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Evaluating the Performances of Gridded Satellite/Reanalysis Products in Representing the Rainfall Climatology of Ethiopia

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EVALUATING THE PERFORMANCES OF GRIDDED SATELLITE/REANALYSIS PRODUCTS IN REPRESENTING THE RAINFALL CLIMATOLOGY OF ETHIOPIA

MSc THESIS

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Evaluating the performances of gridded satellite/reanalysis products in representing the rainfall climatology of Ethiopia

M. Sc. Thesis

By

Endege Aniley Alem

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

Advisor: Temesgen Gashaw (Ph.D.)

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APPROVAL SHEET

As a member of the Board of Examiners of the Master of Science (M.Sc.) thesis open defense examination, we have read and evaluated this thesis prepared by **Mr. Endege Aniley** entitled **"Evaluating the performances of gridded satellite/reanalysis products in representing the rainfall climatology of Ethiopia"**. We hereby certify that the thesis is accepted for fulfilling the requirements for the award of the degree of Master of Science (M.Sc.) program in **"Environment and climate change"**.

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DECLARATION

This is to certify that the thesis prepared by Endege Aniley Alem (ID. No BDU1401283), entitled: **"Evaluating the performances of gridded satellite/reanalysis products in representing the rainfall climatology of Ethiopia"** and submitted in partial fulfillment of the requirements for the Degree of Masters of Science in **"Environment and Climate Change"** complies with the regulation of the University and meets the accepted standards with respect to originality and quality. 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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DEDICATION

This thesis is dedicated to my lovely family for their concern, prayer, and unwavering support and encouragement throughout my whole academic career and life.

LIST OF ABBREVIATIONS AND ACRONYMS

AEZs	Agro-ecological zones
ARC2	Africa rainfall climatology version 2
CFSR	Climate Forecast System Reanalysis System
CHIRPS v2.0	Climate Hazard group infrared precipitation with stations version 2.0
CHPclim	Climate Hazard Precipitation Climatology
CMORPH	Climate Prediction Center Morphing Technique
CPC	Climate Prediction Center
CPC-Global	Gauge-based Analysis of Global daily precipitation
CSI	Critical Success Index
EARA-Interim	Intermediate ECMWF Reanalysis product
ECMWF	European Center for Medium-Range Weather Forecast
ERA5	The Fifth Generation ECMFW Reanalysis
FAR	False alarm ratio
FBI	Frequency Bias index
FEWS NET	The Famine Early Warnings System Networks
FLDAS	FEWS NET -Data Assimilation System
FMAM	February- March-April- May
GHCN-M	Global Historical Climatology Network
GPCC	Global Precipitation Climatology Center
GPCP	Global Precipitation Climatology Project
GPCP_PEN_v2.2	Global Precipitation Climatology Project Pentad version 2.2
GSMap	Global Satellite Mapping of Precipitation
HSS	Heidke skill score
IMERG v6.0	Integrated Multi-Satellite Retrievals Version 6.0
JJAS	June-July-August- September

JRA55	Japanese 55-year reanalysis
KGE	Kling Gupta Efficiency
LEO	Low Earth Orbit
m.a.s.l	meter above sea level
MAE	Mean absolute error
MERRA	Modern-Era Retrospective Analysis for Research and Application
MSWEP v2.2	Mult-Source weighted ensemble precipitation version 2.2
MSWEP v2.1	Mult-Source weighted ensemble precipitation version 2.1
MSWEP v2.8	Mult-Source weighted ensemble precipitation version 2.8
NASA	National Aeronautics and Space Administration
NCEP v1.0	National Centers for Environmental Prediction version 1.0
NCEP v2.0	National Centers for Environmental Prediction version 2.0
NSE	Nash Sutcliffe Efficiency
ONDJ	October-November-December-January
PBIAS	percent bias
PDF	Probability Density Function
PERSIAN	Precipitation Estimation from Remotely Sensed Information
POD	Probability of detection
PRECL	Precipitation Reconstruction over Land
r	Pearson correlation coefficient
R^2	Coefficient of determination
RMSE	Root mean square error
SM2RAIN-SCATT1.1	Soil Moisture to Rain Using Advanced SCAT Terameter Version 1.1
TAMSAT v3.0	Tropical Applications of Meteorology Using Satellite version 3.0
TAMSAT v3.1	Tropical Applications of Meteorology Using Satellite version 3.1
TMPA	Tropical Multi-Satellite Precipitation Analysis
UDEL	University of Delaware

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ABSTRACT

Rainfall is one of the most important hydrological and climatic elements for many applications. Satellite/reanalysis rainfall products have recently become an alternative source to rain gauges and have shown broader application. This study evaluated the performance of Climate Hazard Group Infrared Precipitation with stations version 2.0 (CHIRPS v2.0) and Multi-Source Weighted-Ensemble Precipitation version 2.8 (MSWEP v2.8) products against observed data were evaluated. Rainfall climatology was simulated for different agroecological zones (AEZs) of Ethiopia for the period 1991-2020 at different temporal scales ranging from daily to annual. Rainfall occurrence detection capabilities were assessed using suites of performance evaluation measures, such as the probability of detection (POD), false alarm ratio (FAR), frequency bias index (FBI), and critical success index (CSI). In addition, statistical evaluation metrics were used, including mean absolute error (MAE), root mean square error (RMSE), percent bias (PBIAS), correlation coefficient (r), and Kling Gupta efficiency (KGE). The result showed that_CHIRPS v2.0 is preferable for estimating monthly, seasonal, and annual rainfall totals, and MSWEP v2.8 for daily rainfall have shown better performance over all AEZs. The two products display comparable performance for detecting daily rainfall occurrences over alpine AEZ, but MSWEP v2.8 is superior in the rest four AEZs. CHIRPS v2.0 outperforms MSWEP v2.8 for detecting most of the daily rainfall intensity classes over all AEZs. Overall, the two rainfall products can be used for climate simulation over tropical, subtropical, temperate, and alpine AEZs, but not over the desert AEZ of Ethiopia. The findings of this study will play a noteworthy role to improve the quality of hydro-climate studies in Ethiopia. Generally, for both grid-based and station wise national level studies, I recommend CHIRPS v2.0 for monthly, Bega season, Belg season, Kiremt season and annual temporal scales and MSWEP v2.8 for daily time step studies.

Keywords*: Performance evaluation, Rainfall products, Agroecology zones*

CHAPTER 1. INTRODUCTION

1.1.Background of the study

Rainfall is one of the most important hydrological and climatic elements for many aspects (Dangol *et al*., 2022; Li *et al*., 2022). Rain gauge is considered to be most reliable rainfall data source (Liu *et al*., 2020; Polong *et al*., 2023). However, the sparse and uneven distribution of rain gauges makes their applicability difficult (Cavalcante *et al*., 2020; Bathelemy *et al*., 2022; Guo *et al., 2023)*. Satellite/reanalysis rainfall products have recently become an alternative source to rain gauges and have shown broader applicability in different studies (Dinku *et al*., 2007; Aksu & Akgül, 2020). For example, reliable information from satellite/reanalysis rainfall products with sufficient spatiotemporal scales can be applicable for hydrological modeling (Aksu & Akgül, 2020; Dangol *et al*., 2022; Hafizi & Sorman, 2022), drought monitoring (Li *et al*., 2022; Randriatsara *et al*., 2022) and water resources assessment and modeling (Wiwoho *et al*., 2021; Dangol *et al*., 2022; Randriatsara *et al*., 2022). Accurate rainfall data can be also applied for agricultural decision-making (Paredes-Trejo *et al*., 2017; Randriatsara *et al*., 2022), flood monitoring (Nashwan *et al*., 2019; Bathelemy *et al*., 2022), and climate change impact and adaptation studies (Cavalcante *et al*., 2020; Randriatsara *et al*., 2022).

Due to lack of meteorological data particularly in developing countries, several studies were undertaken to identify best rainfall products over different areas of the world. For instance, the performance of CHIRPS v2.0 with MSWEP v2.8 and other Rainfall products was evaluated at different spatiotemporal resolutions, periods of study, methods of evaluation, and the number of gauge stations used over different areas of the world. Some of the evaluations were CHIRPS v2.0 and MSWEP v2.8 rainfall products with other three over equatorial East Africa (Ageet *et al*., 2022), CHIRPS v2.0 and MSWEP v2.8 with other 6 over Colombia (Valencia et al., 2023), CHIRPS v2.0 with other two over Eastern Africa (Dinku *et al*., 2018) and CHIRPS v2.0 and MSWEP v2.8 with other 11 over eastern Turkey (Hafizi & Sorman, 2022). The majority of the studies indicated that CHIRPS v2.0 was superior in simulating the observed rainfall climatology than the other Rainfall products. But, a study by Ageet *et al*. (2022) over equatorial East Africa indicated that the performance of MSWEP v2.8 was declining as compared with the earlier version of MSWEP v2.2.

Similarly, CHIRPS v2.0 with other Rainfall products were evaluated ranging from national to small scale study areas of Ethiopia such as the evaluation of CHIRPS v2.0 and other three over the Upper Blue Nile basin (Abebe *et al*., 2020), CHIRPS v2.0 with other 19 rainfall products in Ethiopia (Degefu *et al*., 2022), CHIRPS v2.0 with other three over upper Tana Sub-basin (Polong *et al*., 2023), CHIRPS v2.0 with other five and their downscaled version over Wabi-Shebele river basin (Tadesse *et al*., 2022). Most of the studies concluded that CHIRPS v2.0 was superior in replicating regional climatology than other rainfall products by most performance measures, especially at monthly time scale. Moreover, MSWEP v2.8, CHIRPS v2.0 ,and TAMSAT v3.1 were evaluated recently over Bale Eco-Region (Southern Ethiopia) to improve the quality of the input dataset for hydro-climate analysis (Gashaw *et al*., 2023). In their analysis, MSWEP v2.8 was superior to CHIRPS v2.0 to detect daily rainfall total and occurrence. On the other hand, CHIRPS v2.0 outperformed to detect the annual rainfall total in the monthly, dry, and wet seasons and annual temporal scales.

In this study, I evaluated two rainfall products at a national level to facilitate a national-scale decision related to rainfall data and climate. Besides this, MSWEP v2.8 was not intensively evaluated and used for application on a national scale of Ethiopia. So, the study focused on the evaluation of MSWEP v2.8 and CHIRPS v2.0 over AEZs of Ethiopia for simulating rainfall climatology. In the study, rainfall products detection capability of rainfall occurrence, total, and intensity class at daily timescale, the performance of rainfall products rainfall total at monthly, seasonal, and annual time scale was evaluated by using categorical and continuous statistical indices and graphical techniques for the period 1991-2020 with 47-gauge station data based on their respective AEZs were included.

1.2. Statement of the Problem

Even though, numerous applications employ climatic data, there are extremely few climatic data sources, particularly in rural Africa (Dinku *et al*., 2014). Nowadays, satellite precipitation estimations, have been utilized as alternatives source of climate data (Dinku *et al*., 2014).But, the temporal and spatial estimation performance of satellites precipitation products differ from region to region (Kidd, 2001; Wang *et al*., 2017). So, the estimation performance of satellites for each area and time period shall be evaluated and identified before use for any application (Morales-Acuña *et al*., 2021; Jiang *et al*., 2022).

Previous evaluations of rainfall products in Ethiopia were focused on small-scale areas (watersheds, sub-basins, basins) of the country (Fenta *et al*., 2018; Belay *et al*., 2019; Tadesse *et al*., 2022). In addition, majority of previous evaluations of rainfall products in Ethiopia were performed by taking the average values of the study area (Andualem *et al*., 2020; Tadesse *et al*., 2022), except few of them which categories in their study area into broad categories such as highland (>1500 m.a.s.l..) and lowland (<1500 m.a.s.l.) (Fenta et al., 2018; Belay et al., 2019). However, performance of satellite/reanalysis rainfall products depend on topography, season and climate (Dinku *et al*., 2007, Dinku *et al*.,2018; Bathelemy *et al*., 2022; Reddy & Saravanan, 2023) and hence, it can vary from one climate zone to another particularly in mountainous countries such as Ethiopia. Moreover, majority of previous evaluations of rainfall products did not cover the full range of temporal scales (Belay *et al*., 2019; Lemma *et al*., 2019; Tadesse *et al*., 2022). However, a recent finding from the Bale Eco-Region (Southern Ethiopia) indicated that performance of rainfall products can vary from one temporal scale to another (Gashaw *et al*., 2023). Furthermore, most of earlier studies in Ethiopia were evaluated those rainfall products using continuous and categorical performance measures (Fenta *et al*., 2018; Belay *et al*., 2019). However, in addition to these metrics, evaluation of rainfall products using rainfall intensity is important for certainly use the best performing model for hydro-climate and hydro-sediment researches.

Therefore, this study aimed to evaluate the performances of MSWEP v2.8 and CHIRPS v2.0 over AEZs of Ethiopia for simulating rainfall climatology from daily to annual temporal scales for the period 1991-2020 with 47 meteorological stations data. The main reasons for the selection of these two products over others include: A) In Ethiopia, many studies evaluated gridded satellite/reanalysis products in different watersheds/sub-basins/basins, and indicated the superior performance of CHIRPS v2.0 compared to other products, but still there is discrepancy from observed rainfall (Ayehu *et al*., 2018; Belete *et al*., 2020; Wedajo *et al*., 2021; Malede *et al*., 2022). Hence, I focused to evaluate satellite/reanalysis product which have good performance, and B) MSWEP v2.8 is a new product and it has not been evaluated except in the Bale Eco-Region (Gashaw *et al*., 2023). However, the earlier versions of MSWEP2.8 (MSWEP v2.1 and MSWEP v2.2) were evaluated in the Upper Blue Nile Basin (Abebe *et al*., 2020; Lakew, 2020). In addition, MSWEP v2.0 was also used as an input for hydrological modeling in the Central Rift Valley basin (Abraham *et al*., 2022). Therefore, since there are limited studies on MSWEP v2.8, I was interested to compare the most performing rainfall product (CHIPRS v2.0) with the new rainfall product (MSWEP v2.8) at the national scale at different AEZs. Therefore, the novelty of this study is evaluations of the latest versions of the two rainfall products using a comprehensive performance evaluation metrics, which is using continuous, categorical, and intensity performance measure statistics, from daily to annual temporal scales at each AEZs of the country.

1.3. Objectives of the Study

1.3.1. General objective

The general objective of the study was to evaluate the performances of gridded satellite/reanalysis products in representing the rainfall climatology of Ethiopia for the period 1991-2020 using 47 reference observed gauge stations.

1.3.2. Specific objectives

- To analyze/test whether there is significant difference between satellite/reanalysis rainfall products and observed rainfall for the period 1991-2020 overall AEZs at daily, monthly, seasonal, and annual temporal scale.

- To evaluate the rainfall occurrence detection capability (rainy and non-rainy days) of satellite/reanalysis rainfall products over each traditional AEZs of Ethiopia at daily timescale.
- To analysis daily rainfall intensity class detection capability of rainfall products over each AEZ of Ethiopia.
- To evaluate the performance of satellite/reanalysis products for simulating rainfall totals from daily to annual spatio-temporal scales.

1.4. Research questions

- Is there significant difference between satellite/reanalysis rainfall products and observed rainfall for the period 1991-2020 overall AEZs at daily, monthly, seasonal, and annual temporal scales?
- Which satellite/reanalysis rainfall products is preferable to detect rainfall occurrence (rainy and non-rainy days) over each AEZ of Ethiopia at daily temporal scale?
- Which satellite/reanalysis rainfall products is preferable to detect different daily rainfall intensity class over each AEZ of Ethiopia?
- What is the most outperformed satellite/reanalysis rainfall products for detecting rainfall total at daily, monthly, seasonal, and annual timescales for each AEZ of Ethiopia?

1.5. Significance of the study

The study is helpful for researchers and decision makers to fill the data gap problem when rainfall data is needed for research and decision-making process. The study also valuable for analyzing climatology, climate change, and climate variability over any areas of Ethiopia when there is no observed rainfall data in the area by considering bias. The findings will also play key roles for applying the most performing rainfall product for drought monitoring and hydrological forecasting over the country. Moreover, the study is valuable for CHIRPS v2.0 and MSWEP v2.8 product developers, to revise their algorithm and refine the products by reducing errors and improve reliability.

1.6. Scope of the study

The study was covering all traditional AEZs of Ethiopia using 47 reference gauge station data for the period 1991-2020 at daily, monthly, seasonal, and annual temporal scale. Performance evaluation of satellite/reanalysis rainfall products was done in each AEZ separately and draw conclusion AEZ based and for national level at all temporal scales.

1.7. Limitation of the study

Due to the presence of small number of stations those have long timeseries and qualified rainfall data, I only used 47 stations for this study. In line with this, desert and alpine AEZs were only represented by one station each.

CHAPTER 2. LITERATURE REVIEW

2.1. An overview of gridded precipitation products

Most gridded precipitation products with varying temporal and spatial resolutions, have been generated and are freely available at global and regional scale (Macharia *et al*., 2020). They categorized in different classes. They are: gauge only products (which are based on observations from rain gauge stations only, using different interpolation methods and often available coarser resolution more than 0.5^{o}), The reanalysis products (atmospheric models that combine satellite and in-situ observations ,and various atmospheric properties as inputs), satellite only products (uses either infrared information frequently measured from geostationary satellites, micro wave information from less commonly measured from Low earth orbiting satellites, or from a combination of infrared and microwave information for data generation process), and satellite-gauge products (combine satellite-only and gauge-only products through different bias correction or blending procedure). Some satellite-gauge products are TMPA, CMORPH, PERSIANN, and CHIRPS (Macharia *et al*., 2020). The other type of gridded precipitation product is a combination of satellite, gauge, and reanalysis products. The MSWEP gridded product is the unique product which derived from such combination (Beck *et al*., 2017).

2.2. Definition and terminologies of key words

The following definitions and terminologies for key words are obtained from IPCC reports, articles and from world wide web(www).

Rainfall: is the amount of precipitation, in the form of rain (water from clouds), that descends onto the surface of the Earth, whether it is on land or water (IPCC,2001).

Precipitation: Precipitation **is** any liquid or frozen water that forms in the atmosphere and falls back to the earth (IPCC,2001).

Climate: defined as the average weather, or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. **Climatology** is the study of climate (IPCC,2001).

Performance evaluation of satellite products: It is assessing various aspects to ensure their functionality, effectiveness, and reliability of satellite products (www.lawinsider.com/dictionary/satellite performance-evaluation).

