG, J. C. H., LAN, C.-W., CHUNG, C.-H., LIAO, Y.-C. and LEE, C.-J. (2013). Increase in the range between wet and dry season precipitation. *Nature Geoscience*, 6(4), 263–267.
- DANABASOGLU, G., LAMARQUE, J. -F., BACMEISTER, J., BAILEY, D. A., DUVIVIER, A. K., EDWARDS, J., EMMONS, L. K., FASULLO, J., GARCIA, R., GETTELMAN, A., HANNAY, C., HOLLAND, M. M., LARGE, W. G., LAURITZEN, P. H., LAWRENCE, D. M., LENAERTS, J. T. M., LINDSAY, K., LIPSCOMB, W. H., MILLS, M. J., ... STRAND, W. G. (2020). The Community Earth System Model Version 2 (CESM2). *Journal of Advances in Modeling Earth Systems*, 12(2).
- DANIELS, A. E., MORRISON, J. F., JOYCE, L. A., CROOKSTON, N. L., CHEN, S.-C. and MCNULTY, S. G. (2012). *Climate Projections FAQ*.
- de PADUA, V. M. N. and AHN, K.-H. (2024). Toward the reliable use of reanalysis data as a reference for bias correction in climate models: A multivariate perspective. *Journal of Hydrology*, 644, 132102.

- DIEM, J. E., HARTTER, J., RYAN, S. J. and PALACE, M. W. (2014) Validation of Satellite Rainfall Products for Western Uganda. *Journal of Hydrometeorology*, 15(5), 2030–2038.
- DIEM, J. E., KONECKY, B. L., SALERNO, J. and HARTTER, J. (2019) Is equatorial Africa getting wetter or drier? Insights from an evaluation of long-term, satellite-based rainfall estimates for western Uganda. *International Journal of Climatology*, 39(7), 3334–3347.
- DIEM, J. E., SALERNO, J., BAILEY, K. and KONECKY, B. (2023). Comparisons of reanalysis and measured lower-troposphere winds over a portion of equatorial Africa. *International Journal of Climatology*, 43(15), 7082–7098.
- DINKU, T., FUNK, C., PETERSON, P., MAIDMENT, R., TADESSE, T., GADAIN, H. and CECCATO, P. (2018). Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society*, 144(S1), 292–312.
- DIRO, G. T., GRIMES, D. I. F., BLACK, E., O’NEILL, A. and PARDO-IGUZQUIZA, E. (2009). Evaluation of reanalysis rainfall estimates over Ethiopia. *International Journal of Climatology*, 29(1), 67–78.
- DOSIO, A., PINTO, I., LENNARD, C., SYLLA, M. B., JACK, C. and NIKULIN, G. (2021). What Can We Know About Recent Past Precipitation Over Africa? Daily Characteristics of African Precipitation From a Large Ensemble of Observational Products for Model Evaluation. *Earth and Space Science*, 8(10).
- DU, B., WU, L., RUAN, B., XU, L. and LIU, S. (2023). CMADS and CFSR Data-Driven SWAT Modeling for Impacts of Climate and Land-Use Change on Runoff. *Water*, 15(18), 3240.
- EDMOND MOELETSI, M., PHUMLANI SHABALALA, Z., DE NYSSCHEN, G. and WALKER, S. (2016) Evaluation of an inverse distance weighting method for patching

