2025-01

Evaluation of Satellite/Reanalysis Rainfall Products for Simulating Rainfall Extremes in Jemma Sub-Basin

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MSc PROGRAM

EVALUATION OF SATELLITE/REANALYSIS RAINFALL PRODUCTS FOR SIMULATING RAINFALL EXTREMES IN JEMMA SUB-BASIN

MSC THESIS

BY

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JANUARY, 2025

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Evaluation of Satellite/Reanalysis Rainfall Products for Simulating Rainfall Extremes in Jemma Sub-Basin

M.Sc. Thesis

By

Selemon Tsegaye Wubetu

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science (M.Sc.) in "Environment and Climate Change"

Advisor: Temesgen Gashaw (Assoc. prof)

January, 2025

Bahir Dar, Ethiopia

THESIS APPROVAL SHEET

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As members of the Board of Examiners of the Master of Sciences (M.Sc.) thesis open defense examination, we have read and evaluated this thesis prepared by **Mr. Selemon Tsegaye Wubetu** entitled "**Evaluation of Satellite/Reanalysis Rainfall Products for Simulating Rainfall Extremes in Jemma Sub-Basin**". We hereby certify that the thesis is accepted for fulfilling the requirements for the award of the degree of Master of Sciences (M.Sc.) in "**Environment and Climate Change**".

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DECLARATION

This is to certify that this thesis entitled "**Evaluation of Satellite/Reanalysis Rainfall Products for Simulating Rainfall Extremes in Jemma Sub-Basin**" was submitted in partial fulfillment of the requirements for the award of the degree of Master of Science in "**Environment and Climate Change**" to the Graduate Program of College of Agriculture and Environmental Sciences, Bahir Dar University by Mr. **Selemon Tsegaye Wubetu** (ID. No. BDU 1500046) is an authentic work carried out by him under our guidance. This thesis is my work and has not been presented for a degree in any other university or any other award.

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ACKNOWLEDGMENTS

Above all, I give praise to the God and his mom St. Mary who gave me health, strength and patience during this study, and blessed and taking care of me throughout my life.

I would like to express my deepest gratitude to my advisor Dr. Temesgen Gashaw (Assoc. prof), for his assistant, inspiration, comments and constant encouragement throughout this study. I also a great gratitude to acknowledge Bahir Dar University, College of Agriculture and Environmental Sciences for financial support and friendship during my years of study and also for Ethiopian Meteorological Institute (EMI) for providing climate data.

I would like to give special thanks for my best friends, Mr. Melkamu Belay and Mr. Endege Aniley who continuous support, suggestion and advice for this thesis. Finally, but not least, my deepest gratitude for my father Mr. Tsegaye Wubetu, my mother Mrs. Malefiya Bekele, and other family members for their unconditional love, sacrifices and supported me by esteemed advice and consistent encouragement throughout this study.

LIST OF ABBREVIATIONS AND ACRONYMS

AEZ	Agroecological zone
CDD	Consecutive dry days
CHIRPS v2.0	Climate Hazard Group Infrared Precipitation with Stations
CSA	Central statistical agency of Ethiopia
CSI	Critical Success Index
CWD	Consecutive wet days
ECMFW	European Center for Medium-Range Weather Forecast
ERA5	The Fifth Generation ECMFW Reanalysis
ETCCDI	Expert Team on Climate Change Detection and Indices
FAR	False Alarm Ratio
FBI	Frequency Bias Index
GPCP	Global Precipitation Climatology Project
GEOS-5	Goddard Earth Observing System Model, Version 5
ITCZ	Inter-tropical convergent zone
KGE’	Kling Gupta Efficiency
MICE	Multivariate Imputation by Chained Equations
MERRA v2	Modern-Era Retrospective Analysis for Research and Application
MSWEP v2.8	Mult-Source Weighted Ensemble Precipitation
PBIAS	Percent bias
POD	Probability of Detection
r	Correlation Coefficient
R10mm	Number of heavy rainfall days >= 10
R20mm	Number of heavy rainfall days >= 20
R25mm	Number of heavy rainfall days >= 25
R95p	Very wet days
R99p	Extremely wet days
RMSE	Root means square error
RX1day	Max 1-day rainfall amount

RX5day	Max 5-day rainfall amount
SDII	Simple daily intensity index
TAMSAT v3.1	Tropical Application of Meteorology Using Satellite
UBNB	Upper Blue Nile-basin

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ABSTRACT

Reliable rainfall extreme simulation is critical for understanding extreme precipitation patterns and guiding climate adaptation strategies in regions like Jemma sub-basin, Ethiopia. This study evaluates the performance of five satellite/reanalysis rainfall datasets such as the Climate Hazards Group Infrared Precipitation with Stations, version 2.0 (CHIRPS v2.0), Tropical Applications of Meteorology using Satellite *and ground-based observations, version 3.1 (TAMSAT v3.1), Multi-Source Weighted-Ensemble Precipitation, version 2.8 (MSWEP v2.8), Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA v2) and ERA5 against observed data (2000-2023). The evaluation focused on simulating daily rainfall, detecting rainfall events, and capturing extreme rainfall indices across sub-tropical and temperate agroecological zones (AEZs) of Jemma sub-basin. For this study point to pixel evaluation approach was used and the Statistical metrics, including continuous statistical metrics such as root mean square error (RMSE), percent bias (PBIAS), Kling–Gupta efficiency (KGE'), and correlation coefficient (R), and categorical statistical metrics such as probability of detection (POD), false alarm ratio (FAR), critical success index (CSI), and frequency bias Index (FBI), were used to assess their performance by give the rank after calculating comprehensive rating index (CRI) value. The results revealed that based on CRI value MSWEP v2.8 has first ranked better performance than others products over sub-tropical and temperate AEZs at the daily time scales and also it is a better detecting capability of rainfall events. CHIRPS v2.0 demonstrated superior performance across different indices by holding first rank based on CRI value, proving particularly effective in simulating extreme rainfall indices. MSWEP v2.8 ranked second, showing notable strengths in the temperate AEZ. In contrast, ERA5 and MERRA v2 exhibited substantial biases and weaker correlations, indicating limited applicability. These findings highlight the importance of selecting region-specific rainfall datasets to improve disaster management, water resource planning, and sustainable agriculture in climate-vulnerable regions like the Jemma sub-basin.*

Keywords: *Agroecology zones, Performance evaluation, Extreme Rainfall Indices, disaster management*

CHAPTER 1. INTRODUCTION

1.1. Background of the study

The occurrence of weather or climate event that is above or below a threshold level is known as climate extreme, has been increasingly studied due to their widespread impacts on various sectors (IPCC, 2021). These events, including extreme rainfall, drought, and heatwaves, have shown a significant rise in frequency and intensity over recent decades, driven by climate change (Capua & Rahmstorf, 2023; IPCC, 2021; Liu *et al.*, 2023; Narayan *et al.*, 2024), Such changes profoundly affect the natural ecosystem, agriculture, economy development, and human life (Agyekum *et al.*, 2022; Ali *et al.*, 2022; Ali *et al.*, 2023; Liu *et al.*, 2023; Zhang *et al.*, 2024). Rainfall is one of the main climate parameters associated with extreme climate events (Jin *et al.*, 2024; Wang *et al.*, 2022), and its causes for some hazards like, floods, waterlogging, drought and landslides disasters (Jin *et al.*, 2024; Li *et al.*, 2024; Yao *et al.*, 2023). These events are increasingly recognized as one of the most common and impactful climate extremes due to their rising occurrence at both regional and global scales (Li *et al.*, 2024; Munzhedzi *et al.*, 2024).

In regions like Ethiopia, where rain-fed agriculture dominates and adaptation capacities remain limited, variations in rainfall intensity and distribution present critical challenges (Abdisa *et al.*, 2022; Abera *et al.*, 2023; Temesgen *et al.*, 2023a). Rainfall extremes directly influence crop yields, water resources, and disaster management efforts, making accurate rainfall data essential for effective planning (Jemal, 2024a; Jemal *et al.*, 2022; Shalishe *et al.*, 2024; Temesgen *et al.*, 2023b). However, traditional rainfall measurement methods, such as rain gauge networks, are often sparse in developing countries, leading to significant data gaps that hinder accurate monitoring and forecasting (Ayele *et al.*, 2018; Jemal *et al.*, 2022; Ollivier *et al.*, 2023). To bridge this gap, satellite/reanalysis rainfall products have gained prominence due to their high spatiotemporal resolution, near-global coverage, and ability to supplement ground-based observations in data-scarce regions (Jemal, 2024a; Kehase *et al.*, 2023; Solomon *et al.*, 2024; Temesgen *et al.*, 2023b).

Several satellite-based rainfall products have been developed to address the need for comprehensive precipitation monitoring. For example, the Climate Hazards Group InfraRed Precipitation with Stations, version 2.0 (CHIRPS v2.0) dataset combines satellite imagery with in-situ gauge data, offering daily rainfall estimates at a 5km resolution (Funk *et al.*, 2015; Tufa *et al.*, 2018). Similarly, Tropical Applications of Meteorology using Satellite data and ground-based observations, version 3.1 (TAMSAT v3.1) utilizes a cold cloud duration algorithm to estimate precipitation over Africa at a 4km spatial resolution (Getachew *et al.*, 2021). These datasets are widely used for drought and extreme monitoring, agricultural planning, and water resource management. Reanalysis datasets, such as ERA5 and Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA v2), offer additional advantages by integrating observations from multiple sources into climate models, providing consistent and long-term precipitation records (Gelaro *et al.*, 2017; Getachew *et al.*, 2021; Hersbach *et al.*, 2020). The Multi-Source Weighted-Ensemble Precipitation, version 2.8 (MSWEP v2.8) dataset further enhances accuracy by incorporating ground-based measurements, satellite observations, and reanalysis data (Li *et al.*, 2022).

While these products represent significant advancements, their performance varies across regions and climatic conditions. For instance, Subba *et al.* (2024) demonstrated the high accuracy of CHIRPS v2.0 and ERA5 in detecting extreme rainfall events in the hilly regions of Nepal. In contrast, CHIRPS v2.0 perform poorly for simulating rainfall extremes in arid regions of Iran (Zarrin & Dadashi-Roudbari, 2022). Similarly, TAMSAT v3.1 cold cloud duration method may underestimate rainfall in areas with sparse storm coverage, as reported by (Getachew *et al.*, 2021). In Ethiopia, recent evaluations by Endeg *et al.* (2023) revealed that MSWEP v2.8 consistently outperformed CHIRPS v2.0 in capturing daily rainfall patterns. However, its performance was less reliable in detecting high-intensity rainfall events. Solomon *et al.* (2024), also revealed the superior performance of MSWEP v2.8 than TAMSAT v3.1 and CHIRPS v2.0.

This study is particular importance as it addresses the critical need for accurate rainfall data in the Jemma sub-basin, where rain-fed agriculture and natural resource management are vital for livelihoods. By comparing widely-used satellite/reanalysis rainfall products, the findings will help identify the most reliable datasets for simulating rainfall extremes in this region. Such insights are crucial for enhancing early warning systems, disaster risk reduction, and sustainable agricultural planning. Furthermore, the research contributes to a growing body of work focused on improving the accuracy of climate datasets in complex terrains and under varying climatic conditions.

1.2. Statement of the Problem

Hydro-meteorological analyses requires high quality rainfall data (Sintayehu *et al.*, 2020). Understanding the intensity and frequency of extreme rainfall is very crucial, as it affects variety of socio-economic activities (Gebrekidan *et al.*, 2019; Subba *et al.*, 2024; Zhang *et al.*, 2024). However, ground-based measurement networks are either inadequate or nonexistent in both time and location in many populous areas of the world, such as Ethiopia (Getachew *et al.*, 2018).

Satellite/reanalysis rainfall products are alternative source of rainfall data (Amba *et al.*, 2024; Ndemere *et al.*, 2024). However, the accuracy of satellite/reanalysis products influenced by different factors. For instance, topography significantly influences precipitation patterns, and datasets like ERA5 have been found to overestimate rainfall in high-altitude regions due to coarse spatial resolution (Lavers *et al.*, 2022). Seasonal variability also affects dataset performance; certain products excel in capturing monsoonal rainfall but fail to detect short-duration, high-intensity events (Jiang *et al.*, 2024). Additionally, factors such as climate condition, sampling errors, and resolution also affect the performance of satellite/reanalysis products (Ayele *et al.*, 2018; Gizachew *et al.*, 2021; Mekonnen *et al.*, 2014). However, most of previous studies in Ethiopia to evaluate the performance of rainfall products have focused on using average values for the study area (Kindie *et al.*, 2022; Tesfa *et al.*, 2020). In addition, most studies in Ethiopia were also focused on rainfall total (Endeg *et al.*, 2023; Temesgen *et al.*, 2023b), except some studies like Kirubel *et al.* (2021), who evaluate the performance of satellite rainfall products for simulating extreme rainfall rates in the Upper Awash River Basin. Different studies conducted in different parts of Ethiopia indicates that the trend of rainfall extreme driven by climate change has diverse impacts on human life (Gebrekidan *et al.*, 2019; Gizachew *et al.*, 2023; Tegegn *et al.*, 2024), for monitoring the impacts we must have high quality and accessible rainfall data.

This study focuses on the Jemma sub-basin in Ethiopia, a region characterized by diverse agroecological zones and significant vulnerability to rainfall extremes. Previous researches highlighted the sub-basin's susceptibility to soil erosion, floods, and droughts due to extreme rainfall events (Daniel *et al.*, 2015; Gebrekidan *et al.*, 2019; Jemal *et al.*, 2024b; Tadele *et al.*, 2023). The evaluation of satellite/reanalysis rainfall products for simulating rainfall extremes over sub-tropical and temperate AEZs of Jemma sub-basin is essential for understanding their reliability in capturing the region's complex rainfall patterns. This is particularly important for enhancing disaster risk management, including flood and drought mitigation, and for developing sustainable soil and water conservation strategies to effectively combat the impacts of extreme rainfall events (Adnew & Woldeamlak, 2023; Kirubel *et al.*, 2021; Kirubel *et al.*, 2023).

In general, the purpose of this study is evaluating the performance of CHIRPS v2.0, TAMSAT v3.1, ERA5, MERRA v2, and MSWEP v2.8 in simulating rainfall extremes, and these products with high spatial and temporal resolution offer opportunities to monitor extreme rainfall events intensity and frequency. Identifying a rainfall product that accurately simulating rainfall extreme is crucial for effective flood and drought disaster risk management, and these datasets must undergo thorough validation process before used (Elsabet & Getachew, 2024; Houngnibo *et al.*, 2023). However, their accuracy in simulating extreme rainfall in the Jemma sub-basin is unknown. This research aims to identify the most reliable datasets for disaster management and climate adaptation planning in the Jemma sub-basin.

1.3. Objective

1.3.1. General objective

- The general objective of this study was to evaluate the performance of satellite/reanalysis rainfall products for simulate rainfall extremes over sub-tropical and temperate AEZs of Jemma sub-basin for the period 2000 to 2023.

1.3.2. Specific objective

The specific objectives of the study include;

- To compare the performance of satellite/reanalysis rainfall products for simulating daily rainfall total over sub-tropical and temperate AEZs of Jemma sub-basin.
- To evaluate rainfall occurrence detection capability of satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin at daily timescale.
- To evaluate the performance of satellite/reanalysis rainfall products for simulating extreme rainfall indices over sub-tropical and temperate AEZs of Jemma sub-basin.

1.4. Research Question

- Which satellite/reanalysis rainfall product has best performance for simulating daily rainfall total over sub-tropical and temperate AEZs of Jemma sub-basin?
- Which satellite/reanalysis rainfall product has the best capability of detecting rainfall occurrence (rainy and non-rainy days) over sub-tropical and temperate AEZs of Jemma sub-basin?
- Which satellite/reanalysis rainfall product has the best performance to simulate extreme rainfall indices over sub-tropical and temperate AEZs of Jemma sub-basin?

1.5. Significant of the Study

The purpose of this study is to assess the performance of satellite/reanalysis rainfall products for simulating extreme rainfall in the Jemma sub-basin. Satellite/reanalysis rainfall products have an alternative source for understanding extremes rainfall patterns, particularly in regions with limited availability of ground-based meteorological data. This study will helpful for researchers, decision makers, and farmers to fill the data gap problems.

The result identifies the best performing data sources for simulating rainfall extremes, which are crucial for mitigating the impacts of extreme rainfall events in the Jemma sub-basin. This, supports better decision-making in agriculture, disaster risk reduction, water resource planning, infrastructure development, and climate resilience.

1.6. Scope of Study

The study was covering sub- tropical and temperate AEZs of Jemma sub-basin and requires 24-year daily rainfall data (2000-2023). This data from satellite/reanalysis (CHIRPS v2.0, TAMSAT v3.1, ERA5, MERRA v2 and MSWEP v2.8) and ground-based data from Ethiopian Meteorological Institute (EMI) for seven stations on Jemma sub-basin, to assess the accuracy of these satellite/reanalysis rainfall products.

The performance of satellite/reanalysis rainfall products evaluated by using statistical metrics (continuous and categorical) and line graph for visual comparison. Continues statistical metrics including percent bias (PBIAS), correlation coefficient (r), root mean square error (RMSE), and Kling Gupta efficiency (KGE'). Categorical statistical metrics includes probability of detection (POD), false alarm ratio (FAR), critical success index (CSI), and frequency bias index (FBI).

CHAPTER 2. LITERATURE REVIEW

2.1. Over View of Precipitation Observation Techniques

As an essential part of the hydrological cycle, precipitation has a significant effect on ecosystems, agriculture, human society, and water supplies (Liu *et al.*, 2020; Rohatyn *et al.*, 2018). The precipitation observation databases are necessary for many applications, such as climate change research, water resource management, flood and drought monitoring, and weather forecasting (Duan *et al.*, 2020; Marye *et al.*, 2020). However, ground-based measurement networks either inadequate or nonexistent in both time and location in many populous areas of the world, especially in developing countries (Getachew *et al.*, 2018). The precipitation data sources are ground-based, satellite, and reanalysis-based (Macharia *et al.*, 2020; Sun *et al.*, 2018), describes below,

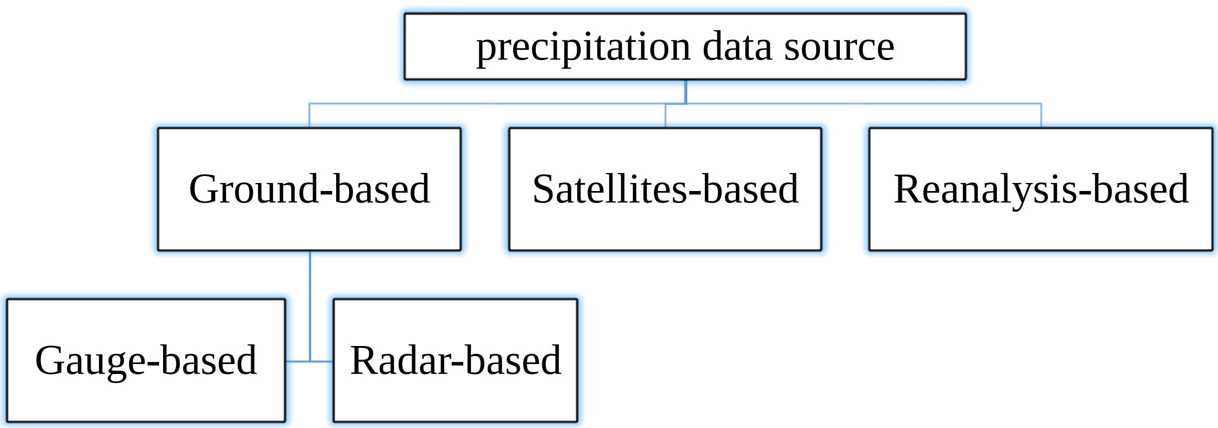


Figure 2. 1. Precipitation data source.

2.1.1. Ground based

Among the sources of precipitation data, ground-based observation networks have long been the main source of accurate precipitation observations.

2.1.1.1. Gauge-based

A gauge-based dataset is the most accurate kind of ground-based precipitation dataset, because provide point measurements (Gizachew *et al.*, 2021), and it influenced due to different factors like adjustments in instruments and data recorder problems. Rain gauges measure the depth or weight of precipitation over time using a measurement scale and tools (Allison *et al.*, 2009; Grimaldi *et al.*, 2018). Gauge-based datasets provide precise measurements and historical records, which are required for trend analysis, climate change research, and data validation (Beck *et al.*, 2020; Maidment *et al.*, 2014).

