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Research Article

Assessing ENACTS and CHIRPS Precipitation Estimates in Jimma Zone, Ethiopia

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Abstract

The availability of satellite and other climate datasets has significantly advanced for hydro-climatic studies. However, these climatic products still face substantial uncertainties. Thus, the main objectives of this paper was to assess the performance of ENACTS and CHIRPS version 2 precipitations from 1991 to 2020 in the daily, monthly, seasonal level, annual and during wet/dry year based on observed ground station data over Jimma Zone, Oromia, Ethiopia. The two products were evaluated by using correlation coefficient (CC), root mean square error (RMSE), mean absolute error (MAE), and percentage bias (PBIAS) against gauge data from ground station. On a daily scale, ENACTS exhibits a correlation coefficient (CC) of 0.43, indicating a strong positive relationship with observed rainfall, while CHIRPS has a lower CC of 0.34, reflecting a weaker correlation. ENACTS shows a root mean square error (RMSE) of 8.2 mm and a mean absolute error (MAE) of 4.5 mm, suggesting high accuracy and relatively low average prediction error. In contrast, CHIRPS has an RMSE of 7.4 mm and an MAE of 4.6 mm, indicating fewer discrepancies but slightly less precision. On a monthly scale, ENACTS demonstrates a robust CC of 0.96, significantly outperforming CHIRPS, which has a CC of 0.87. ENACTS's RMSE is 29.9 mm with an MAE of 23.8 mm, while CHIRPS has a higher RMSE of 59.8 mm and an MAE of 47.3 mm. Additionally, ENACTS outperforms CHIRPS across all seasons—Belg, Kiremt, and Bega—with CCs of 0.75, 0.65, and 0.75, respectively, particularly excelling in replicating observed precipitation patterns during the Bega (dry) and Belg (short rainy) seasons. Overall, ENACTS consistently demonstrates superior correlation and accuracy in rainfall predictions compared to CHIRPS across all time scales and seasonal contexts. Therefore, this findings show that Both ENACTS and CHIRPS are more effective at the monthly time scale compared to the daily level, whereas the ENACTS re-mains the more accurate product across all time scales in the Jimma zone. This findings show that both ENACTS and CHIRPS are more effective at the monthly time scale, with correlation coefficients of 0.96 and 0.87, respectively, compared to the daily level, where the coefficients are 0.43 and 0.34. ENACTS remains the more accurate product across all time scales in the Jimma zone. This finding is crucial for guiding the selection of the most suitable precipitation products for agricultural planning, water resource management, and climate adaptation strategies in the region.

Keywords

Precipitation, ENACTS, CHIRPS, Rainfall, Evaluation

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1. Introduction

A quantitative assessment of precipitation levels and their spatial and temporal distribution is crucial for various scientific and operational purposes. These include enhancing our understanding of the hydrological cycle, evaluating the effects of human activities on hydrology, assessing water resources, planning irrigation, and predicting droughts and floods [20]. Because of the significant spatiotemporal variability, it is difficult to obtain reliable information on the quantity, duration, and intensity of rainfall episodes [5, 9, 19]. This issue is exacerbated by limited spatial coverage and a decreasing number of ground gauge stations in the historical climatological observation network, particularly in developing countries [26]. Unreliable or incomplete datasets cannot accurately capture seasonal or short-term temporal patterns [15]. While the availability of satellite and reanalysis climate datasets has significantly advanced hydro-climatic studies, these climatic products still face substantial uncertainties. Therefore, evaluating these products is essential for their use in specific regions [21].

The application of climate data for research and various uses in Africa has been restricted, mainly because of the limited availability and quality of such data. There are few weather stations, and their numbers are declining [6]. Challenges in accessing the existing climate data arise from national data policies, inadequate financial support, insufficient tools for dissemination and capacity, as well as high costs associated with access [8]. There are different climate data that has been using to solve this problem. One of the initiatives addressing this issue is ENACTS (Enhancing National Climate Services), led by the International Research Institute for Climate and Society (IRI) at Columbia University. This program collaborates with National Meteorological Services (NMS) in Africa and other developing nations [2, 8] And the Climate Hazards Group Infra-Red Precipitation with Stations (CHIRPS) product from the Climate Hazard Group [7].