Grid: is a network of intersecting parallel lines, whether real or imaginary (https://www.vocabulary.com/dictionary/grid).

Satellite rainfall estimates: using data from satellite to measure earth's rainfall and snow fall (Kidd, 2001).

Reanalysis data: is a continually updating gridded data set that represents the state of the atmosphere (Bosilovich *et al*., 2008).

Observed rainfall: refers to the actual amount of rainfall that has fallen at specific location over a given period of time and measured using rain gauges (Sun *et al*., 2018).

Agroecology zones (AEZs): Distinguished and defined through the examination of altitude, rainfall, and temperature of an area (MOA,1998).

2.3. Characteristics of global satellite, reanalysis, and gauge-based rainfall products

2.3.1. Gauge-based rainfall estimates

The study of climate change and variability commonly depends on surface gauge observation (Strangeways, 2006). Rain gauge is the most commonly tool for directly analyzing point rainfall at the surface measuring the amount of rainfall as it accumulates over time. There are several types of rain gauge, such as accumulation gauges, tipping bucket gauges, weighing gauges, and optical gauges, and all these gauges have their own strengths and weaknesses. Details about gauge instruments are given in (Strangeways, 2006; Tapiador *et al*., 2012).

Gauge-based observation of precipitation is collected by national weather services. For climate research and other applications, it is necessary to organize all of the data from different countries in to one integrated global dataset. The World Meteorological organization (WMO), which is established in 1873, is an intergovernmental organization with 191 member states and territories (http://www.wmo.int). The WMO facilitates the development of observation networks for fields of climatology, hydrology, and physics as well as the exchange, processing, and standardization of related data. The WMO Global Telecommunication System (GTS) is a complex worldwide communication system for the exchange of meteorological data that forms the basis for many applications (Spence & Townshend, 1996) .The total number of rain gauges operated worldwide is estimated to be between 150000 and 250000 (Groisman & Legates, 1995; New *et al*., 2001). Although many gauges exist, not all have operated in a continuous manner or concurrently (Kidd, 2001). Due to the irregular distribution of gauge stations, gridding of data is required for many climate and related applications. The Gridded precipitation datasets based fully on gauge information have been constructed and in wide used. The climate research unit (CRU) dataset comprises a suit of climate variables, including precipitation. The primary sources used for construction of the CRU monthly precipitation dataset were obtained through the help of the national meteorological agencies (NMAs), the WMO, the CRU, the international Tropical Agriculture Center, the food and Agriculture Organization (FAO), and others (Sun *et al*., 2018).

The Global Precipitation Climatology Center (GPCC) has established a unique ability to collect, organize, quality control, and analyze rain gauge data from across the globe. The NMAs provide the primary data for the GPCC, with 158 countries and 31 regional suppliers providing the majority of the gauge data in to the GPCC dataset. Details of gauge dataset are given by (Sun *et al*., 2018). Some characteristics of gauge-based products are listed in Table (2.1).

Table 2. 1. Summary characteristics of global gauge-based Products

Dataset	Resolution	Frequency	Coverage	Period	Source	Reference
CRU	$0.5^o \times 0.5^o$	monthly	Global-Land	1901-2015	The CRU of the university of East Angelia	Harris *et al*. (2014)
GHCN-M	$5^o \times 5^o$	monthly	Global-Land	1900-present	NCDC	Peterson & Vose (1997)
GPCC	$0.5^o \times 0.5^o$ $1^o \times 1^o$ $2.5^o \times 2.5^o$	monthly	Global-Land	1901-2013	GPCC	Rudolf *et al.* (2011)
GPCC-daily	$1^o \times 1^o$	daily	Global-Land	1988-2013	GPCC	Schamm *et al*. (2014)
PRECL	$0.5^o \times 0.5^o$ $1^o \times 1^o$ $2.5^o \times 2.5^o$	monthly	Global-Land	1948-2012 (1(0.5)) 1948-present	NCEP/NOAA	Chen *et al*. (2002)
UDEL	$0.5^o \times 0.5^o$	monthly	Global-Land	1900-2014	University of Delaware	Willmott & Matsuura (1995)

CPC-Global	0.5°×0.5°	daily	Global-Land	1979-2005	CPC	Xie *et al*. (2010)

2.3.2. Satellite rainfall estimates

Satellite estimates are helpful tools for global measurements of atmospheric parameters at regular intervals. During April 1960, the first Television and IR observation Satellite (TIROS) was launched, produce images of clouds that were parallel to meteorological observations (Kidd, 2001). Since then, the number of satellite sensors for observing the atmosphere has advanced obviously. The sensors are categorized in to three, those are Visible/Infrared (VIS/IR) sensors on geostationary (GEO) and low earth orbit (LEO) satellites, Passive micro wave (PMW) sensors on low earth orbit (LEO) satellites, and active micro wave sensors on LEO satellites (Michaelides *et al*., 2009). The Reliable methods used to drive precipitation have been developed, including the VIS/IR based methods, active and passive micro wave techniques, and merged VIS/IR and micro wave approaches (Kidd & Levizzani, 2011) . Details about methods of deriving precipitation is described by (Sun *et al*., 2018). Characteristics of Some satellite related products are given in Table (2.2).

Table 2. 2. Characteristics of major satellite related precipitation products

Dataset	Resolution	Frequency	Coverage	Period	Reference
GPCP	2.5° ×2.5°	Monthly	Global	1979-present	Adler *et al*. (2003)
GPCP-1day	1.0° ×1.0°	daily	Global	1996-present	Huffman & Bolvin (2013)
GPCP-PEN_v2.2	2.5° ×2.5°	5 -daily	Global	1979-2014	Xie *et al*. (2003)

CPC	$0.5^o \times 0.5^o$	daily	Global-Land	2006-present	Xie *et al*. (2010)
TRMM3B43	$0.25^o \times 0.25^o$	Monthly	50^oS-50^oN	1998-present	George *et al*. (2007)
TRMM3B42	$0.25^o \times 0.25^o$	3h/daily	50^oS-50^oN	1998-present	Huffman & Bolvin (2013)
GSMap	$0.1^o \times 0.1^o$	1h/daily	60^oS-60^oN	2002-2012	Ushio *et al*. (2009)
PERSIANN-CCS	$0.04^o \times 0.04^o$	30min/3h/6h	60^oS-60^oN	2003-present	Sorooshian *et al*. (2000)
PERSIANN-CDR	$0.25^o \times 0.25^o$	3h/6h/daily	60^oS-60^oN	1983-present	Ashouri *et al*. (2015)
CMORPH	$0.25^o \times 0.25^o$	30min/3h/daily	60^oS-60^oN	2002-present	Joyce *et al*. (2004)
IMERG	$0.1^o \times 0.1^o$	30minute	Global	2000-present	Hou *et al*. (2014)
MSWEP	$0.1^o \times 0.1^o$	3h/daily/monthly	Global	1979-present	Beck, *et al*. (2017)
CHIRPS	$0.5^o \times 0.5^o$ /$0.25^o \times 0.25^o$	Daily/pentad	50^oS-50^oN	1981-present	Funk *et al*. (2015)

SM2RAIN	0.1° ×0.1°	daily	Global	2007-present	Ashouri *et al*. (2015)

2.3.3. Reanalysis rainfall estimates

Reanalysis rainfall estimation system is to merge irregular observations and models that include many physical and dynamical processes in order to generate a manufactured estimate of the state of the system across a uniform grid, with a spatial homogeneity, temporal continuity, and a multi-dimensional hierarchy. Many crucial climate variables output from reanalysis systems maintain a physically consistent framework and can be obtained after only a short time delay. A reanalysis system includes a back ground forecast model and data assimilation routine (Bosilovich *et al*., 2008). Some reanalysis products are listed in Table (2.3).

Table 2. 3. Characteristics of some reanalysis rainfall products

Data sets	Spatial resolution	Temporal resolution	Coverage	Period	Source	Reference
NCEP1	2.5°×2.5°	6h/daily/monthly	Global	1948-present	NCEP/NCAR	Kalnay *et al*. (1996)
NCEP2	1.875°×1.875°	6h/monthly	Global	1979-present	NCEP/DOE	Kanamitsu *et al.* *(*2002)
ERA-Interim	1.5°×1.5° 0.75°×0.75°	6h/monthly	Global	1979-present	ECMWF	Dee *et al*. (2011)
JRA55	60km	3h/6h/monthly	Global	1958-present	Japan Meteorology Agency	Square *et al*. (2011)

MERRA	0.5°×0.67°	Daily	Global	1979-present	NASA	Mason *et al*. (2015)
MERRA-Land	0.5°×0.67°	1h/daily/monthly	Global-Land	1980-present	NASA	Reichle *et al*. (2011)
ERA5	0.25°×0.25°	daily	Global	1950-present	ECMWF	Meng *et al*. (2018)

2.4. The performance evaluation techniques of models (Satellite/reanalysis products)

2.4.1. The Evaluation Approaches for comparison of rainfall products with observed

For comparison of Rainfall products and ground-based datasets, three evaluation approaches are recommended. Those are: pixel-to-pixel, point-to-pixel, and point-to-point. The spatial interpolation method kriging was used by most studies to estimate spatial rainfall from rain gauge networks and then carried out pixel to pixel comparisons (Shrestha *et al.*, 2017b).When extract areal average of rainfall estimates over the pixel in which the observation gauge is located and then carried out point-to-pixel comparison (Shrestha *et al.*, 2017b). When a study compared the gauge observed value with rainfall products grid value nearest to the ground-based rain gauge, the nearest grid value could be established by calculating the minimum of the square of the distance between the gauge and the grid point. Hence, the approach is point to point comparison approach (Dangol *et al.*, 2022). A study by Dangol *et al*. (2022) ,use point-to-point approach to evaluate the performance of rainfall products in Nepal. For areas those have complex topography and few number of gauge stations ,most studies suggested point-to-pixel comparison instead of interpolating the observed data for pixel-to-pixel comparison (Fenta *et al*., 2018; Gashaw *et al*., 2023). But observed stations may not located in similar location with a grid data. Hence some random inconsistence may be introduced (Fenta *et al.*, 2018; Gashaw *et al.*, 2023).The application of pixel-to-pixel methodology requires to have a gridded reference dataset or spatially interpolate reference observed data (Bathelemy *et al*., 2022).

2.4.2. Performance evaluation using Categorical statistical indices

The precipitation detection capability of satellite products has been evaluated using categorical statistical indices. The most commonly used categorical statistical indices used for detection of rainfall occurrence of rainfall products are probability of detection (POD), false alarm ratio (FAR), critical success index (CSI), frequency bias index (FBI) (Guo *et al*., 2023). The POD is the ability of rainfall products to recognize the real occurrences of rainfall encountered by ground-based rain gauge. The FAR is the evaluation tool that measures the rainfall observed by rainfall products even though a ground-based rain gauge measured no rainfall. On the other hand CSI measures the portion of observed rainfall's event that was correctly estimated by rainfall products (Mashingia *et al*., 2014; Tan & Santo, 2018).The CSI takes both the advantage of POD and FAR in to account. The threshold for rain or no-rain classification is set to 1mm/day in the calculation of categorical indices to exclude the impact of extensive drizzles and morning frost or dew (Guo *et al*., 2023).The perfect score for POD, FAR, CSI, and FBI is 1, 0, 1, and 1 respectively (Dangol *et al*., 2022). The FBI represents a bias between precipitation events estimated by rainfall products and precipitation events measured by ground based rain gauge (Talchabhadel *et al.*, 2021).The value of FBI ranges from 0 to ∞. If FBI greater than 1,it indicates overestimation of precipitation event detection ,and if FBI less than 1,it indicates an underestimation of precipitation event detection (Talchabhadel *et al.*, 2021).

For rainfall detection capability of rainfall products, authors used different number of categorical statistical indices performance measures. For instance a study by Guo *et al*. (2023) ,used POD, FAR, CSI and bias for evaluation of rainfall occurrence of rainfall products. Moreover, a study by Nashwan *et al*. (2019) ,used POD, FAR, CSI ,and FBI for evaluation of the rainfall occurrence detection capability of rainfall products. But using multiple performance metrics from various scales and approaches can increase the credibility of the evaluation result and provide a more comprehensive picture of the product's performance (Guo *et al.*, 2023). For calculation of those categorical statistical indices, the number of the observed rainfall detected incorrectly by rainfall products, the observed rainfall that has been missed by rainfall products even when gauge has detect rainfall event, and correct estimation of the no-rain event by rainfall products are needed (Dangol *et al*., 2022).

2.4.3. Performance evaluation using continuous statistical metrics

Continuous statistical metrics have been employed over different study areas to evaluate the performance of rainfall products rainfall total at different spatial and temporal scales (Nashwan *et al*., 2019).The continuous statistical indices most commonly employed by most studies are: Root mean square error (RMSE), Mean error (ME), Mean absolute error (MAE), 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). The RMSE represents the standard deviation of residuals. The ME and MAE measure the average magnitude of the error between the rainfall products and the ground-based observation. The major differences between the ME and MAE is that ME can give positive and negative results ,whereas MAE only gives positive results (Tan & Santo, 2018). The RMSE ,MAE, ME, and MSE value of 0.0 indicates a perfect fit between rainfall products and observed data set (Singh *et al*., 2004; Moriasi *et al*., 2007). A study by Singh *et al*. (2004) state that RMSE and MAE values less than half the standard deviation of the measured data may be considered as low and that either is appropriate for model evaluation. The r and R^2 describe the degree of collinearity between rainfall products and observed (gauge) rainfall data. The correlation coefficient, which ranges from -1 to 1, is an index of the degree of linear relationship between observed and simulated (observed) data. If r= 0, no correlation between observed and simulated (rainfall products) data. If r=1 or -1, a perfect positive or negative relationship exists between the observed and simulated data set. The R^2 is the proportion of the variance in measured data explained by the model. The value of R^2 ranges from 0 to 1, with a higher value indicating less error variance, and typically values greater than 0.5 are considered acceptable (Santhi *et al*., 2001; Van Liew *et al*., 2003).Even though r and R^2 have been widely used for model evaluation, these statistics are over sensitive for high extreme values (outliers) and in sensitive to additive and proportional differences between model prediction and measured data (Legates & McCabe Jr, 1999).

The KGE integrates the correlation, bias ,and variability of the ground observed and Rainfall products in to one index (Gupta *et al*., 2009). As compared with the Nash-Sutcliffe Efficiency (NSE), the KGE is less sensitive to extreme rainfall and therefore can be describe and measure the overall fitness of rainfall having different intensities (Radcliffe & Mukundan, 2017). The NSE is the normalized statistic which determines the relative magnitude of the residua variance compared to the measured data variance. The NSE indicates how well the plot of the observed versus simulated data fits the 1:1 line. The value of NSE ranges from -∞ to 1, with the optimal value of 1. The NSE value of 0.0 to 1.0 are generally acceptable levels of performance, whereas NSE values less than or equal to 0.0 indicates that the mean observed value is a better predictor than the rainfall products (simulated) value (Nash & Sutcliffe, 1970).The RMSE-observations standard deviation ratio (RSR) ,standardizes RMSE using the observations standard deviation ,and it combines both an error index and the additional information recommended by (Legates & McCabe Jr, 1999). Even though the lower the RMSE ,the better the model (rainfall products) performance, a study by Singh *et al*. (2004) have published a guide line to qualify what was considered a low RMSE based on the observations standard deviations. The PBIAS measures the average tendency of the rainfall products or models to the larger or smaller than their observed counterparts (Gupta *et al*., 1999). The optimal value of PBIAS is 0.0, with low magnitude values indicate accurate model or simulated estimation performance. The positive values of PBIAS indicates a model underestimation bias ,and negative values indicate model overestimation bias (Gupta *et al.*, 1999).

Literatures showed that different study have been used different statistical metrics for the performance evaluation of rainfall products. For instance a study by Dangol *et al*. (2022), used statistical metrics like RMSE, MAE, PBIAS , and R^2 , a study by Guo et al. (2023) used continuous statistical indices like r, RMSE, MAE ,Relative bias, KGE , and NSE. More over a study by Beck *et al*. (2017) used only KGE to evaluate 22 precipitation datasets at global scale.

2.4.4. The performance evaluation of models and satellite/reanalysis rainfall products using graphical techniques

Graphical techniques provide a visual comparison of simulated and measured data and is considered a first overview of model performance (ASCE, 1993). According to Legates & McCabe Jr (1999), graphical techniques are essential to appropriate model evaluation. The two commonly used graphical techniques are hydrograph and percent exceedance probability curves, are especially valuable. Other graphical techniques like bar graphs, box plots, and others can also be used to examine the variations and data distributions with respect to reference (measured) dataset. For instance, a study by Dangol *et al*. (2022) , used box plots, bar graphs , and Tylor diagrams to evaluate the performance of Rainfall products. On the other hand, graphical techniques like line graphs ,and bar graphs were used to evaluate the performance of rainfall products in addition to categorical and continuous statistical indices over Bale Eco-region in Southern Ethiopia by Gashaw *et al*. (2023). Moreover, a study by Polong *et al*. (2023) , also used line graph and bar graphs to compare rainfall products with observed measured data with different temporal and spatial scales.

2.5. Previous findings on the performance of CHIRPS and MSWEP with other datasets

2.5.1. Performance of CHIRPS and MSWEP with other datasets outside Ethiopia

The performance of rainfall products has been evaluated in different areas of the world for different applications. Literatures showed that different researchers used different number of stations, study time period, evaluation approach, and also type of continuous and categorical statistical indices used as well as study area coverage and evaluation timescale. For instance, a study by Ageet *et al*., (2022), evaluate the performance of CHIRPS v2.0 and MSWEP v2.8 with other datasets over Equatorial East Africa for the period 2001-2018 and study time scales of daily to annual by compared with 36-gauge stations data for reference. The categorical statistical indices used for evaluation of rainfall products rainfall occurrence capability were POD, FAR, and HSS. In addition, the performance of rainfall products rainfall total was evaluated using continuous statistical indices like MAE, PBIAS, RMSE, and NSE and also graphs like line graph, boxplot and Tylor diagram. Another study conducted over Arun River Basin in Nepal (Dangol *et al.*, 2022), also evaluate the performance of CHIRPS v2.0 and MSWEP v2.8 and other datasets for the period 1983 to 2014 using categorical statistical and visual comparison using graphs. The number of gauge stations used for reference were ten. On this study, the performance of rainfall products rainfall occurrence was evaluated by using categorical indices like Accuracy, POD, FAR, CSI, and Frequency bias index. More over the authors used continuous statistical indices like RMSE, R^2, ME, MAE, and PBIAS for evaluation of rainfall products rainfall totals at daily, monthly, and annual timescales. Summary of gridded satellite products performance outside Ethiopia given in Table (2.4).