2.1.1.2. Radar-based

Radar-based precipitation estimation makes use of ground-based weather radar systems to record precipitation data at high-resolution (Chang *et al.*, 2016). Radar datasets covers large area and high spatial and temporal resolution (Sahlaoui & Mordane, 2019), making it is ideal for short-term forecasting and flood risk management (Lengfeld *et al.*, 2020). The radar-based precipitation measurements have limitations that affect the quality of rainfall measurement, due to the attenuation of the radar signal by several factors (Sahlaoui & Mordane, 2019).

2.1.2. Satellites-based

Global satellite precipitation products with high spatial and temporal resolution have been successively available in the recent decades. These products are generated through combined use of infrared (IR) and passive microwave (PMW) observations from multiple satellite sensors (Guo *et al.*, 2015; Sist *et al.*, 2021). Satellite-based precipitation products have significant importance for regional and global hydrological studies, especially for remote regions and developing countries because they have large-scale coverage, high spatial and temporal resolution. Moreover, these high-resolution products have been increasingly used in a wide range of applications, such as natural hazards (e.g., flood, drought and landslide) monitoring, water resource management, climate research, and hydrology-related fields (Xue *et al.*, 2013; Yong *et al.*, 2014).

2.1.3. Reanalysis-based

Reanalysis-based precipitation is used a widespread collection of observational data from various sources and models to produce a temporally and spatially continuous global or regional best estimate of numerous atmospheric, terrestrial and oceanographic variables (Bosilovich *et al.*, 2008; Kistler *et al.*, 2001). Reanalysis precipitation products response to the need for long-term, accurate, and consistent precipitation data sets for hydrological and meteorological applications. These products provide high spatial and temporal resolution precipitation data at global, regional, and local scales by combining observations and model outputs (Ramon *et al.*, 2019). Global coverage, long-term consistency, and high spatial-temporal resolutions are among the benefits of reanalysis precipitation products (Su & Feng, 2015). These products evaluation and validation are critical for ensuring reliable and accurate precipitation data for a variety of applications (Jiang *et al*., 2021).

2.2. Factors Affecting the Performance of Satellite/Reanalysis Rainfall Products

The ground based stations in many areas of the world such as Ethiopia are sparsely located and non-adequate (Getachew *et al.*, 2018; Tufa *et al.*, 2022) but many activities requires climate data (Jemal *et al.*, 2022; Temesgen *et al.*, 2023b). Satellite/reanalysis products are alternative sources (Getachew *et al.*, 2018; Gizachew *et al.*, 2021), and they requires performance evaluation with ground based data to identify the accuracy of those products (Aster *et al.*, 2021; Beck *et al.*, 2017; C. Li *et al.*, 2018), because the performance is varies from region to region in case of different factors (Aster *et al.*, 2021). The results of different studies show that the performance of satellite/reanalysis products affected by topography and season (Getachew *et al.*, 2018; Tufa *et al.*, 2018), climatic conditions (Nguyen *et al.*, 2018), spatial resolution of satellite/reanalysis products (Kofidou *et al.*, 2023) and measurement error and sampling (Gizachew *et al.*, 2021; Mekonnen *et al.*, 2014).

2.3. Performance Evaluation Techniques of Satellite/Reanalysis Products

Evaluating the performance of satellite/reanalysis products require different statistical metrices (categorical and continues) and graphical techniques. The common categorical statistical metrices used to determine detecting capability of satellite/reanalysis rainfall products are probability of detection (POD), false alarm ratio (FAR), critical success index (CSI), frequency bias index (FBI). The study conducted by, Endeg *et al.* (2023) over Ethiopia and Solomon *et al.* (2024) over Abay basin, used POD, FAR, CSI, and FBI. In addition, Temesgen *et al.* (2023b) used POD, FAR, and FBI categorical statistical metrices to determine detecting capability of satellite/reanalysis rainfall products. The categorical statistical metric calculates only by using daily rainfall data.

The continues statistical metric have used to determine the performance of satellite/reanalysis rainfall products. The most common continuous statistical metrics are: Root mean square error (RMSE), Mean absolute error (MAE), Mean error (ME), Pearson correlation coefficient (r) and Coefficient of determination (R^2),Kling-Gupta Efficiency (KGE'), Nash-Sutcliffe Efficiency

(NSE), Percent bias (PBIAS), RMSE-observations standard deviation ratio (RSR), and Mean square error (MSE) (Moriasi *et al.*, 2007).

To determine the performance of rainfall products, different studies used different continues statistical metric. The study conducted by Ageet *et al.* (2022) used, *r*, ME, PBIAS, MAE, and RMSE, Ahmed *et al.* (2024) used, KGE', RMSE, and PBIAS, Tufa *et al.* (2018) used, MAE, ME, r, and PBIAS.

Graphical techniques provide a visual comparison of satellite/reanalysis and observed data by using different types of graph like, line, box, scatter, bar and other graphs and is considered a first overview of model performance (ASCE, 1993). The study conducted by Temesgen *et al.* (2023b) over Bale Eco-region in Southern Ethiopia used, line and bar graph and Endeg *et al.* (2023) in Ethiopia also used line, bar, and scatter graph to represent the performance of satellite/reanalysis rainfall products. Other studies like (Aster *et al.*, 2021; Gizachew *et al.*, 2021; Kirubel *et al.*, 2021), used different graphical techniques when conduct over different parts of Ethiopia.

2.4. Previous Findings on the Performance of Satellite/Reanalysis Rainfall Products

Numerous studies evaluate the performance of satellite/reanalysis rainfall products in different areas of the world for different purpose. Those studies used different statistical evaluation metrices with different number of stations, evaluation approach, and time period. For example, the study conducted by Gorjizadeh & Moridi (2024) comparative analysis of the performance of ERA5, CHIRPS v2.0, and other two datasets with 41 gauge observations at daily, monthly and annual time scale over Iran. The continuous statical metrics used for this study are RMSE, r, and relative bias (RBias), and for categorical statistical metrics use POD and FAR. Tayler diagram and line graphs used for visual comparison. A study by Kirubel *et al.* (2023), evaluate the accuracy of MSWEP v2.8, CHIRPS v2.0, TAMSAT v3.1, ERA5, and other four rainfall products over Africa through the period 2001–2020. the performance of the rainfall products quantified in ten African countries. Four continuous (RMSE, BIAS, R, and r) and five categorical (POD, FAR, CSI, and FBI) statistical metrics were used for performance evaluation at daily, monthly, and annually timescale. For visual comparison used scatter plot, boxplot, and Taylor diagram. In addition, Ageet *et al.* (2022), evaluate the performance of CHIRPS v2.0, MSWEP (v2.2 and v2.8) and other two products over equatorial east Africa with daily to annual time scale from 2001 to 2018 time period. The categorical statistical indices used for evaluation the detecting capability of rainfall products were POD, FAR, FBI, and Heidke skill score (HSS), and the performance of rainfall products evaluated using MAE, PBIAS, RMSE, and NSE continuous statistical metrices. The graphs used for visual comparison are line graph, boxplot and Tylor diagram.

In Ethiopia, Temesgen *et al.* (2023b), evaluate the performance of satellite/reanalysis rainfall products in the Bale Eco-Region (BER) in Southern Ethiopia from daily to annual time scale. The point to pixel evaluation approach was used and from categorical statistical metrices POD, FAR, and FBI and also from continuous statistical metrices such as r, MAE, RMSE, PBIAS, and KGE', were used for evaluating the rainfall products. In addition, Solomon *et al.* (2024), evaluating the performances of gridded satellite products in simulating the rainfall characteristics of Abay Basin, Ethiopia from the period 1991–2020, the rainfall products are CHIRPS v2.0, MSWEP v2.8, and TAMSAT v.3.1. The categorical statistical metrices use for this study to evaluate the detecting capability of rainfall products are POD, FAR, CSI, and FBI, and the performance of rainfall products evaluated by continuous statistical metrices (MAE, RMSE, PBIAS, r, and KGE'), and line, bar, and scatter graphs used for visual comparison. In addition, Awel *et al.* (2024) evaluate the performance of CHIRPS v2, MSWEP and TRMM rainfall products at daily and seasonal time scale over Bilate river basin, Ethiopia at different time scales by using point to pixel approach. The continuous (RMSE and R^2) and categorical (POD and FAR) statistical metric are used to evaluate the performance satellite rainfall products.

Table 2. 1. Performance of satellite/reanalysis rainfall products at difference area of the world.

Study area	Datasets	Main findings	Reference
Iran	ERA5, CHIRPS v2.0, and other two products	On daily scale, products of CHIRPS V2.0 and P-CDR present more consistency with ground observation data, ERA5 and P-CDR is found to be the best in capering monthly precipitation. CHIRPS v2.0 good spatial precipitation pattern, in agreement with ground observation	Gorjizadeh & Moridi (2024)

		data set at annual scale.	
Africa	MSWEP v2.8, CHIRPS v2.0, TAMSAT v3.1, ERA 5, and other 6 products	MSWEP v2.8 and CHIRPS v2.0 are best performance at daily time scale, and also CHIRPS v2.0 is best performance in monthly and seasonal scales the other product. TAMSAT v3.1 provide high resolution data then other but produced poor results for all temporal scales.	Kirubel *et al.* (2023)
Equatorial East Africa	CHIRPS, MSWEP (v2.2 and v2.8) and other two products	The three rainfall products perform well over four AEZs, in seasonal and annual time scale also perform very well over tropical, sub-tropical, and temperate AEZs, but, poor performance over alpine AEZ. MSWEP v2.8 had superior performance than CHIRPS v2.0 and TAMSAT v3.1 over tropical and sub-tropical AEZs while in temperate and alpine AEZs at daily time scale.	Ageet *et al.* (2022)
Bale Eco- Region Southern Ethiopia	MSWEP v2. 8, CHIRPS v2. 0 and TAMSAT v3.1	MSWEP v2.8 has better detection Capability of rainfall occurrence and CHIRPS v2.0 has better performance at monthly timescale over tropical, sub-tropical, and temperate AEZs. In addition, MSWEP v2.8 has better performance t han CHIRPS v2.0 and TAMSAT v3.1 at daily, dry season and annual time scales in temperate and tropical AEZs and also it has good performance in	Temesgen *et al.* (2023b)

		Sub-tropical AEZ in dry season and annual timescales.	
Upper Blue Nile basin	MSWEP v2.8, CHIRPS v2.0 and TAMSAT v3.1	The three rainfall products can detect rainfall occurrence over tropical, subtropical, temperate and alpine AEZs, but comparatively they showed low performance over alpine AEZ.	Solomon *et al.* (2024)
Bilate river basin, Ethiopia	TRMM, CHIRPS v2.0, MSWEP v2.8	The three products rainfall estimates are more or less comparably underestimate the ground-based gauge observation at daily and seasonal scales and MSWEP has the best probability of detection followed by TRMM at all observation stations whereas CHIRPS performs the least in the study area.	Awel *et al.* (2024)
Upper Blue Nile basin	MSWEP v2.2, CHIRPS v2.0 and other three products.	CHIRPS v2.0 and MSWEP v2.2 rainfall products showed better ability on monthly timescale for areas below 1500 m.a.s.l. and detect no-rain events (rain<1mm/day) correctly. But their skill decreases for higher intensity events.	Sintayehu *et al.* (2020)

2.5. Previous Findings on the Performance of Satellite/Reanalysis Rainfall Products for Simulating Rainfall Extreme

Variations in rainfall, whether excessive or insufficient, can lead to catastrophic events such as floods, drought, agricultural losses and loss of biodiversity. Rainfall information is an important input for disaster management, now a time due to high spatiotemporal resolution satellite/reanalysis products are the source of rainfall data, but before use must be undergo through evaluation process by using statistical and graphical techniques. For instance, Cavalcante *et al.* (2020) evaluate the performance of CHIRPS v2.0 for simulating extreme rainfall indices over the Brazilian Amazonia. Four continuous statistical metrics (r, ME, MAE and MRE) and for visual comparison line and box plot were used. There is different extreme rain fall indices used for this study such as, number of days with R ≥ 1 mm (np), Max 1-day rainfall amount (RX1day), Max 5-day rainfall amount (RX5day), Consecutive dry days (CDD), (Consecutive wet days) CWD, Simple daily intensity index (SDII), Number of heavy rainfall days (R10mm), R20mm, R50mm, Very wet days (R95p), Extremely wet days (R99p), R95pad, R99pad, and Annual total wet-day rainfall (PRCPTOT) indices. In addition, Zarrin & Dadashi-Roudbari (2022) evaluate the performance of CHIRPS v2.0, MSWEP v2.2, MERRA-2 and other datasets for simulating extreme rainfall indices over Iran. This study used four continues statistical metric such as RMSE, KGE'', MBE and PBIAS to evaluate the performance for simulating CDD, CWD, R10mm, R20mm, SDII, Rx1day indices.

The study conducted by, Subba *et al.* (2024) also evaluate the performance of CHIRPS v2.0, ERA5 and other datasets over Nepal. Four continuous (RMSE, MAE, R and PBIAS) and categorical (POD, FAR, CSI and ACC) statistical metric and for visual comparison line graph, box plot and Taylor diagram were used. The extreme rainfall indices used for this study are R10mm, R20mm, R25mm, CDD, CWD, RX1day, RX5day, R95p, R99p, SDII and PRCPTOT indices.

Table 2. 2. Performance of satellite/reanalysis rainfall products for simulating rainfall extreme at different part of the world.

Study area	Datasets	Main findings	Reference
Brazilian Amazonia	CHIRPS v2.0	CHIRPS v2.o rainfall product produces more similar results to rain gauge data for the indices PRCPTOT, nP, and R95p.	Cavalcante *et al.* (2020)
Iran	CHIRPS v2.0, MSWEP v2.2, MERRA v2 and other datasets	MSWEP v2.2 provide better performance than others and MEERA v2 less performance to estimate R10mm, R20mm and SDII indices in	Zarrin & Dadashi-Roudbari (2022)

		central and south eastern part of Iran. CHIRPS v2.0 product overestimate the CDD index and underestimated the CWD	
Beijing, China	MSWEP V2.2 and other datasets	MSWEP has higher accuracy in terms of the RX1day, CDD, CWD, SDII and PRCPTOT indices.	Li *et al.* (2022)
Nepal	CHIRPS v2.0, ERA5 and other datasets	CHIRPS v2.0 accurately estimate the number of days for rainfall exceeding 20 mm (R20mm), 25 mm (R25mm) and the simple daily intensity index (SDII) indices. ERA5 overestimate RX1day and PRCPTOT indices.	Subba *et al.* (2024)

2.6. Rainfall Extremes in Ethiopia

Ethiopia's climatic variability, influenced by factors such as the Indian Ocean Dipole and El Niño-Southern Oscillation, plays a pivotal role in shaping extreme rainfall events (Bereket *et al.*, 2021; Getachew *et al.*, 2019). More recently in 2015-2016, the country experienced the most intense El Nino in decades, triggering multiple droughts and flood disaster (Andualem & Gokcekus, 2020). Extreme rainfall disasters such as droughts or floods have long presented in Ethiopia with a challenge that has an impact on agricultural productivity, economic growth, and food security (Amogne & Yimer, 2024; Assefa & Degnet, 2021).

Yimer *et al.* (2018) examined the annual maximum CDD was decreased except in Amba Mariam station, and at the Dessie, Haik, and Wereilu stations were decreased significantly. The CWD trend increasing in all stations except Wereilu and its significant at Amba Mariam, Mekaneselam, and Dessie stations. The trends of the number of wet days, annual total wet day rainfall, and simple daily rainfall intensity index showed no significant in all six stations.

In addition, Gebrekidan *et al.* (2019), examined changes in extremes of daily rainfall and temperature in Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia from the period of 1981 to

2014. The trend of rainfall extreme is PRECPTOT, R95p, and R99p increase in the majority of stations and the R99p index in Fichie and Lemi stations were significant. All rainfall extreme indices (e.g., Rx1DAY, Rx5DAY, R99p, and R95p) were negative trend in Alemketema station. The Rx5day index trends significantly increase in Fichie and Mendida stations and the Rx1day trend significantly decrease in Alemketema station. The rainfall extreme of R10mm and R20mm in Fichie station and CWD in Debrebirhan and Mendida stations characterized by significant increase and CDD was significantly decreasing in Lemi station, and suggested that, the extreme rainfall indices showed an increase in most extreme rainfall indices in the Jemma sub-basin so that the extreme rainfall events may damages on socio-economic activities and ecosystems. The other studies conducted by (Getnet *et al.*, 2011), showed more than any other sub-basin in the Upper Blue Nile basin, the Jemma Sub-Basin is distinguished by significant levels of soil erosion and sedimentation.

(Jemal *et al.*, 2022) examine Changes in observed rainfall and temperature extremes in the Upper Blue Nile Basin of Ethiopia from 1980 to 2019. The result of Rainfall extremes indicates such as RX1day, Rx5day, CDD, R10mm, R20mm, PRECPTOT, R95p, and R99p showed an increasing trend in most of the stations and no significant trend was observed at any of the climate stations for very wet days (R95p). But Significant increasing trends in R99p (up to 4.06 days/year) in the Nedjo station, PRECPTOT in the Debre Berhan, RX1day and Rx5day in Debre Tabor, Rx5day in the northern, northern central (Bahir Dar), and eastern central (Fiche) regions of UBNB, R20mm in the central (Chagni) and Southwestern (Bedele) and significantly decrease Rx5day index in the central, western central, and northwestern regions, R10mm and R20mm in northwestern and central (Guduru station), CWD in the western central, SDII in the western central, northwestern, and northern (Debre Tabor station) parts of the upper blue Nile basin. The most rainfall indices revealed an increasing trend over large areas of the basin so it impacts on the hydro-ecosystem and socio-economic aspects of the Basin. Gizachew *et al.* (2023), conducted in Ethiopia indicates, the majority of rainfall extreme such as CDD, CWD, R20mm and R10mm showed an upward trend in most stations this indicates increased flood, seasonal droughts, crop damages, landslide, and soil erosion in Ethiopia, to monitor these impacts we must have high quality and easily accessible rainfall data sources.

2.7. Characteristics of Rainfall Extremes and its Impact

Climate change is causes of many weather and climate extremes in all regions of the world. Evidence of observed climate extremes such as heat waves, flood, droughts, and tropical cyclones (Behera, 2024; Seneviratne *et al.*, 2021). Increases in the frequency and intensity of droughts and floods anticipated changes in precipitation, temperature, humidity, soil moisture, runoff, and other crucial elements of the hydrologic cycle (Tabari, 2020).

The occurrence of a weather or climate variable value that is above or below a threshold is known as a climate extreme (IPCC, 2021). In recent decades climate extremes have profound effects on human life, the environment, the economy, and society, these events have received extensive attention (Agyekum *et al.*, 2022; Ali *et al.*, 2023; Raihan, 2023). Almost every element of human well-being, including the availability of water, agricultural productivity, and energy generation, will be impacted by climate extremes (Hettiarachchi *et al.*, 2018; Jeitany *et al.*, 2024). Climate extremes, particularly severe storms, landslides, floods, heatwaves, frequent droughts, and extreme cold events, seriously disrupt the crop production system of smallholders (Raza *et al.*, 2024). Subsistence farmers are particularly vulnerable to climate fluctuations from year to year due to their low adaptability and dependence on constant agricultural production (Melese, 2019; Schlenker & Lobell, 2010).

CHAPTER 3. MATERIALS AND METHODS

3.1. Description of the Study Area

The Jemma sub-basin, located in the south-eastern parts of Abbay Basin of Ethiopia. The sub-basin is situated between latitudes 9.12°-10.57°N and longitudes 38.7°-39.48°E(Fig. 3.1) (Gebrekidan *et al.*, 2018; Tadele *et al.*, 2023), covering approximately 15,166.77 km² and contributes 14% of the total annual flow to the Abbay basin (Jemal *et al.*, 2024b). Elevation in the region varies significantly, ranging from 1,032 m.a.s.l in the lowlands to 3,837 m.a.s.l in the highlands. This topographical variability impacts both the hydrological behavior of the sub-basin and its susceptibility to soil erosion, making it particularly vulnerable to extreme weather events such as heavy rainfall, floods and drought (Gebrekidan *et al.*, 2021; Jemal *et al.*, 2024b).