- daily and dekadal rainfall over the free state province, South Africa. *Water SA*, 42(3), 466–474. <https://doi.org/10.4314/wsa.v42i3.12>
- EHRET, U., ZEHE, E., WULFMEYER, V., WARRACH-SAGI, K. and LIEBERT, J. (2012) HESS Opinions "Should we apply bias correction to global and regional climate model data?" *Hydrology and Earth System Sciences*, 16(9), 3391–3404.
- ENAYATI, M., BOZORG-HADDAD, O., BAZRAFSHAN, J., HEJABI, S. and CHU, X. (2021). Bias correction capabilities of quantile mapping methods for rainfall and temperature variables. *Journal of Water and Climate Change*, 12(2), 401–419.
- ENDRIS, H. S., OMONDI, P., JAIN, S., LENNARD, C., HEWITSON, B., CHANG'A, L., AWANGE, J. L., DOSIO, A., KETIEM, P., NIKULIN, G., PANITZ, H.-J., BÜCHNER, M., STORDAL, F. and TAZALIKA, L. (2013) Assessment of the Performance of CORDEX Regional Climate Models in Simulating East African Rainfall. *Journal of Climate*, 26(21), 8453–8475.
- EYRING, V., BONY, S., MEEHL, G. A., SENIOR, C. A., STEVENS, B., STOUFFER, R. J. and TAYLOR, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–1958.
- EYRING, V., COX, P. M., FLATO, G. M., GLECKLER, P. J., ABRAMOWITZ, G., CALDWELL, P., COLLINS, W. D., GIER, B. K., HALL, A. D., HOFFMAN, F. M., HURTT, G. C., JAHN, A., JONES, C. D., KLEIN, S. A., KRASTING, J. P., KWIATKOWSKI, L., LORENZ, R., MALONEY, E., MEEHL, G. A., ... WILLIAMSON, M. S. (2019). Taking climate model evaluation to the next level. *Nature Climate Change*, 9(2), 102–110.
- FLATO, G., MAROTZKE, J., BABATUNDE, A. and PASCALE, B. (2013). *Evaluation of*

climate models. In Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

FRANÇOIS, B., VRAC, M., CANNON, A. J., ROBIN, Y. and ALLARD, D. (2020). Multivariate bias corrections of climate simulations: which benefits for which losses? *Earth System Dynamics*, 11(2), 537–562.

FUNK, C., VERDIN, A., MICHAELSEN, J., PETERSON, P., PEDREROS, D. and HUSAK, G. (2015). A global satellite-assisted precipitation climatology. *Earth System Science Data*, 7(2), 275–287.

GAMPE, D. and LUDWIG, R. (2017). Evaluation of Gridded Precipitation Data Products for Hydrological Applications in Complex Topography. *Hydrology*, 4(4), 53.

GARIBAY, V. M., GITAU, M. W., KIGGUNDU, N., MORIASI, D. and MISHILI, F. (2021). Evaluation of Reanalysis Precipitation Data and Potential Bias Correction Methods for Use in Data-Scarce Areas. *Water Resources Management*, 35(5), 1587–1602.

GITAU, W. (2011). *Diagnosis And Predictability Of Intraseasonal Characteristics Of Wet And Dry Spells Over Equatorial East Africa.*

GLEIXNER, S., DEMISSIE, T. and DIRO, G. T. (2020). Did ERA5 Improve Temperature and Precipitation Reanalysis over East Africa? *Atmosphere*, 11(9), 996.

GRUBER, A. and LEVIZZANI, V. (2008). *Assessment of Global Precipitation Products A project of the World Climate Research Programme Global Energy and Water Cycle Experiment (GEWEX) Radiation Panel.*

GUDMUNDSSON, L., BREMNES, J. B., HAUGEN, J. E. and ENGEN-SKAUGEN, T. (2012). Technical Note: Downscaling RCM precipitation to the station scale using

- statistical transformations – a comparison of methods. *Hydrology and Earth System Sciences*, 16(9), 3383–3390.
- HAILE, G. G., TANG, Q., HOSSEINI-MOGHARI, S., LIU, X., GEBREMICAEL, T. G., LENG, G., KEBEDE, A., XU, X. and YUN, X. (2020). Projected Impacts of Climate Change on Drought Patterns Over East Africa. *Earth's Future*, 8(7).
- HARADA, Y., KAMAHORI, H., KOBAYASHI, C., ENDO, H., KOBAYASHI, S., OTA, Y., ONODA, H., ONOGI, K., MIYAOKA, K. and TAKAHASHI, K. (2016) The JRA-55 Reanalysis: Representation of Atmospheric Circulation and Climate Variability. *Journal of the Meteorological Society of Japan. Ser. II*, 94(3), 269–302.
- HERSBACH, H., BELL, B., BERRISFORD, P., HIRAHARA, S., HORÁNYI, A., MUÑOZ-SABATER, J., NICOLAS, J., PEUBEY, C., RADU, R., SCHEPERS, D., SIMMONS, A., SOCI, C., ABDALLA, S., ABELLAN, X., BALSAMO, G., BECHTOLD, P., BIAVATI, G., BIDLOT, J., BONAVIDA, M. and THÉPAUT, J. (2020) The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049.
- INES, A. V. M. and HANSEN, J. W. (2006). Bias correction of daily GCM rainfall for crop simulation studies. *Agricultural and Forest Meteorology*, 138(1–4), 44–53.
- INGUULA ODONGO, R., ALEX OGWANG, B., KISEMBE, J. and NGOMA, H. N. (2022). An observational study of Lake Breeze over the Victoria basin in Uganda. *North American Academic Research*, 5(9), 109–123.
- KIMANI, M., HOEDJES, J. and SU, Z. (2017). An Assessment of Satellite-Derived Rainfall Products Relative to Ground Observations over East Africa. *Remote Sensing*, 9(5), 430.
- KOBAYASHI, S., OTA, Y., HARADA, Y., EBITA, A., MORIYA, M., ONODA, H., ONOGI, K., KAMAHORI, H., KOBAYASHI, C., ENDO, H., MIYAOKA, K. and TAKAHASHI,