Table 2. 4. Performance of CHIRPS and MSWEP with other datasets outside Ethiopia

Study area	Evaluated Datasets	Main Findings	Reference
Equatorial East Africa	CHIRPS v2.0 and MSWEP v2.8 with other five datasets	Rainfall products reproduce seasonal and annual rainfall cycle well, exhibiting biases up to 9%, but MSWEP v2.2 and CHIRPS v2.0 good for monthly and annual timescales. MSWEP v2.8 decline as compared with MSWEP v2.2.	Ageet *et al.*(2022)
Eastern Turkey	CHIRPS v2.0 and MSWEP v2.8 with other 11 datasets	CPC v1.0 has high performance than CHIRPS v2.0 and MSWEP v2.8 at daily timescale.	Hafizi & Sorman (2022)
Central Asia	MSWEP v2.8	MSWEP v2.8 has high correlation with ground data and has the ability to capture dry and wet changes and characterize drought events.	Li *et al.* (2022)

Greater and lesser Antille	CHIRPS v2.0 and MSWEP v2.8 with other 3 datasets	MSWEP v2.8 recommended for most hydro M eteorological research. The CHIRPS v2.0 performs well to estimate heavy rainfall.	Bathele my *et al* . (2022)
Arun Riverb asin in Nepa l	CHIRPS v2.0 and MSWEP v2.8 wit h other 2 datasets	APHRODITE and MSWEP v2.8 better than C HIRPS v2.0 and PERSIANN on daily, monthly, and annual timescales.	Dangol *et al.* (2022)
Globe	MSWEP v1.1 wit h other four datasets	MSWEP v1.1 obtained highest correlation coef ficient among other datasets at daily time scale.	Beck, *et al*. (2017)
CONUS	MSWEP v2.2 and other 25 dataset	The best overall performance was obtained by MSWEP v2.2 using KGE, bias, correlation, and variability metrics.	Beck *et al*. (2019)
Mozambiqu	CHIRPS v2.0 and other 4 datasets	Rainfall products overestimate low and undere stimate high rainfall values. CHIRPS v2.0 overestimate the rainfall event frequency.	Toté *et al*. (2015)
Madagascar	CHIRPS v2.0 and MSWEP v2.2 with other 13 datasets	The CHIRPS v2.0 showed low biases in Seasonal and annual timescales. MSWEP v2.2 and ERA5 are the next preferable datasets.	Randriat sara *et al.* (2022)
Egypt	CHIRPS v2.0 and other 2 datasets	CHIRPS v2.0 was found the best product in est imating rainfall amounts. But, accurate estimation on hot climate remains a callenge.	Nashwa n *et al*. (2019)
Bali Island	CHIRPS v2.0 and other two	IMERG achieved best performance at daily, pentad, and seasonal timescale. But, CHIRPS	(Liu *et al.*,

		v2.0 was best at monthly timescale.	2020)
Amazon in Brazil	CHIRPS v2.0	Mean monthly rainfall similar with gauge stations. But CHIRPS v2.0 tend to underestimate the rainiest months.	Cavalcante *et al*. (2020)

2.5.2. Performance of CHIRPS and MSWEP with other datasets in Ethiopia

In Ethiopia, to fill the rainfall data gap problems satellite products have been evaluated and used as alternative source for different applications (Belay *et al.*, 2019; Taye *et al.*, 2020; Abraham *et al.*, 2022). Among the dataset CHIRPS v2.0 extensively evaluated in different small-scale areas and as a national scale of Ethiopia with other datasets. But the newly version of MSWEP (i.e the MSWEP v2.8), only evaluated in Bale Eco-Region in Southern Ethiopia by Gashaw et al (Gashaw *et al.*, 2023). Literatures showed that CHIRPS v2.0 were the most outperformed product to detect rainfall total, especially at monthly timescale (Ayehu *et al.*, 2018; Gashaw *et al*., 2023). Hence, CHIRPS v2.0 were the most preferable product for drought monitoring and other applications (Belay *et al*., 2019). Moreover, the old version of MSWEP has good performance in most studied areas and used for application next to CHIRPS v2.0 (Abebe *et al*., 2020). The new version of MSWEP v2.8 were the most outperformed product by most performance measures over Bale Eco-Region and recommended for application (Gashaw *et al*., 2023). Previous findings indicated that the performance of rainfall products vary for different spatial and temporal scales of Ethiopia. In addition, the different versions of MSWEP were recommended for rainfall occurrence detection and daily rainfall total estimation over small scale areas of Ethiopia (Gashaw *et al.*, 2023). The summary of Previous findings on MSWEP and CHIRPS in Ethiopia is given in Table (2.5).

Table 2. 5. Performance of CHIRPS and MSWEP with other datasets in Ethiopia

Study area	Evaluated Datasets	Main findings	Reference
Bale Eco- Region Southern Ethiopia	MSWEP v2.8 and CHIRPS v2.0 with other datasets	MSWEP v2.8 has better performance than CHIRPS v2.0 and TAMSAT v3.1 at daily, dry season and annual timescales in temperate and tropical AEZs. In addition, has good performance in Sub-tropical AEZ in dry season and annual timescales. CHIRPS v2.0 has superior performance at monthly timescale over tropical, sub-tropical, and temperate AEZs. MSWEP v2.8 has better detection Capability of rainfall occurrence.	Gashaw *et al.* (2023)
Ethiopia	CHIRPS v2.0 and other 19 datasets	CHIRPS v2.0, FLDAS, and GPCC performed relatively better performance for drought analysis. But still there were discrepancy of Rainfall products from observed dataset.	Degefu *et al.* (2022)
Beles Sub Basin of Ethiopia	CHIRPS v2.0	Slight overestimation of rainfall occurrence by CHIRPS v2.0 for the low land and underestimation for the highland region. The CHIRPS v2.0 underestimate light daily rainfall events and overestimate intensity of daily rainfall events. The accuracy of CHIRPS v2.0 increase as the integration time increase from days to months.	Belay *et al.* (2019)
Upper Blue Nile Ethiop	CHIRPS v2.0 and MSWEP v2.0	CHIRPS v2.0 has better performance than MSWEP v2.0. Hence CHIRPS v2.0 has been recommended for drought analysis.	Taye *et al.* (2020

ia			)
Upper Blue Nile Ethiopia	MSWEP v2.2 and CHIRPS v2.0 with other 3 datasets	Except SM2RAIN-ASCAT1.1, all other data datasets showed better ability on monthly timescale for areas below 1500 m.a.s.l. All datasets could detect no-rain events (rain<1mm/day) correctly. But their skill decreases for higher intensity events.	Abebe *et al*. (2020)
Upper Tana River Basin	CHIRPS v2.0 and other 2 datasets	ARC2 and CHIRPS v2.0 are better in reproducing the occurrence frequency of daily events for the different intensity ranges. All datasets could detect low intensity events, but poor in detecting higher than 25 mm/day.	Polong *et al*. (2023)
Lake Tana Sub Basin/Ethiopia	CHIRPS v2.0 and other 2 datasets	The result indicated that the three datasets underestimate rainy events, but TAMSAT relatively captured rainfall occurrence both in the lowland and high land regions. CHIRPS v2.0 better estimate second rainy season (March-May) better than others. cumulative rainfall tended to increase as the integration time increase (i.e., from days to seasons).	Fenta *et al*. (2018)
Tekeze Atbara Ethiopia	CHIRPS v2.0 and other 7 datasets	The dataset of CHIRPS v2.0 outperformed all other datasets at daily, monthly, and seasonal timescale and at all spatial scale.	Gebremicael *et al*. (2019)

CHAPTER 3. MATERIALS AND METHODS

3.1. Description of study area

3.1.1. Location

The study is conducted in Ethiopia, which is in the horn of Africa. Ethiopia lies between equator and tropic of cancer between 3^o and 15^o N and 33^o and 48^o E and covers 1.12 million squares kilometers (Degefu & Bewket, 2023). The country is bordered by Sudan and South Sudan on the west, Eritrea in the North, Djibouti and Somalia on the east and Kenya on the south (Wubaye *et al.*, 2023).

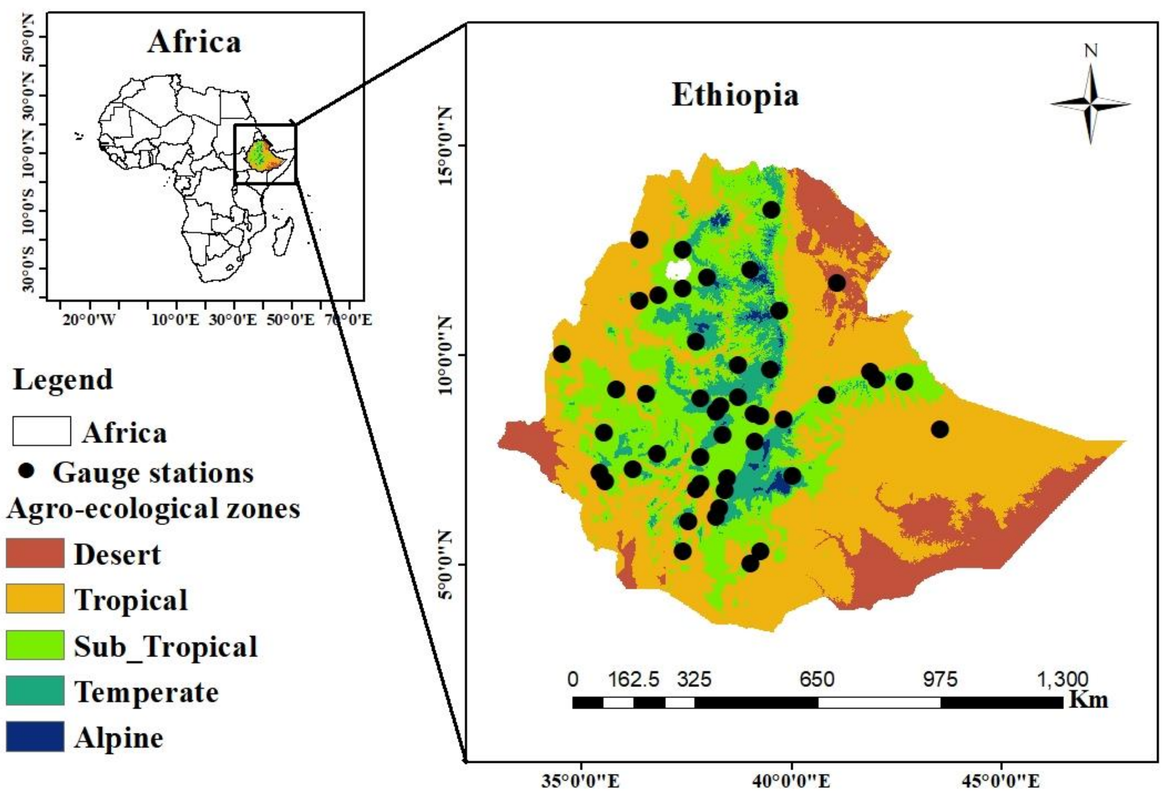


Figure 3. 1. The location of Ethiopia from Africa and the meteorological stations used in this study

3.1.2. Topography

Ethiopia is characterized by very complex topography with elevation ranging from 152 meter below sea-level in the north eastern part (Denkel depression) to more than 4600 m.a.s.l at mount Ras Dejen in the northern part of the country (Wubaye *et al.*, 2023). The country has varied topography including craggy, high mountains, deep gorges with rolling plains, rivers, and plateaus with flat tops (Cheung *et al.*, 2008). About 40% of the country is covered by mountains and plateaus with elevation greater than 1500 m.a.s.l and is classified as highland. The remaining part of the area of less than 1500 m.a.s.l is classified as lowland (Degefu *et al*., 2022).

3.1.3. Traditional agroecology zone

Ethiopia is characterized by five traditional AEZs (Figure 3.1; Appendix Table 1). These zones are known as *Bereha*/Desert, *Kolla*/Tropical, *Woina Dega*/Sub-tropical, *Dega*/Temperate, and *Wurch*/Alpine. Each AEZ is associated with specific elevations: *Bereha*/Desert encompasses areas below 500 meters above sea level (m.a.s.l.), Kolla/Tropical ranges from 500 to 1500 m.a.s.l., Wo*ina Dega*/Subtropical spans from 1500 to 2300 m.a.s.l., *Dega*/Temperate covers elevations between 2300 and 3200 m.a.s.l., while *Wurch*/Alpine represents regions above 3200 m.a.s.l. (MOA, 1998). These AEZs have been distinguished and defined through the examination of altitude, annual rainfall, and temperature patterns in various studies. A brief discussion of the definition and specific characteristics of the traditional AEZs can be found in the work of MOA (1998).

3.1.4. Climate

The complex topographic features have created many local climatic conditions that range from hot deserts in the northeast and southern lowland to very cold mountain .ranges in the Semein and Arsi-Bale mountains systems (Degefu *et al.*, 2022). In Ethiopia, gauges which are used to measure rainfall are sparse and uneven. Even those sparse gauges do not have continuous records and lack quality (Dinku *et al*., 2007). There are different types of gauge stations built in Ethiopia to collect rainfall data. Those are synoptic, principal, ordinary, and rainfall stations. Ethiopia has three distinct seasons, locally known as *Bega*, *Belg*, and *Kiremt*.

For the majority of Ethiopia, the short rainy season, known as the *Belg* lasts from February to May, while the main rainy season/*Kiremt* stays from June to September and the dry season/*Bega* lasts from October to January. Geographically speaking, the length of each season on average and the amount of rainfall vary from season to season (Evangelista *et al.*, 2013).

According to the long-term annual average rainfall (1991-2020) estimates of the 47 observed meteorological stations (Appendix Table 1.), the mean annual rainfall extends from 217 mm over the desert AEZ to 1251 mm over the sub-tropical AEZ (Figure 3.2), which is computed by taking the average values of stations found in the same AEZ (Appendix Table 1). The mean annual temperature of the country ranges from less than 10°C to 40°C (Degefu & Bewket, 2023). Overall, the north-south shift of Inter-Tropical Convergence Zone (ITCZ) and the complex topographic features of the country have huge control over seasonal and spatial distribution of rainfall and other climatic elements (Degefu *et al.*, 2022).

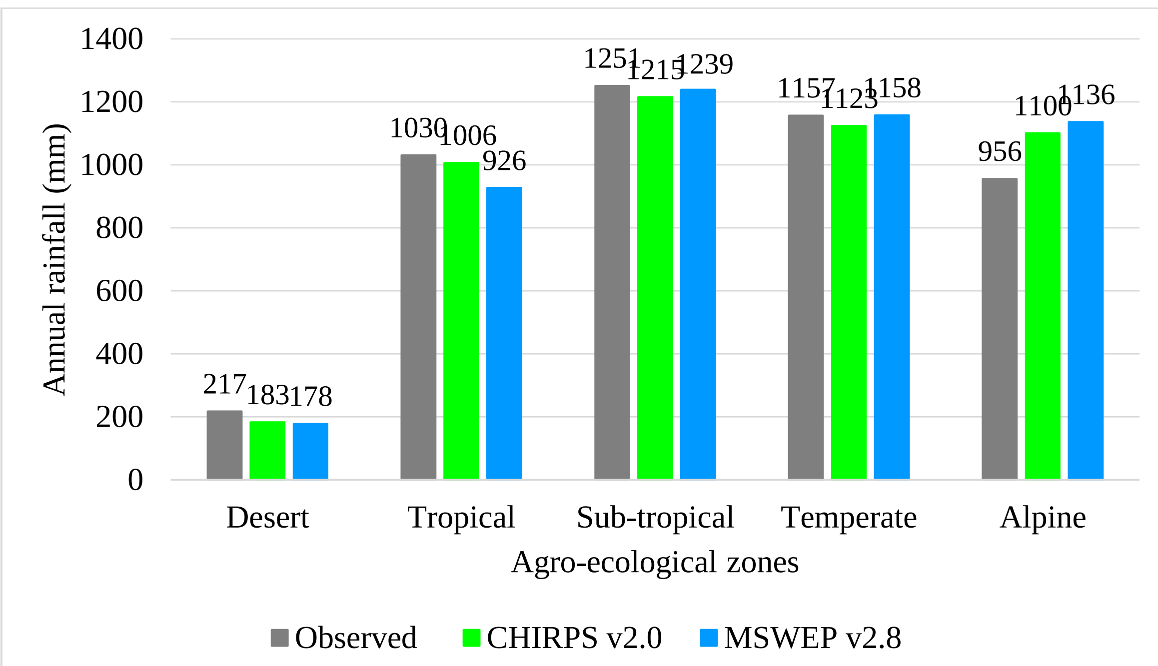


Figure 3. 2. The long-term annual average rainfall (1991-2020) values of the observed, CHIRPS v2.0, and MSWEP v2.8 over the different AEZs of the country.

3.2. Data types and sources

3.2.1. Ground-based (Observed) rainfall data

Daily observed rainfall data from 47 meteorological stations (Figure 3.1; Appendix Table 1) for the period 1991-2020 were obtained from the Ethiopian Meteorology Institute (EMI). The main reason why this study used only 47 stations is due to the absence of other stations which have long data series and less percentage of missing data. Of the 47 meteorological stations, 28, 9 and 8 of them are located in *Woyna Dega*/Sub-tropical, *Kolla*/tropical and *Dega*/temperate AEZs, respectively. The remaining two stations are located in *Wurch*/Alpine and *Bereha*/Desert AEZs (i.e., one station from each) (Figure 3.1; Appendix Table 1). This study used stations which have missing values less than 25%, which is reasonable in data scarce regions such as Ethiopia. Due to the absence of many stations which have lower missing values, Gashaw *et al*. (2023) in the Bale Eco-Region, Mohammed et al. (2022) in the Upper Blue Nile Basin and Diro et al. (2009) over Ethiopia have also used stations that contain up to 20%, 30% and 20% missing data, respectively. Mekasha et al. (2014) have also used stations data with up to 25% missing values to study trends and variability of climate in three eco-environments in Ethiopia. The missing values of this study were filled using the Multivariate Imputation by Chained Equations (MICE) package in R software. Then after, the rainfall data have been subjected for quality control in RClimDex package within R software (Zhang et al., 2004) and errors such as negative rainfall were replaced with the nearest station. Outliers were also treated according to the suggestion given by the World Meteorological Organization (WMO, 2009). The details of the data processing and the methods used for filling missing values are given in Wubaye et al. (2023).