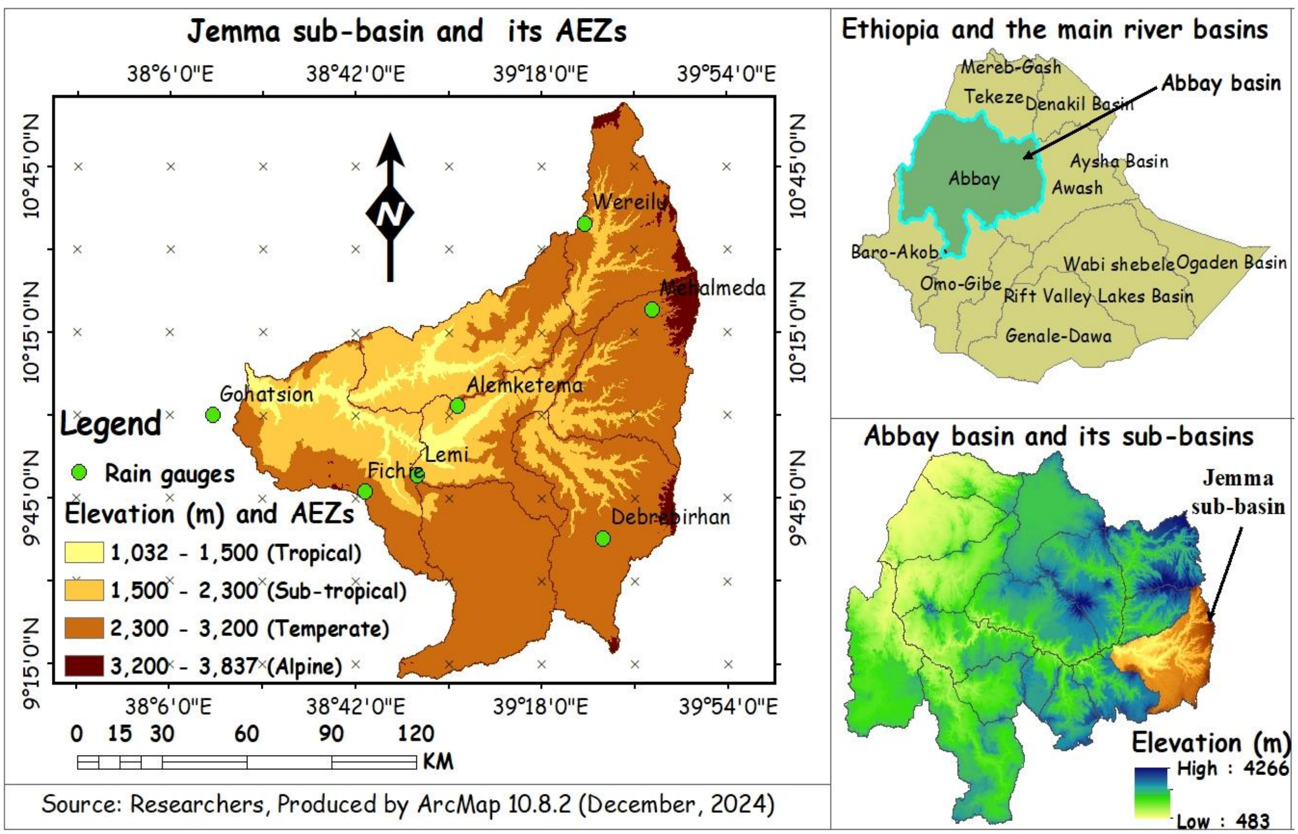


Figure 3. 1. Map of Jemma sub-basin and the spatial distribution of meteorological stations.

According to the long-term annual average rainfall (2000 to 2023) estimates from the observed meteorological stations, the mean annual precipitation ranges from 1079 mm in sub-tropical AEZ to 1106 mm in temperate AEZ (fig. 3.2). The region's rainfall distribution exhibits substantial spatial and temporal variation, with two main rainy seasons: the spring (March–May) and summer (June–August) seasons (Gebrekidan *et al.*, 2019; Tadele *et al.*, 2023). These variations are crucial for agriculture, as they directly influence the productivity of staple crops such as wheat, barley, teff, maize, and sorghum, which dominate the region's economy (Gebrekidan *et al.*, 2019). The Jemma sub-basin average annual temperature ranges from 9 °C to 24 °C (Gebrekidan *et al.*, 2021; Tadele *et al.*, 2023).

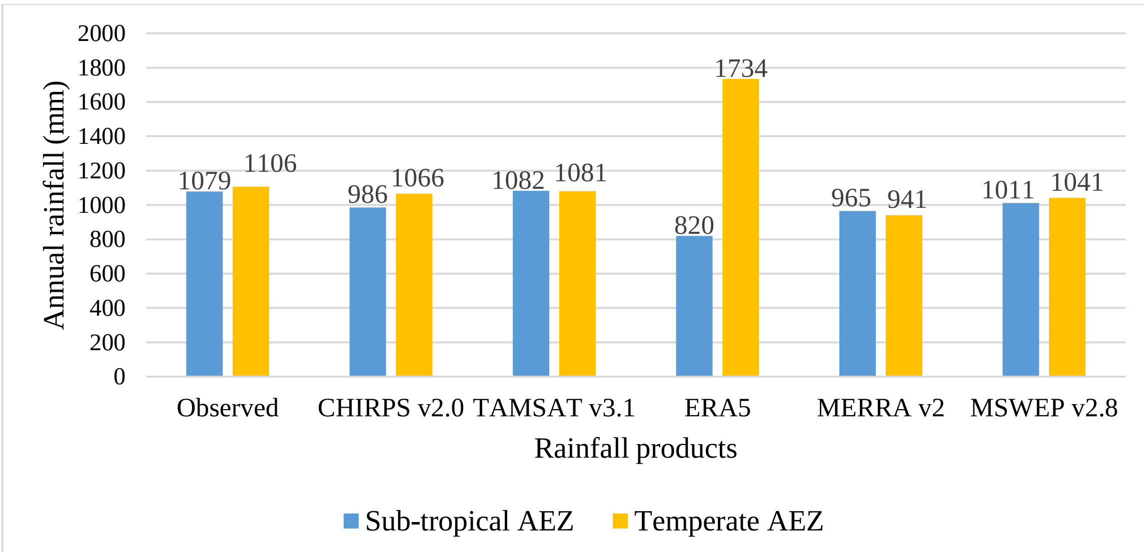


Figure 3. 2. The long-term annual average rainfall (2000 - 2023) values of the observed and satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin.

According to, the 2007 Ethiopian census, the total population of Jemma Sub-Basin was 1,605,876, with a population growth rate of 1.7 and an average population density of 106 people per square kilometer(CSA, 2007). The land cover within the sub-basin is primarily composed of agricultural land (56.72%), followed by grazing land (14.64%), shrublands (6.44%), and forests, which are minimal at 1.2% of the total area (Gebrekidan *et al.*, 2021).

3.2. Data Type and Source

3.2.1. Meteorological data and data quality control

The daily observed rainfall data for seven meteorological stations in the Jemma sub-basin (Table 3.1) were obtained from the Ethiopian Meteorological Institute (EMI) for the periods from 2000 to 2023. The study period, spanning 2000 to 2023, was selected based on the availability and completeness of observed rainfall data from meteorological stations in the Jemma sub-basin. The reason of this study used only seven stations because of no longer data series and high percentage of messing data > 25% of the other stations. The previous studies, Temesgen *et al.* (2023b) in the Bale Eco-Region (Southern Ethiopia), Endeg *et al.* (2023) in Ethiopia, and Amba *et al.* (2024) in Abaya–Chamo basin: Southern Ethiopia, used station observed data less than 20%, 25% and 10% missing values.

Table 3. 1. Description of study area meteorological station.

Stations	Longitude	Latitude	Elevation	AEZs	Missing data (%)	Period
Alemketema	39.03	10.03	2280	Sub-tropical	2.09	2000-2023
Debrebirhan	39.50	9.63	2750	Temperate	4.37	2000-2023
Fichie	38.73	9.77	2784	Temperate	4.01	2000-2023
Mehalmeda	39.66	10.32	3084	Temperate	4.93	2000-2023
Lemi	38.90	9.82	2500	Temperate	3.17	2000-2023
Gohatsion	38.24	10.0	2507	Temperate	5.61	2000-2023
Wereilu	39.44	10.58	2708	Temperate	5.01	2000-2023

The values of the missing data were filled with Multivariate Imputation by Chained Equations (MICE) algorithm (Buuren *et al.*, 2015). It is accessed through R statistical software (Core Team, 2015). The MICE algorithm fills missing values at a single station using the whole observed values of all inspected stations as predictors and every missing value is predicted multiple times, calculation uncertainties are taken into account and provides standard errors (Buuren *et al.*, 2015). As a result, compared to other techniques like inverse distance weighting (IDW) and multiple linear regression (MLR), the MICE algorithm performs better at filling in missing data.

Station-derived meteorological data influenced due to different factors, this leads to unreasonable values such as minimum temperature greater than maximum temperature, and negative rainfall values. Additionally, this may result in outliers, which are expressed as values that above or below the mean plus or minus four times the standard deviation of the daily value (Gebrekidan *et al.*, 2019). The quality of meteorological data of all station were controlled with RClimDex package (Zhang & Yang, 2004). The quality-controlled and imputed data were used for the evaluation of satellite/reanalysis rainfall products.

3.2.2. Satellite/reanalysis rainfall products

This study evaluates satellite/reanalysis rainfall products such as CHIRPS v2.0, TAMSAT v3.1, ERA5, MERRA v2, and MSWEP v2.8 for simulating rainfall extremes in Jemma sub-basin. These rainfall products selected due to their high spatial and temporal resolution, long time series and better detecting capability in different part of Ethiopia. The descriptions of these rainfall products are provided below.

CHIRPS v2.0 is a multi-source product data base developed by the United States Geological Survey and the Climate Hazards Group at the University of California, Santa Barbara (UCSB). CHIRPS v2.0 incorporates 5km (0.05^0) spatial resolution rainfall time series with daily temporal scale and quasi-global (50°S-50°N) coverage from 1981 to the present and at each pixel, a variety of temporal series are accessible, including daily, pentad (accumulation of five days), decadal (accumulation of ten days), and monthly, and it is a combined product of remotely sensed and gauge observation .In Ethiopia, CHIRPS v2.0 has used 76 meteorological/gauged observations(Funk *et al.*, 2014; Funk *et al.*, 2015). CHIRPS v2.0 is mainly developed for monitoring droughts and extremes (Endeg *et al.*, 2023). The dataset accessed on ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS v2.0.

TAMSAT v3.1 is a satellite-based rainfall estimation dataset developed for Africa including Madagascar by Reading University (Getachew *et al.*, 2021). TAMSAT v3.1 estimate rainfall by cloud index method (Gizachew *et al.*, 2021), and the algorithm works by determine cold cloud duration with a predetermined temperature threshold (obtained from Meteosat thermal-infrared images) of tropical storms (Getachew *et al.*, 2021). TAMSAT v3.1 has a spatial resolution of 0.0375° (4km), and data are available at the daily, pentadal (5 day), decadal (10 days), monthly and seasonal timescales and the data is available from 1983 to present (Getachew *et al.*, 2021; Gizachew *et al.*, 2021). TAMSAT v3.1 dataset is available at www.tamsat.org.uk.

MSWEP v2.8 is a globally available dataset. It was produced by integrating ground site data, satellite data, and reanalysis data. As a global precipitation product, MSWEP v2.8 has a temporal resolution of 3 h, daily, and monthly time scales and a spatial resolution of 0.1° (11 km) from

1979 to present (Beck *et al.*, 2019). The following features make MSWEP unique: (1) new data source; (2) improved weight diagram; (3) less estimation of peak precipitation; (4) longer data records; (5) near-real-time estimation; and (6) compatibility with multi-weather. The MSWEP v2.8 dataset is available at http://www.gloh2o.org/.

ERA5 (The latest European Centre for Medium-Range Weather Forecasts (ECMWF)) climate reanalysis is 5th generation and provides hourly estimates of a wide range of atmospheric, land, and oceanic climate variables. Reanalysis involves assimilating observations from various sources, including satellites, weather stations, and ocean buoys, into a numerical weather prediction model to produce a consistent and coherent representation of the Earth's atmosphere, land surface, and oceans over a specified period (Hersbach *et al.*, 2020). ERA5 provides data approximately 0.25° (30 km at the equator) spatial resolution and temporal resolution of hourly intervals from 1979 to the present (Lavers *et al.*, 2022). The ERA5 dataset acquired through website, https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5.

MERRA v2 is an atmospheric reanalysis that began in 1980. The data are derived from a combination of satellite and ground-based measurement. It was inspired by the realization that various aspects of the hydrologic cycle represented in previous generations of reanalysis were insufficient for climate and weather studies (Gelaro *et al.*, 2017), Version 5 of the Goddard Earth Observing System Model is being used, GEOS-5 data assimilation system, These techniques enable the use of observations from newer microwave sounders and hyperspectral infrared radiance instruments. MERRA-2 has generated precipitation and many other hydro-climate data products at 0.625° × 0.5° spatial resolution with one/ hour temporal resolution (Bosilovich *et al.*, 2015; Reichle *et al.*, 2017).

The MERRA-2 data are available online through the Goddard Earth Sciences (GES) Data and Information Services Center (DISC) https://goldsmr4.gesdisc.eosdi.nasa.gov/data/MERRAv2.0.

Table 3. 2. Description of satellite/reanalysis rainfall products.

Rainfall products	coverage	Spatial resolution	Temporal resolution	Data available	input
CHIRPS v2.0	50°S-50°N	0.05° (~5 km)	Daily	1981- present	TIR-satellite observation, Gauge

					Meteosat TIR imagery
TAMSAT v3.1	Africa	0.0375° (~4 km)	Daily	1983- present	Cold cloud duration
ERA5	Global	0.25° (~30 km)	Daily	1979 - present	Satellites, weather stations, and ocean buoys
MERRA-2	Global	0.5 × 0.625° (~50 km)	1h	1980- present	Satellite and ground-based measurement
MSWEP v2.8	Global	0.1° (~11 km)	3h	1979- present	Satellite estimates, Reanalysis data, Gridded gauge

3.3. Method of Analysis

When evaluating the performance of satellite/reanalysis rainfall products with observed rainfall, there is two general approaches can be used: point to pixel and pixel to pixel methods. For this study used point to pixel evaluation approach, as it is effective for assessing the performance of satellite/reanalysis products using point rainfall data from rain gauge observations. This method is particularly useful when rain gauge station networks are sparse, helping to detect extreme precipitation events and avoid errors due to uneven distribution and limited station locations (Ayele *et al.*, 2018; Cavalcante *et al.*, 2020; Kirubel *et al.*, 2021).

In contrast, the pixel-to-pixel method is used when there is a dense network of rain gauges and involves spatial interpolation of rainfall station data to match pixel-based satellite product data. However, this process can introduce uncertainties, especially when rainfall stations are unevenly distributed and sparsely located (Kiany *et al.*, 2020; Mahbod *et al.*, 2019). In this study, both the observed and extracted satellite/reanalysis rainfall products were grouped according to their respective AEZs, and daily rainfall values from stations within the same AEZ were averaged (Endeg *et al.*, 2023; Temesgen *et al.*, 2023b).

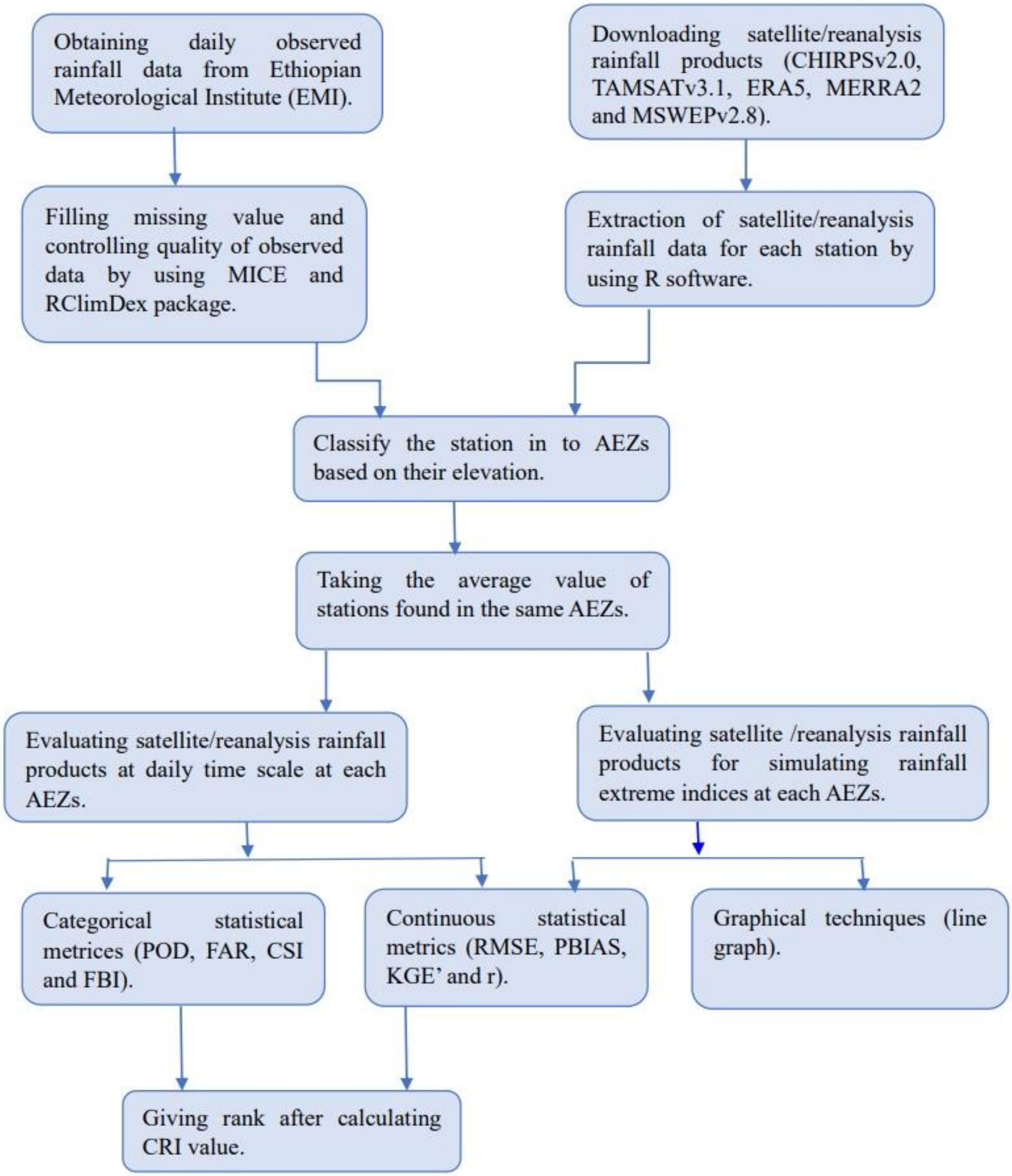


Figure 3. 3. Methodological flows.

3.3.1. Performance evaluation of rainfall Datasets

In this study, to evaluate the performance of satellite/reanalysis rainfall products for simulating daily time scales rainfall total and rainfall extreme indices over Jemma sub basin by using Continuous statistical metrics, such as RMSE, PBIAS, KGE', r and Graphical comparison technique (Palharini *et al.*, 2020; Solomon *et al.*, 2024; Temesgen *et al.*, 2023b; Xiao *et al.*, 2020).

The RMSE measures the magnitude of error between the satellite/reanalysis and observed rainfall values. RMSE values have a range from 0 to ∞, with a perfect score of 0 (Abdelmoneim *et al.*, 2020; Getachew *et al.*, 2018). PBIAS determines the average bias of the simulated data differ from the observed data by a certain amount. PBIAS value set to 0, with low magnitude levels denoting precise model simulation. Positive values show model underestimation bias, whereas model overestimation bias is indicated by negative values(Gupta *et al.*, 1999).