- K. (2015). The JRA-55 Reanalysis: General Specifications and Basic Characteristics. *Journal of the Meteorological Society of Japan. Ser. II*, 93(1), 5–48.
- KOUAKOU, C., PATUREL, J.-E., SATGÉ, F., TRAMBLAY, Y., DEFRANCE, D. and ROUCHÉ, N. (2023) Comparison of gridded precipitation estimates for regional hydrological modeling in West and Central Africa. *Journal of Hydrology: Regional Studies*, 47, 101409.
- KUMAR, S., ALLAN, R. P., ZWIERS, F., LAWRENCE, D. M. and DIRMEYER, P. A. (2015). Revisiting trends in wetness and dryness in the presence of internal climate variability and water limitations over land. *Geophysical Research Letters*, 42(24).
- LE COZ, C. and VAN DE GIESEN, N. (2020). Comparison of Rainfall Products over Sub-Saharan Africa. *Journal of Hydrometeorology*, 21(4), 553–596.
- MAGGIONI, V., SAPIANO, M. R. P. and ADLER, R. F. (2016). Estimating Uncertainties in High-Resolution Satellite Precipitation Products: Systematic or Random Error? *Journal of Hydrometeorology*, 17(4), 1119–1129.
- MAIDMENT, R. I., ALLAN, R. P. and BLACK, E. (2015). Recent observed and simulated changes in precipitation over Africa. *Geophysical Research Letters*, 42(19), 8155–8164.
- MAIDMENT, R. I., GRIMES, D. I. F., ALLAN, R. P., GREATREX, H., ROJAS, O. and LEO, O. (2013). Evaluation of satellite-based and model re-analysis rainfall estimates for Uganda. *Meteorological Applications*, 20(3), 308–317.
- MAINTAINER, G. and GUDMUNDSSON, L. (2022). *Package “qmap” Title Statistical Transformations for Post-Processing Climate Model Output*.
- MARAUN, D., WETTERHALL, F., IRESO, A. M., CHANDLER, R. E., KENDON, E. J., WIDMANN, M., BRIENEN, S., RUST, H. W., SAUTER, T., THEMEßL, M., VENEMA,

- V. K. C., CHUN, K. P., GOODESS, C. M., JONES, R. G., ONOF, C., VRAC, M. and THIELE-EICH, I. (2010). Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user. *Reviews of Geophysics*, 48(3), RG3003.
- MEEHL, G. A., ARBLASTER, J. M. and TEBALDI, C. (2005). Understanding future patterns of increased precipitation intensity in climate model simulations. *Geophysical Research Letters*, 32(18).
- MEKONNEN, K., VELPURI, N. M., LEH, M., AKPOTI, K., OWUSU, A., TINONETSANA, P., HAMOUDA, T., GHANSAH, B., PARANAMANA, T. P. and MUNZIMI, Y. (2023) Accuracy of satellite and reanalysis rainfall estimates over Africa: A multi-scale assessment of eight products for continental applications. *Journal of Hydrology: Regional Studies*, 49, 101514.
- MENDOZA PAZ, S. and WILLEMS, P. (2022) Uncovering the strengths and weaknesses of an ensemble of quantile mapping methods for downscaling precipitation change in Southern Africa. *Journal of Hydrology: Regional Studies*, 41, 101104.
- MIRDASHTVAN, M., NAJAFINEJAD, A., MALEKIAN, A. and SA'DODDIN, A. (2018). Downscaling the contribution to uncertainty in climate-change assessments: representative concentration pathway scenarios for the South Alborz Range, Iran. *Meteorological Applications*, 25(3), 414–422.
- MISRA, S., PABITRA, S. S., HITESHRI, M. and SHASTRI, K. (2022). *Statistical Downscaling of High Resolution Precipitation in India using Convolutional Long Short Term Memory Networks*.
- MOGES, D. M., KMOCH, A. and UUEMAA, E. (2022). Application of satellite and reanalysis precipitation products for hydrological modeling in the data-scarce Porijõgi catchment,