3.2.2. Satellite/reanalysis rainfall products

Brief descriptions of satellite/reanalysis rainfall products (CHIRPS v2.0 and MSWEP v2.8) evaluated in this study are given below.

CHIRPS v2.0 is a quasi-global dataset available at daily, pentadal and monthly temporal scales with a spatial resolution of 0.05^{o} (~5 km) (Funk *et al.*, 2015). CHIRPS is a combined product of remotely sensed and gauge observations. The main input data sources used in CHIRPS are monthly CHIRPS climatology from the Climate Hazard Group (CHPclim), quasi global geostationary thermal infrared observations from National Oceanic and Atmospheric Administration - Climate Prediction Center (NOAA-CPC), the National Climate Data Center (NCDC), TRMM3B42, NOAA climate forecast system version 2 (CFSv2), and Observations from various source. In Ethiopia, CHIRPS v2.0 has used 76 meteorological/gauged observations (Funk *et al.* 2015). The CHIRPS v2.0 rainfall product is mainly developed for monitoring droughts and extremes. The CHIRPS v2.0 dataset is downloaded from (ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS v2.0).

MSWEP v2.8 is a globally available dataset (Beck *et al.*, 2019), which was produced through the weighted merging of gauge, satellite and reanalysis-based rainfall products. The merged weights are determined by assessing the performance of the input datasets individually against quality-controlled gauge rainfall. The weighted merged results into 3 hours reference rainfall data set, which is then calibrated using daily and monthly gauge rainfall to produce MSWEP v2.2. The production of MSWEP v2.8 includes the reduction of satellite and reanalysis datasets from five(CMORPH, GSMap-MVK,TMPA 3B42RT,ERA-Interim,and JRA-55) in MSWEP v2.2 to two (ERA5 and IMERG) and a reduction in the amount of gauge data used without a change in the algorithm (Beck *et al.*, 2019). MSWEP v2.8 dataset is available with a spatial resolution of 0.1^{o} (~11 km) and temporal resolution of 3 hours, daily, and monthly time basis at all latitudes and longitudes of the globe from 1979 to the present (Beck *et al.*, 2019). MSWEP is a unique rainfall data set among others because MSWEP: 1) is a new data source 2) improved weight diagram 3) is less estimation of peak precipitation 4) has longer data record 5) has near real time estimation 6) is compatible with multi weather. Summary characteristics of CHIRPS v2.0 and MSWEP v2.8 is given in Table (3.1). The MSWEP dataset is available at http://www.gloh2o.org/.

Table 3. 1. Descriptions of MSWEP v2.8 and CHIRPS v2.0 rainfall products

Rainfall products	Coverage	Spatial resolution	Temporal resolution	Owned by	Data available	Input	Reference
MSWEP v2.8	Global	0.1^o	3h/daily	G-WADI(USA)	1979-Present	Satellite-estimates, Reanalysis data, Gridded gauge	Beck *et al*.,2019
CHIRPS v2.0	50^o N-50^o S & all longitudes	0.05^o	Daily/monthly	California university	1981-present	TIR-satellite observation, Gauge data, Meteosat TIR imagery, CHPclim	Funk *et al*.,2015

3.3. Methods of Analysis

Student's t-test was used for verifying the significant difference between observed rainfall and rainfall products at different AEZs of Ethiopia for the period 1991-2020 at daily, monthly, seasonal, and annual temporal scales. This test indirectly confirmed the historical rainfall product's mean bias. The test was conducted at the most recommended significance level of 0.05. Student's t-test value was calculated by using SPSS statistical software. If the p value of rainfall products greater than 0.05, accept the null hypothesis (no significant difference between observed rainfall and rainfall products) else reject the null hypothesis and accept the alternative hypothesis (there is significant difference between observed rainfall and rainfall products) (Tan *et al*., 2015).

The spatial representativeness of gauge-based observations (i.e. points) and satellite-based datasets (grids) is different. Hence, to reconcile the spatial scale difference between satellite and gauge-based products, the grids of satellite closest to the stations are extracted following a point-to-pixel evaluation approach. The main reason why I did not do spatial comparisons in the present study is due to the unavailability of enough data. As it is mentioned before, this study used 47 stations and hence, making spatial comparisons through interpolation of these stations data would be misleading as rainfall in Ethiopia vary within small distance since it is highly determined by topography. As a result, I focused only to a point-to-pixel evaluation approach. In line with this, for areas with complex topography and small number of gauging stations, most studies suggested a point-to-pixel comparison (Ageet *et al.*, 2022). Hence, a point-to-pixel evaluation approach was performed by comparing gauge (observed) data to the closest satellite/reanalysis product pixel value (Ageet *et al.*, 2022). The rainfall products, which are in Network Common Data Form (NetCDF) format, were extracted for observed stations using the R software. The observed as well as the extracted satellite/reanalysis rainfall products were grouped into their respective AEZs. The list of stations and their respective AEZs are given in (Appendix Table 1). After that, the average values of stations that are found in the same AEZs were used following a similar approach of previous studies (Fenta *et al*., 2018; Belay *et al*., 2019; Gashaw *et al*., 2023).

Performance evaluations of CHIRPS v2.0 and MSWEP v2.8 rainfall datasets in this study were carried out using continuous and categorical statistical performance measures as well as Probability Density Function (PDF). In addition to these performance measure statistics, comparison of the studied rainfall products and observed rainfall were made using graphical techniques such as line graph, scatter plot, and bar graph (Reddy & Saravanan, 2023). The methodological flows followed for evaluation of CHIRPS v2.0 and MSWEP v2.8 rainfall products in this study is shown in Figure (3.2).

Figure 3. 3. Schematic diagram showing the methodological flows of this study

3.3.1. Evaluation of satellite/reanalysis products rainfall occurrence detection capability

This study employed four categorical scores to determine the rainfall occurrence detection capability of the satellite/reanalysis products (rainy and dry days). These categorical scores include Probability of Detection (POD), False Alarm Ratio (FAR), Frequency Bias Index (FBI), and Critical Success Index (CSI), which was extracted from a 2 × 2 contingency table (Table 3.2) (the threshold for rainy day is ≥ 1mm). In the contingency table, the number of hits describes the number of correctly estimated rain events by the satellite/reanalysis rainfall products while false alarm refers to when rain is estimated by the satellite/reanalysis but no rain occurs. Conversely, misses refer to when rain is not estimated by the satellite/reanalysis but the rain occurs, and correct negative refers to the satellite/reanalysis correctly detect the no rain case. This study used rainfall threshold ≥ 1 mm to detect the rainy days (Nashwan *et al*., 2019; Gashaw *et al*., 2023). The number of hits, misses, false alarms and correct negatives for each AEZs were counted.

POD score is defined as the ability of the satellite products to correctly estimate rain events (Eq. 1). POD value ranges from 0 to 1, with 1 being the optimal POD value (Dinku *et al*., 2018; Fenta *et al*., 2018). On the other hand, FAR measures how often the satellite products detect rainfall not confirmed by ground observation (Eq. 2). The value of FAR ranges from 0 to 1 with a perfect score of 0 (Dinku *et al.*, 2018; Fenta *et al.*, 2018). CSI is known as a threat score and computes the ratio of all events estimated and observed that were correctly diagnosed (Ebert, 2007; Abebe *et al.*, 2020). The value of CSI ranges from 0 to 1 with an optimal or correct value of 1 (Eq. 3). FBI compares the rainy-day detection frequency of rainfall products with rain gauge measurements (Eq. 4). The value of FBI ranges from 0 to ∞, with an optimal value of 1. FBI less than 1 indicates underestimation while FBI values larger than 1 specifies over estimation by the satellite/reanalysis products (Fenta *et al*., 2018; Polong *et al*., 2023). In addition all those metrics have not unit (Gashaw *et al*., 2023).

$$POD = \frac{Hits}{Hits+Misses} \quad (1)$$

$$FAR = \frac{FalseAlarms}{Hits+FalseAlarms} \quad (2)$$

$$CSI = \frac{Hits}{Hits+Misses+FalseAlarms} \quad (3)$$

$$FBI = \frac{Hits+FalseAlarms}{Hits+Misses} \quad (4)$$

Table 3. 2. The contingency table presents the agreement between observed rainfall (Po) and rainfall products (Ps) different rainfall intensity.

	$Po \geq Threshold$	$Po \leq Threshold$
Ps ≥ Threshold	Hits	False Alarms
Ps ≤ Threshold	Misses	Correct Negatives

3.3.2. Evaluations of satellite/reanalysis products rainfall intensity detection capability

This study used the PDF to evaluate the quality of the studied satellite/reanalysis rainfall products in capturing the occurrence probability of rainfall rates at different intensity levels. PDF is commonly used to evaluate the quality of various rainfall products in capturing the occurrence probability of rainfall rates at different intensity levels (Jiang *et al*., 2022). PDF is an integral of the density of variable density over a given range. For this study, the World Meteorological Organization (WMO) rainfall intensity range classification was used. WMO classifies rainfall intensity class as non-rainfall (0-0.1 mm/day), slight rainfall (0.1-1.0 mm/day), thin rainfall (1.0-2.0 mm/day), small rainfall (2.0-5.0 mm/day), light rainfall (5.0-10.0 mm/day), moderate rainfall (10.0-25.0 mm/day), heavy rainfall (25.0-50.0 mm/day), and extreme rainfall (> 50.0 mm/day), with the corresponding daily rainfall amount (Jiang *et al*., 2022). The PDF results of CHIRPS v2.0 and MSWEP v2.8 with the observed rainfall intensity were displayed in a line graph for each traditional AEZs of Ethiopia.

3.3.3. Evaluation of satellite/reanalysis products rainfall total detection capability

Continuous statistical error metrics were calculated to evaluate the performance of MSWEP v2.8 and CHIRPS v2.0 in estimating total rainfall at daily, monthly, seasonal and annual timescales. Evaluations were performed based on mean absolute error (MAE), root mean square error (RMSE), percent bias (PBIAS), correlation coefficient (r), and Kling Gupta efficiency (KGE) and also graphical comparison techniques (Ageet *et al*., 2022). MAE gives information about the average estimation error (Eq. 6). The value of MAE ranges from 0 to ∞, with a perfect score of 0 (Dinku *et al.*, 2018; Ageet *et al.*, 2022). RMSE measures the average magnitude of the deviation of rainfall products from the ground based observed data (Eq. 7). A smaller RMSE value indicates that rainfall products are closer to observed rainfall data. The optimum value of RMSE is 0 (Ageet *et al*., 2022). PBIAS measures the average tendency of rainfall products data to be larger or smaller than the observed data. The percent bias (PBIAS) is a statistical metric that spans from -∞ to ∞, with an ideal value of zero. A low magnitude of PBIAS suggests that the rainfall products accurately estimate the observed data. Negative values of PBIAS indicate a bias of overestimation in the rainfall products, while positive values of PBIAS indicate a bias of underestimation in the rainfall products when compared to the observed data (Gupta *et al*., 1999). Rainfall products are said to be a reliable rainfall measurement source where PBIAS value ranging between -10% and 10% (Dangol *et al.*, 2022). PBIAS can be calculated using Eq. 8. Correlation coefficient (r) is used to measure the goodness of fit and linear association between variables, in this case the linear association between observed rainfall and Rainfall products data (Eq. 9). The values of r ranges from -1 to 1, with r = 0 no linear relationship, r = -1 or 1 indicates a perfect negative or positive score (Dinku *et al.*, 2018; Ageet *et al*., 2022). KGE is an objective performance metric combining correlation, bias and variability (Eq. 10). The value of KGE ranges from 0 to 1, with optimum value of KGE is 1. The bias and variability component of KGE calculated using Eq. 11 and the optimum value of r, β and γ are 1 (Kling *et al.*, 2012; Gashaw *et al.*, 2023).

$$MAE = \sum|(S - G)| \quad (6)$$

$$RMSE = \sqrt{\frac{\sum(G-S)^2}{N}} \quad (7)$$

$$PBIAS = \frac{\sum(G-S)}{\sum(G)} \times 100\% \quad (8)$$

$$r = \sqrt{\frac{\sum(G-\bar{G})(S-\bar{S})}{\sum(G-\overline{G})^2(S-\overline{S})^2}} \quad (9)$$

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2} \quad (10)$$

$$\beta = \frac{\mu s}{\mu G} \quad \text{and } \gamma = \frac{\delta s/\mu s}{\delta G/\mu G} \quad (11)$$

where G is observed rainfall total at a gauge station, $\bar{G}$ is the mean of observed rainfall total at reference gauging station, S is rainfall total for satellite rainfall product, N is the number of data pairs compared, r is Pearson's correlation coefficient, β is the bias component, γ is the variability component, μ is distribution mean, δ is distribution standard deviation.

Table 3. 3. Summary of continuous performance measure metrics used in this study

Continuous metrics	Statistical Formula	Value range	Unit	Optimal value	Reference
MAE	$MAE = \sum \lvert (S - G) \rvert$	0 to ∞	mm	0	Ageet *et al.* (2022)
RMSE	$RMSE = \sqrt{\frac{\sum (G - S)^2}{N}}$	0 to ∞	mm	0	Ageet *et al.* (2022)
PBIAS	$PBIAS = \frac{\sum (G - S)}{\sum (G)}$ ×100%	-∞ to ∞	%	0	Dangol *et al.* (2022)
r	$r = \sqrt{\frac{\sum (G - \bar{G})(S - \bar{S})}{\sum (G - \overline{G})^2 \, (S - \overline{S})^2}}$	-1 to 1	none	1	Dinku *et al.* (2018)
KGE	$KGE = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2}$	0 to 1	none	1	Kling *et al.* (2012)

CHAPTER 4. RESULTS AND DISCUSSIONS

4.1. Significance test analysis of rainfall products

Table 4.1 presents the student's t-test analysis of the daily, monthly, seasonal and annual rainfall (1991-2020) between rainfall products and observed rainfall in each AEZ. The two rainfall products exhibited significant differences with observed rainfall over desert AEZ at daily timescale at $p < 0.05$ level of significance, except CHIRPS v2.0 over temperate and MSWEP over sub-tropical AEZs. At monthly timescale, the two rainfall products have not significant difference from observed rainfall over all AEZs at 0.05 level of significance, except CHIRPS v2.0 over alpine AEZ and MSWEP v2.8 over tropical and alpine AEZs. However, at *Bega, Belg, Kiremt*, and annual temporal scales, both CHIRPS v2.0 and MSWEP v2.8 have significant differences over most AEZs at a given level of significance. Moreover, both rainfall products have significant difference from observed rainfall over alpine AEZ from daily to annual temporal scale at $p < 0.0$A study by Tan *et al*. (2015) also showed the significance difference of precipitation products from observed precipitation at 0.05 level of significance at daily, monthly, seasonal, and annual temporal scales over Malaysia using student's t-test.

Table 4. 1. Student's t-test analysis of observed and rainfall products during 1991-2020.Significant at 0.05 represented by *.

Rainfall products	AEZs	t-test	Time scale					
			Daily	Monthly	*Bega*	*Belg*	*Kiremt*	Annual
CHIRPS v2.0	Desert	t stat	2.592	1.749	1.415	0.287	2.951	2.800
		p	0.010*	0.108	0.168	0.776	0.006*	0.009*
	Tropical	t stat	2.296	1.044	7.213	-0.867	-0.937	1.920
		p	0.022*	0.319	0.000*	0.393	0.357	0.065
	Sub-tropical	t stat	4.148	2.098	2.669	1.938	0.317	3.343
		p	0.000*	0.060	0.012*	0.062	0.753	0.002*

	Temperate	t stat	1.143	0.533	1.385	0.722	1.687	2.926
		p	0.253	0.605	0.177	0.476	0.102	0.007*
	Alpine	t stat	-4.991	-3.419	-5.637	-7.601	-3.280	-5.482
		p	0.000*	0.006*	0.000*	0.000*	0.003*	0.000*
MSWEP v2.8	Desert	t stat	2.989	2.166	1.404	-0.190	2.755	2.483
		p	0.003*	0.053	0.171	0.851	0.010*	0.019*
	Tropical	t stat	12.153	3.922	7.805	0.026*	6.595	6.161
		p	0.000*	0.002*	0.000*	0.980	0.000*	0.000*
	Sub-tropical	t stat	1.700	0.743	1.193	-1.035	1.070	0.650
		p	0.089	0.473	0.242	0.309	0.293	0.521
	Temperate	t stat	-2.080	-1.071	0.157	-3.352	1.436	-0.050
		p	0.038*	0.307	0.877	0.002*	0.162	0.960
	Alpine	t stat	-7.994	-6.004	-6.232	-5.624	-3.207	-5.079
		p	0.000*	0.000*	0.000*	0.000*	0.003*	0.000*

4.2. Performance of satellite/reanalysis products rainfall occurrence detection capability

The daily rainfall detection skills of CHIRPS v2.0 and MSWEP v2.8 over the five AEZs of Ethiopia using categorical metrics was shown in Table 4.2. The result revealed that the studied rainfall products have a good rainfall detection skill over tropical, sub-tropical, temperate and alpine AEZs of the country with POD values greater than 0.59 which means that both products can detect more than 59% of the rainfall events over those AEZs. However, CHIRPS v2.0 and MSWEP v2.8 missed around 74% and 70% rainfall events over desert AEZ, respectively. The two rainfall products have the highest POD over sub-tropical AEZ with a value of 0.95 for CHIRPS v2.0 and 0.94 for MSWEP v2.8, which means that the two satellite/reanalysis rainfall products correctly detect 95% and 94% of the observed rainfall events, respectively. FAR value, which is the problem of detecting rainfall by the rainfall products when there was no rainfall, showed that around 54% and 49% of the estimated rainy days by CHIRPS v2.0 and MSWEP v2.8, respectively were falsely estimated over desert

AEZ. In addition, about 45% of the rainfall days over the alpine AEZ is false estimated by CHIRPS v2.0. However, the FAR values of both CHIRPS v2.0 and MSWEP v2.8 over temperate, sub-tropical and tropical AEZs are lower than 0.22. Among the CHIRPS v2.0 daily rainfall event for the period 1991-2020 over alpine AEZ,45% of the event were detected as rainy day without confirmed by ground gauge.