The KGE' is an objective performance metrics combining correlation, bias and variability. It decomposes the total performance of satellite/reanalysis datasets into three different terms with the same weight 1, the linear correlation (r) measuring the temporal rainfall dynamics, 2, the bias ratio (β) to measure the overestimation or underestimation compared to the ground based data, and 3, the variability ratio (γ) which is a relative measure of the dispersion (Kling *et al.*, 2012). The r is used to assess the agreement and linear association between satellite/reanalysis and rain gauge observations. The range of r between -1 to +1, with +1 indicate perfect positive and -1 indicate perfect negative score and also if the r value closest to 0 it indicates weak linear correlation (Moriasi *et al.*, 2007).

Table 3. 3. List of the continuous statistical metrics used for the evaluation of satellite/reanalysis rainfall products.

Evaluation Metrics	Equation	Unit	Range	Best Value
Root means square error (RMSE)	$RMSE = \sqrt{\frac{\sum_{I=1}^{n}(G-S)^2}{N}}$	mm	[0~∞)	0

Percent bias (PBIAS)	$PBIAS = \frac{\sum_{i=1}^{n}(G - S)}{\sum_{i=1}^{n}(G)} * 100$	%	(-∞-∞)	0
Kling Gupta efficiency (KGE'')	$KGE' = 1 - \sqrt{(r-1)^2 + (\beta - 1)^2 + (\gamma - 1)^2}$	-	(-∞ to 1]	1
Correlation coefficient(r)	$r = \frac{\sum_{i=1}^{n}(G - G_{mean})(S - S_{mean})}{\sqrt{(G - G_{mean})^2}\sqrt{\sum_{i=1}^{n}(S - S_{mean})^2}}$	-	[−1to1]	-1 or 1

Where, G is observed rainfall total at a gauge station, G_{mean} is the mean of observed rainfall total at reference gauging station, S is rainfall total for the satellite/reanalysis rainfall product, S_{mean} is the mean rainfall total of the satellite/ reanalysis rainfall products, N is the number of data pairs compared, r is Pearson's correlation coefficient, β is the bias component, γ is the variability component.

3.3.2. Evaluation of detecting Capability

The capabilities of satellite/reanalysis rainfall product to detecting rainfall occurrence examined by using different categorical statistical metrics like, POD, FAR, CSI and FBI statistical indicators (Kirubel *et al.*, 2021; Li *et al.*, 2022; Mulugojjam *et al.*, 2023). This study used rainfall threshold ≥1 mm to detect the rainy days (Table 3.4) (Endeg *et al.*, 2023; Solomon *et al.*, 2024; Temesgen *et al.*, 2023b).

Assessment system of satellite/reanalysis products estimation using a contingency table that reflects the frequency of "Yes" indicates an event will happen and "No" indicates the event will not happen.

Table 3. 4. Contingency table of the Satellite/reanalysis derived precipitation data and rainfall station data

Rain gage	Satellite/reanalysis	
	Yes	No
Yes	Hit	miss
No	false	0

POD represent the capability of Satellite/reanalysis rainfall products to detect the observed rain events correctly. FAR indicates the false detection of Satellite/reanalysis rainfall products. CSI indicates a summarized skill measure from POD and FAR. FBI evaluate the capability of satellite/reanalysis rainfall product to detect the frequency of rainy days compared to the observed data. Respectively, the value of POD, FAR, F and CSI is ranges from 0 to 1, with the perfect value is 1 for POD and CSI, Where 0 for FAR. The value of FBI is ranges from 0 to ∞, if the value less than 1 indicate underestimation and greater than 1 indicate over estimation of satellite/reanalysis, while 1 is the perfect value of FBI. For additional ideas of these categorical statistical matrices refer (Kirubel *et al.*, 2021; Sintayehu *et al.*, 2020; Temesgen *et al.*, 2023b).

Table 3. 5. List of the categorical statistical metrics used for the evaluation of satellite/reanalysis rainfall products.

Evaluation Metrics	Equation	Unit	Range	Best Value
Probability of Detection (POD)	$POD = \frac{N_{hit}}{N_{hit} + N_{miss}}$	-	0 to 1	1
False Alarm Ratio (FAR)	$FAR = \frac{N_{false}}{N_{hit} + N_{false}}$	-	0 to 1	0
Critical Success Index (CSI)	$CSI = \frac{N_{hit}}{N_{hit} + N_{miss} + N_{false}}$	-	0 to 1	1
Frequency Bias Index (FBI)	$FBI = \frac{N_{hit} + N_{false}}{N_{hit} + N_{miss}}$	-	0 to ∞	1

Where N_{hit} is the total count of days when both rainfall stations and satellite/reanalysis products observe rain, N_{false} is the total count of days when the satellite/reanalysis products detect rain that is not detected by the rainfall stations, N_{miss} is the total count of days when the satellite/reanalysis products miss rain that is detected by the rainfall stations.

The performance evaluation of satellite/reanalyses precipitation productes for this study used RMSE, PBIAS, KGE' and r Continuous statistical metrics, and POD, FAR, CSI and FBI categorical statistical metrics, by giving rank after calculating Comprehensive Rating Index (CRI) value (Guo *et al.*, 2021; Temesgen *et al.*, 2024; Zhang *et al.*, 2024).

$$CRI = 1 - \frac{1}{nm}\sum_{i=1}^{n} Rank_i$$

Where, n is the number of the continuous and/or categorical statistical metrics used for the evaluation of satellite/reanalysis rainfall products and m is the total number of satellite/reanalysis precipitation products. $Rank_i$ is the rank of the products (from 1 to 5) for each performance measure. The CRI value varies between 0 and 1, and, the better the performance product is the CRI value closer to 1.

3.3.3. Assessment of extreme rainfall index

The R-based statistical package of RClimDex v1.1 was created to efficiently analyze and process climate data, particularly for calculating various climate indices (WMO, 2009). The development of the RClimdex package, which is designed to calculate 27 core climate indices based on daily temperature and precipitation data, including 11 precipitation-related indices and 16 temperature-related indices (Wang & Feng, 2010).

In this study, as Expert Team on Climate Change Detection and Indices (ETCCDI) and World Meteorological Organization recommended 11 extreme rainfall indices (Table 3.6) are used to evaluate the performance of CHIRPS v2.0, TAMSAT v3.1, ERA5, MERRA v2, and MSWEP v2.8 for simulating rainfall extreme in the Jemma sub basin. Following Xiao *et al.* (2020), these indices grouped in to two based on their unit 1, extreme precipitation intensity, expressed in millimeters (example, rx1day, rx5day, R95p, R99p, SDII and PRCPTOT) and 2, extreme precipitation frequency, express in days (example, R10mm, R20mm, R25mm, CDD and CWD). The previous studies use these indices to evaluate the performance of rainfall products and models (Cavalcante *et al.*, 2020; Kirubel *et al.*, 2021; Medeiros *et al.*, 2022; Xiao *et al.*, 2020).

Table 3. 6. Rainfall indices and their definition

Indices	Indicator name	Definitions	Units
RX1day	Max 1-day rainfall amount	Monthly maximum 1-day rainfall	mm
RX5day	Max 5-day rainfall amount	Monthly maximum consecutive 5-day rainfall	mm
SDII	Simple daily intensity index	Annual total rainfall divided by the number of wet days (defined as PRCP>=1.0mm) in	mm/day

		the year	
R10mm	Number of heavy rainfall days	Annual count of days when PRCP>=10mm	Days
R20mm	Number of heavy rainfall days	Annual count of days when PRCP>=20mm	Days
R25mm	Number of heavy rainfall days	Annual count of days when PRCP>=25mm	Days
CDD	Consecutive dry days	Maximum number of consecutive days with RR<1mm	Days
CWD	Consecutive wet days	Maximum number of consecutive days with RR>=1mm	Days
R95p	Very wet days	Annual total PRCP when RR>95th percentile	mm
R99p	Extremely wet days	Annual total PRCP when RR>99th percentile	mm
PRCPTOT	Annual total wet-day rainfall	Annual total PRCP in wet days (RR>=1mm)	mm

CHAPTER 4. RESULTS AND DISCUSSIONS

4.1. The Performance of Satellite/Reanalysis Rainfall Products at Daily Time Scale

The performance of CHIRPS v2.0, TAMSAT v3.1, ERA5, MERRA v2, and MSWEP v2.8 rainfall products for simulating daily rainfall total from 2000 to 2023 over sub-tropical and temperate AEZs of Jemma sub-basin shows in Table 4.1. MSWEP v2.8 product consistently outperformed the other products in both sub-tropical and temperate AEZs, demonstrating its robustness in replicating observed daily rainfall data of the Jemma sub-basin. This performance aligns with the findings of Li *et al.* (2022), who evaluated MSWEP v2.8 in regions with complex topography and variable climate patterns, emphasizing the superior performance of MSWEP v2.8 due to its integrate with multiple data sources. The integration of satellite, ground, and reanalysis data allows MSWEP v2.8 to better capture the full range of precipitation events, including both light rain and extreme events, compared to other satellite-derived products that rely on single-source data.

The rank is given based on CRI value, the findings indicated that MSWEP v2.8 has superior performance with consistently ranks first across sub-tropical and temperate AEZs of Jemma sub-basin. the product showed the smallest RMSE and highest r values across both AEZs, indicating its effectiveness, and also in temperate AEZ, this product have highest KGE' value, it indicates superior performance in terms of capturing the temporal and spatial variability of precipitation. TAMSAT v3.1 and CHIRPS v2.0 are the second and third ranked best performing rainfall products. TAMSAT v3.1 achieved the lowest PBIAS value in both AEZs. In sub-tropical AEZ, it has high KGE' value. TAMSAT v3.1, recognized for its performance in Africa, demonstrated strong performance in accurately replicating observed daily rainfall events across both AEZs. As a result, its performance was slightly lower compared to MSWEP v2.8.

Similarly, CHIRPS v2.0 has gained widespread acceptance due to its high spatial resolution and calibration with ground-based rainfall station data, making it effective in capturing rainfall events in regions with dense vegetation or mountainous terrain (Jemal, 2024a; Temesgen *et al.*, 2023b). In contrast, ERA 5 is fourth ranked and MERRA v2 fifth ranked over sub-tropical AEZ, while MERRA v2 has fourth ranked and ERA 5 is fifth ranked over temperate AEZ, both of these rainfall products are weakly performing rainfall products at daily time scale over both AEZs of Jemma sub-basin.

According to PBIAS value all rainfall products are positive value except TAMSAT v3.1, which has a negative PBIAS value of -0.30% over sub-tropical AEZ. This indicates that, the products with positive PBIAS values are underestimating and TAMSAT v3.1 is overestimating daily rainfall. In the temperate AEZ, all rainfall products except ERA5 are underestimating daily rainfall, as indicated by their positive PBIAS values. The highest PBIAS value over both AEZs shows by ERA5 ranges from -26.80% in temperate AEZ to 24% in sub-tropical AEZ and it followed by MERRA v2 with highest PBIAS value over both AEZ. This underperformance aligns with findings from Zarrin & Dadashi-Roudbari (2022), who noted that reanalysis-based datasets like ERA5 tend to struggle with local precipitation variability, particularly in areas with complex topography, such as the Jemma sub-basin.

The result of this study aligned with different studies like, Solomon *et al.* (2024) in Abay Basin, who found that MSWEP v2.8 is superior performance than TAMSAT v3.1 and CHIRPS v2.0. Temesgen *et al.* (2023b) study conducted over the Bale Eco-Region (Southern Ethiopia) also indicate the better performance of MSWEP v2.8 than TAMSAT v3.1 and CHIRPS v2.0. Endeg *et al.* (2023), also found that MSWEP v2.8 is better performance than CHIRPS v2.0 for daily rainfall over Ethiopia. In contrast, a study by Ageet *et al.* (2022) in Equatorial East Africa indicates that, the better performance of CHIRPS v2.0 for simulating daily rainfall than MSWEP v2.8, and also indicates MSWEP v2.2 (the earlier version) is better performance when compare to CHIRPS v2.0 and MSWEP v2.8 (the recent version). In this study, TAMSATv3.1 is the second ranked best performing rainfall product than CHIRPS v2.0. This argument aligned with different studies like (Ayele *et al.*, 2018; Solomon *et al.*, 2024; Temesgen *et al.*, 2023b).

Table 4. 1. The performance of satellite/reanalysis rainfall products for simulating daily rainfall total from 2000 to 2023 over sub-tropical and temperate AEZs of Jemma sub-basin.

		Continuous statistical metrics					
AEZs	Rainfall products	RMSE	PBIAS	KGE’	r	CRI	Rank
	CHIRPS v2.0	7.71	11.40	0.41	0.51	0.30	3rd
	TAMSAT v3.1	6.22	-0.30	0.53	0.55	0.65	2nd

Sub-tropical	ERA 5	6.17	24.00	0.35	0.44	0.25	4th
	MERRA v2	6.71	11.60	0.31	0.40	0.10	5th
	MSWEP v2.8	5.70	3.40	0.45	0.58	0.70	1st
	CHIRPS v2.0	4.29	3.60	0.68	0.76	0.50	3rd
	TAMSAT v3.1	3.87	2.30	0.74	0.74	0.60	2nd
Temperate	ERA 5	5.61	-26.80	0.25	0.66	0.05	5th
	MERRA v2	4.83	14.90	0.49	0.53	0.15	4th
	MSWEP v2.8	3.07	5.90	0.75	0.81	0.70	1st

4.2. Detecting Capability of Satellite/Reanalysis Rainfall Products

In this study, four categorical statistical metrics (POD, FAR, CSI and FBI) were used to evaluate the performance of satellite/reanalysis rainfall products in detecting rainy day (threshold $\geq$1mm). The categorical statistical metrics value of CHIRPS v2.0, TAMSAT v3.1, ERA5, MERRA v2, and MSWEP v2.8 rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin shown in Table 4.2.

The result indicated that the satellite/reanalysis rainfall products have better rainfall detection capability with POD values range from 0.74 to 0.84 over both AEZs. In sub-tropical AEZ, MSWEP v2.8, TAMSAT v3.1, and CHIRPS v2.0 have the highest detecting capability with 84%, 80% and 78% respectively, indicates better ability to detect rainfall events. ERA5 and MERRA v2 missed 26% and 24%, respectively. According to the false alarm ratio (FAR) value, MSWEP v2.8 and ERA5 falsely estimating non rainy days by 29% and 30% respectively. On the other hand, TAMSAT v3.1 and CHIRPS v2.0, MERRA v2 detected rainy days falsely by 33% ,34%, and 44% respectively. The highest CSI value recorded by MSWEP v2.8 with 0.62. The rest rainfall products also have greater than 0.51 CSI value, except ERA 5, it indicates better correlation between these products and observed rainfall events. FBI value of TAMSAT v3.1, ERA5, MERRA v2, and MSWEP v2.8 were >1, it indicates they slightly over estimate. CHIRPS v2 has 0.96 FBI value so it slightly under estimate.

According to, POD value MSWEP v2.8 and CHIRPS v2.0 are the highest value with 83% and 80% detecting capability of rainy days over temperate AEZ. The highest messing value recorded by ERA 5 with 25%. The FAR value of all five products < 0.26, this indicates less falsely detecting non rainy days. MSWEP v2.8 with 18% and 19% for CHIRPS v2.0 and TAMSAT v3.1 indicating minimal false detection. CSI value ranges from 0.62 to 0.70, with MERRA v2 the lowest value and MSWEP v2.8 the highest value, it indicates better correlation between products and observed rainfall events. Based on FBI value, CHIRPS v2.0 and TAMSAT v3.1 slightly under estimate with 0.89 and 0.91 FBI value. The highest value is 1.15 by ERA5, the other products are slightly over estimate.

In general, based on CRI value, MSWEP v2.8 has first ranked superior performed rainfall product over both AEZs, this indicates, the highest performance in rainfall occurrence detecting capability over sub-tropical and temperate AEZs when comparing with other products. CHIRPS v2.0 and TAMSAT v3.1 are the second and third ranked best performed rainfall product over both AEZs. MERRA v2 and ERA5 has respectively, fourth and fifth ranked poorly performing rainfall products. This result is consistent with (Palharini *et al.*, 2020), who observed that ERA5 struggles to capture short, intense rainfall events, particularly in regions prone to convective storms.

Similarly, MSWEP v2.8 has better POD value than CHIRPS v2.0 and TAMSAT v3.1 over sub-tropical and temperate AEZs of Bale Eco-Region (Temesgen *et al.*, 2023b). A study by Solomon *et al.* (2024), over Abay Basin, Ethiopia and Endeg *et al.* (2023) over Ethiopia showed the better value of FAR, CSI and FBI. CHIRPS v2.0 showed the weakest detecting capability than MSWEP v2.8 over sub-tropical and temperate AEZs of Upper Blue Nile River Basin (Sintayehu *et al.*, 2020).TAMSAT v3.1 by Considering all categorical performance measures better performance than CHIRPS v2.0 over sub-tropical AEZ of Abay Basin (Solomon *et al.*, 2024). CHIRPS v2.0 has better POD and CSI value than TAMSAT v3.1 over temperate AEZ of Jemma sub-basin. In contrast, Temesgen *et al.* (2023b) finding indicated as TAMSAT v3.1 has better performance in detecting capability of rainy days (POD) in temperate AEZ over Bale Eco-Region.

Table 4. 2. The categorical statistical matrices value of satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub basin.

AEZs	Rainfall products	Categorical statistical metrics				CRI	Rank
		POD	FAR	CSI	FBI		
	CHIRPS v2.0	0.78	0.34	0.56	0.96	0.45	2nd
	TAMSAT v3.1	0.80	0.33	0.56	1.14	0.40	3rd

Sub-tropical	ERA 5	0.74	0.30	0.47	1.07	0.20	5th
	MERRA v2	0.76	0.44	0.51	1.04	0.25	4th
	MSWEP v2.8	0.84	0.29	0.62	1.02	0.80	1st
	CHIRPS v2.0	0.80	0.19	0.67	0.89	0.50	2nd
	TAMSAT v3.1	0.76	0.19	0.64	0.91	0.35	3rd
Temperate	ERA 5	0.75	0.26	0.66	1.15	0.10	5th
	MERRA v2	0.77	0.25	0.62	1.02	0.30	4th
	MSWEP v2.8	0.83	0.18	0.70	1.01	0.80	1st

4.3. Performance of Satellite/Reanalysis Rainfall Products for Simulating Rainfall Extreme

4.3.1. Absolute threshold indices

The absolute threshold indices are R10mm, R20mm and R25mm because they measure the number of days with rainfall exceeding 10 mm, 20 mm, and 25 mm, respectively and unit of these three indices have day so refer extreme precipitation frequency. Table 4.3 Shows, the R10mm, R20mm, and R25mm extreme rainfall indices value of CHIRPS v2.0, TAMSAT v3.1, ERA5, MERRA v2, and MSWEP v2.8 over sub-tropical and temperate AEZs of Jemma sub-basin.

According to, CRI value of the R10mm index over sub-tropical AEZ, CHIRPS v2.0 ranked first, with the lowest RMSE and PBIAS, and the highest KGE’ and r value, indicating its best performance for simulating days with greater than or equal to10 mm of rainfall, and it’s followed by MSWEP v2.8. TAMSAT v3.1 has third ranked relatively best performing rainfall product. MERRA v2 is the fifth ranked weakly performing product in capturing R10mm events in this AEZ and it followed by ERA5. In temperate AEZ, MSWEP v2.8 is ranked first for simulating R10mm index, it records the lowest RMSE, and the highest KGE’ and r value. CHIRPS v2.0 and TAMSAT v3.1 are equally second ranked best performing rainfall products. MERRA v2 and ERA5 are the poorest performing rainfall products by ranked fourth and fifth, respectively.

The performance of satellite/reanalysis rainfall products for simulating the R20mm index over the sub-tropical AEZ, CHIRPS v2.0 and TAMSAT v3.1 are the first and second ranked best performing rainfall products for detecting days with the rainfall greater than or equal to 20mm.

CHIRPS v2.0 records the lowest RMSE and PBIAS, and the highest r value. The highest KGE' value records by TAMSAT v3.1. MERRA v2 ranks third but the performance is considered weaker when compared to CHIRPSv2.0 and TAMSAT v3.1. The poorest performing rainfall products in this AEZ are MSWEP v2.8 and ERA5 by gating equally forth rank. In temperate AEZ, CHIRPS v2.0 is the best performing rainfall product with lowest RMSE and highest KGE' value, and it ranked first and it followed by MSWEP v2.8 with strong correlation. TAMSAT v3.1 is the third ranked best performing rainfall product. The weakly performing rainfall products for simulating R20mm index in this AEZ is ERA5 and the other low performing rainfall product is MERRA v2.