- Estonia. *Journal of Hydrology: Regional Studies*, 41, 101070.
- MUBIALIWO, A., ABEBE, A. and ONYUTHA, C. (2021) Performance of rainfall–runoff models in reproducing hydrological extremes: a case of the River Malaba sub-catchment. *SN Applied Sciences*, 3(4), 515.
- MUGUME, I., NGAILO, T. and SEMYALO, R. (2020) Examining the Impact of Bias Correction on the Prediction Skill of Regional Climate Projections. *Atmospheric and Climate Sciences*, 10(04), 573–596.
- MUÑOZ-SABATER, J., DUTRA, E., AGUSTÍ-PANAREDA, A., ALBERGEL, C., ARDUINI, G., BALSAMO, G., BOUSSETTA, S., CHOULGA, M., HARRIGAN, S., HERSBACH, H., MARTENS, B., MIRALLES, D. G., PILES, M., RODRÍGUEZ-FERNÁNDEZ, N. J., ZSOTER, E., BUONTEMPO, C. and THÉPAUT, J.-N. (2021). ERA5-Land: a state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13(9), 4349–4383.
- NAJJUMA, M., NIMUSIIMA, A., SABIITI, G. and OPIO, R. (2021). Characterization of Historical and Future Drought in Central Uganda Using CHIRPS Rainfall and RACMO22T Model Data. *International Journal of Agriculture and Forestry*, 11(1), 9–15.
- NAKKAZI, M. T., SEMPEWO, J. I., TUMUTUNGIRE, M. D. and BYAKATONDA, J. (2022). Performance evaluation of CFSR, MERRA-2 and TRMM3B42 data sets in simulating river discharge of data-scarce tropical catchments: a case study of Manafwa, Uganda. *Journal of Water and Climate Change*, 13(2), 522–541.
- NGOMA, H., AYUGI, B., ONYUTHA, C., BABAOUSMAIL, H., LIM KAM SIAN, K. T. C., IYAKAREMYE, V., MUMO, R. and ONGOMA, V. (2022) Projected changes in rainfall over Uganda based on CMIP6 models. *Theoretical and Applied Climatology*, 149(3–4),

1117–1134.

NGOMA, H., WANG, W., AYUGI, B., BABAOUSMAIL, H., KARIM, R. and ONGOMA, V. (2020) *Evaluation of the Global Climate Models in CMIP6 over Uganda*.

NGOMA, H., WEN, W., OJARA, M. and AYUGI, B. (2021). Assessing current and future spatiotemporal precipitation variability and trends over Uganda, East Africa, based on CHIRPS and regional climate model datasets. *Meteorology and Atmospheric Physics*, 133(3), 823–843.

NICHOLSON, S. E. and KLOTTER, D. A. (2021). Assessing the Reliability of Satellite and Reanalysis Estimates of Rainfall in Equatorial Africa. *Remote Sensing*, 13(18), 3609.

O’NEILL, B. C., TEBALDI, C., VAN VUUREN, D. P., EYRING, V., FRIEDLINGSTEIN, P., HURTT, G., KNUTTI, R., KRIEGLER, E., LAMARQUE, J.-F., LOWE, J., MEEHL, G. A., MOSS, R., RIAHI, K. and SANDERSON, B. M. (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*, 9(9), 3461–3482.