Evaluation of different satellite based rainfall products is important over complex topography like Jimma zone to select suitable rainfall products. They are a number of studies that have been conducted over different parts of Ethiopia to compare the satellite based rainfall products with ground based gauge station rainfall measurements [3, 4, 9, 28]. Currently, both the ENACTS and CHIRPS data have been using to fill data gap by the different researchers. However, most of previous studies are focused only specific area (river basin) of the country [1, 14, 21, 22]. The results of these studies indicated the skill of satellite based rainfall estimation is affected with variation in altitude and temporal rainfall distributions. Thus, evaluating these satellites based rainfall products with ground based gauge station measurements at different area and time scales before using for different application is important [10]. Therefore, this study focuses on the evaluation of both ENACTS and CHIRPS. These datasets are selected because of they are widely used for different application in Ethiopia [9], but both products have not been well studied in capturing precipitation in the study area. Therefore, evaluating the performance of both climate products is a prerequisite for accurately assessing variability in climate extremes. Thus, the main objectives of this paper was to assess the performance of ENACTS and CHIRPS in precipitation estimates in the daily, monthly, seasonal level, annual and during wet/dry year based observed data over Jimma Zone, Oromia, Ethiopia. The study's finding is pivotal in guiding the selection of optimal precipitation products for agricultural planning, water resource management, and climate adaptation strategies in the region.

2. Material and Methods

2.1. Description of Study Area

Jimma zone is located in Oromia regional state, southwest Ethiopia between 7.2-8.9 N and 35.8-37.6 E The zone is dominated with highland area in the eastern, south and center part, whereas the lowland area is found at tip of south and north western parts of the zone (Figure 1). The climate of the study area is warm temperate rainy climate with heavy rainfall, warm temperatures, and a long wet period or mono modal rainfall type [16]. The mean annual rainfall the study area ranges from 1368.4 to 2042.6 mm (Table 1).

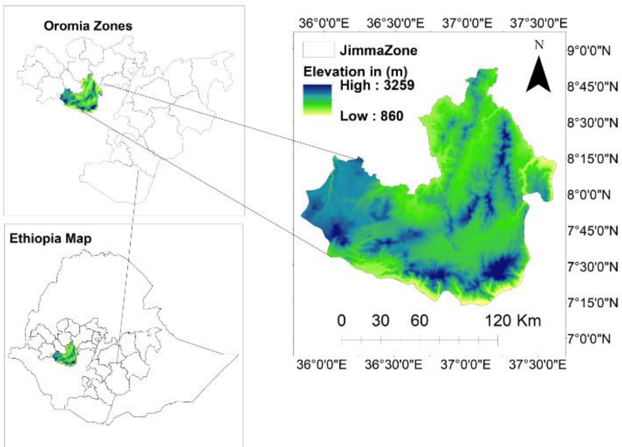


Figure 1. Map of study area.

2.2. Data Types and Sources

2.2.1. Station Data

Five stations is used for evaluation of enhancing national climate service (ENACTS) and Climate Hazards group Infrared Precipitation with Stations (CHIRPS). These stations are selected based on their data quality, length of record and minimum percent of missing data.

For this study, daily rainfall gauge (stations) and gridded data of Chira, Gatira, Jimma, Limu genet and Sokoru stations from 1991-2020 were taken from the Ethiopian Meteorology Institute (EMI).

Table 1. Description of ground stations used for this study.

Station name	Location			Data availability		
	latitude	Longitude	Elevation	Data length (years)	Data availability in %	Mean annual rainfall in mm
Chira	7.7	36.2	2105	30	95.6	1609.4
Gatira	8.0	36.2	2361	30	92.4	1945.0
Jimma	7.7	36.8	1710	30	99.9	1805.5
Limugenet	8.1	37.0	1767	30	93.5	2042.6
Sokoru	7.9	37.4	1937	30	94.1	1368.4

2.2.2. Enhancing National Climate Cervices (ENACTS) Precipitation Data

Over 30 years of temporally and geographically comprehensive rainfall and temperature time series data for each 4 km grid throughout Ethiopia are the results of the ENACTS the procedure [7]. Through the use of proxies like satellite rainfall estimates and climate model reanalysis products, the ENACTS initiative of the International research institute (IRI), Columbia University, aims to enhance data availability, quality, and accessibility by combining station quality-controlled data from the entire national observation network [6].