For the R25mm index over sub-tropical AEZ, CHIRPS v2.0 and TAMSAT v3.1 are first and second ranked best performing rainfall products. CHIRPS v2.0 records the lowest RMSE and PBIAS, and the highest KGE' and r value. MSWEP v2.8 and MERRA v2 are equally third ranked, while ERA5 is fifth ranked weakly performing product. In temperate AEZ, CHIRPS v2.0 with lowest RMSE and the highest KGE' and r value, and MSWEP v2.8 are first and second ranked best performing rainfall products. TAMSAT v3.1 is third ranked, while ERA5 is fifth ranked weakly performing product and it followed by MERRA v2.

Table 4. 3. The absolute threshold indices value of satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000-2023.

	Sub-tropical R10mm						Temperate R10mm					
	RMSE	PBIAS	KGE'	r	CRI	Rank	RMSE	PBIAS	KGE'	r	CRI	Rank
CHIRPSv2.0	2.65	0.90	0.83	0.91	0.80	1st	5.12	-0.10	0.79	0.95	0.60	2nd
TAMSATv3.1	31.31	-6.20	0.71	0.74	0.40	3th	3.76	-1.30	0.81	0.83	0.60	2nd
ERA5	9.41	19.60	0.44	0.50	0.30	4rd	12.32	-20.90	0.55	0.67	0.05	5th
MERRAv2	12.42	22.00	0.14	0.43	0.05	5th	6.67	9.30	0.64	0.69	0.25	4th
MSWEPv2.8	9.64	13.40	0.58	0.81	0.45	2nd	3.23	6.50	0.83	0.95	0.70	1st
	Sub-tropical R20mm						Temperate R20mm					
	RMSE	PBIAS	KGE'	r	CRI	Rank	RMSE	PBIAS	KGE'	r	CRI	Rank
CHIRPSv2.0	3.65	7.80	0.55	0.77	0.75	1st	1.33	-2.10	0.89	0.90	0.70	1st

TAMSATv3.1	4.27	11.90	0.62	0.70	0.65	2nd	1.74	1.60	0.75	0.81	0.50	3rd
ERA5	8.13	18.90	0.14	0.47	0.15	4th	3.47	-20	0.56	0.70	0.00	5th
MERRAv2	8.39	16.80	0.34	0.53	0.30	3rd	2.47	17.60	0.66	0.72	0.20	4th
MSWEPv2.8	9.31	20.00	0.33	0.65	0.15	4th	1.59	16.10	0.83	0.93	0.60	2nd
	Sub-tropical R25mm						Temperate R25mm					
	RMSE	PBIAS	KGE’	r	CRI	Rank	RMSE	PBIAS	KGE’	r	CRI	Rank
CHIRPSv2.0	1.70	11.10	0.74	0.90	0.8	1st	1.73	14.40	0.46	0.71	0.70	1st
TAMSATv3.1	2.63	14.30	0.63	0.79	0.60	2nd	2.12	16.40	0.43	0.62	0.40	3rd
ERA5	5.84	21.90	0.10	0.57	0.10	5th	4.57	19.30	0.16	0.21	0.00	5th
MERRAv2	5.30	19.20	0.21	0.48	0.25	3rd	2.72	13.60	0.18	0.26	0.30	4th
MSWEPv2.	5.97	16.80	0.18	0.66	0.25	3rd	1.77	15.00	0.41	0.77	0.55	2nd

Figure 4.1 shows, the line graph of satellite/reanalysis rainfall products compare with observed data for simulating absolute threshold indices over both AEZs, the result revealed that MERRA v2 and ERA5 are poor performance for simulating absolute threshold indices over both AEZs. CHIRPS v2.0 hold first rank over both AEZs of absolute threshold indices except temperate AEZ of R10mm index. TAMSAT v3.1 is best performance on temperate AEZ of R10mm(2nd), both AEZs of R20mm(2nd,3rd) and sub-tropical AEZ of R25mm index (2nd). On the other hand, MSWEP v2.8 is weakly performance on sub-tropical AEZ of R20mm(4th) and R25mm indices(3rd). However, MSWEP v2.8 best performance over both AEZs of R10 indices(2nd,1st) and temperate AEZ of R20mm(2nd) and R25mm indices(2nd) so it is better than TAMSAT v3.1.

In general, CHIRPS v2.0 is the best performing rainfall products and MSWEPv2.8 is the second one than others products for simulating absolute threshold indices over Jemma sub-basin. Other studies, like Cavalcante *et al.* (2020) study conducted over the Brazilian Amazonia and Subba *et al.* (2024) study conducted over hilly area of Nepal, CHIRPS v2.0 is more similar result with observed data for represent number of days above 20mm (R20mm) and number of days above 25mm (R25mm) indices. MSWEP v2.8 have the best performance for simulating R10mm and R20mm indices than MERRA v2 rainfall product (Zarrin & Dadashi-Roudbari, 2022). In addition, MSWEPv2.8 is best performance for daily precipitation is <50mm/d (Li *et al.*, 2022).

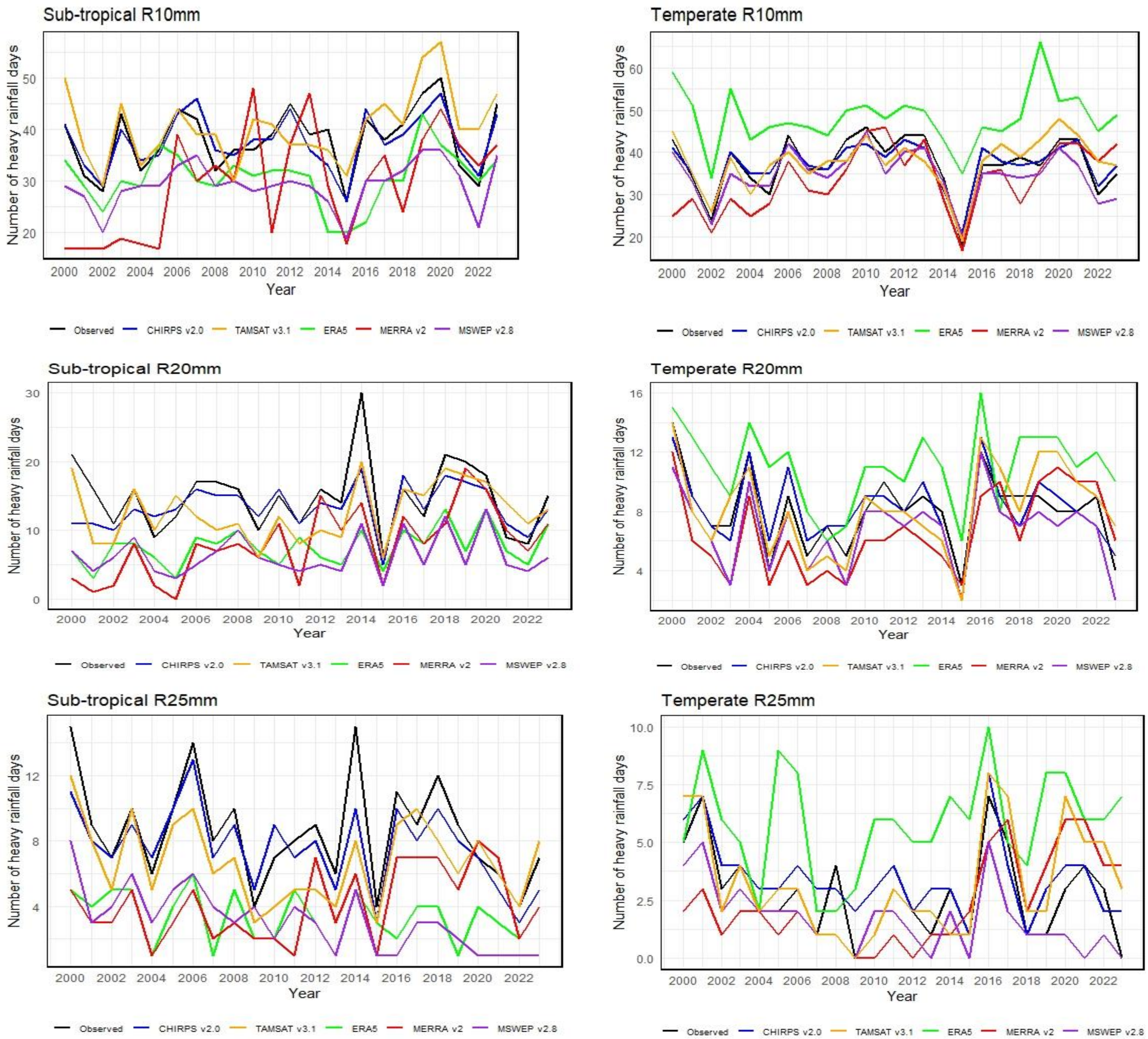


Figure 4. 1. Line graph of observed R10mm, R20mm, and R25mm indices compares with satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000 – 2023.

In terms of bias, the satellite/reanalysis rainfall products for simulating absolute threshold indices (Table 9), all rainfall products are positive PBIAS value over sub-tropical AEZ except TAMSAT v3.1in R10mm index, indicates underestimation of absolute threshold indices and TAMSAT v3.1 overestimate with -6.20 % PBIAS value. In temperate AEZ also MSWEP v2.8 and MERRA v2 are underestimate the absolute threshold indices. CHIRPS v2.0 and ERA5 shows negative value in R10 mm and R20 mm indices, while positive value in R25 mm index. TAMSAT v3.1 shows negative PBIAS value in R10 mm index and positive value in R20 mm and R25 mm indices.

In general, CHIRPS v2.0 is the lowest bias estimation over both AEZs of R10 mm index with 7.80% and -2.10% PBIAS value, and also it is lowest bias estimation over sub-tropical AEZ of R20 mm and R25 mm indices. TAMSAT v3.1 over temperate AEZ of R20 mm index and MERRA v2 in R25 mm index are lowest PBIAS value with 1.60% and 13.60%. The highest PBIAS value records by reanalysis rainfall products over both AEZs are observed. in sub-tropical AEZ, MERRA v2 showing a bias of 22% for the R10 mm index and ERA5 recording 21.90% for R25 mm index. In temperate AEZ also ERA5 recording -20.90% in R10mmindex.

4.3.2. Persistent indices

The consecutive dry days (CDD) and consecutive wet days (CWD) indices are called persistent indices because they represent prolonged periods or the continuation of dry and wet conditions over a stretch of consecutive days, and their unit is day so refer extreme precipitation frequency.

The evaluation of CHIRPS v2.0, TAMSAT v3.1, ERA5, MERRA v2, and MSWEP v2.8 rainfall products for simulating CDD and CWD ranked based on the CRI values (Table 4.4). CHIRPS v 2.0 got the highest rank, with the lowest RMSE and highest KGE' and r value, indicating that the superior performance in capturing CDD over the Sub-tropical AEZ of Jemma sub-basin. MSWEP v2.8 and MERRA v2 are the second and third ranked best performing rainfall products. MSWEP v2.8 recorded the lowest PBIAS value and similar KGE' value with CHIRPS v2.0 and MERRA v2. TAMSAT v3.1 and ERA5 ranked fourth and fifth respectively, with ERA5 the least matched for simulating CDD. In temperate AEZ, MSWEP v2.8 and CHIRPS v2.0 are the first and second ranked best performing rainfall products. MSWEP v2.8 records lower PBIAS value and also achieved the highest KGE' value, reflecting its strong agreement with observed data. CHIRPS v2.0 followed closely, it records the lowest RMSE and the highest r value. MERRA v2 consistently third ranked best performing rainfall products across both AEZs. ERA5 and TAMSAT v3.1 ranked fourth and fifth, respectively, with TAMSAT v3.1 in least position performed poorly, with higher biases.

When analyzing CWD index over the Sub-tropical AEZ, CHIRPS v2.0 rank first, indicating its strong performance with the lowest RMSE and the highest KGE’ and r value and also it records best PBIAS value and it followed by TAMSAT v3.1 by hold the second rank. MSWEP v2.8 is third ranked relatively weaker performing rainfall products than CHIRPS v2.0 and TAMSAT v3.1. ERA5 is the least performing by got fifth rank and it followed by MERRA v2. In temperate AEZ, MSWEP v2.8 takes the top rank, reflecting its best in capturing CWD with in lowest RMSE and highest KGE’ value and it followed by MERRA v2, it records the lowest PBIAS value. CHIRPS v2.0 is third ranked and strong correlation, in overall value relatively weaker performance than MSWEP v2.8. TAMSAT v3.1 is fourth ranked weakly performing rainfall product, while ERA5 holds the last position weakly performing rainfall product in both AEZs.

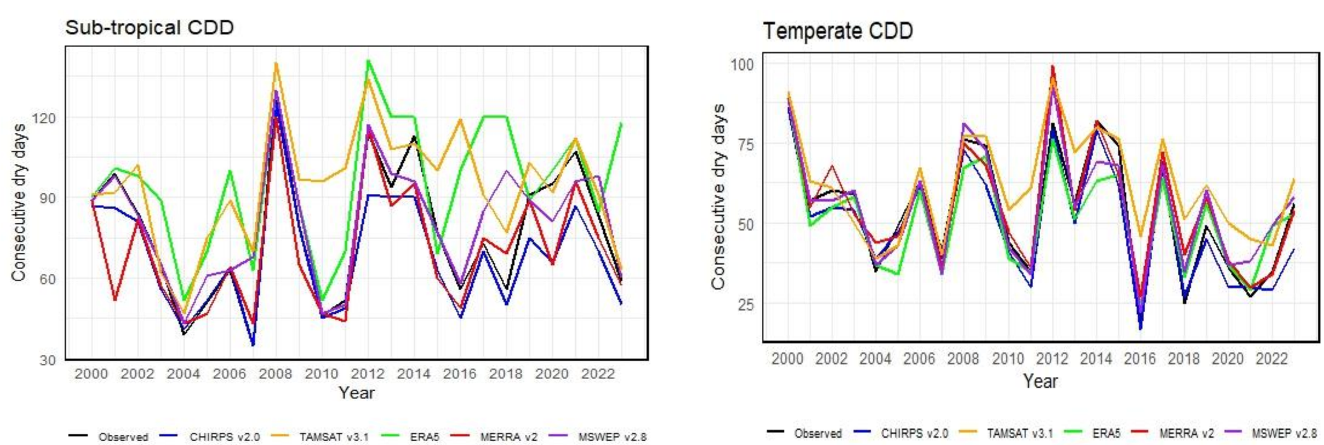
Table 4. 4. The persistent indices value of satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000-2023.

	Sub-tropical CDD						Temperate CDD					
	RMSE	PBIAS	KGE’	r	CRI	Rank	RMSE	PBIAS	KGE’	r	CRI	Rank
CHIRPSv2.0	12.05	11.00	0.80	0.95	0.70	1st	5.76	5.10	0.91	0.97	0.60	2nd
TAMSATv3.1	24.48	19.30	0.62	0.73	0.30	4th	8.25	-9.40	0.73	0.87	0.15	5th
ERA5	26.76	-21.10	0.60	0.69	0.10	5th	7.47	4.70	0.82	0.94	0.40	4th
MERRAv2	14.00	8.90	0.80	0.87	0.60	3rd	6.73	-3.40	0.91	0.94	0.55	3rd
MSWEPv2.8	13.28	-4.90	0.80	0.86	0.65	2nd	6.56	-2.60	0.92	0.94	0.70	1st
	Sub-tropical CWD						Temperate CWD					
	RMSE	PBIAS	KGE’	r	CRI	Rank	RMSE	PBIAS	KGE’	r	CRI	Rank
CHIRPSv2.0	2.82	-2.50	0.75	0.89	0.80	1st	13.05	17.90	0.70	0.90	0.45	3rd
TAMSATv3.1	8.19	19.40	0.60	0.68	0.50	2nd	13.82	16.40	0.67	0.83	0.30	4th
ERA5	19.92	22	0.51	0.51	0.10	5th	16.50	-24.40	0.58	0.9	0.20	5th
MERRAv2	28.46	18.9	0.54	0.51	0.25	4th	12.62	-1.90	0.73	0.74	0.55	2nd
MSWEPv2.8	19.83	21.00	0.59	0.62	0.40	3rd	12.18	-13.80	0.75	0.86	0.70	1st

Figure 4.2 shows, the line graph of observed CDD and CWD indices compares with satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000-2023. The result of this study indicates, TAMSAT v3.1 has the second ranked best

performed product over sub-tropical AEZ of CWD but weakly performance over both AEZs for CDD and temperate AEZ of CWD. MERRA v2 is third ranked best performing product for simulating CDD over both AEZs and second ranked over temperate AEZ for CWD but the weakly performance over sub-tropical AEZ. CHIRPS v2.0 is first ranked over sub-tropical AEZ of both persistent indices and second ranked over temperate AEZ of CDD index, and MSWEP v2.8 has first ranked over temperate AEZ of both persistent indices and second ranked in CDD and third ranked in CWD over sub-tropical AEZ.

In general, CHIRPS v2.0 in sub-tropical and MSWEP v2.8 in temperate AEZs are the best performing rainfall products than others for simulating CDD and CWD indices over Jemma sub basin. Previous studies, like Zhang *et al.* (2022) results CHIRPS v2.0 is best performance for simulating CDD and it also performs well for CWD indices (Subba *et al.*, 2024). MSWEP v2.8 is the best performance for simulating CDD and CWD than MERRA v2 (Zarrin & Dadashi-Roudbari, 2022) and Li *et al.* (2022) found that MSWEP v2.8 has a higher accuracy in terms of the persistent indices over Beijing, China.



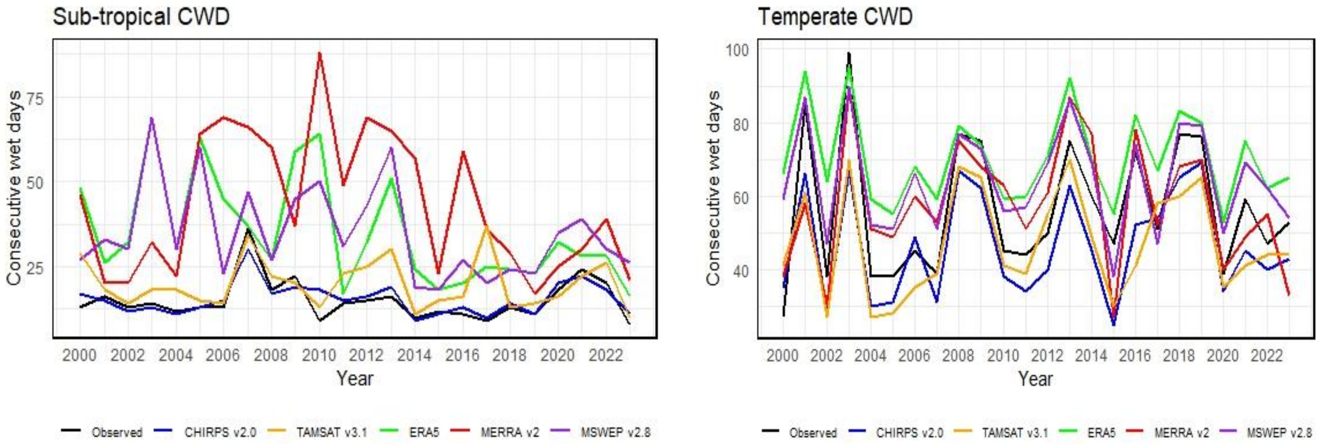


Figure 4. 2. Line graph of observed CDD and CWD indices compares with satellite/reanalysis precipitation products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000 – 2023.

According to the biases of satellite/reanalysis rainfall products for simulating persistent indices, CHIRPS v2.0 shows positive value in both AEZs of CDD which means underestimation of the CDD indices. TAMSAT v3.1 also underestimation over Sub-tropical AEZ but overestimation over temperate AEZ with negative value result. ERA5 determines overestimation in the sub-tropical AEZ, while showing underestimate in the temperate zone. MERRA v2 provides underestimation and MSWEP v2.8 overestimation over Sub-tropical AEZ and both are overestimate over temperate AEZ. For CWD**,** CHIRPS v2.0 overestimation in the sub-tropical AEZ and underestimation in the temperate AEZ. TAMSAT v3.1 show consistent underestimated across both AEZs. MSWEP v2.8, ERA5, and MERRA v2 are overestimation bias over Sub-tropical AEZ and underestimation over temperate AEZ.