OBUBU, J. P., MENGISTOU, S., FETAHI, T., ALAMIREW, T., ODONG, R. and EKWACU, S. (2021). Recent Climate Change in the Lake Kyoga Basin, Uganda: An Analysis Using Short-Term and Long-Term Data with Standardized Precipitation and Anomaly Indexes. *Climate*, 9(12), 179.

ONGOMA, V., CHEN, H. and GAO, C. (2019). Evaluation of CMIP5 twentieth century rainfall simulation over the equatorial East Africa. *Theoretical and Applied Climatology*, 135(3–4), 893–910.

ONGOMA, V., CHEN, H., GAO, C., NYONGESA, A. M. and POLONG, F. (2018). Future changes in climate extremes over Equatorial East Africa based on CMIP5 multimodel

- ensemble. *Natural Hazards*, 90(2), 901–920.
- ONYUTHA, C. (2016) Geospatial Trends and Decadal Anomalies in Extreme Rainfall over Uganda, East Africa. *Advances in Meteorology*, 2016, 1–15.
- ONYUTHA, C. (2018) Trends and variability in African long-term precipitation. *Stochastic Environmental Research and Risk Assessment*, 32(9), 2721–2739.
- ONYUTHA, C. (2020) Analyses of rainfall extremes in East Africa based on observations from rain gauges and climate change simulations by CORDEX RCMs. *Climate Dynamics*, 54(11–12), 4841–4864.
- ONYUTHA, C., ASIIMWE, A., AYUGI, B., NGOMA, H., ONGOMA, V. and TABARI, H. (2021). Observed and Future Precipitation and Evapotranspiration in Water Management Zones of Uganda: CMIP6 Projections. *Atmosphere*, 12(7), 887.
- ONYUTHA, C., TABARI, H., RUTKOWSKA, A., NYEKO-OGIRAMOI, P. and WILLEMS, P. (2016). Comparison of different statistical downscaling methods for climate change rainfall projections over the Lake Victoria basin considering CMIP3 and CMIP5. *Journal of Hydro-Environment Research*, 12, 31–45.
- PANOFSKY, H. A. and BRIER, G. W. (1968). *Some applications of statistics to meteorology*. Earth and Mineral Sciences Continuing Education, College of Earth and Mineral Sciences.
- PIANI, C., WEEDON, G. P., BEST, M., GOMES, S. M., VITERBO, P., HAGEMANN, S. and HAERTER, J. O. (2010). Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. *Journal of Hydrology*, 395(3–4), 199–215.
- QIAN, W. and CHANG, H. H. (2021) Projecting Health Impacts of Future Temperature: A Comparison of Quantile-Mapping Bias-Correction Methods. *International Journal of*

Environmental Research and Public Health, 18(4), 1992.

- ROSA, D. and COLLINS, W. D. (2013) A case study of subdaily simulated and observed continental convective precipitation: CMIP5 and multiscale global climate models comparison. *Geophysical Research Letters*, 40(22), 5999–6003.
- ROTH, V. and LEMANN, T. (2016) Comparing CFSR and conventional weather data for discharge and soil loss modelling with SWAT in small catchments in the Ethiopian Highlands. *Hydrology and Earth System Sciences*, 20(2), 921–934.
- SAHA, S., MOORTHY, S., WU, X., WANG, J., NADIGA, S., TRIPP, P., BEHRINGER, D., HOU, Y.-T., CHUANG, H., IREDELL, M., EK, M., MENG, J., YANG, R., MENDEZ, M. P., VAN DEN DOOL, H., ZHANG, Q., WANG, W., CHEN, M. and BECKER, E. (2014). The NCEP Climate Forecast System Version 2. *Journal of Climate*, 27(6), 2185–2208.
- SELAND, Ø., BENTSEN, M., OLIVIE, D., TONIAZZO, T., GJERMUNDSEN, A., GRAFF, L. S., DEBERNARD, J. B., GUPTA, A. K., HE, Y.-C., KIRKEVÅG, A., SCHWINGER, J., TJIPUTRA, J., AAS, K. S., BETHKE, I., FAN, Y., GRIESFELLER, J., GRINI, A., GUO, C., ILICAK, M. and SCHULZ, M. (2020). Overview of the Norwegian Earth System Model (NorESM2) and key climate response of CMIP6 DECK, historical, and scenario simulations. *Geoscientific Model Development*, 13(12), 6165–6200.
- SENATORE, A., FUOCO, D., MAIOLO, M., MENDICINO, G., SMIA TEK, G. and KUNSTMANN, H. (2022) Evaluating the uncertainty of climate model structure and bias correction on the hydrological impact of projected climate change in a Mediterranean catchment. *Journal of Hydrology: Regional Studies*, 42, 101120.
- SHARMA, OJHA, SHUKLA, PHAM, LINH, FAI, LOC,. and DUNG. (2019) Modified Approach to Reduce GCM Bias in Downscaled Precipitation: A Study in Ganga River