2.2.3. Chirps Data

The Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset enhances previous methods by utilizing advanced interpolation techniques and providing high-resolution, long-term precipitation estimates derived from infrared Cold Cloud Duration (CCD) observations. The algorithm: i) relies on a 0.05° climatology that integrates satellite data to represent areas with sparse gauge coverage, ii) includes daily, pentadal, and monthly CCD-based precipitation estimates from 1981 to the present at a 0.05° resolution, iii) combines station data to create a preliminary product with approximately 2 days of latency and a final product with an average latency of about 3 weeks, and iv) employs an innovative blending method that uses the spatial correlation structure of CCD estimates to determine interpolation weights [7, 12]. For this study, the latest or version 2 of the CHIRPS precipitation data from 1991 to 2020 was used and the data is downloaded at study area level from https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/p05/.

Table 2. Summary of precipitation data used in this study.

Datasets	Spatial coverage	Spatial resolution	Time resolution	Data sources	Description
Gauge data	Jimma zone			gauge	
ENACTS	Selected developing countries	0.0375°	daily	gauge and satellite	The estimating process combines satellite rainfall estimates, quality-controlled station data, and other proxies like elevation data [7].
CHIRPS	Global	0.05°	daily, pentad, monthly	gauge and satellite	Infrared precipitation (CHIRP) data from the Climate Hazard Group is combined with in-situ gauge readings to create the data [12].

2.3. Data Processing

The precipitation data from the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) dataset was processed to correspond with the specific locations of ground gauge stations. This was achieved by employing a bilinear interpolation method, which estimates precipitation values at the gauge locations by considering the nearest surrounding grid cells. This technique effectively smooths the data, allowing for a more accurate representation of precipitation at the point of interest. Following this extraction, the CHIRPS precipitation data was regridded to align with the Enacts (Enhanced National Climate Services) resolution of 0.0375°. This regridding process ensures that the CHIRPS data is compatible with the finer resolution of the Enacts dataset, facilitating a more precise comparison and analysis of precipitation estimates. By standardizing the data resolution, the integration of CHIRPS data with ground gauge measurements becomes more effective, enhancing the reliability of assessments aimed at evaluating the accuracy of satellite-derived precipitation estimates against actual ground observations.

2.3.1. Data Quality Control

Apart from the obstacles associated with the accessibility and availability of climate data, another significant problem is ensuring the quality of the data that is readily available. Both missing observations and poor accuracy or precision are indicators of low data quality. Measurement mistakes from instruments, people, and other sources can occur in station measurements. The other, more frequent source of inaccuracy arises when data is entered into computers [6]. Observed and downscaled rainfall data were plotted against time in days of the year format and subjected to visual examination for the presence of discontinuities. Typing mistakes and special codes were eliminated, and each case was handled individually, utilizing data from the day before and after the occurrence in addition to references to neighbouring stations. Stations with more than 10% were excluded.

2.3.2. Outliers Detection

Using the Tukey fence, outliers were filtered. For non-normally distributed data, such as rainfall, this method is advised. The range of data is the Tukey fence.

$$[Q_1\text{-}1.5{*}IQR,\ Q_3\text{+}1.5{*}IQR] \quad (1)$$

Q_1 and Q_3 are the lower and upper quartile points, respectively, with 25% of the data falling between them. The interquartile range (IQR) is defined as follows: 1.5 represents the standard deviation from the mean, and Q_1 and Q_3 are the corresponding points. Outlier values are those that fall outside of the Tukey fence [18].

2.4. Methodology

Standardize Rainfall Anomalies (SRA)

Standard rainfall anomaly was used to examine the nature of rainfall over the period of observation or to determine wet and dryness year in the record.

Standardize Rainfall Anomalies (SRA) is calculated as:

$$SRA = \frac{(X-\mu)}{\delta} \quad (2)$$

Where, x is the seasonal total rainfall of a particular year; is the standard deviation of observation & is the mean of observation. The drought severity classes are classified as extreme drought (SRA < -1.65), severe drought (-1.28 > SRA > -1.65), moderate drought (-0.84 < SRA < 1.28), and no drought (SRA > -0.84) [27]. The method was also used by [25] to identify wet and dry years.

2.5. Performance Evaluation Metrics

Pearson Correlation (r) is a statistical measure that shows how much two or more factors fluctuate at the same time. It determines the degree of linear dependence between real values and perspectives. In most cases, the correlation ranges from -1 to +1, with zero denoting no correlation, +1 denoting a high positive correlation, and -1 denoting a high negative correlation [23].