The FBI values of the studied rainfall products over temperate, sub-tropical and tropical AEZs are above 0.93. CHIRPS v2.0 was also achieved a higher FBI value over the alpine AEZ. Comparatively, both of these rainfall products recorded lower FBI values in the desert AEZ, indicating the relatively poor performance of those products in this AEZ. FBI values of CHIRPS v2.0 were greater than 1 over tropical, sub-tropical, temperate and alpine AEZs, which shows a slight overestimation. CHIRPS v2.0 has an FBI value of 0.57 over desert AEZ, which means an underestimation of observed rainy day events by 43%. Conversely, MSWEP v2.8 underestimates the number of observed rainy day events over desert, tropical, temperate and alpine AEZs by 40%,2%,6%, and 33% respectively. But, MSWEP v2.8 overestimates the number of observed rainy day events over sub-tropical AEZ by 3%. CSI value, which showed that the overall correspondence between the studied rainfall products and the observed rainfall occurrence events, was unsatisfactory over desert AEZs with a CSI value less than 0.5. But, over other AEZs, except CHIRPS v2.0 over alpine AEZ with a CSI value of 0.41, CSI values were greater than 0.50 with the highest value of CSI recorded over sub-tropical AEZ for CHIRPS v2.0 and MSWEP v2.8 with a value of 0.82 and 0.86, respectively. In general, the performance of MSWEP v2.8 is superior than CHIRPS v2.0 over temperate, sub-tropical, tropical and desert AEZs of Ethiopia by most/entire categorical performance measures, but both of them achieved comparable performance in the alpine AEZ.

Considering all categorical performance measures (POD, FAR, FBI and CSI), MSWEP v2.8 is better than CHIRPS v2.0 over temperate, sub-tropical, tropical and desert AEZs by most/entire metrics, but both MSWEP v2.8 and CHIRPS v2.0 attained comparable performance over the alpine AEZ. Regarding the specific indices, MSWEP v2.8 is superior than CHIRPS v2.0 in POD over desert and tropical AEZs, but CHIRPS v2.0 outperforms MSWEP v2.8 over the sub-tropical, temperate and alpine AEZs. In terms of FAR, FBI and

CSI, MSWEP v2.8 is superior than CHIRPS v2.0 over the desert, tropical, sub-tropical and temperate AEZs. Similarly, MSWEP v2.8 was achieved better POD and FBI than CHIRPS v2.0 over temperate, sub-tropical and tropical AEZs of the Bale Eco-Region. However, CHIRPS v2.0 is better in terms of FAR in the Bale Eco-Region (Gashaw *et al.*, 2023). A study by Ageet *et al*. (2022) also showed the good performance of MSWEP v2.8 to detect rainfall occurrence over equatorial East Africa.

Table 4. 2. Daily rainfall occurrence detection skill results of CHIRPS v2.0 and MSWEP v2.8 for Ethiopian AEZs during 1991-2020.

AEZs	Rainfall products	Categorical statistical indices			
		POD	FAR	FBI	CSI
Desert	CHIRPS v2.0	0.26	0.54	0.57	0.20
	MSWEP v2.8	0.30	0.49	0.60	0.23
Tropical	CHIRPS v2.0	0.85	0.20	1.07	0.70
	MSWEP v2.8	0.87	0.13	0.98	0.75
Sub-tropical	CHIRPS v2.0	0.95	0.14	1.10	0.82
	MSWEP v2.8	0.94	0.09	1.03	0.86
Temperate	CHIRPS v2.0	0.87	0.21	1.09	0.71
	MSWEP v2.8	0.85	0.09	0.94	0.79
Alpine	CHIRPS v2.0	0.62	0.45	1.14	0.41
	MSWEP v2.8	0.60	0.10	0.67	0.56

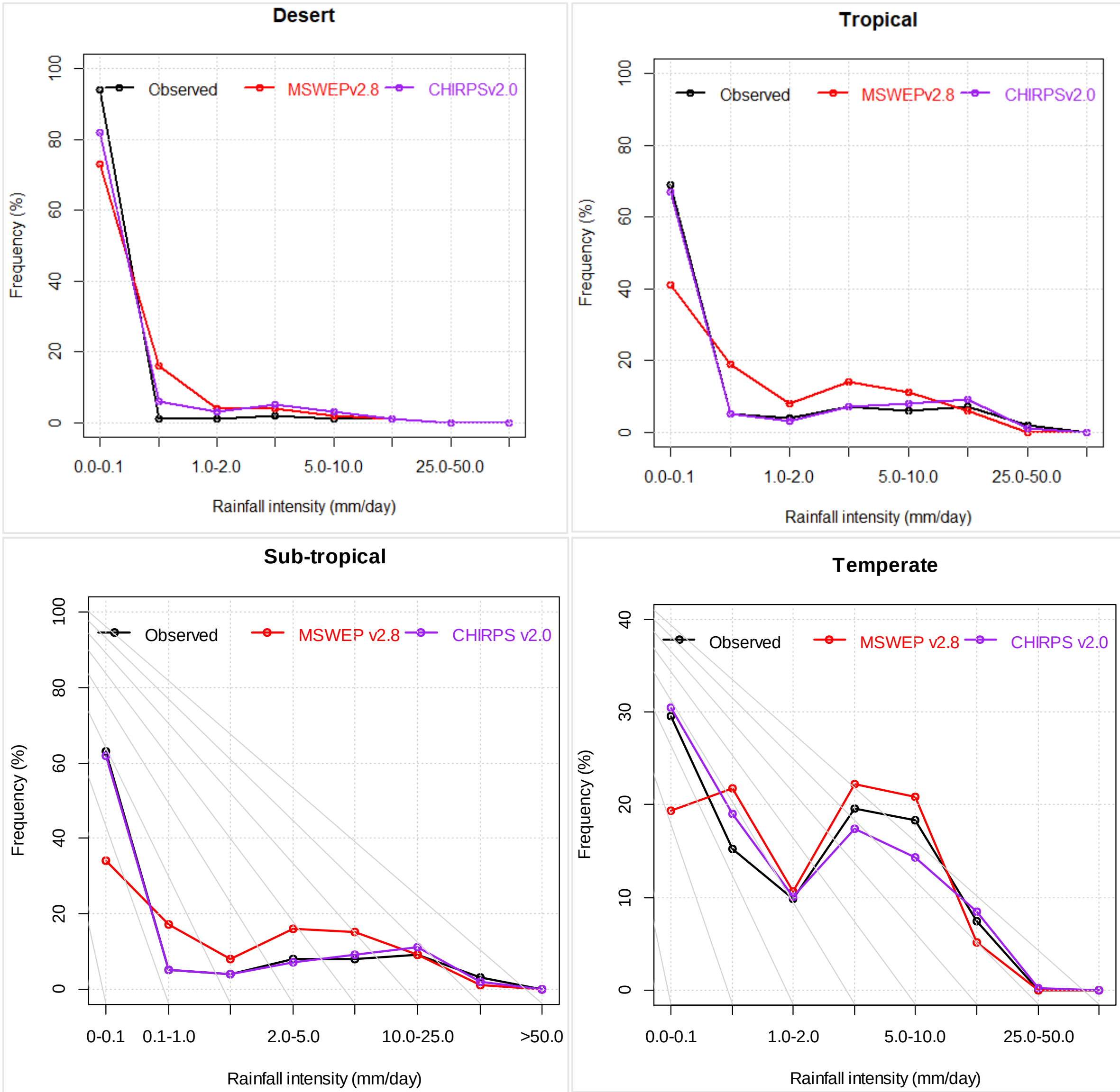
4.3. Performance of satellite/reanalysis products rainfall intensity detection capability

Figure 4.1. compares the daily rainfall intensity classes of observed, CHIRPS v2.0, and MSWEP v2.8 data during 1991-2020 periods across five AEZs of Ethiopia using PDF. As mentioned in the methods part, the daily rainfall intensity classes were categorized into eight classes. The result showed that the frequency of non-rainfall (0-0.1 mm/day) intensity class was higher than other classes for the two rainfall products and the observed rainfall in all AEZs, except the case reported for MSWEP v2.8 in temperate AEZ. In temperate AEZ, the rainfall intensity classes of small rainfall (2.0-5.0 mm/day), slight rainfall (0.1-1.0 mm/day) and light rainfall (5.0-10 mm/day) daily rainfall intensity classes of MSWEP v2.8 accounted the highest coverage, which are representing 22.2%, 21.8% and 20.8%, respectively.

Moreover, the non-rainfall intensity class had the highest frequency in the desert AEZ than in other AEZs. For example, from 10958 daily rainfall data during the period 1991-2020 periods, the observed rainfall frequency for non-rainfall class was 94% in the desert AEZ, while it was between 29.6% and 69% in other AEZs. Similarly, CHIRPS v2.0 had a frequency of 82% for this class in the desert AEZ and between 30.5% and 71.3% in the rest of the AEZs. MSWEP v2.8 had a frequency of 73% for this class in the desert AEZ and between 19.3% and 41% in the rest of the AEZs.

In general, from the PDF graph, the frequency of non- rainfall class was much higher than other classes across all AEZs of Ethiopia, except MSWEP v2.8 in temperate AEZ. Moreover, the MSWEP v2.8 and CHIRPS v2.0 frequency was lower than this class's observed frequency, except CHIRPS v2.0 in temperate and alpine AEZs where the frequency of CHIRPS v2.0 is higher than the observed and MSWEP v2.8. CHIRPS v2.0 frequency of 0-0.1(mm/day) intensity class was closer/identical to the observed frequency, particularly in tropical, sub-tropical and alpine AEZs. In general, the findings of this study indicated that the rainfall intensity detection skills of CHIRPS v2.0 is better than MSWEP v2.8 over the five studied AEZs in the majority of the rainfall intensity classes (Figure 4.1).

Considering eight daily rainfall intensity classes, CHIRPS v2.0 performed better for all intensity classes than MSWEP v2.8. A similar study over the upper Tana sub-basin found that CHIRPS v2.0 are better at reproducing the occurrence frequency of daily events for different intensity ranges over the upper Tana basin for the period 2007-2016, which is part of Ethiopia (Polong *et al.*, 2023).


Desert
Observed
MSWEPv2.8
CHIRPSv2.0
Frequency (%)
0
20
40
60
80
100
0.0-0.1
1.0-2.0
5.0-10.0
25.0-50.0
Rainfall intensity (mm/day)
Tropical
Observed
MSWEPv2.8
CHIRPSv2.0
Frequency (%)
0
20
40
60
80
100
0.0-0.1
1.0-2.0
5.0-10.0
25.0-50.0
Rainfall intensity (mm/day)
Sub-tropical
Observed
MSWEP v2.8
CHIRPS v2.0
Frequency (%)
0
20
40
60
80
100
0-0.1
0.1-1.0
2.0-5.0
10.0-25.0
>50.0
Rainfall intensity (mm/day)
Temperate
Observed
MSWEP v2.8
CHIRPS v2.0
Frequency (%)
0
10
20
30
40
0.0-0.1
1.0-2.0
5.0-10.0
25.0-50.0
Rainfall intensity (mm/day)

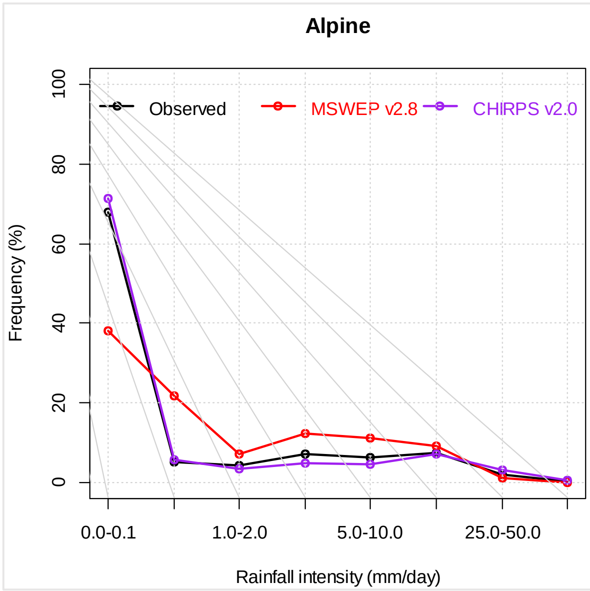


Figure 4.1. The PDF of CHIRPS v2.0 and MSWEP v2.8 daily rainfall events against observed rainfall at different intensity class over AEZs of Ethiopia during 1991-2020.

4.4. Performance of satellite/reanalysis products rainfall total detection capability

4.4.1. Performance of satellite/reanalysis products at daily time scale

Table 4.3 shows the performance of CHIRPS v2.0 and MSWEP v2.8 for estimating daily rainfall during 1991-2020 periods in the different AEZs of the country using continuous statistical metrics. The result displayed that MSWEP v2.8 is superior than CHIRPS v2.0 in terms of achieving lower MAE and RMSE in all AEZs, except attaining identical RMSE in desert AEZ. MSWEP v2.8 is also better than CHIRPS v2.0 in terms of achieving higher r and KGE in all AEZs. Conversely, CHIRPS v2.0 outperforms the MSWEP v2.8 in terms of achieving a lower PBIAS in the desert, tropical and alpine AEZs, but MSWEP v2.8 attained a smaller PBIAS than CHIRPS v2.0 over the temperate and sub-tropical AEZs. The two rainfall products highly overestimate (negative PBIAS) and underestimate (positive PBIAS) daily rainfall total over alpine and desert AEZs respectively. According to the results, I conclude that MSWEP v2.8 performs better than CHIRPS v2.0 in detecting daily rainfall by most/entire continuous statistical indices across all AEZs of Ethiopia.

Concerning the direction of estimation biases, both rainfall products have positive PBIAS values over the desert, tropical and sub-tropical AEZs, indicating underestimation of daily rainfall by these rainfall products. There were positive PBIAS values for CHIRPS v2.0 and negative PBIAS values for MSWEP v2.8 over temperate AEZ. The value implied that CHIRPS v2.0 underestimated and MSWEP v2.8 overestimated daily rainfall over temperate AEZ. The two rainfall products have a negative PBIAS over alpine AEZ, which means that the two rainfall products overestimate daily rainfall over alpine AEZ.

On daily basis, my finding indicated the better performance of MSWEP v2.8 than CHIRPS v2.0 in the five studied AEZs by entire/most performance measure statistics. This may be because the MSWEP v2.8 dataset considers daily gauge data in the product generation process (Funk *et al*., 2019). The results of this study is also aligned with the findings obtained in the Bale Eco-Region in Southern Ethiopia (Gashaw *et al*., 2023). Dangol *et al*. (2022) also found the superior performance of MSWEP v2.8 than CHIRPS v2.0 over the Run River Basin (Nepal). In contrast, a study in the Equatorial East Africa indicated the superior performance of CHIRPS v2.0 than MSWEP v2.8 for simulating daily rainfall (Ageet *et al*., 2022). Of the considered temporal scales in this study, the performance of both rainfall products is comparatively lower at the daily timestep. This could be due to the difficulties in capturing variabilities at high temporal scales (Abebe *et al*., 2020). Reading this, Dinku *et al.* (2018) described that the daily rainfall product is more vulnerable to errors due to the ability of satellite/reanalysis rainfall products generally not favorable on the daily timescale over complex terrain (Dinku *et al*., 2018).

Table 4. 3. Continuous metrics result of CHIRPS v2.0 and MSWEP v2.8 compared with observed rainfall over AEZs of Ethiopia during1991-2020 at daily timescale.

AEZs	Rainfall Products	Continuous Statistical metrics				
		MAE	RMSE	PBIAS (%)	r	KGE
Desert	CHIRPS v2.0	0.85	3.76	15.70	0.26	0.06
	MSWEP v2.8	0.82	3.76	18.00	0.28	0.11
Tropical	CHIRPS v2.0	2.00	3.01	2.30	0.48	0.48
	MSWEP v2.8	1.65	2.49	10.10	0.57	0.52
Subtropical	CHIRPS v2.0	1.64	2.52	2.90	0.73	0.70
	MSWEP v2.8	1.29	2.08	1.00	0.79	0.79
Temperate	CHIRPS v2.0	2.00	3.40	2.90	0.68	0.66
	MSWEP v2.8	1.54	2.84	-0.10	0.74	0.73
Alpine	CHIRPS v2.0	3.43	8.29	-15.10	0.38	0.31
	MSWEP v2.8	2.66	6.47	-18.80	0.49	0.46