- Basin. *Water*, 11(10), 2097.
- SHEFFIELD, J., GOTETI, G. and WOOD, E. F. (2006). Development of a 50-Year High-Resolution Global Dataset of Meteorological Forcings for Land Surface Modeling. *Journal of Climate*, 19(13), 3088–3111.
- SLIVINSKI, L. C. (2018). Historical Reanalysis: What, How, and Why? *Journal of Advances in Modeling Earth Systems*, 10(8), 1736–1739.
- SMITH, S. R., LEGLER, D. M. and VERZONE, K. V. (2001). Quantifying Uncertainties in NCEP Reanalyses Using High-Quality Research Vessel Observations. *Journal of Climate*, 14(20), 4062–4072.
- SORIANO, E., MEDIERO, L. and GARIJO, C. (2019). Selection of Bias Correction Methods to Assess the Impact of Climate Change on Flood Frequency Curves. *Water*, 11(11), 2266.
- SUN, Q., MIAO, C., DUAN, Q., ASHOURI, H., SOROOSHIAN, S. and HSU, K. (2018). A Review of Global Precipitation Data Sets: Data Sources, Estimation, and Intercomparisons. *Reviews of Geophysics*, 56(1), 79–107.
- SWART, N. C., COLE, J. N. S., KHARIN, V. V., LAZARE, M., SCINOCCHA, J. F., GILLETT, N. P., ANSTEY, J., ARORA, V., CHRISTIAN, J. R., HANNA, S., JIAO, Y., LEE, W. G., MAJAESS, F., SAENKO, O. A., SEILER, C., SEINEN, C., SHAO, A., SIGMOND, M., SOLHEIM, L. and WINTER, B. (2019) The Canadian Earth System Model version 5 (CanESM5.0.3). *Geoscientific Model Development*, 12(11), 4823–4873.
- TAYLOR, K. E. (2001) Summarizing multiple aspects of model performance in a single diagram. In *JOURNAL OF GEOPHYSICAL RESEARCH* (Vol. 106, Issue D7).
- TAYLOR, K. E., STOUFFER, R. J. and MEEHL, G. A. (2012). An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society*, 93(4), 485–498.

- VAN DE VELDE, J., DEMUZERE, M., DE BAETS, B. and VERHOEST, N. E. C. (2022). Impact of bias nonstationarity on the performance of uni- and multivariate bias-adjusting methods: a case study on data from Uccle, Belgium. *Hydrology and Earth System Sciences*, 26(9), 2319–2344.
- van VUUREN, D. P., EDMONDS, J., KAINUMA, M., RIAHI, K., THOMSON, A., HIBBARD, K., HURTT, G. C., KRAM, T., KREY, V., LAMARQUE, J.-F., MASUI, T., MEINSHAUSEN, M., NAKICENOVIC, N., SMITH, S. J. and ROSE, S. K. (2011). The representative concentration pathways: an overview. *Climatic Change*, 109(1–2), 5–31.
- VIGNA, I., BIGI, V., PEZZOLI, A. and BESANA, A. (2020). Comparison and Bias-Correction of Satellite-Derived Precipitation Datasets at Local Level in Northern Kenya. *Sustainability*, 12(7), 2896.
- WAINWRIGHT, C. M., BLACK, E. and ALLAN, R. P. (2021). Future Changes in Wet and Dry Season Characteristics in CMIP5 and CMIP6 Simulations. *Journal of Hydrometeorology*, 22(9), 2339–2357.
- WANG, A. and ZENG, X. (2012). Evaluation of multireanalysis products with in situ observations over the Tibetan Plateau. *Journal of Geophysical Research: Atmospheres*, 117(D5).
- WANZALA, M. A., FICCHI, A., CLOKE, H. L., STEPHENS, E. M., BADJANA, H. M. and LAVERS, D. A. (2022). Assessment of global reanalysis precipitation for hydrological modelling in data-scarce regions: A case study of Kenya. *Journal of Hydrology: Regional Studies*, 41, 101105.
- WHEELER, M. C. and HENDON, H. H. (2004). An All-Season Real-Time Multivariate MJO Index: Development of an Index for Monitoring and Prediction. *Monthly Weather Review*, 132(8), 1917–1932.