It is calculated by the following equation:

$$r = \frac{\sum_{i=1}^{n}(mi-\bar{m})(Oi-\bar{o}_i)}{\sqrt{\sum_{i=1}^{n}(mi-\bar{m})^2 . \sum_{i=1}^{n}(Oi-\bar{o}_i)^2}} \quad (3)$$

Where $\bar{m}$ is the average model predicted, $\bar{o}_i$ is represent the averaged of observed forecast, m_i is the predicted value for the i^{th} observation or actual value, o_i is the observed value for the i^{th} observation in the dataset.

Root Mean Square Error (RMSE) is used to measure the average magnitude forecast error, where n is number of observation, (i=1, 2, 3...n), m and o are models, observed value consecutively. The RMSE Ranges from 0 to positive infinity (0 to ∞) and a perfect fit, where the model perfectly predicts the actual values.

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(o_i - m_i)^2}{n}} \quad (4)$$

Mean Absolute Error (MAE) is used to measure the difference between actual
values and forecasts. The MAE Ranges from 0 to positive infinity (0 to ∞) and a perfect fit, where the model perfectly predicts the actual values.

The *MAE* is calculated using the equation:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |o_i - m_i| \quad (5)$$

Bias Percentage Calculation (PBIAS). By comparing the predicted values to the observed values, the PBIAS assesses whether there is a tendency in the values predicted by the model (i.e., whether they are higher or lower). A positive PBIAS implies that the predicted variable is overestimated by the model, whereas a negative PBIAS suggests that the anticipated variable is underestimated. A PBIAS of zero is the ideal value.

It is calculated by the flowing equation:

$$\text{PBIAS}=\sum_{i=1}^{n}\frac{(O_i-m_i)}{\sum_{i=1}^{n}(O_i)}x100 \quad (6)$$

3. Result and Discussion

3.1. Standardized Rainfall Anomaly (SRA)

The standardized spatial annual rainfall anomaly of the Jimma zone was calculated using ground gauge to select wet and dry years in the zone during study periods. Based on the result shown in Figure 2, the standardized anomaly of the spatial annual average rainfall during the study the period was 46.7 % above long term average rainfall, whereas 53.3 % below the long-term average value. On the other hand, 2014, 1999 year was very wet and very dry respectively.

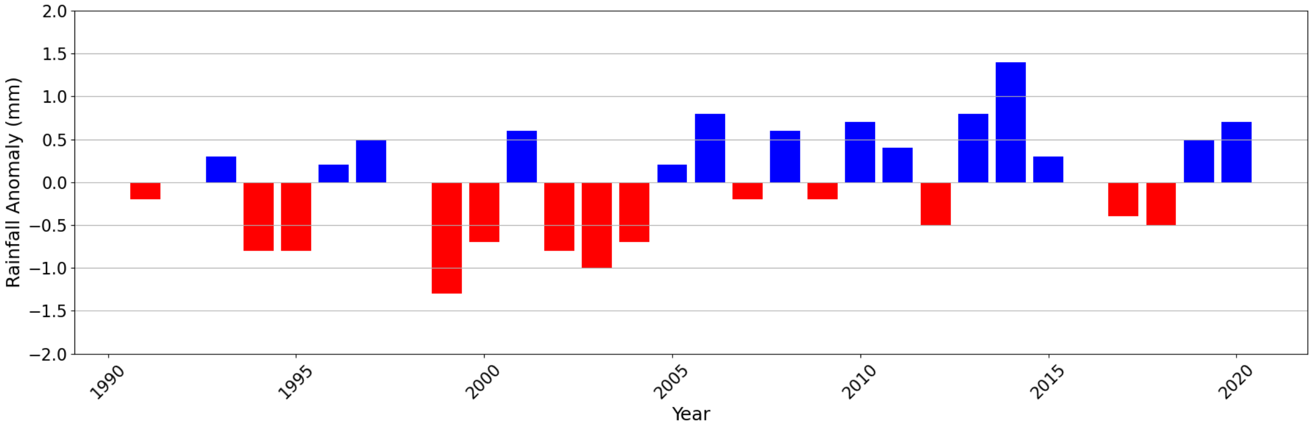


Figure 2. Standardized annual rainfall anomaly of gauge station 1991-2020.