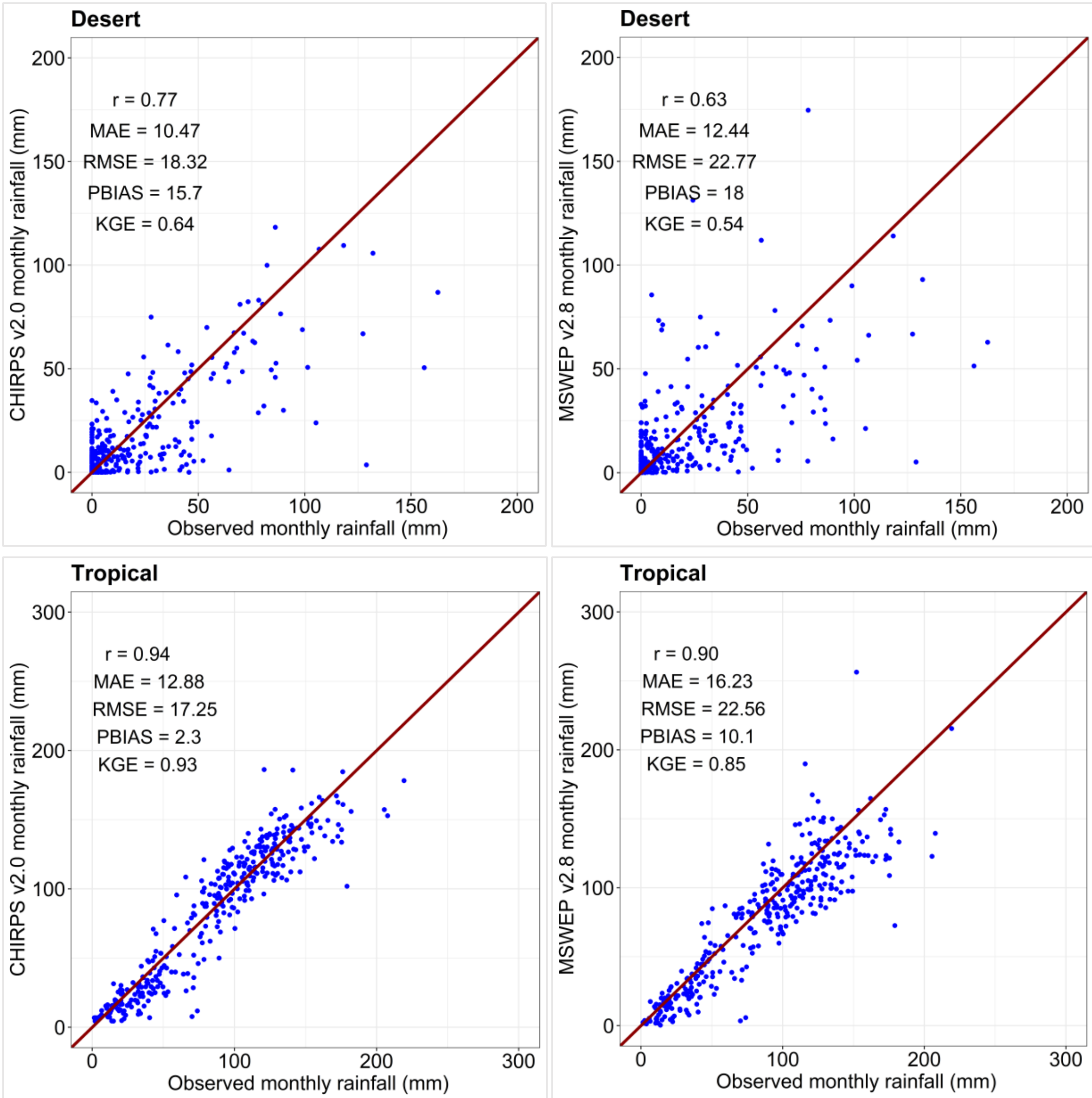
4.4.2. Performance of satellite/reanalysis products at monthly timescale

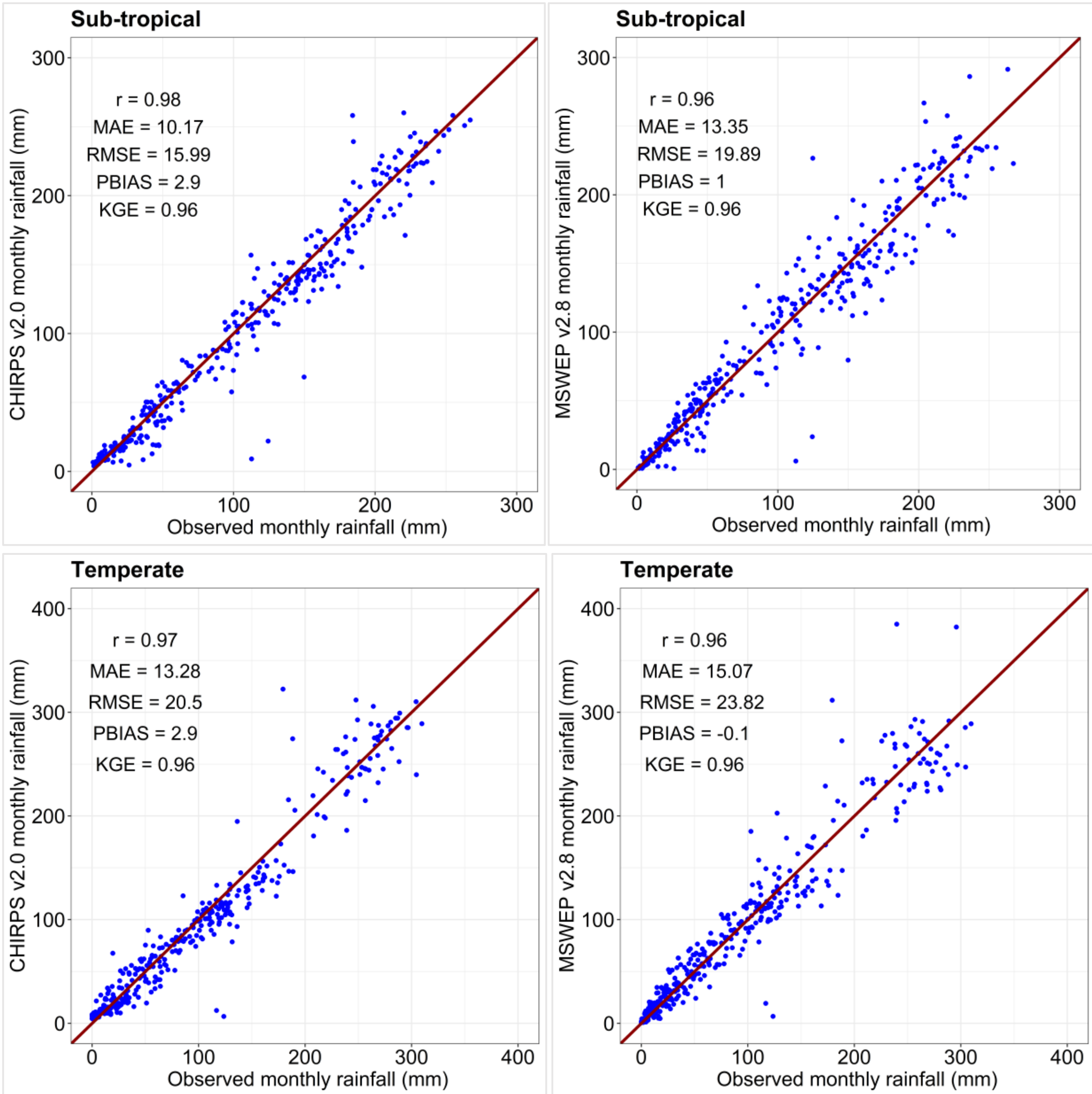
Figure 4.2 shows the scatter plot of the two rainfall products (MSWEP v2.8 and CHIRPS v2.0) against the observed data at the monthly temporal scale over the five AEZs of Ethiopia. The results revealed that the rainfall products agree well with the observed data over all AEZs, except for the desert AEZ, where the rainfall product scatter the values more away from the reference line (dark red color). This indicates a lower performance of the rainfall products in the desert AEZ than in the other AEZs. The r and KGE value of the two rainfall products in AEZs of Ethiopia ranges from 0.63 to 0.97and 0.54 to 0.96 respectively. The continuous statistical performance metrics results revealed that CHIRPS v2.0 was better than MSWEP v2.8 in all the considered continuous statistical measures in the desert, tropical and alpine AEZs. CHIRPS v2.0 is also better than MSWEP v2.8 in temperate and sub-tropical AEZs in terms of R, MAE and RMSE, but both of them obtained a similar KGE in these

AEZs. Conversely, MSWEP v2.8 is better than CHIPRS v2.0 by achieving a lower PBIAS in the temperate and sub-tropical AEZs (Figure 4.2). Therefore, CHIRPS v2.0 have shown superior performance than MSWEP v2.8 for simulating monthly rainfall in all AEZs in the entire/majority of the considered statistical performance measure indices.

The PBIAS value is positive over desert, tropical, sub-tropical and temperate AEZs for both rainfall products, except MSWEP v2.8 over temperate AEZ. Thus, this finding indicates that the two rainfall products underestimate monthly rainfall over these AEZs, but MSWEP v2.8 overestimates monthly rainfall over temperate AEZ. Moreover, CHIRPS v2.0 and MSWEP v2.8 overestimate monthly rainfall by 15.1% and 18.8%, over alpine AEZ respectively. Over tropical, sub-tropical, and temperate AEZs, the points are scattered closer with the 1:1 line, showed the better agreement between rainfall products and observed rainfall. But over desert and alpine AEZs, the points scattered away from the 1:1 line (deep red color) showed less agreement as compared with other three AEZs.

The finding of my study indicated that both of the rainfall products have overestimation problem over the alpine AEZ at monthly timescale. On the other hand, CHIRPS v2.0 have shown underestimation problem over the remining four AEZs monthly timescale. Aligned with this study, underestimation of CHIRPS v2.0 at the monthly temporal scale was also reported for the lowland and highland parts of the Lake Tana sub-basin (Ethiopia) (Fenta *et al*.,2018). This study also indicated that MSWEP v2.8 overestimated rainfall over temperate AEZ in monthly timescale (Gashaw *et al.*, 2023). In sub-tropical, tropical and desert AEZs, however, MSWEP v2.8 underestimated rainfall at monthly temporal scales.


Desert
r = 0.77
MAE = 10.47
RMSE = 18.32
PBIAS = 15.7
KGE = 0.64
CHIRPS v2.0 monthly rainfall (mm)
Observed monthly rainfall (mm)
Desert
r = 0.63
MAE = 12.44
RMSE = 22.77
PBIAS = 18
KGE = 0.54
MSWEP v2.8 monthly rainfall (mm)
Observed monthly rainfall (mm)
Tropical
r = 0.94
MAE = 12.88
RMSE = 17.25
PBIAS = 2.3
KGE = 0.93
CHIRPS v2.0 monthly rainfall (mm)
Observed monthly rainfall (mm)
Tropical
r = 0.90
MAE = 16.23
RMSE = 22.56
PBIAS = 10.1
KGE = 0.85
MSWEP v2.8 monthly rainfall (mm)
Observed monthly rainfall (mm)


Sub-tropical
r = 0.98
MAE = 10.17
RMSE = 15.99
PBIAS = 2.9
KGE = 0.96
CHIRPS v2.0 monthly rainfall (mm)
Observed monthly rainfall (mm)
Sub-tropical
r = 0.96
MAE = 13.35
RMSE = 19.89
PBIAS = 1
KGE = 0.96
MSWEP v2.8 monthly rainfall (mm)
Observed monthly rainfall (mm)
Temperate
r = 0.97
MAE = 13.28
RMSE = 20.5
PBIAS = 2.9
KGE = 0.96
CHIRPS v2.0 monthly rainfall (mm)
Observed monthly rainfall (mm)
Temperate
r = 0.96
MAE = 15.07
RMSE = 23.82
PBIAS = -0.1
KGE = 0.96
MSWEP v2.8 monthly rainfall (mm)
Observed monthly rainfall (mm)

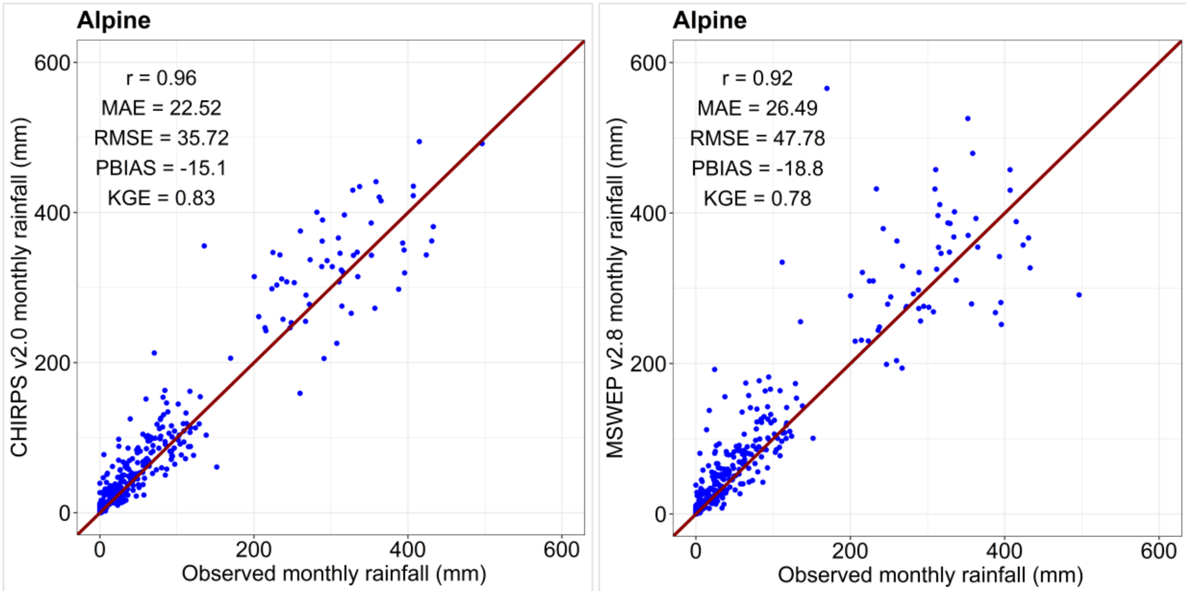


Figure 4.2. Scatter plot of monthly rainfall of observed against CHIRPSv2.0 and MSWEPv2.8 over AEZs of Ethiopia from 1991-2020.

Figure 4.3 shows the line graph representation of mean monthly rainfall (1991-2020) of CHIRPS v2.0 and MSWEP v2.8. The results revealed that both MSWEP v2.8 and CHIRPS v2.0 detected dry months (October-January) and wet months (both February-May and June-September) rainfall reasonably since the graph of the two rainfall products are closer to the observed line graph. Comparatively, the performance of MSWEP v2.8 showed low for wet months over desert and tropical AEZs. Even though, CHIRPSv2.0 outperformed at monthly time basis than MSWEP v2.8, MSWEP v2.8 has comparable performance with CHIRPSv2.0 at monthly time basis (Figure 4.2 and 4.3). Moreover, the two rainfall products were best explaining mean monthly rainfall over sub-tropical and temperate AEZs. The performance of MSWEP v2.8 monthly rainfall total over some study areas other than Ethiopia showed comparable with CHIRPS v2.0 (Ageet et al., 2022; Dangol et al., 2022;Valencia et al., 2023)

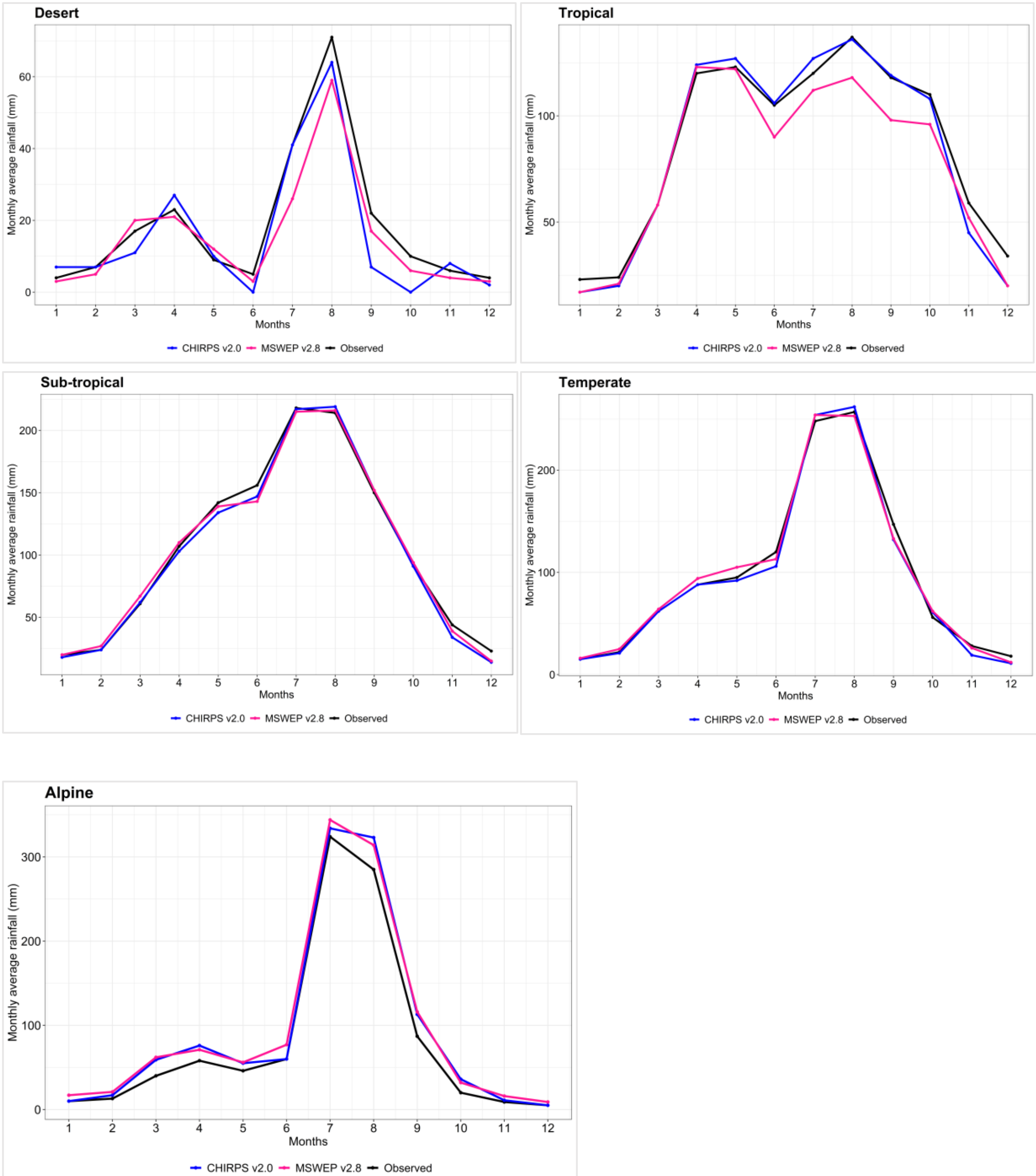


Figure 4.3. Line graph of mean monthly observed rainfall with MSWEP v2.8 and CHIRPS v2.0 rainfall over AEZs of Ethiopia during 1991-2020.