In general, MSWEP v2.8 is the lowest bias estimation over both AEZs of CDD index with -4.90% and -2.60% PBIAS value. ERA5 is the highest bias estimation with -21.10% PBIAS value over sub-tropical AEZ and TAMSAT v3.1 over temperate AEZ with -9.40% 0f PBIAS value. CHIRPS v2.0 shows the lowest bias estimation of CWD index with -2.50% over sub-tropical AEZ and MERRA v2 over temperate AEZ with -1.90%. ERA5 displayed the highest bias estimation over both AEZs, with PBIAS value of 22% over sub-tropical and -24% over temperate AEZs.

4.3.3. Max indices

To analysis the capability of satellite/reanalysis rainfall products for simulating rainfall extreme in Jemma sub basin one of the indices is max indices, it means RX1day and RX5day because these indices focus on capturing the maximum rainfall intensity within a fixed period. The performances of the five satellite/reanalysis rainfall products for simulating RX1day and RX5day indices over two AEZs of the Jemma sub basin given in table 4.5.

In sub-tropical AEZ, CHIRPS v2.0 is the first ranked best performing rainfall product for simulating RX1day index by achieving the lowest RMSE and PBIAS value, and the highest KGE’ and r value. TAMSAT v3.1 and MSWEP v2.8 following it by got equally second rank. ERA5 and MERRA v2 are fourth and fifth ranked weak performing products, with MERRA v2 least position. MSWEP v2.8 is first ranked, indicate a strong performance product to simulate RX1day index in the temperate AEZ, it achieved the lowest RMSE, and the highest KGE’ and strong correlation(r). The second and third ranked best performing products are CHIRPS v2.0 and TAMSAT v3.1. ERA5 and MERRA v2 got the fourth and fifth ranks, respectively, indicating that these two products have weaker performance.

For RX5day index, CHIRPS v2.0 and TAMSAT v3.1 ranked first and second, indicating strong performing products. In this index CHIRPS v2.0 records the lowest RMSE and PBIAS, and the highest KGE’ and r value. MSWEPv2.8, ERA5, and MERRA v2 similar as RX1day index, they are third, fourth and fifth ranked products, with MERRA v2 least position over sub-tropical AEZ. In temperate AEZ, similar to RX1day index MSWEPv2.8, CHIRPSv2.0, and TAMSATv3.1 are first, second and third ranked strong performing rainfall products. ERA5 and MERRAv2 are equally fourth ranked poorly performing rainfall products.

Table 4. 5. The max indices value of satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000-2023.

	Sub-tropical RX1day						Temperate RX1day					
	RMSE	PBIAS	KGE’	r	CRI	Rank	RMSE	PBIAS	KGE’	r	CRI	Rank
CHIRPSv2.0	2.74	-1.20	0.86	0.87	0.80	1st	1.79	-2.20	0.87	0.95	0.60	2nd
TAMSATv3.1	9.34	9.20	0.28	0.35	0.40	2nd	2.59	0.18	0.83	0.88	0.50	3rd

ERA5	11.63	21.20	0.28	0.36	0.30	4th	3.98	-9.00	0.68	0.68	0.15	4th
MERRAv2	13.60	21.70	0.31	0.33	0.15	5th	4.24	2.70	0.60	0.65	0.10	5th
MSWEPv2.8	11.54	24.30	0.50	0.58	0.40	2nd	1.59	2.80	0.91	0.97	0.65	1st
	Sub-tropical RX5day						Temperate RX5day					
	RMSE	PBIAS	KGE'	r	CRI	Rank	RMSE	PBIAS	KGE'	r	CRI	Rank
CHIRPSv2.0	5.07	1.30	0.94	0.96	0.80	1st	7.20	-2.60	0.81	0.86	0.60	2nd
TAMSATv3.1	12.54	3.10	0.53	0.73	0.50	2nd	9.04	1.40	0.72	0.72	0.50	3rd
ERA5	19.43	12.70	0.46	0.58	0.20	4th	17.07	15.00	0.48	0.57	0.10	4th
MERRAv2	22.81	11.40	0.30	0.32	0.10	5th	15.22	7.90	0.43	0.47	0.10	4th
MSWEPv2.8	15.27	12.90	0.72	0.92	0.40	3rd	6.18	4.30	0.87	0.91	0.70	1st

The result of this study displays by line graph (Figure 4.3), shows CHIRPS v2.0 is first ranked over sub-tropical AEZ and second ranked over temperate AEZ for simulating both max indices, and MSWEP v2.8 has first ranked over temperate AEZ for both indices, and second ranked in RX1day index and third ranked in RX5day index over sub-tropical AEZ. TAMSAT v3.1 is second ranked over sub-tropical AEZ and third ranked over temperate AEZ. In general, CHIRPSv2.0 and MSWEPv2.8 are respectively, the best performing products than others for simulating RX1day and RX5day indices over Jemma sub-basin.

Other studies like Zarrin & Dadashi-Roudbari (2022), study conducted over Iran, for max indices use only RX1day and the result shows MSWEP v2.8 is the high accuracy for estimating Rx1day, and according to Subba *et al.* (2024), CHIRPS V2.0 is one of best performing precipitation product for capturing the RX5 day index over Nepal. Conversely, ERA5 and MERRA v2 underperformance aligns with critiques by Guo *et al.* (2021), who found these datasets less effective in regions with complex climatic variability.

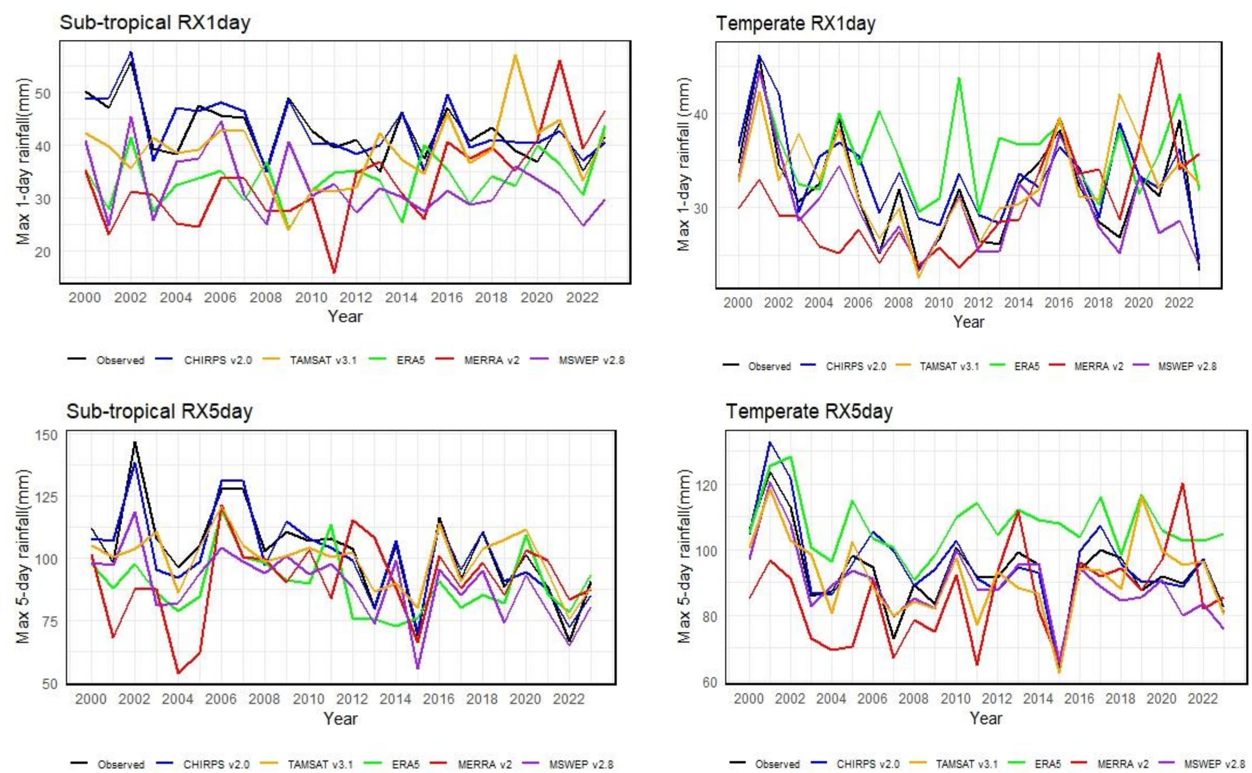


Figure 4. 3. Line graph of observed RX1day and RX5day indices compares with satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000 – 2023.

In terms of the biases of satellite/reanalysis rainfall products for simulating persistent indices, CHIRPSv2.0 overestimated over both AEZs. TAMSATv3.1, MSWEPv2.8 and MERRAv2 shows underestimated over both AEZs, while ERA5 tends underestimated over sub-tropical AEZ and overestimate over temperate AEZ for RX1day index. For RX5day index all rainfall products has underestimated over both AEZs except CHIRPSv2.0 over temperate AEZ. The lowest bias estimation values over sub-tropical AEZ of both indices displayed by CHIRPSv2.0 with PBIAS value of -1.20% (RX1day) and 1.30 (RX5day) and TAMSATv3.1 over temperate AEZ with PBIAS value of 0.18% (RX1day) and 1.40% (RX5day). On the other hand, MSWEPv2.8 over sub-tropical AEZ and ERA5 over temperate AEZ are the highest bias estimation rain all products for both indices.

4.4.4. Percentile indices

The Percentile indices mean R95p and R99p indices because these indices are used to identify extreme rainfall events based on percentile thresholds rather than fixed amounts and measure extreme precipitation intensity. to evaluate the performance of satellite/reanalysis rainfall products for simulating percentile indices the result ranked by using CRI value for both AEZs (Table 4.6).

In sub-tropical AEZ, CHIRPS v2.0 achieved the first ranked superior performance rainfall product for simulating R95p indices with a high KGE' and minimal bias PBIAS values. MSWEP v2.8 and TAMSAT v3.1 have equally second ranked best performing rainfall products. MERRA v2 fifth ranked weakly performance product and it followed by ERA5 by got fourth rank. Additionally, CHIRPS v2.0 and TAMSAT v3.1 are the first and second ranked best performing rainfall products over temperate AEZ, with CHIRPS v2.0 records the lowest RMSE and highest r value, and MSWEP v2.8 is the third ranked best performing product. MERRA v2 and ERA5 are fourth and fifth ranked weaky performing rainfall products.

For R99p index sub-tropical AEZ, the result indicates CHIRPS v2.0 is the first ranked best performing product by recording the lowest RMSE and PBIAS, and the highest KGE' and r value. MSWEP v2.8 is second ranked best performing rainfall products and it followed by TAMSAT v3.1. ERA5 has the fourth ranked and MERRA v2 with fifth ranked poorly performing products. Similar as sub-tropical AEZ, in temperate AEZ also CHIRPS v2.0, MSWEP v2.8, and TAMSAT v3.1 are first to third ranked best performing rainfall products. MERRA v2 and ERA5 are fourth and fifth ranked poorly performing rainfall products.

In terms of the bias estimation of satellite/reanalysis rainfall products, all rainfall products show underestimated over both AEZs for R95p index and also overestimated over Sub-tropical AEZ for R99p indices. CHIRPS v2.0, TAMSAT v3.1, MERRA v2, and MSWEP v2.8 shows underestimate over temperate AEZ, while ERA5 tends overestimated. CHIRPSv2.0, TAMSATv3.1, and MERRAv2 are the lowest bias estimation rainfall products over sub-tropical AEZ of R95p and MERRAv2 is the lowest one over temperate AEZ. CHIRPSv2.0 is the lowest bias estimation over both AEZs of R99 index and in addition, TAMSATv3.1 also the lowest one over temperate AEZ. ERA5 is the highest bias estimation over both AEZs of R95p indices and temperate AEZ of R99p index, while MERRAv2 on Sub-tropical of R99p.

In general, CHIRPS v2.0 is the best performing rainfall products and MSWEPv2.8 is the second one than others products for simulating percentile indices over Jemma sub-basin. These results align with findings by Subba *et al.* (2024), who reported similar superior performance of CHIRPS v2.0 in capturing high-intensity precipitation in Nepal's hilly regions. Other studies, like Li *et al.* (2022) the R95p index values of MSWEP v2.8 are closest to the values of the rainfall stations. In contrast, He *et al.* (2021) indicates less performance of CHIRPSv2.0 for simulating percentile indices over the Qinghai-Tibet Plateau.

Table 4. 6. The percentile indices value of satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000-2023.

	Sub-tropical R95p						Temperate R95p					
	RMSE	PBIAS	KGE'	r	CRI	Rank	RMSE	PBIAS	KGE'	r	CRI	Rank
CHIRPSv2.0	21.91	2.00	0.92	0.95	0.75	1st	27.34	5.40	0.88	0.90	0.65	1st
TAMSATv3.1	31.35	1.70	0.75	0.83	0.50	2nd	30.89	4.20	0.72	0.92	0.60	2nd
ERA5	34.63	8.30	0.61	0.83	0.20	4th	50.86	14.80	0.69	0.80	0.15	5th
MERRAv2	56.92	2.10	0.56	0.59	0.15	5th	81.93	1.00	0.21	0.29	0.20	4th
MSWEPv2.8	22.85	8.00	0.82	0.96	0.50	2nd	32.23	9.30	0.85	0.89	0.40	3rd
	Sub-tropical R99p						Temperate R99p					
	RMSE	PBIAS	KGE'	r	CRI	Rank	RMSE	PBIAS	KGE'	r	CRI	Rank
CHIRPSv2.0	5.09	-5.50	0.94	0.99	0.80	1st	5.86	0.60	0.95	0.99	0.70	1st
TAMSATv3.1	18.44	-9.50	0.78	0.87	0.45	3rd	8.69	0.80	0.91	0.99	0.50	3rd
ERA5	22.03	-19.10	0.65	0.82	0.20	4th	16.50	-17.10	0.80	0.96	0.15	5th
MERRAv2	28.9	-23.10	0.35	0.49	0.00	5th	20.91	2.30	0.84	0.91	0.20	4th
MSWEPv2.8	12.30	-11.10	0.82	0.95	0.55	2nd	5.53	3.40	0.94	1.00	0.60	2nd

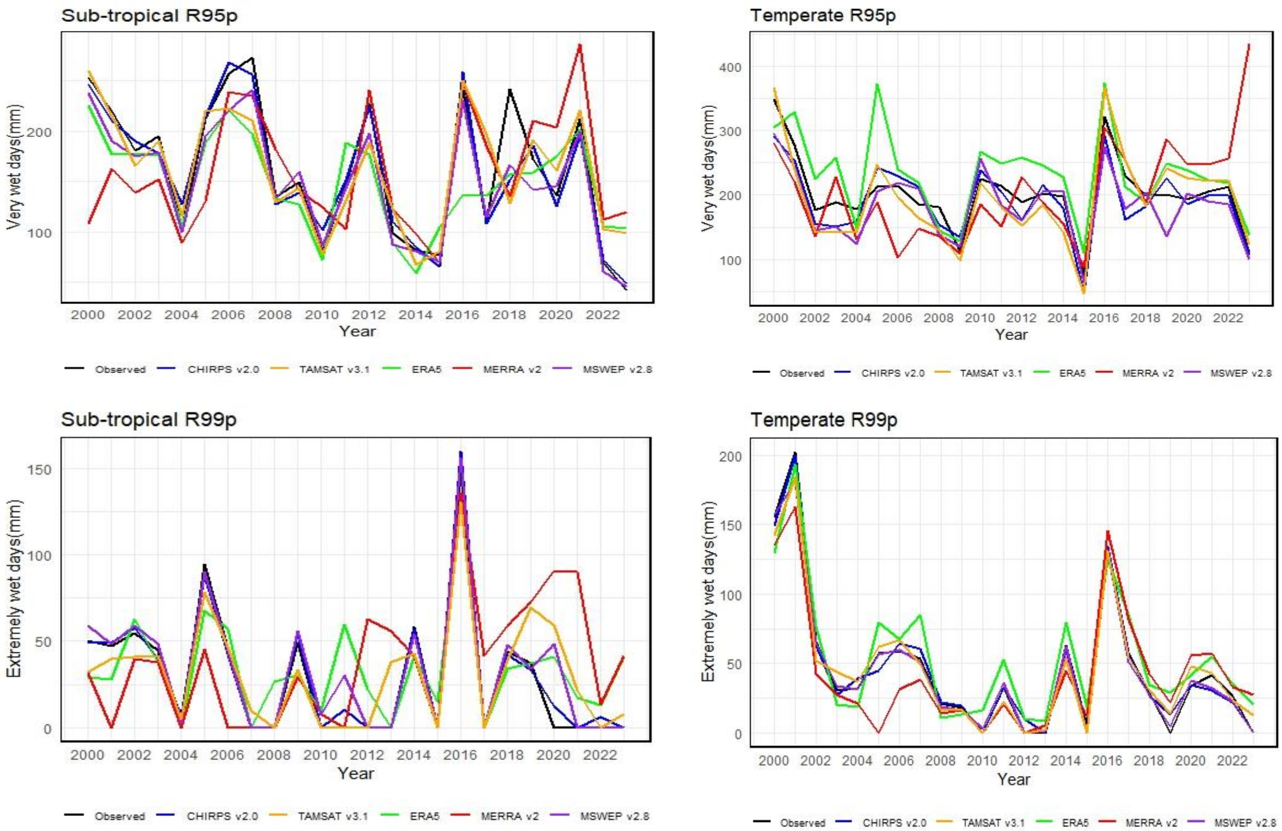


Figure 4. 4. Line graph of observed R95p and R99p indices compares with satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000 – 2023.

4.5.5. Total indices

The total indices are representing the total annual precipitation in wet days (PRCPTOT) and the total precipitation's spread over wet days when precipitation is ≥1 mm (SDII), and they represent intensity of extreme rainfall because the unit is mm and mm/day. Table 4.7 displays, the result of satellite/reanalysis rainfall products over sub-tropical and temperate AEZs for simulating total indices. In sub-tropical AEZ, CHIRPS v2.0 and TAMSAT v3.1 have achieved the highest performance by got first and second rank for simulating PRCPTOT. CHIRPS v2.0 achieved the lowest RMSE and PBIAS, and the highest KGE’ and r value. MSWEP v2.8 and ERA5 are equally third ranked, while MERRAv2 fifth ranked weakly performing rainfall products. In temperate AEZ, CHIRPS v2.0 and TAMSAT v3.1 are equally first ranked best performing rainfall products. CHIRPS v2.0 records the lowest RMSE and the strong correlation value, and

TAMSAT v3.1 records the lowest PBIAS and the highest KGE' values, and they followed by MSWEPv2.8. ERA5 has weakly performing by hold fifth rank and it followed by MERRAv2.

CHIRPSv2.0 and TAMSATv3.1 again performs best, by achieving first and second ranks in sub-tropical AEZ for simulating SDII index also and followed by MSWEPv2.8. ERA5 and MERRAv2 are fourth and fifth ranked weakly performing rainfall products. In temperate AEZ, MSWEPv2.8 and CHIRPSv2.0 are first and second ranked best performing rainfall products. MSWEPv2.8 records the lowest RMSE and PBIAS, and the highest KGE' and r value. TAMSATv3.1 is the third ranked, while ERA5 and MERRAv2 are the weakly performing rainfall products.

The finding of this study displayed, CHIRPS v2.0 has superior performance for simulating PRCPTOT and SDII indices over sub-tropical and temperate AEZs of Jemma sub-basin, this result aligned with the Cavalcante *et al.* (2020) finding, CHIRPS v2.0 product produces more similar results with rain gauge data for the PRCPTOT index and it is strong correlation with station in PRECIPTOT index (Al-Shamayleh *et al.*, 2024). CHIRPS v2.0 properly reflected the simple daily intensity index (SDII) (Subba *et al.*, 2024). TAMSAT v3.1 is better performance over both AEZs(2nd,1st) of PRECIPTOT and SDII(2nd,3rd) indices. MSWEP v2.8 is better performance over temperate AEZ of SDII index and neither good nor poor performance over sub-tropical AEZ of SDII index and both AEZs of PRECIPTOT index. The study under taken on Iran MSWEP v2.8 is better performance for simulating SDII index(Zarrin & Dadashi-Roudbari, 2022). this result is displayed by line graph on figure 4.5.