3.2. Performance of ENACTS and CHIRPS

3.2.1. Daily Performance of ENACT and CHIRPS

The daily time scale spatial average comparison of ENACTS and CHIRPS with the gauge stations from 1991 to 2020 was analyzed and indicated in Table 1 below. Based on the analysis, the comparison of precipitation products from ENACTS and CHIRPS against observed gauge station data shows that ENACTS is the superior choice for the Jimma zone. The correlation coefficient (CC) for ENACTS is 0.43, indicating a strong positive relationship with the observed rainfall data, while CHIRPS has a lower CC of 0.34, suggesting a weaker correlation. The Root Mean Square Error (RMSE) for ENACTS stands at 8.2 mm, reflecting that its predictions are, on average, only 8.2 away from the observed values, which indicates a high level of accuracy. In contrast, CHIRPS has a lower RMSE of 7.4 mm, indicating fewer discrepancies from actual rainfall amounts. The Mean Absolute Error (MAE) for ENACTS is 4.5 mm, suggesting that its average prediction error is relatively low, whereas CHIRPS exhibits an MAE of 4.6 mm, indicating slightly less precise estimations. Lastly, the Percent Bias (PBIAS) for ENACTS is -9.3%, reflecting a slight underestimation of rainfall that is minimal and acceptable, while CHIRPS has a PBIAS of 0.73%, indicating a slight overestimation. Similar to this finding, [9] show that the CHIRPS product has a low correlation over both the northwest and southeast parts of Ethiopia.

In conclusion, while both ENACTS and CHIRPS provide valuable precipitation estimates, the analysis clearly demonstrates that ENACTS outperforms CHIRPS in terms of correlation with observed data and overall predictive accuracy. The lower CC and higher RMSE of CHIRPS suggest that it may not be as reliable for precipitation estimation in this region. Therefore, for applications requiring accurate rainfall data in the Jimma zone, ENACTS is the recommended choice.

Table 3. Comparison ENACTS and CHIRPS against observed gauge station at daily time scale.

Product type	CC	RMSE	MAE	Pbias
CHIRPS	0.34	7.4	4.6	0.73
ENACTS	0.43	8.2	4.5	-9.3

3.2.2. Monthly ENACTS and CHIRPS Performance

The monthly time scale spatial average comparison of ENACTS and CHIRPS precipitation products against gauge station data from 1991 to 2020 is presented in Table 4 below. The analysis reveals that ENACTS is the superior choice for the Jimma zone. The correlation coefficient (CC) for ENACTS is 0.96, indicating a robust positive relationship with observed rainfall data. In contrast, CHIRPS exhibits a lower CC of 0.87, suggesting a comparatively weaker correlation. The Root Mean Square Error (RMSE) for ENACTS is 29.9 mm, indicating that its predictions deviate, on average, only 29.9 mm from the observed values, which reflects a high level of accuracy. Conversely, CHIRPS has a significantly higher RMSE of 59.8 mm, indicating greater discrepancies from actual rainfall amounts. The Mean Absolute Error (MAE) for ENACTS is 23.8 mm, suggesting that its average prediction error is relatively low. In contrast, CHIRPS demonstrates an MAE of 47.3 mm, which indicates less precise estimations. Lastly, the Percent Bias (PBIAS) for ENACTS is -9.3%, reflecting a minimal and acceptable slight underestimation of rainfall, while CHIRPS shows a PBIAS of -26.7%, indicating a more substantial underestimation. In conclusion, the analysis clearly demonstrates that ENACTS outperforms CHIRPS in terms of correlation with observed data and overall predictive accuracy. The higher CC and lower RMSE, MAE, and PBIAS for ENACTS indicate its reliability for precipitation estimation in the Jimma zone. Therefore, for applications requiring precise rainfall data, ENACTS is strongly recommended over CHIRPS. [1] also found that during the monthly time scale, both products show the highest correlation coefficient, but ENACTS is stronger than CHIRPS and they indicate that this improvement of correlation during the monthly time scale than daily time was based on the cancellation of positive and negative errors on a daily scale following the aggregation to a monthly scale.

Table 4. *Comparison ENACTS and CHIRPS against observed gauge station at monthly time scale.*

Product type	CC	RMSE	MAE	Pbias
CHIRPS	0.87	59.8	47.3	-26.7
ENACTS	0.96	29.9	23.8	-9.3

As shown Table 5, the analysis of long-term average statistics for rainfall estimation from 1991 to 2020 reveals notable differences in performance between the ENACTS and CHIRPS products for each month. For ENACTS, the correlation coefficient with ground gauge data is lowest in January at 0.51, indicating a moderate correlation during this month, which suggests that ENACTS captures the variability in rainfall reasonably well. Conversely, ENACTS achieves its highest correlation coefficient of 0.78 in November, indicating a strong relationship with observed data, suggesting that the model effectively accounts for the climatic factors influencing rainfall during this month. In contrast, CHIRPS shows a significantly lower performance. The correlation coefficient in July is only 0.11, indicating a very weak relationship with ground gauge data. This suggests that CHIRPS fails to accurately capture rainfall patterns during the mid-year, possibly due to limitations in the satellite data or environmental factors that are not well-represented in this product. The highest correlation coefficient for CHIRPS is 0.38 in October, which, while better than July, still indicates a weak correlation overall.