- WILBY, R. L., WIGLEY, T. M. L., CONWAY, D., JONES, P. D., HEWITSON, B. C., MAIN, J. and WILKS, D. S. (1998). Statistical downscaling of general circulation model output: A comparison of methods. *Water Resources Research*, 34(11), 2995–3008.
- WONG, J. S., RAZAVI, S., BONSAI, B. R., WHEATER, H. S. and ASONG, Z. E. (2017). Inter-comparison of daily precipitation products for large-scale hydro-climatic applications over Canada. *Hydrology and Earth System Sciences*, 21(4), 2163–2185.
- WOOD, A. W., LEUNG, L. R., SRIDHAR, V. and LETTENMAIER, D. P. (2004). *Hydrologic Implications Of Dynamical And Statistical Approaches To Downscaling Climate Model Outputs*.
- WU, T., LU, Y., FANG, Y., XIN, X., LI, L., LI, W., JIE, W., ZHANG, J., LIU, Y., ZHANG, L., ZHANG, F., ZHANG, Y., WU, F., LI, J., CHU, M., WANG, Z., SHI, X., LIU, X., WEI, M. and LIU, X. (2019) The Beijing Climate Center Climate System Model (BCC-CSM): the main progress from CMIP5 to CMIP6. *Geoscientific Model Development*, 12(4), 1573–1600.
- YIN, J., GUO, S., GU, L., ZENG, Z., LIU, D., CHEN, J., SHEN, Y. and XU, C.-Y. (2021). Blending multi-satellite, atmospheric reanalysis and gauge precipitation products to facilitate hydrological modelling. *Journal of Hydrology*, 593, 125878.
- YUKIMOTO, S., KAWAI, H., KOSHIRO, T., OSHIMA, N., YOSHIDA, K., URAKAWA, S., TSUJINO, H., DEUSHI, M., TANAKA, T., HOSAKA, M., YABU, S., YOSHIMURA, H., SHINDO, E., MIZUTA, R., OBATA, A., ADACHI, Y. and ISHII, M. (2019). The Meteorological Research Institute Earth System Model Version 2.0, MRI-ESM2.0: Description and Basic Evaluation of the Physical Component. *Journal of the Meteorological Society of Japan. Ser. II*, 97(5), 931–965.
- ZHAN, W., GUAN, K., SHEFFIELD, J. and WOOD, E. F. (2016). Depiction of drought over

- sub-Saharan Africa using reanalyses precipitation data sets. *Journal of Geophysical Research: Atmospheres*, 121(18).
- ZHANG, L., KUMAR, A. and WANG, W. (2012). Influence of changes in observations on precipitation: A case study for the Climate Forecast System Reanalysis (CFSR). *Journal of Geophysical Research: Atmospheres*, 117(D8).
- ZHANG, X., ALEXANDER, L., HEGERL, G. C., JONES, P., TANK, A. K., PETERSON, T. C., TREWIN, B. and ZWIERS, F. W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. *WIREs Climate Change*, 2(6), 851–870.
- ZIEHN, T., CHAMBERLAIN, M. A., LAW, R. M., LENTON, A., BODMAN, R. W., DIX, M., STEVENS, L., WANG, Y. P. and SRBINOVSKY, J. (2020) The Australian Earth System Model: ACCESS-ESM1.5. *Journal of Southern Hemisphere Earth Systems Science*, 70(1), 193–214.