Table 4. 7. The total indices value of satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000-2023.

	Sub-tropical PRCIPTOT						Temperate PRCIPTOT					
	RMSE	PBIAS	KGE'	r	CRI	Rank	RMSE	PBIAS	KGE'	r	CRI	Rank
CHIRPSv2.0	19.20	0.80	0.98	0.99	0.80	1st	49.04	1.60	0.88	0.94	0.70	1st
TAMSATv3.1	57.61	-2.20	0.85	0.90	0.55	2nd	57.53	0.80	0.89	0.90	0.70	1st
ERA5	96.37	8.30	0.74	0.87	0.30	3rd	197	-28	0.36	0.55	0.00	5th
MERRAv2	99.55	-1.70	0.54	0.64	0.20	5th	122	6.30	0.62	0.79	0.25	4th
MSWEPv2.8	98.01	8.30	0.74	0.89	0.30	3rd	96.28	3.90	0.68	0.74	0.35	3rd

	Sub-tropical SDII						Temperate SDII					
	RMSE	PBIAS	KGE’	r	CRI	Rank	RMSE	PBIAS	KGE’	r	CRI	Rank
CHIRPSv2.0	1.33	4.50	0.53	0.63	0.80	1st	0.58	-5.20	0.69	0.74	0.60	2nd
TAMSATv3.1	1.73	-8.50	0.53	0.46	0.60	2nd	0.70	-5.60	0.63	0.69	0.40	3rd
ERA5	3.10	24.30	0.45	0.42	0.35	4th	1.79	-21.00	0.56	0.64	0.10	4th
MERRAv2	4.29	37.60	0.18	0.21	0.05	5th	1.46	14.00	0.27	0.28	0.10	4th
MSWEPv2.8	3.54	30.30	0.51	0.52	0.40	3rd	0.48	4.80	0.74	0.86	0.80	1st

Regarding the estimation bias of satellite/reanalysis rainfall products, CHIRPSv2.0 and MSWEPv2.8 are under estimations over both AEZs of PRECIPTOT indices and ERA5 also underestimation over sub-tropical AEZ, while overestimate over temperate AEZ. TAMSATv3.1 and MERRAv2 shows over estimation over sub-tropical AEZ and underestimation over temperate AEZ. All products underestimate the bias over sub-tropical AEZ of SDII indices except TAMSATv3.1. CHIRPSv2.0, TAMSATv3.1, and ERA5 are over estimates over the temperate AEZ and the others, mean MERRAv2 and MSWEPv2.8 are under estimate the bias.

The result shows, CHIRPSv2.0 has the lowest bias estimation value over sub-tropical AEZ of both indices, in temperate AEZ of PRECIPTOT indices TAMSATv3.1 and MSWEPv2.8 over SDII indices are lowest bias estimation. The highest bias estimated products of PRECIPTOT indices are ERA5 and MSWEPv2.8 with 8.30% PBIAS value over sub-tropical AEZ and ERA5 again on temperate AEZ with -28% PBIAS value. MERRAv2(37.60%) and MSWEPv2.8(30.30%) are higher bias value over sub-tropical AEZ of SDII indices and in temperate AEZ the highest PBIASE value is ERA5(-21%).

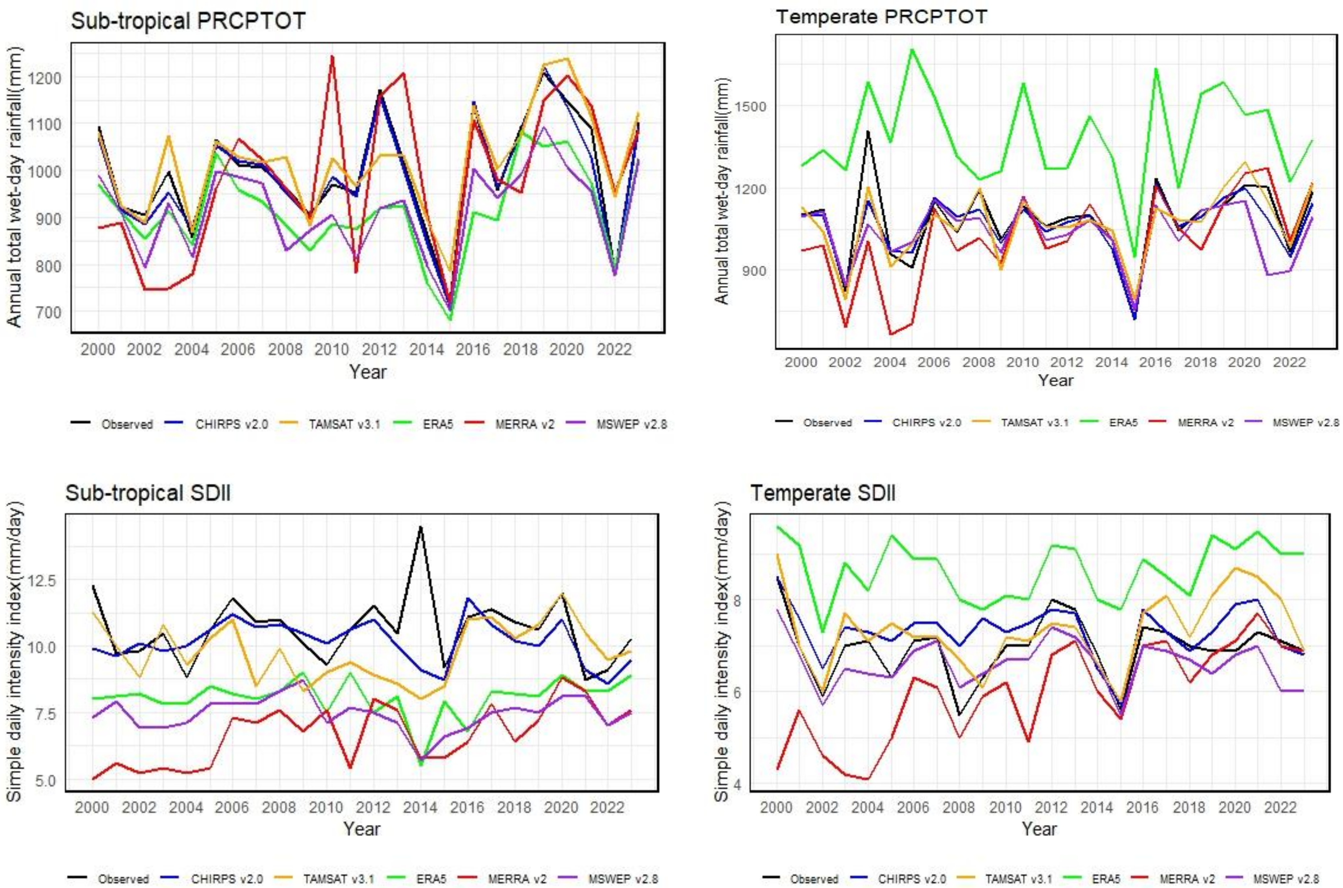


Figure 4. 5. Line graph of observed PRCPTOT and SDII indices compares with satellite/reanalysis rainfall products over sub-tropical and temperate AEZs of Jemma sub-basin from 2000 – 2023.

CHAPTER 5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study evaluated the performance of satellite/reanalysis rainfall products with observed rainfall data for simulating daily rainfall, detecting rainfall events, and extreme rainfall indices across sub-tropical and temperate AEZs in Jemma sub-basin, Ethiopia, from 2000 to 2023. Four continuous and categorical statistical metrices and line graph for visual comparison used to examine the performance of satellite/reanalysis products. The finding of this study at daily timescale due to integrate multiple data sources, MSWEP v2.8 product consistently outperformed the other products in both sub-tropical and temperate AEZs. The detecting capability of rainfall events of rainfall products was better detection capability and MSWEP v2.8 the superior performed product than others. In sub-tropical AEZ, TAMSAT v3.1 better performance than CHIRPS v2.0, and in temperate AEZ CHIRPS v2.0 better than TAMSAT v3.1.

CHIRPS v2.0 is the most reliable dataset, demonstrating superior performance for detection of extreme rainfall events, such as absolute threshold, persistent, percentile, and total indices. It achieved high accuracy and strong correlations than others, its underscoring robustness for applications in hydrological and climate studies. MSWEP v2.8, while the second-best performing product, and slightly less accurate in some indices like R20mm index in sub-tropical AEZ, exhibited competitive performance particularly in the temperate AEZ. Conversely, ERA5 and MERRA v2 showed significant limitations, characterized by high biases, and weaker correlations, limiting their applicability for regional studies. These findings highlight the necessity of selecting datasets tailored to specific regional and climatic conditions to ensure accurate simulations.

The findings suggested the use of CHIRPS v2.0 and MSWEP v2.8 in climate resilience initiatives in Jemma sub-basin, Ethiopia, particularly in addressing the increasing variability and frequency of extreme weather events. By integrating these datasets into hydrological models and early warning systems, policymakers can improve flood forecasting, water resource management, and sustainable agricultural planning in vulnerable regions. The ability of these products to accurately simulate extreme rainfall events makes them indispensable for enhancing disaster preparedness and supporting climate adaptation strategies. Future research should explore blending datasets to refine precipitation estimates further and expand their utility in other regions with complex climatic characteristics.

5.2. Recommendation

Based on the findings of this study, I recommend MSWEP v2.8 for daily time scale and CHIRPS v2.0 for extreme rainfall events study. MSWEP v2.8 also one of the best performing products specially in temperate AEZ. The finding of this study is value of selecting region-specific rainfall datasets to improve disaster management, water resource planning, and sustainable agriculture in climate-vulnerable regions like the Jemma sub-basin.

Extreme rainfall events are increasingly recognized as one of the most common and impactful climate extremes due to their rising occurrence at both regional and global scales (Gizachew *et al.*, 2023; Munzhedzi *et al.*, 2024), so for managing of this events it requires accurate rainfall products, but the performance of rain fall products for simulating rainfall extreme in Ethiopia is unknow because there is no enough researches except some studies like Kirubel *et al.* (2021) in awash. Therefore, this study recommends further studies on the performance of satellite/reanalysis rainfall product for simulating rainfall extreme in different areas of Ethiopia.

REFERENCE

Abdelmoneim, H., Soliman, M. R., & Moghazy, H. M. (2020). Evaluation of TRMM 3B42V7 and CHIRPS satellite precipitation products as an input for hydrological model over Eastern Nile Basin. *Earth Systems and Environment, 4*(4), 685-698.

Abdisa, B., Teka, Mamo Diga, G., & Regassa Tolessa, A. (2022). Impact of climate variability on rain-fed maize and sorghum yield among smallholder farmers. *Cogent Food & Agriculture, 8*(1), 2057656.

Abera, H., Worku, W., Mamo, G., Ayalew, D., & Gayler, S. (2023). Rainfall variability and its seasonal events with associated risks for rainfed crop production in Southwest Ethiopia. *Cogent Food & Agriculture, 9*(1), 2231693.

Adnew, M. D., & Woldeamlak, B. (2023). Drought monitoring performance of global precipitation products in three wet seasons in ethiopia: Part i—quasi-objective examination. *Meteorological Applications, 30*(4), e2143.

Ageet, S., Fink, A. H., Maranan, M., Diem, J. E., Hartter, J., Ssali, A. L., & Ayabagabo, P. (2022). Validation of satellite rainfall estimates over equatorial East Africa. *Journal of Hydrometeorology, 23*(2), 129-151.

Agyekum, J., Annor, T., Quansah, E., Lamptey, B., & Okafor, G. (2022). Extreme precipitation indices over the Volta Basin: CMIP6 model evaluation. *Scientific African, 16,* e01181.

Ahmed, J. S., Buizza, R., Dell'Acqua, M., Demissie, T., & Pè, M. E. (2024). Evaluation of ERA5 and CHIRPS rainfall estimates against observations across Ethiopia. *Meteorology and Atmospheric Physics, 136*(3), 17.

Al-Shamayleh, S., Tan, M. L., Samat, N., Rahbeh, M., & Zhang, F. (2024). Performance of CHIRPS for estimating precipitation extremes in the Wala Basin, Jordan. *Journal of Water and Climate Change, 15*(3), 1349-1363.

Ali, Asgher, M., Hassan, M., Mehmood, M., Kazmi, D. H., Chishtie, F. A., & Shahid, I. (2022). The potential impact of climate extremes on cotton and wheat crops in Southern Punjab, Pakistan. *Sustainability, 14*(3), 1609.

Ali, Zulfiqar, Hamed, M. M., Muhammad, M. K. I., Iqbal, Z., & Shahid, S. (2023). Performance evaluation of CMIP6 GCMs for the projections of precipitation extremes in Pakistan. *Climate Dynamics, 61*(9), 4717-4732.

Allison, I., Béland, M., Alverson, K., Bell, R., Carlson, D., Cutler, P., . . . Hovelsrud, G. (2009). The state of polar research: A statement from the International Council for Science/World Meteorological Organization Joint Committee for the International Polar Year 2007-2008.

Amba, S., Berihu, T., & Arba, Y. (2024). Performance evaluation of multi-satellite rainfall products for analyzing rainfall variability in Abaya–Chamo basin: Southern Ethiopia. *Journal of Earth System Science, 133*(3), 139.

Amogne, A. E., & Yimer, H. (2024). Determinants of smallholder farmers' adaptation to the effects of climate extremes: evidence from Legambo district in northcentral Ethiopia. *Environment, Development and Sustainability*, 1-29.

Andualem, M. Y., & Gokcekus, H. (2020). Causes and effects of drought in northern parts of Ethiopia.

Assefa, A., & Degnet, A. (2021). Ethiopia-land, climate, energy, agriculture and development: A study in the sudano-sahel initiative for regional development, jobs, and food security.

Aster, T. H., Leta, O. T., Alamirew, T., Kawo, N. S., & Chukalla, A. D. (2021). Performance evaluation and comparison of satellite-derived rainfall datasets over the Ziway lake basin, Ethiopia. *Climate*, *9*(7), 113.

Awel, H. I., Molla, D. D., & Lohani, T. K. (2024). Performance evaluation of satellite-based rainfall estimates for hydrological modeling over Bilate river basin, Ethiopia. *World Journal of Engineering*, *21*(1), 1-15.

Ayele, A. F., Yasuda, H., Shimizu, K., Ibaraki, Y., Haregeweyn, N., Kawai, T., . . . Ebabu, K. (2018). Evaluation of satellite rainfall estimates over the Lake Tana basin at the source region of the Blue Nile River. *Atmospheric Research, 212*, 43-53.

Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Van Dijk, A. I., Weedon, G. P., . . . Wood, E. F. (2017). Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrology and Earth System Sciences, 21*(12), 6201-6217.

Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., van Dijk, A. I., Weedon, G. P., . . . Wood, E. F. (2020). Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Satellite Precipitation Measurement: Volume 2*, 625-653.

Beck, H. E., Wood, E. F., Pan, M., Fisher, C. K., Miralles, D. G., Van Dijk, A. I., . . . Adler, R. F. (2019). MSWEP V2 global 3-hourly 0.1 precipitation: methodology and quantitative assessment. *Bulletin of the American Meteorological Society, 100*(3), 473-500.

Behera, S. K. (2024). Understanding the impact of climate change on extreme events. In (Vol. 2, pp. 1433766): Frontiers Media SA.

Bereket, T. H., Zeleke, T. T., Beketie, K. T., Ayal, D. Y., & Feyisa, G. L. (2021). Analysis of El Niño Southern Oscillation and its impact on rainfall distribution and productivity of selected cereal crops in Kembata Alaba Tembaro zone. *Climate Services, 23*, 100254.

Bosilovich, M. G., Chen, J., Robertson, F. R., & Adler, R. F. (2008). Evaluation of global precipitation in reanalyses. *Journal of applied meteorology and climatology, 47*(9), 2279-2299.

Bosilovich, M. G., Lucchesi, R., & Suarez, M. (2015). *MERRA-2: File specification*. Retrieved from

Buuren, S., Groothuis-Oudshoorn, K., Robitzsch, A., Vink, G., Doove, L., & Jolani, S. (2015). Package 'mice'Version 2.25. *Multivariate Imputation by Chained Equations*.

Capua, G. D., & Rahmstorf, S. (2023). Extreme weather in a changing climate. *Environmental Research Letters, 18*(10), 102001.

Cavalcante, R. B. L., da Silva Ferreira, D. B., Pontes, P. R. M., Tedeschi, R. G., da Costa, C. P. W., & de Souza, E. B. (2020). Evaluation of extreme rainfall indices from CHIRPS precipitation estimates over the Brazilian Amazonia. *Atmospheric Research, 238*, 104879.

Chang, W.-Y., Vivekanandan, J., Ikeda, K., & Lin, P.-L. (2016). Quantitative precipitation estimation of the epic 2013 Colorado flood event: Polarization radar-based variational scheme. *Journal of Applied Meteorology and Climatology, 55*(7), 1477-1495.

Core Team, R. (2015). R: A language and environment for statistical computing. *R Foundation for Statistical Computing.*

CSA, C. S. A. o. E. (2007). *Summary and Statistical Report of the 2007 Population and Housing Census*

Results. Retrieved from

Daniel, M., Bewket, W., & Lal, R. (2015). Soil erosion hazard under the current and potential climate change induced loss of soil organic matter in the Upper Blue Nile (Abay) River

Basin, Ethiopia. *Sustainable intensification to advance food security and enhance climate resilience in Africa*, 137-163.

Duan, J., Liu, Y.-J., Yang, J., Tang, C.-J., & Shi, Z.-H. (2020). Role of groundcover management in controlling soil erosion under extreme rainfall in citrus orchards of southern China. *Journal of Hydrology, 582*, 124290.

Elsabet, T. A., & Getachew, T. A. (2024). Validating the Skills of Satellite Rainfall Products and Spatiotemporal Rainfall Variability Analysis over Omo River Basin in Ethiopia. *Hydrology, 12*(2), 36-51.

Endeg, A., Gashaw, T., Abraham, T., Demessie, S. F., Bayabil, H. K., Worqlul, A. W., . . . Haileslassie, A. (2023). Evaluating the performances of gridded satellite/reanalysis products in representing the rainfall climatology of Ethiopia. *Geocarto International, 38*(1), 2278329.

Funk, C, C., Peterson, P. J., Landsfeld, M. F., Pedreros, D. H., Verdin, J. P., . . . Verdin, A. P. (2014). *A quasi-global precipitation time series for drought monitoring* (2327-638X). Retrieved from

Funk, Chris, Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., . . . Hoell, A. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data, 2*(1), 1-21.

Gebrekidan, W., Teferi, E., Bantider, A., & Dile, Y. T. (2019). Observed changes in extremes of daily rainfall and temperature in Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia. *Theoretical and Applied Climatology, 135*, 839-854.

Gebrekidan , W., Teferi, E., Bantider, A., & Dile, Y. T. (2021). Modelling hydrological processes under climate change scenarios in the Jemma sub-basin of upper Blue Nile Basin, Ethiopia. *Climate Risk Management, 31*, 100272.

Gebrekidan , W., Teferi, E., Bantider, A., Dile, Y. T., & Taye, M. T. (2018). Evaluation of regional climate models performance in simulating rainfall climatology of Jemma sub-basin, Upper Blue Nile Basin, Ethiopia. *Dynamics of Atmospheres and Oceans, 83*, 53-63.

Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., . . . Reichle, R. (2017). The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *Journal of Climate, 30*(14), 5419-5454.

Getachew, Dubache, Asmerom, B., Ullah, W., Ogwang, B. A., Amiraslani, F., . . . Gul, C. (2021). Testing the accuracy of high-resolution satellite-based and numerical model output precipitation products over Ethiopia. *Theoretical and Applied Climatology, 146*, 1127-1142.

Getachew, Dubache, Ogwang, B. A., Ongoma, V., & Towfiqul Islam, A. R. M. (2019). The effect of Indian Ocean on Ethiopian seasonal rainfall. *Meteorology and Atmospheric Physics, 131*(6), 1753-1761.

Getachew , T. A., Tadesse, T., Gessesse, B., & Dinku, T. (2018). Validation of new satellite rainfall products over the Upper Blue Nile Basin, Ethiopia. *Atmospheric Measurement Techniques, 11*(4), 1921-1936.

Getnet, D. B., Mohamed, Y. A., van Griensven, A., & Srinivasan, R. (2011). Sediment management modelling in the Blue Nile Basin using SWAT model. *Hydrology and Earth System Sciences, 15*(3), 807-818.