These findings highlight that ENACTS consistently outperforms CHIRPS across the months analyzed. The stronger correlations observed in ENACTS may be attributed to its methodology, which integrates ground-based observations with satellite data, allowing for a more nuanced representation of local climatic conditions. This could be particularly beneficial in months like November, where precipitation patterns may be influenced by specific weather systems that ENACTS can better capture. In contrast, CHIRPS, while useful in some contexts, appears less effective in accurately modeling rainfall in this region, especially during critical months such as July.

On the hands, analysis of the RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) values for the ENACTS product provides important insights into its performance during specific months. The RMSE values range from 10.5 mm in August to 24.0 mm in December, indicating that the product's accuracy varies significantly across these months. The higher RMSE in December suggests that ENACTS struggles more to predict rainfall accurately during this time, with average prediction errors reaching 24.0 mm, which could have implications for water resource management and agricultural planning, especially during crucial rainy seasons. In contrast, the lower RMSE of 10.5 mm in August indicates that ENACTS performs relatively better during this month, capturing rainfall patterns more effectively. This suggests that the product may be more adept at handling the climatic conditions and precipitation patterns typical of August, perhaps due to more consistent weather patterns or better representation of local conditions. The MAE values, ranging from 5.4 mm in February to 17.5 mm in December, further illustrate this variability in performance. The lower MAE in February indicates that, on average, the model's predictions deviate by only 5.4 mm from observed values, reflecting a higher level of precision. In contrast, the higher MAE of 17.5 mm in December reveals a considerable average error during this month, suggesting that users should exercise caution when relying on ENACTS for rainfall predictions in December. The analysis of RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) for the CHIRPS product also reveals significant variability in performance across different months. The RMSE for CHIRPS ranges from 17.6 mm in February to 56.8 mm in July, indicating a substantial increase in prediction error during the latter month. This high RMSE in July suggests that CHIRPS struggles significantly to accurately estimate rainfall during this period, which could have serious implications for agricultural planning and water resource management, especially in regions dependent on reliable rainfall data. Furthermore, the MAE values for CHIRPS range from 9.0 mm in January to 17.5 mm in July. The MAE in July is notably high, indicating that the average prediction error is considerable during this critical month. In comparison, the lower MAE in January suggests that CHIRPS performs reasonably well early in the year, but the performance deteriorates significantly during the summer months. When comparing CHIRPS to the ENACTS product, it becomes evident that ENACTS consistently demonstrates better accuracy and the ENACT emerges as the better product for rainfall estimation in this analysis, as it exhibits lower RMSE and MAE values across various months, indicating higher accuracy and reliability. The consistent performance of ENACTS, particularly in capturing rainfall patterns during critical periods, underscores its suitability for applications in agricultural planning and water resource management compared to CHIRPS.

Table 5. Comparison of long-term spatial average of ENACTS and CHIRPS against observed gauge station at each monthly level.

Product name	Month	CC	RMSE	MAE
CHIRPS	January	0.17	18.3	9.0
ENACTS	January	0.51	10.8	5.8
CHIRPS	February	0.30	17.6	9.2
ENACTS	February	0.61	10.7	5.4
CHIRPS	March	0.33	29.9	17.8
ENACTS	March	0.67	15.0	9.3
CHIRPS	April	0.27	35.2	23.4
ENACT	April	0.76	16.7	11.3
CHIRPS	May	0.29	39.4	28.6
ENACTS	May	0.70	21.5	15.2
CHIRPS	June	0.12	46.4	35.1
ENACTS	June	0.68	21.8	15.7
CHIRPS	July	0.11	56.8	40.9
ENACTS	July	0.64	23.1	16.9
CHIRPS	August	0.14	54.0	40.3
ENACTS	August	0.57	24.0	17.5
CHIRPS	September	0.20	44.9	34.5
ENACTS	September	0.61	22.6	16.5
CHIRPS	October	0.38	32.8	20.9
ENACTS	October	0.74	17.8	11.7
CHIRPS	November	0.34	19.4	10.3
ENACTS	November	0.78	12.1	6.9
CHIRPS	December	0.17	15.2	7.4
ENACTS	December	0.64	10.5	5.6