4.4.3. Performance of satellite/reanalysis products at seasonal timescale

Table 4.4 shows the observed *Bega* seasonal mean rainfall (mm) and continuous statistical metrics values of the two rainfall products for each AEZ for the period 1991-2020. The MAE and RMSE values show errors in rainfall products. The RMSE values are higher than the observed mean *Bega* rainfall (mm). The PBIAS value of CHIRPS v2.0 was negative in alpine AEZ with a value of -43.70 % and positive over the rest AEZs with PBIAS value ranges from 10.50% (in temperate AEZ) to 27.20% (in desert AEZ). These PBIAS values show that CHIRPS v2.0 underestimate over most AEZs and overestimates over alpine AEZ. Similarly, the PBIAS value of MSWEP v2.8 ranges from -68.20% (in alpine) to 29.60% (over desert) AEZs. From these values of PBIAS MSWEP v2.8 underestimate over desert, tropical, subtropical, and temperate AEZs, but overestimate over alpine AEZ. The two rainfall products extremely underestimate and overestimate the *Bega* season rainfall total over the desert and alpine AEZs respectively. The value of r and KGE values of the two rainfall products in desert AEZ were less than 0.5, which implied the poor performance of rainfall products to detect *Bega* seasonal rainfall total over desert AEZ. The value of r value reaches 0.89 over tropical AEZ for both MSWEP v2.8 and CHIRPS v2.0, which implied better agreement between rainfall products and observed *Bega* seasonal rainfall total. The KGE value also consolidate the above statement that the overall performance of rainfall products was good over tropical AEZ and poor over desert AEZ. Overall, the performance of CHIRPS v2.0 and MSWEP v2.8 to detect *Bega* seasonal rainfall total was low, but, good over other AEZ. Comparatively, CHIRPS v2.0 has a preferable performance than MSWEP v2.8 to detect *Bega* seasonal rainfall total over AEZs of Ethiopia.

The performances of the two studied satellite/reanalysis rainfall products for simulating *Belg* season rainfall (mm) for the period 1991-2020 over the five AEZs of the country are given in Table 4.4. The results showed that CHIRPS v2.0 attained lower MAE and RMSE in all AEZs compared to MSWEP v2.8, indicating the better performance of CHIRPS v2.0 rainfall product. CHIRPS v2.0 is also superior than MSWEP v2.8 in terms of achieving higher r and KGE in all AEZs, except its lower KGE attained in temperate AEZ. CHIRPS v2.0 is also superior in terms of achieving lower PBIAS in sub-tropical, temperate and alpine AEZs. Conversely, MSWEP v2.8 attained a lower PBIAS in tropical and desert AEZs. In general, CHIRPS v2.0 is better for estimating *Belg* season rainfall in all AEZs compared to MSWEP v2.8 in majority/entire of the considered statistical metrics (Table 4.4).

With regard to the estimation biases of the studied satellite/reanalysis rainfall products, CHIRPS v2.0 exhibited positive PBIAS over the desert, sub-tropical and temperate AEZs, implying the underestimation of the *Belg* season rainfall. Whereas, CHIRPS v2.0 attained negative PBIAS over tropical and alpine AEZs, which signifies overestimation of *Belg* season rainfall. Conversely, the PBIAS values of MSWEP v2.8 were negative overall AEZs except for tropical AEZ, which implied the overestimation of the *Belg* season rainfall total in majority of the AEZs. MSWEP v2.8 only underestimates *Belg's* season rainfall total over tropical AEZ. The PBIAS values of MSWEP v2.8 ranges from -34.3% (over alpine) to 0.1% (over tropical) AEZs while CHIRPS v2.0 PBIAS extends from -31.7 over alpine to 1.3 over temperate AEZs. Therefore, the highest estimation basis of both CHIRPS v2.0 and MSWEP v2.8 products is observed in the alpine AEZ (Table 4.4).

Aligned with this study, underestimation of CHIRPS v2.0 at the seasonal temporal scale was also reported for the lowlands (<1500 m a.s.l) and highlands (>1500 m a.s.l) parts of the Lake Tana sub-basin (Ethiopia). In contrast to my finding, CHIRPS v2.0 underestimated the *Kiremt* season rainfall over the highland and lowland parts of the Lake Tana sub-basin (Fenta *et al*., 2018). My finding also indicated that MSWEP v2.8 overestimated rainfall over temperate AEZ in *Belg* season. MSWEP v2.8 overestimated *Belg* rainfall in sub-tropical AEZ but it underestimated rainfall during *Bega* and *Belg* season over tropical AEZ. According to authors (Dinku et al., 2018; Fenta et al., 2018) seasonal differences in the performance of satellite rainfall estimates may be due to the fact that rainfall during the secondary rainy season (*Belg*) most probably dominated by convective systems, whereas both convective and stratiform systems contributed to the rainfall during primary rainy season of Ethiopia (*Kiremt* season).The good seasonal performance of MSWEPv2.8 and CHIRPSv2.0 was also verified by (Ageet et al., 2022) over equatorial East Africa.

Table 4. 4. Continuous metrics result of seasonal rainfall of CHIRPS v2.0 and MSWEP v2.8 with observed over AEZs of Ethiopia from 1991-2020.

	Desert					
	Bega (ONDJ)		*Belg* (FMAM)		*Kiremt* (JJAS)	
	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8
MAE	18.77	18.63	26.00	33.70	39.77	61.11
RMSE	24.78	26.93	33.87	45.01	54.03	74.55
PBIAS	27.20	29.60	3.20	-2.80	18.80	24.60
r	0.38	0.26	0.56	0.24	0.42	0.17
KGE	0.02	0.15	0.41	0.20	0.25	0.14
	Tropical					
	Bega (ONDJ)		*Belg* (FMAM)		*Kiremt* (JJAS)	
	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8
MAE	38.77	43.03	24.33	31.90	34.43	70.12
RMSE	46.22	50.43	30.61	42.97	46.49	80.44
PBIAS	16.30	18.30	-1.50	0.10	-1.70	13.00
r	0.89	0.89	0.83	0.70	0.69	0.63
KGE	0.75	0.78	0.80	0.69	0.59	0.58
	Subtropical					
	Bega (ONDJ)		*Belg* (FMAM)		*Kiremt* (JJAS)	
	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8
MAE	26.82	28.41	21.22	42.48	29.98	46.48
RMSE	54.41	55.08	28.51	53.47	45.45	53.99
PBIAS	13.40	6.60	2.90	-3.00	0.40	1.40
r	0.74	0.68	0.90	0.70	0.70	0.60
KGE	0.55	0.59	0.82	0.66	0.70	0.60
	Temperate					
	Bega (ONDJ)		*Belg* (FMAM)		*Kiremt* (JJAS)	
	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8
MAE	22.74	22.42	21.07	30.20	43.60	60.65
RMSE	49.60	45.97	25.17	41.02	58.73	75.89
PBIAS	10.50	1.10	1.30	-8.10	2.30	2.50
r	0.68	0.71	0.95	0.88	0.72	0.52
KGE	0.47	0.65	0.74	0.83	0.68	0.49
	Alpine					
	Bega (ONDJ)		*Belg* (FMAM)		*Kiremt* (JJAS)	
	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8	CHIRPSv2.0	MSWEPv2.8
MAE	20.62	31.78	53.96	59.07	111.74	59.07

RMSE	26.54	39.60	60.92	74.34	144.86	74.34
PBIAS	-43.70	-68.20	-31.70	-34.30	-10.00	-34.30
r	0.87	0.85	0.73	0.61	0.51	0.61
KGE	0.54	0.20	0.58	0.35	0.42	0.35

The *Kiremt* season continuous statistical metrics of the two studied rainfall products are shown in Table 4.4. The finding displayed that CHIRPS v2.0 is better than MSWEP v2.8 for simulating *Kiremt* season rainfall over the five AEZs of the country in the considered entire performance measures. Concerning the estimations bias directions of the rainfall products, CHIRPS v2.0 underestimates (Positive PBIAS) the *Kiremt* season rainfall total over the desert, sub-tropical and temperate AEZs, but it overestimates (negative PBIAS) the *Kiremt* rainfall total over the tropical and alpine AEZs. The PBIAS values of MSWEP v2.8 were positive over the desert, tropical, sub-tropical, and temperate AEZs, indicating that MSWEP v2.8 underestimates the observed *Kiremt* rainfall. But, MSWEP v2.8 overestimates the *Kiremt* season rainfall over alpine AEZ. The estimation bias of MSWEP v2.8 ranges from -24.6% (over desert AEZ) to 1.4% (over sub-tropical AEZ) while the highest and lowest PBIAS values of CHIRPS v2.0 is 18.8% (over desert AEZ) and 0.4% (over sub-tropical AEZ), respectively. Hence, both MSWEP v2.8 and CHIRPS v2.0 rainfall products have shown a maximum estimation bias of the observed *Kiremt* season rainfall over the desert AEZ.

In contrast to my finding, CHIRPS v2.0 underestimated the *Kiremt* season rainfall over the highland and lowland parts of the Lake Tana sub-basin (Fenta *et al*., 2018).My finding also indicated that MSWEP v2.8 overestimated rainfall over temperate AEZ in seasonal temporal scale, except in *Kiremt* season which exhibited underestimation bias. Conversely, MSWEP v2.8 overestimated *Kiremt* rainfall over temperate AEZ in the Bale Eco-Region (Gashaw *et al*., 2023).

4.4.4. Performance of satellite/reanalysis products at annual timescale

The performances of CHIRPS v2.0 and MSWEP v2.8 for representing the annual rainfall in the studied AEZs are shown in Table 4.5. The MAE and RMSE values of CHIRPS v2.0 were lower than those of MSWEP v2.8 overall AEZs, indicating its better accuracy. CHIRPS v2.0

is also better than MSWEP v2.8 in all AEZs in terms of achieving better KGE. The performance of CHIRPS v2.0 is also superior in terms of having lower PBIAS in desert, tropical and alpine AEZs, but MSWEP v2.8 attained better PBIAS than CHIRPS v2.0 in sub-tropical and temperate AEZs. In terms of r, CHIRPS v2.0 attained a better correlation coefficient than MSWEP v2.8 in desert, sub-tropical, temperate and alpine AEZs, but MSWEP v2.8 achieved improved correlation coefficient than CHIRPS v2.0 in the tropical AEZ.

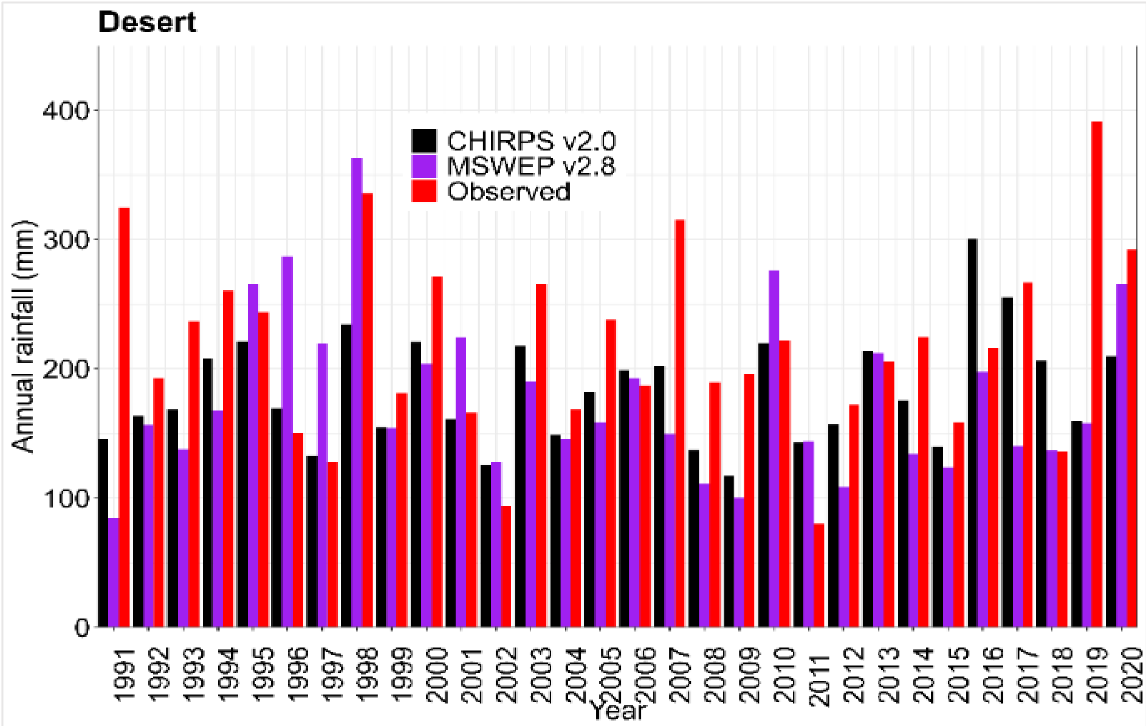
In terms of the directions of biases of the studied rainfall products, both of them have shown positive PBIAS in the desert, tropical and sub-tropical AEZs, meaning that they underestimated the annual rainfall. Over temperate AEZ, CHIRPS v2.0 has a positive PBIAS, and MSWEP v2.8 has a negative PBIAS which means that CHIRPS v2.0 underestimates and MSWEP v2.8 overestimates annual rainfall over the temperate AEZ. The two satellite/reanalysis rainfall products have negative PBIAS over alpine AEZ implying that they overestimate the annual rainfall total. The highest underestimation bias was observed over the desert AEZ, with a PBIAS of 15.7% for CHIRPS v2.0 and 18% for MSWEP v2.8. Conversely, the maximum overestimation of annual rainfall total was detected over alpine AEZ with PBIAS of -15.1% and -18.8% for CHIRPS v2.0 and MSWEP v2.8, respectively (Table 4.4). In general, CHIRPS v2.0 has superior performance than MSWEP v2.8 for simulating annual rainfall in all AEZs in the majority/entire of the considered statistical measures.

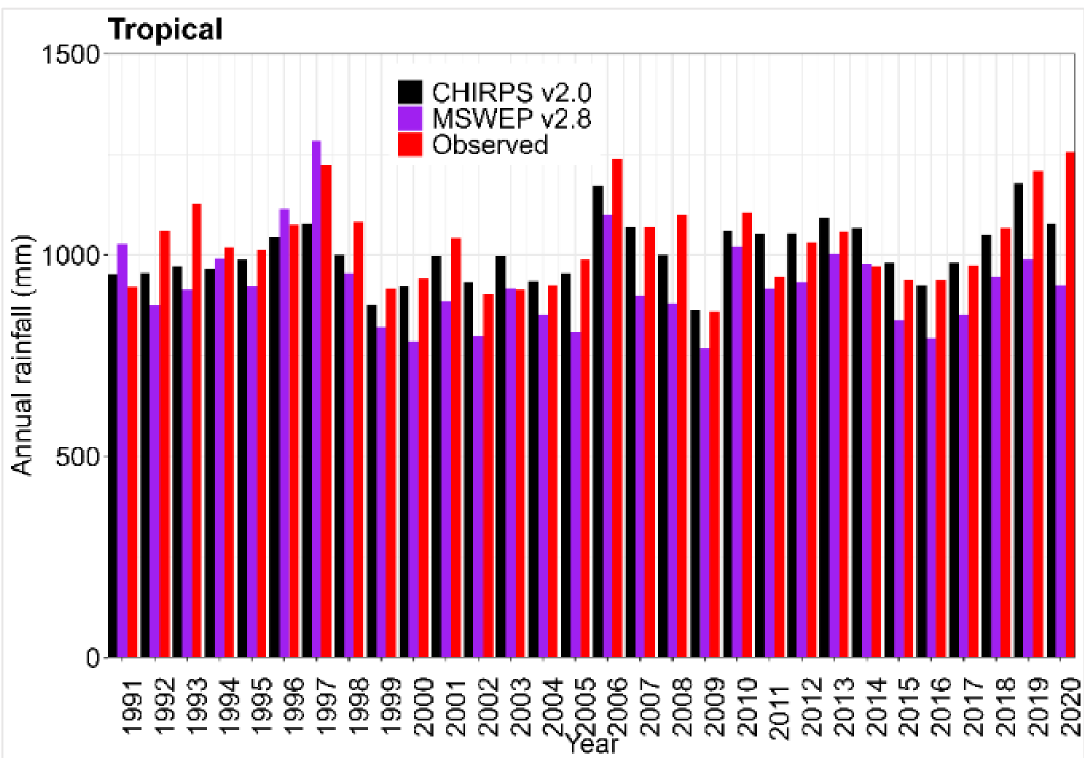
The superior performance of CHIRPSv2.0 compared to MSWEPv2.8 at monthly, seasonal and annual temporal scale corresponds with the findings of Ageet *et al.* (2022) and (Dinku *et al.* 2018).The reason may be due to the use of gauge-satellite climatology, CHPClim which reduces mean biases and the fact that gauge calibration is done at longer temporal resolution (pentadal and monthly).The good performance of MSWEPv2.8 and CHIRPSv2.0 in annual timescale also showed by (Ageet et al., 2022).The performance of the studied rainfall products varies considerably from place to place. This may be due to Ethiopia's complex topography and climate (Dinku *et al.*, 2011, Dinku *et al.*, 2018). Aligned with this result, previous studies undertaken in Lake Tana sub-basin (Fenta *et al*., 2018) and Belese sub-basin (Belay *et al.*, 2019) ,also reported the performance difference of CHIRPS v2.0 rainfall estimates over the highland and lowland areas. In addition, Gashaw *et al*. (2023) also indicated performance variations of CHIRPS v2.0 and MSWEP v2.8 over the AEZs of the Bale Eco-Region. My finding also clearly indicated the poor performance of both of the rainfall products over the desert AEZ compared to the remaining AEZs.

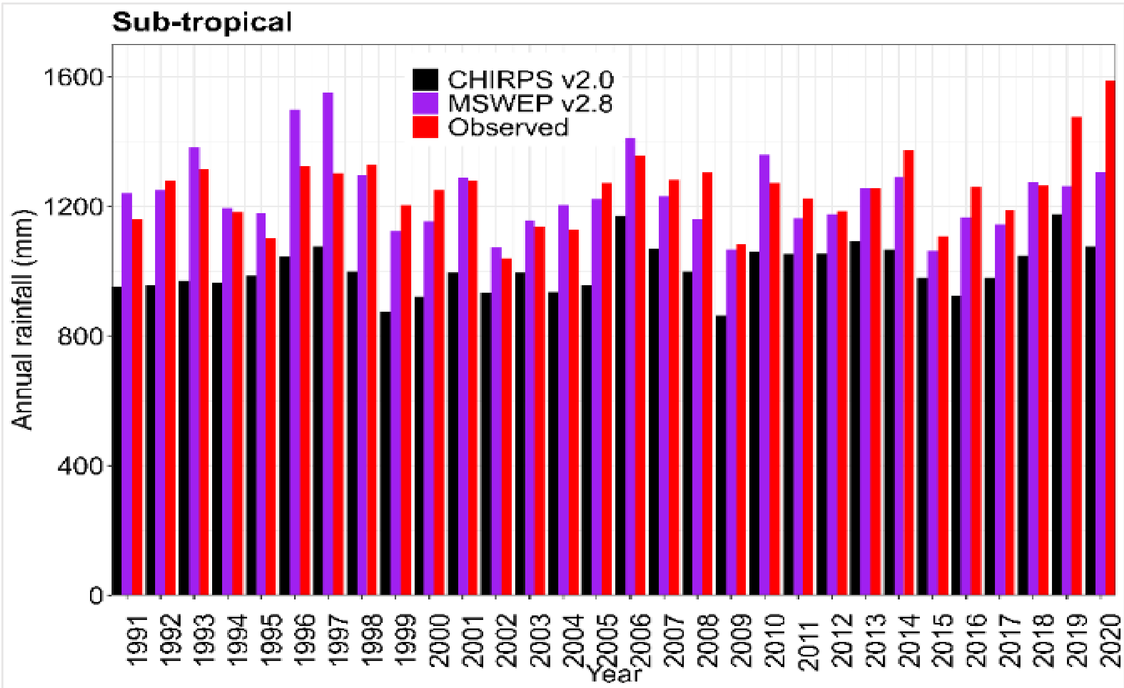
Table 4. 5. Performances of CHIRPS v2.0 and MSWEP v2.8 annual rainfall over five AEZs of Ethiopia during 1991-2020.