Gizachew , B. W., Gashaw, T., Worqlul, A. W., Dile, Y. T., Taye, M. T., Haileslassie, A., . . . Mohammed, J. A. (2023). Trends in rainfall and temperature extremes in Ethiopia: Station and agro-ecological zone levels of analysis. *Atmosphere, 14*(3), 483.

Gizachew, K. W., Muleta, M. K., & Awoke, B. G. (2021). Performance evaluation of multiple satellite rainfall products for Dhidhessa River Basin (DRB), Ethiopia. *Atmospheric Measurement Techniques, 14*(3), 2299-2316.

Gorjizadeh, A., & Moridi, A. (2024). Comparative Analysis of the Performance of Gridded Precipitation Products Over Iran. *Water Harvesting Research, 7*(2), 175-193.

Grimaldi, S., Petroselli, A., Baldini, L., & Gorgucci, E. (2018). Description and preliminary results of a 100 square meter rain gauge. *Journal of hydrology, 556*, 827-834.

Guo, Lijie, Huang, L., Li, J., Liu, L., Huang, L., . . . Ren, C. (2021). A comprehensive evaluation of key tropospheric parameters from ERA5 and MERRA-2 reanalysis products using radiosonde data and GNSS measurements. *Remote Sensing, 13*(15), 3008.

Guo , H., Bao, A., Chen, T., Zheng, G., Wang, Y., Jiang, L., & De Maeyer, P. (2021). Assessment of CMIP6 in simulating precipitation over arid Central Asia. *Atmospheric Research, 252*, 105451.

Guo , H., Chen, S., Bao, A., Hu, J., Gebregiorgis, A. S., Xue, X., & Zhang, X. (2015). Inter-comparison of high-resolution satellite precipitation products over Central Asia. *Remote Sensing, 7*(6), 7181-7211.

Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of hydrologic engineering, 4*(2), 135-143.

He, Q., Yang, J., Chen, H., Liu, J., Ji, Q., Wang, Y., & Tang, F. (2021). Evaluation of extreme precipitation based on three long-term gridded products over the Qinghai-Tibet Plateau. *Remote Sensing, 13*(15), 3010.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., . . . Schepers, D. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society, 146*(730), 1999-2049.

Hettiarachchi, S., Wasko, C., & Sharma, A. (2018). Increase in flood risk resulting from climate change in a developed urban watershed–the role of storm temporal patterns. *Hydrology and Earth System Sciences, 22*(3), 2041-2056.

Houngnibo, M. C., Minoungou, B., Traore, S. B., Maidment, R. I., Alhassane, A., & Ali, A. (2023). Validation of high-resolution satellite precipitation products over West Africa for rainfall monitoring and early warning. *Frontiers in Climate, 5*, 1185754.

IPCC. (2021). Summary for policymakers. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, B. Zhou (Eds.), Climate Change 2021: the Physical Science Basis. . *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. , 2*(1), 2391.

Jeitany, J., Pacetti, T., & Caporali, E. (2024). Evaluating climate change effects on hydrological functionality and water-related ecosystem services. *Ecohydrology, 17*(4), e2557.

Jemal, A., Mohammed. (2024a). Trend analysis of extreme rainfall indices from CHIRPS precipitation estimates over the Lake Tana sub-basin, Abbay Basin of Ethiopia. *Environmental Monitoring and Assessment, 196*(6), 575.

Jemal, A., Mohammed, Gashaw, T., Tefera, G. W., Dile, Y. T., Worqlul, A. W., & Addisu, S. (2022). Changes in observed rainfall and temperature extremes in the Upper Blue Nile Basin of Ethiopia. *Weather and Climate Extremes, 37*, 100468.

Jemal , A. M., Gashaw, T., & Yimam, Z. A. (2024b). Identification of erosion-prone watersheds for prioritizing soil and water conservation in a changing climate using morphometric analysis and GIS. *Natural Hazards*, 1-19.

Jiang, Qin, Li, W., Fan, Z., He, X., Sun, W., . . . Wang, J. (2021). Evaluation of the ERA5 reanalysis precipitation dataset over Chinese Mainland. *Journal of hydrology, 595*, 125660.

Jiang, Zhiyu, Liu, D., Dong, G., Tang, J., Wang, S., & Xiong, Y. (2024). Convection-permitting regional climate simulations over coastal regions in China. *Climate Dynamics*, 1-21.

Jin, H., Chen, X., Adamowski, J., & Hatami, S. (2024). Determination of duration, threshold and spatiotemporal distribution of extreme continuous precipitation in nine major river basins in China. *Atmospheric Research, 300*, 107217.

Kehase, N. G., Tamrie, M. B., & Desta, H. B. (2023). Performance evaluation of multi-satellite rainfall products in the Gidabo catchment, Rift Valley Basin, Ethiopia. *Journal of Water and Climate Change, 14*(11), 3950-3966.

Kiany, M. S. K., Masoodian, S. A., Balling Jr, R. C., & Montazeri, M. (2020). Evaluation of the TRMM 3B42 product for extreme precipitation analysis over southwestern Iran. *Advances in Space Research, 66*(9), 2094-2112.

Kindie, E. T., Melesse, A. M., Abebe, A., Lakew, H. B., & Paron, P. (2022). Evaluation of global precipitation products over wabi shebelle river basin, Ethiopia. *Hydrology, 9*(5), 66.

Kirubel, M., Melesse, A. M., & Woldesenbet, T. A. (2021). Spatial evaluation of satellite-retrieved extreme rainfall rates in the Upper Awash River Basin, Ethiopia. *Atmospheric Research, 249*, 105297.

Kirubel, M., Velpuri, N. M., Leh, M., Akpoti, K., Owusu, A., Tinonetsana, P., . . . 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.

Kistler, R., Kalnay, E., Collins, W., Saha, S., White, G., Woollen, J., . . . Kousky, V. (2001). The NCEP–NCAR 50-year reanalysis: monthly means CD-ROM and documentation. *Bulletin of the American Meteorological society, 82*(2), 247-268.

Kling, H., Fuchs, M., & Paulin, M. (2012). Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios. *Journal of hydrology, 424*, 264-277.

Kofidou, M., Stathopoulos, S., & Gemitzi, A. (2023). Review on spatial downscaling of satellite derived precipitation estimates. *Environmental Earth Sciences, 82*(18), 424.

Lavers, D. A., Simmons, A., Vamborg, F., & Rodwell, M. J. (2022). An evaluation of ERA5 precipitation for climate monitoring. *Quarterly Journal of the Royal Meteorological Society, 148*(748), 3152-3165.

Lengfeld, K., Kirstetter, P.-E., Fowler, H. J., Yu, J., Becker, A., Flamig, Z., & Gourley, J. (2020). Use of radar data for characterizing extreme precipitation at fine scales and short durations. *Environmental Research Letters, 15*(8), 085003.

Li, Shuai, Chen, Y., Wei, W., Fang, G., & Duan, W. (2024). The increase in extreme precipitation and its proportion over global land. *Journal of hydrology, 628*, 130456.

Li , Yu, Pang, B., Ren, M., Shi, S., Peng, D., . . . Zuo, D. (2022). Evaluation of performance of three satellite-derived precipitation products in capturing extreme precipitation events over Beijing, China. *Remote Sensing, 14*(11), 2698.

Li, Yu, Pang, B., Ren, M., Shi, S., Peng, D., . . . Zuo, D. (2022). Evaluation of performance of three satellite-derived precipitation products in capturing extreme precipitation events over Beijing, China. *Remote Sensing, 14*(11), 2698.

Li , C., Tang, G., & Hong, Y. (2018). Cross-evaluation of ground-based, multi-satellite and reanalysis precipitation products: Applicability of the Triple Collocation method across Mainland China. *Journal of Hydrology, 562*, 71-83.

Liu, Junzhi, Ma, X., Duan, Z., Jiang, J., Reichstein, M., & Jung, M. (2020). Impact of temporal precipitation variability on ecosystem productivity. *Wiley Interdisciplinary Reviews: Water, 7*(6), e1481.

Liu, Ke, Harrison, M. T., Yan, H., Liu, D. L., Meinke, H., . . . Jaegermeyr, J. (2023). Silver lining to a climate crisis in multiple prospects for alleviating crop waterlogging under future climates. *Nature communications, 14*(1), 765.

Macharia, J. M., Ngetich, F. K., & Shisanya, C. A. (2020). Comparison of satellite remote sensing derived precipitation estimates and observed data in Kenya. *Agricultural and Forest Meteorology, 284*, 107875.

Mahbod, M., Shirvani, A., & Veronesi, F. (2019). A comparative analysis of the precipitation extremes obtained from tropical rainfall-measuring mission satellite and rain gauges datasets over a semiarid region. *International Journal of Climatology, 39*(1), 495-515.

Maidment, R. I., Grimes, D., Allan, R. P., Tarnavsky, E., Stringer, M., Hewison, T., . . . Black, E. (2014). The 30 year TAMSAT African rainfall climatology and time series (TARCAT) data set. *Journal of Geophysical Research: Atmospheres, 119*(18), 10,619-610,644.

Marye, B., Deng, J., Wang, K., Zhou, M., Zhu, E., Shifaw, E., & Bayissa, Y. (2020). Evaluation of satellite rainfall products for modeling water yield over the source region of Blue Nile Basin. *Science of the Total Environment, 708*, 134834.

Medeiros, F. J., de Oliveira, C. P., & Avila-Diaz, A. (2022). Evaluation of extreme precipitation climate indices and their projected changes for Brazil: From CMIP3 to CMIP6. *Weather and Climate Extremes*, *38*, 100511.

Mekonnen , G., Bitew, M. M., Hirpa, F. A., & Tesfay, G. N. (2014). Accuracy of satellite rainfall estimates in the B lue N ile B asin: L owland plain versus highland mountain. *Water Resources Research, 50*(11), 8775-8790.

Melese, G. (2019). Farmer’s response to climate change and variability in Ethiopia: A review. *Cogent Food & Agriculture, 5*(1), 1613770.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE, 50*(3), 885-900.

Mulugojjam, T., Mengistu, D., & Sahlu, D. (2023). Performance evaluation of multiple satellite rainfall data sets in central highlands of Abbay Basin, Ethiopia. *European Journal of Remote Sensing, 56*(1), 2233686.

Munzhedzi, L., Mugari, E., Nethengwe, N. S., & Gumbo, A. D. (2024). Trends in extreme rainfall and their relationship to flooding episodes in Vhembe district, South Africa. *Environmental Research Communications, 6*(9), 095016.

Narayan, M., Singh, N., Solanki, P., & Srivastava, R. (2024). Impact of Extreme Events on Global Food Security. In *Food Security in a Developing World: Status, Challenges, and Opportunities* (pp. 133-152): Springer.

Ndemere, K., Gumindoga, W., Makurira, H., & Rwasoka, D. T. (2024). Performance evaluation of multiple satellite rainfall products in mountainous catchment of Eastern Zimbabwe. *Scientific African, 23*, e02120.

Nguyen, P., Ombadi, M., Sorooshian, S., Hsu, K., AghaKouchak, A., Braithwaite, D., . . . Thorstensen, A. R. (2018). The PERSIANN family of global satellite precipitation data: A review and evaluation of products. *Hydrology and Earth System Sciences, 22*(11), 5801-5816.

Ollivier, C. C., Carrière, S. D., Heath, T., Olioso, A., Rabefitia, Z., Rakoto, H., . . . Satgé, F. (2023). Ensemble precipitation estimates based on an assessment of 21 gridded precipitation datasets to improve precipitation estimations across Madagascar. *Journal of Hydrology: Regional Studies, 47*, 101400.

Palharini, R. S. A., Vila, D. A., Rodrigues, D. T., Quispe, D. P., Palharini, R. C., de Siqueira, R. A., & de Sousa Afonso, J. M. (2020). Assessment of the extreme precipitation by satellite estimates over South America. *Remote Sensing, 12*(13), 2085.

Raihan, A. (2023). A review of the global climate change impacts, adaptation strategies, and mitigation options in the socio-economic and environmental sectors. *Journal of Environmental Science and Economics, 2*(3), 36-58.

Ramon, J., Lledó, L., Torralba, V., Soret, A., & Doblas-Reyes, F. J. (2019). What global reanalysis best represents near-surface winds? *Quarterly Journal of the Royal Meteorological Society, 145*(724), 3236-3251.

Raza, A., Safdar, M., Adnan Shahid, M., Shabir, G., Khil, A., Hussain, S., . . . Sattar, J. (2024). Climate Change Impacts on Crop Productivity and Food Security: An Overview. *Transforming Agricultural Management for a Sustainable Future: Climate Change and Machine Learning Perspectives*, 163-186.

Reichle, R. H., Liu, Q., Koster, R. D., Draper, C. S., Mahanama, S. P., & Partyka, G. S. (2017). Land surface precipitation in MERRA-2. *Journal of Climate, 30*(5), 1643-1664.

Rohatyn, S., Rotenberg, E., Ramati, E., Tatarinov, F., Tas, E., & Yakir, D. (2018). Differential impacts of land use and precipitation on “ecosystem water yield”. *Water Resources Research, 54*(8), 5457-5470.

Sahlaoui, Z., & Mordane, S. (2019). Radar rainfall estimation in Morocco: Quality control and gauge adjustment. *Hydrology, 6*(2), 41.

Schlenker, W., & Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters, 5*(1), 014010.

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Luca, A. D., . . . Lewis, S. (2021). Weather and climate extreme events in a changing climate.

Shalishe, A., Berihu, T., & Arba, Y. (2024). Performance evaluation of multi-satellite rainfall products for analyzing rainfall variability in Abaya–Chamo basin: Southern Ethiopia. *Journal of Earth System Science, 133*(3), 139.

Sintayehu, A. A., Qin, T., Yan, D., Gelaw, E. B., Workneh, H. T., Kun, W., . . . Dong, B. (2020). Spatial and temporal evaluation of the latest high-resolution precipitation products over the Upper Blue Nile River Basin, Ethiopia. *Water, 12*(11), 3072.

Sist, M., Schiavon, G., & Del Frate, F. (2021). A New Data Fusion Neural Network Scheme for Rainfall Retrieval Using Passive Microwave and Visible/Infrared Satellite Data. *Applied Sciences, 11*(10), 4686.

Solomon, A., Aniley, E., Gashaw, T., Kelemu, S., & Fetene Demessie, S. (2024). Evaluating the performances of gridded satellite products in simulating the rainfall characteristics of Abay Basin, Ethiopia. *Sustainable Environment, 10*(1), 2381349.

Su, T., & Feng, G. (2015). Spatial-temporal variation characteristics of global evaporation revealed by eight reanalyses. *Science China Earth Sciences, 58*, 255-269.

Subba, S., Ma, Y.-M., Ma, W.-Q., & Han, C.-B. (2024). Extreme precipitation detection ability of four high-resolution precipitation product datasets in hilly area: a case study in Nepal. *Advances in Climate Change Research, 15*(3), 390-405.

Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., & Hsu, K. L. (2018). A review of global precipitation data sets: Data sources, estimation, and intercomparisons. *Reviews of Geophysics, 56*(1), 79-107.

Tabari, H. (2020). Climate change impact on flood and extreme precipitation increases with water availability. *Scientific reports, 10*(1), 13768.

Tadele , M. L., Gashaw, T., Tefera, G. W., & Mohammed, J. A. (2023). Trend analysis of hydro-climate variables in the Jemma sub-basin of Upper Blue Nile (Abbay) Basin, Ethiopia. *SN Applied Sciences, 5*(5), 129.

Tegegn, B., Simane, B., & Abi, M. (2024). Analysis of DailyTemperature and Precipitation Climate Extremes in Hamassa Watershed, Southern Ethiopia. *F1000Research, 13,* 1132.

Temesgen, G., Worqlul, A. W., Lakew, H., Taye, M. T., Seid, A., & Haileslassie, A. (2023b). Evaluations of satellite/reanalysis rainfall and temperature products in the Bale Eco-Region (Southern Ethiopia) to enhance the quality of input data for hydro-climate studies. *Remote Sensing Applications: Society and Environment, 31*, 100994.

Temesgen, G., Worqlul, A. W., Taye, M. T., Lakew, H. B., Seid, A., Ayele, G., & Haileslassie, A. (2024). Performance evaluations of CMIP6 model simulations and future projections of rainfall and temperature in the Bale Eco-Region, Southern Ethiopia. *Theoretical and Applied Climatology*, 1-24.

Temesgen, G., Wubaye, G. B., Worqlul, A. W., Dile, Y. T., Mohammed, J. A., Birhan, D. A., . . . Chukalla, A. D. (2023a). Local and regional climate trends and variabilities in Ethiopia: Implications for climate change adaptations. *Environmental Challenges, 13,* 100794.

Tesfa, G. A., Malede, D. A., & Ejigu, M. T. (2020). Performance evaluation of integrated multi-satellite retrieval for global precipitation measurement products over Gilgel Abay watershed, Upper Blue Nile Basin, Ethiopia. *Modeling Earth Systems and Environment, 6*(3), 1853-1861.

Tufa, D., Faniriantsoa, R., Islam, S., Nsengiyumva, G., & Grossi, A. (2022). The climate data tool: enhancing climate services across Africa. *Frontiers in Climate, 3*, 787519.

Tufa, D., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H., & Ceccato, P. (2018). Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society, 144*, 292-312.

Wang, & Feng, Y. (2010). RHtestsV4 user manual, climate research division, science and technology branch, environment Canada, Toronto, Ontario, Canada. In.

Wang, Lei, Li, Y., Li, M., Li, L., Liu, F., . . . Pulatov, B. (2022). Projection of precipitation extremes in China's mainland based on the statistical downscaled data from 27 GCMs in CMIP6. *Atmospheric Research, 280*, 106462.

WMO. (2009). Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation. *1500*, 72.

Xiao, S., Xia, J., & Zou, L. (2020). Evaluation of multi-satellite precipitation products and their ability in capturing the characteristics of extreme climate events over the Yangtze River Basin, China. *Water, 12*(4), 1179.

Xue, X., Hong, Y., Limaye, A. S., Gourley, J. J., Huffman, G. J., Khan, S. I., . . . Chen, S. (2013). Statistical and hydrological evaluation of TRMM-based Multi-satellite Precipitation Analysis over the Wangchu Basin of Bhutan: Are the latest satellite precipitation products 3B42V7 ready for use in ungauged basins? *Journal of hydrology, 499*, 91-99.

Yao, Y., Zhang, W., & Kirtman, B. (2023). Increasing impacts of summer extreme precipitation and heatwaves in eastern China. *Climatic Change, 176*(10), 131.

Yimer, M., Yimer, F., Tadesse, M., & Tesfaye, K. (2018). Variability and trends of rainfall extreme events in north east highlands of Ethiopia. *International Journal of Hydrology, 2*(5), 594-605.

Yong, B., Chen, B., Gourley, J. J., Ren, L., Hong, Y., Chen, X., . . . Gong, L. (2014). Intercomparison of the Version-6 and Version-7 TMPA precipitation products over high and low latitudes basins with independent gauge networks: Is the newer version better in both real-time and post-real-time analysis for water resources and hydrologic extremes? *Journal of hydrology, 508*, 77-87.

Zarrin, A., & Dadashi-Roudbari, A. (2022). Evaluation of reanalysis-based, satellite-based, and "bias-correction"-based datasets for capturing extreme precipitation in Iran. *Meteorology and Atmospheric Physics, 134*(4), 67.

Zhang, Binglin, Song, S., Wang, H., Guo, T., & Ding, Y. (2024). Evaluation of the performance of CMIP6 models in simulating extreme precipitation and its projected changes in global climate regions. *Natural Hazards*, 1-27.

Zhang, & Yang, F. (2004). RClimDex (1.0) user manual. *Climate Research Branch Environment Canada, 22*, 13-14.

Zhang, Yuefen, Wu, C., Yeh, P. J.-F., Li, J., Hu, B. X., . . . Lei, Y. (2022). Evaluation of multi-satellite precipitation products in estimating precipitation extremes over mainland China at annual, seasonal and monthly scales. *Atmospheric Research, 279*, 106387.

Zhang , B., Song, S., Wang, H., Guo, T., & Ding, Y. (2024). Evaluation of the performance of CMIP6 models in simulating extreme precipitation and its projected changes in global climate regions. *Natural Hazards*, 1-27.

Biography Sketch

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