3.2.3. Seasonal time Scale Performance of ENACTS and CHIRPS

The Annual rainfall characteristics of Ethiopia are classified into three rainy seasons namely Belg (February- May), Kiremt (June-September) and Bega (October-January) as documented by [11, 13, 24]. Based this, The performance of ENACTS and CHIRPS in estimating seasonal precipitation over the Jimma zone has been thoroughly evaluated and summarized using a Taylor diagram, which visually represents the correlation, standard deviation, and centered root-mean-square difference of the two precipitation products. The analysis reveals that ENACTS outperforms CHIRPS across all seasons Belg, Kiremt, and Bega with correlation coefficients of 0.75, 0.65, and 0.75, respectively. This indicates that ENACTS has a superior ability to replicate observed precipitation patterns, particularly during the Bega (dry) and Belg (short rainy) seasons, compared to the Kiremt (long rainy) season. Similar to this finding, [1] found that both the ENACTS and CHIRPS perfumed well during short rainy season in the Upper Blue Nile basin. The standard deviation values of 20.91, 21.89, and 15.62 for the Belg, Kiremt, and Bega seasons further underscore the variability captured by ENACTS. In contrast, CHIRPS demonstrates lower correlation coefficients of 0.34 for both the Belg and Bega seasons and a notably weak correlation of 0.14 for Kiremt, suggesting its inadequacy in accurately estimating precipitation during this critical rainy season. Overall, the findings highlight that while ENACTS provides a more reliable representation of seasonal precipitation in Jimma Zone, CHIRPS falls short, particularly in the long rainy season, indicating a need for improved methodologies or calibration for this product to enhance its predictive capabilities. This finding near similar with [17] findin^g that states the CHIRPS product has no significant correlation in sub-humid area during winter season and it is well in estimating small rainfall season in the moist highlands.