AEZs	Rainfall products	Continuous statistical metrics				
		MAE	RMSE	PBIAS (%)	r	KGE
Desert	CHIRPS v2.0	53.59	73.73	15.70	0.42	0.27
	MSWEP v2.8	72.45	93.54	18.00	0.19	0.17
Tropical	CHIRPS v2.0	55.10	71.89	2.30	0.53	0.63
	MSWEP v2.8	118.5	131.15	10.10	0.64	0.62
Subtropical	CHIRPS v2.0	47.43	69.20	2.90	0.62	0.73
	MSWEP v2.8	75.52	102.95	1.00	0.60	0.60
Temperate	CHIRPS v2.0	53.46	69.65	2.90	0.84	0.77
	MSWEP v2.8	68.39	83.30	-0.10	0.79	0.72
Alpine	CHIRPS v2.0	162.99	202.21	-15.10	0.42	0.32
	MSWEP v2.8	200.15	262.43	-18.80	0.20	-0.02

Bar graph representations of the annual rainfall total showed that the two rainfall products are far away from observed over desert and alpine AEZs (Figure 4.4). Both CHIRPS v2.0 and MSWEP v2.8 underestimate the observed annual rainfall over desert AEZ, but over temperate AEZ the two rainfall products overestimate the annual rainfall total. On the other hand, over tropical, sub-tropical, and temperate AEZs, the bar graph of the two studied rainfall products were more or less close to observed. The highest and least year-to-year performance variation between the two rainfall products and observed was displayed over desert and temperate AEZs respectively.


Desert
CHIRPS v2.0
MSWEP v2.8
Observed
Annual rainfall (mm)
Year


Tropical
CHIRPS v2.0
MSWEP v2.8
Observed
Annual rainfall (mm)
Year


Sub-tropical
CHIRPS v2.0
MSWEP v2.8
Observed
Annual rainfall (mm)
Year
0
400
800
1200
1600
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
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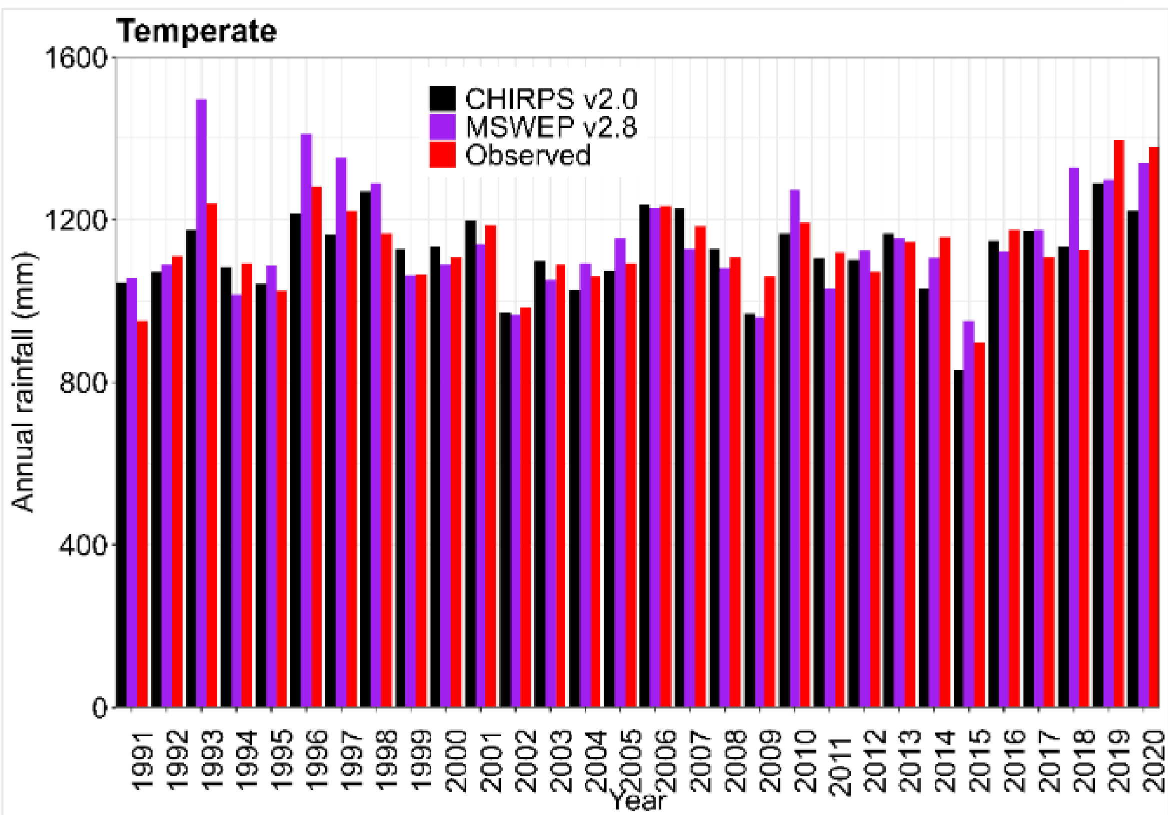
Temperate
CHIRPS v2.0
MSWEP v2.8
Observed
Annual rainfall (mm)
Year
0
400
800
1200
1600
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
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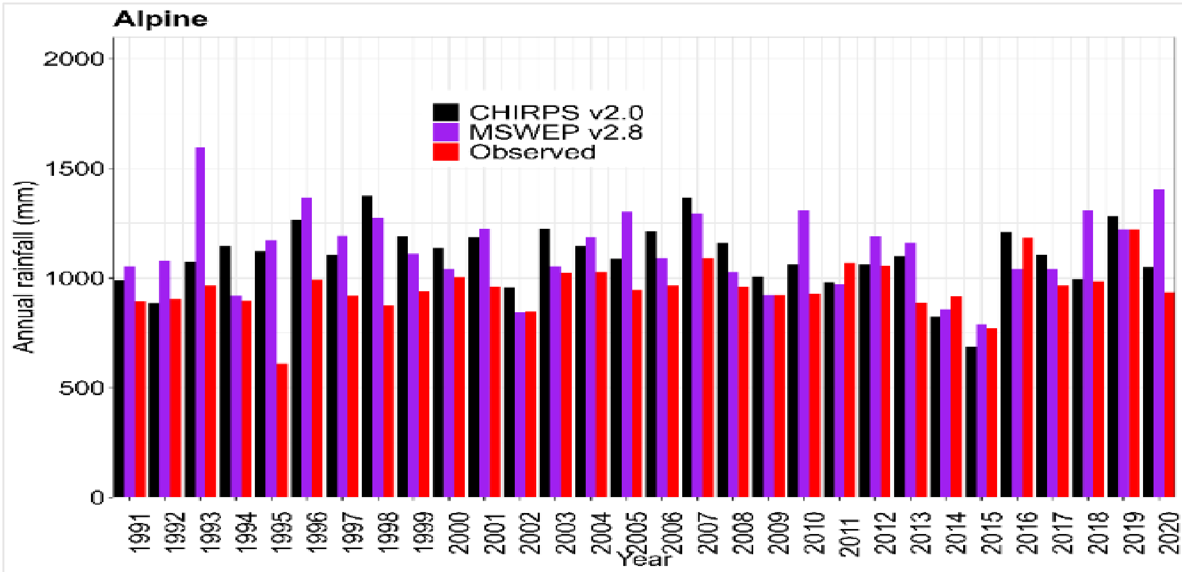

Figure 4. 4. The bar graph representation of the observed annual rainfall with MSWEP v2.8 and CHIRPS v2.0 over AEZs of Ethiopia from 1991-2020

Table 4.6 shows the summary of the overall performance of CHIRPS v2.0 and MSWEP v2.8 rainfall products over all AEZs for the period 1991-2020.From the table, CHIRPS v2.0 takes the superior performance to detect daily to annual rainfall total and daily rainfall intensity category. Whereas, MSWEP v2.8 was better to detect daily rainfall total and daily rainfall occurrence detection skill by most/all performance measures.

Table 4. 6. Summary of overall performance of CHIRPS v2.0 and MSWEP v2.8 rainfall from daily to annual temporal scales over the five AEZs of Ethiopia in the majority/entire performance measure statistics.

Temporal scales	Desert		Tropical		Sub-tropical		Temperate		Alpine	
	CHIRPS v2.0	MSWEP v2.8	CHIRPS v2.0	MSWEP v2.8	CHIRPS v2.0	MSWEP v2.8	CHIRPS v2.0	MSWEP v2.8	CHIRPS v2.0	MSWEP v2.8
Continuous statistical measures										
Daily										
Monthly										
Bega										
Belg										
Kirmet										
Annual										
Categorical metrics										
PDF										

Note: The dark green filled boxes illustrate best performing products in the entire metrics, the light green filled boxes indicate the best performing product in majority performance measures, and the yellow filled boxes represents comparable/equal performance of the two studied rainfall products over the studied five AEZs of the country.

CHAPTER 5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study evaluated performances of CHIRPS v2.0 and MSWEP v2.8 rainfall estimates with observed rainfall data during 1991-2020 periods over the five AEZs of Ethiopia from daily to annual temporal scales. The results demonstrate that there were significant discrepancies in the quality of the two rainfall products from observed rainfall for daily timescale. But less discrepancy was demonstrated at monthly timescale. In most AEZs, there were also significant difference of rainfall products and observed rainfall at *Bega*, *Belg*, *Kiremt* and annual temporal scales. The findings also revealed the superior performance of CHIRPS v2.0 compared to MSWEP v2.8 for estimating monthly, *Bega*, *Belg*, *Kiremt*, and annual rainfall total over the five AEZs of the country by most/entire performance measure statistics (Table 4.6). On daily basis, however, the performance of MSWEP v2.8 outperforms the CHIRPS v2.0 estimates over all AEZs of Ethiopia by the entire/majority of the performance measure metrics. Concerning the detection capability of daily rainfall occurrence, the performance of MSWEP v2.8 is also superior than CHIRPS v2.0 over temperate, sub-tropical, tropical and desert AEZs of Ethiopia by most/entire categorical performance measures, but both of them achieved comparable performance in the alpine AEZ. However, different rainfall intensity classes were better captured by CHIRPS v2.0 than MSWEP v2.8 overall AEZs by majority of the intensity classes (Table 4.6). The study found the low performances of both rainfall products over the desert AEZ of the country compared to the remining AEZs. Therefore, employing MSWEP v2.8 for monthly, *Bega*, *Belg*, *Kiremt*, and annul temporal scale applications may contain higher uncertainties on the outputs compared to studies undertaken using CHIRPS v2.0 rainfall dataset. Likewise, using either of these rainfall products in the desert AEZ for any applications may provide results far from the actual conditions.

5.2. Recommendation

Therefore, for both grid-based and station wise national level studies, I recommend CHIRPS v2.0 for monthly, *Bega*, *Belg*, *Kiremt*, and annual temporal scales and MSWEP v2.8 for daily time step studies. The findings of the study will be important for data developers of both rainfall products to improve the algorithms used and/or the numbers of stations used for producing the data in desert AEZ in particular and the remaining AEZs in general.

In this study, CHIRPS v2.0 is better than MSWEP v2.8 for estimating annual rainfall over the five AEZs of the country. Conversely, Gashaw *et al.* (2023) reported the better performance of MSWEP v2.8 for estimating annual rainfall in temperate, sub-tropical and tropical AEZs of the Bale Eco-Region compared to CHIRPS v2.0. On the other hand, MSWEP v2.2, which is the earlier version of MSWEP v2.8, outperforms both CHIRPS v2.0 and MSWEP v2.8 for estimating annual rainfall over Equatorial East Africa (Ageet *et al.*, 2022). Therefore, this study recommends further studies on the following research areas: 1) evaluations of CHIRPS v2.0, MSWEP v2.1 and MSWEP v2.8 under hydrological models, and 2) evaluations of CHIRPS v2.0, MSWEP v2.1 and MSWEP v2.8 for simulating rainfall extremes and varying types of droughts over different AEZs at daily to annual temporal scales. Furthermore, since this study evaluated rainfall products only with a point-to-pixel approach that is attributed to the small number and sparsely distributed stations, which is the limitations of this study, I recommend a grid-to-grid evaluations of these rainfall products in watershed/sub-basins where relatively higher numbers of stations are existed.

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APPENDIX

Appendix Table 1. Description of studied meteorological stations over traditional AEZs of Ethiopia

No	Station Name	Geographic coordinate		Elevation	Traditional AEZs	
		Longitude	Latitude		AEZs (Amharic name)	AEZs (English name)
1	Abomsa	39.83	8.47	1630	Woyina Dega	Subtropical
2	Adama	39.28	8.56	1648	Woyina Dega	Subtropical
3	Addis Ababa	38.75	9.02	2386	Dega	Temperate
4	Ambo	37.84	8.99	2068	Woyina Dega	Subtropical
5	Arba Minch	37.56	6.06	1220	Kolla	Tropical
6	Asebe Teferi	40.87	9.07	1796	Kolla	Tropical
7	Asela	39.14	7.96	2420	Dega	Temperate
8	Asgori	38.33	8.79	1979	Woyina Dega	Subtropical
9	Asosa	34.55	10.05	1541	Woyina Dega	Subtropical
10	Bahir Dar	37.42	11.60	1770	Woyina Dega	Subtropical
11	Boditi	37.86	6.96	2043	Woyina Dega	Subtropical
12	Bonga	36.24	7.28	1599	Woyina Dega	Subtropical
13	Butajira	38.38	8.12	2074	Woyina Dega	Subtropical
14	Dangila	36.85	11.43	2116	Woyina Dega	Subtropical
15	Debre Birhan	39.51	9.67	3206	Dega	Temperate
16	Debre Markos	37.74	10.33	2446	Dega	Temperate
17	Debretabor	38.00	11.87	2612	Dega	Temperate
18	Degehabur	43.56	8.23	1070	Kolla	Tropical
19	Dilla	38.31	6.38	1515	Woyina Dega	Subtropical
20	Dire Dawa	41.90	9.61	1045	Kolla	Tropical
21	Dubity	41.09	11.73	381	Bereha	Desert
22	Fiche	38.74	9.77	2798	Dega	Temperate
23	Gimbi	35.84	9.20	1844	Woyina Dega	Subtropical
24	Gonder	37.43	12.52	1973	Woyina Dega	Subtropical
25	Gore	35.55	8.16	2024	Woyina Dega	Subtropical
26	Haramaya	42.04	9.42	2025	Woyina Dega	Subtropical
27	Hawassa	38.48	7.07	1694	Woyina Dega	Subtropical
28	Hosanna	37.86	7.57	2306	Dega	Temperate
29	Jijiga	42.72	9.37	1557	Woyina Dega	Subtropical
30	Jimma	36.82	7.67	1710	Woyina Dega	Subtropical
31	Kombolcha	39.72	11.08	1857	Woyina Dega	Subtropical

32	Konso	37.44	5.34	1431	Kolla	Tropical
33	Lalibela	39.04	12.04	2487	Dega	Temperate
34	Mekele	39.53	13.47	2221	Woyina Dega	Subtropical
35	Metema	36.41	12.77	790	Kolla	Tropical
36	Mizan Teferi	35.58	7.00	1444	Kolla	Tropical
37	Mojo	39.11	8.61	1763	Woyina Dega	Subtropical
38	Moyale	39.05	5.05	1166	Woyina Dega	Subtropical
39	Negele	39.27	5.33	1439	Woyina Dega	Subtropical
40	Nekemte	36.55	9.08	2119	Woyina Dega	Subtropical
41	Pawe	36.41	11.31	1119	Kolla	Tropical
42	Robe	40.05	7.13	2480	Dega	Temperate
43	Teppi	35.44	7.20	1208	Kolla	Tropical
44	Tulu bolo	38.22	8.67	2100	Woyina Dega	Subtropical
45	Wolaita	37.75	6.82	1854	Woyina Dega	Subtropical
46	Yirgachefe	38.21	6.15	1856	Woyina Dega	Subtropical
47	Yirgalem	38.43	6.80	1786	Woyina Dega	Subtropical

Biographic sketch

The author was born on June 1987 in Quarite district, West Gojjam zone Amhara National Regional State, and North West of Ethiopia. He attended his primary and Secondary education at Feresbet from 1995-2006.Then after, he attended preparatory education in Dembecha from 2007 to 2008. After successfully passing the Ethiopian Higher Education Entrance Examination, he joined Hawassa University, College of Applied science in 2009 and graduate with Bsc degree in Statistics in July 2011. Then after, he served in Wombera Meteorological station, National Meteorology Agency of Ethiopia in 2013. After serving one year, he joined 31st round Meteorological observation training at NMA education and training center which was given by NMA collaboration with Arba Minch University in 2015. After completion of training, he served at Debre Markos Synoptic Meteorological station in 2016. After a successful service for one year at Debre Markos station, he joined the 1st round post graduate diploma in Meteorology science at NMA education and training center which was given collaboration with Arba Minch University and Addis Ababa university in 2018. Then after successful completion of training, he moved to West Amhara Meteorological Service center/Bahir Dar and served as meteorological data analysis, forecast and early warning expert. After serving for about four years, he joined the regular post graduate program at Bahir Dar University College of Agriculture and Environmental Science on November 2022 to pursue his study leading to Msc degree in the field of Environment and Climate Change.