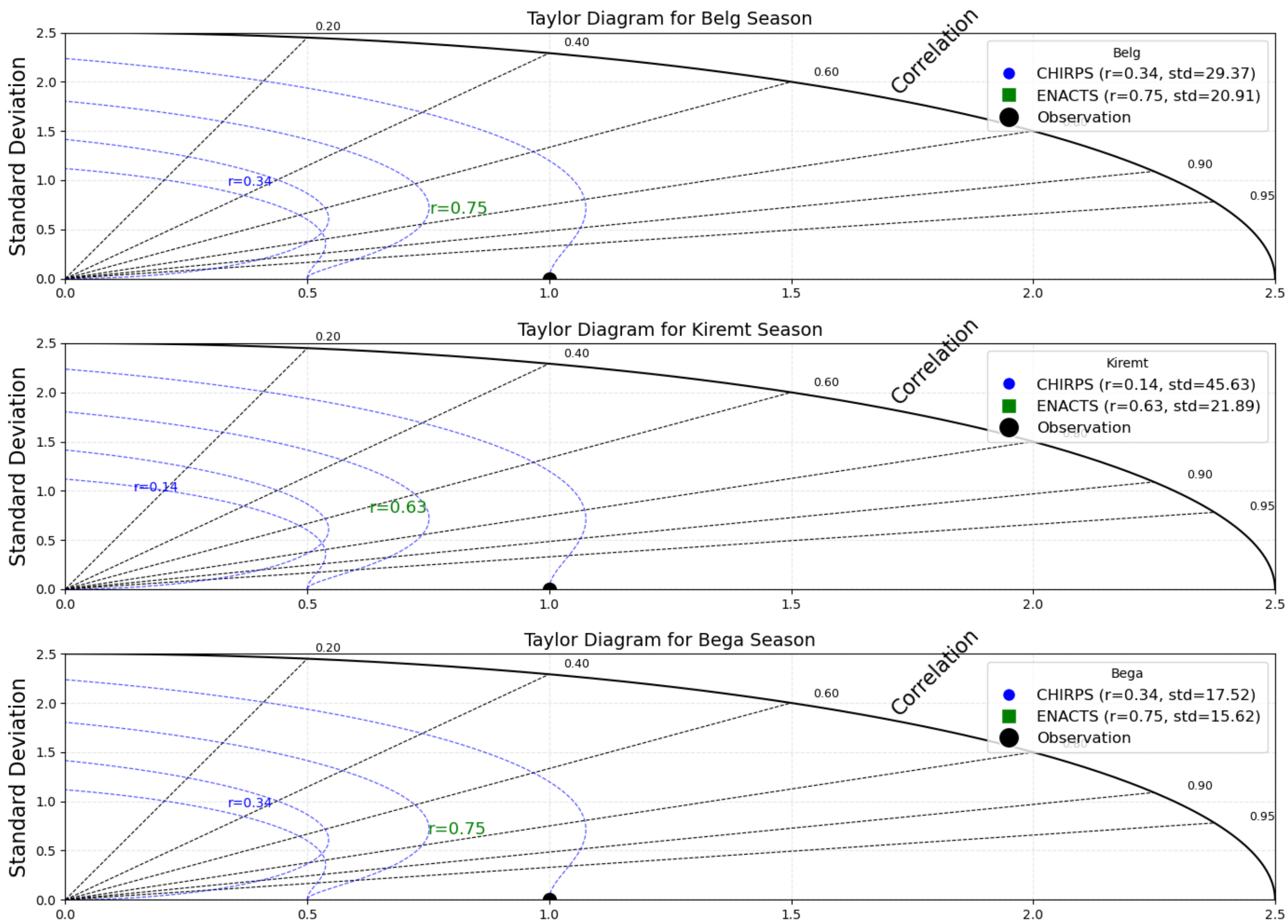
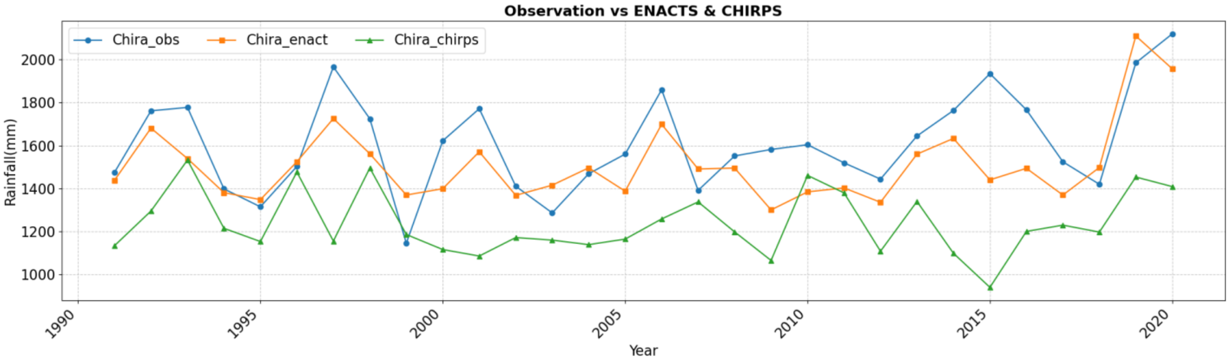


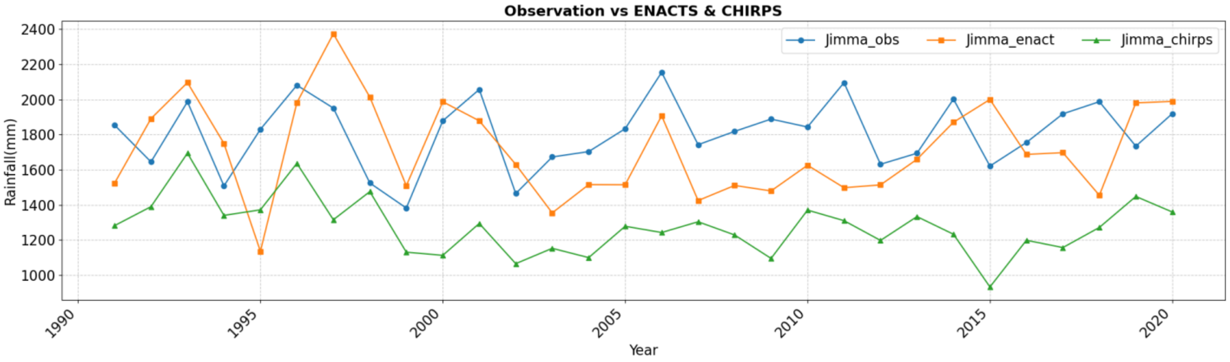
Figure 3. *Comparison ENACTS and CHIRPS against observed gauge station at seasonal time scale.*

3.2.4. Annual Performance of ENACTS and CHIRPS at Ground Station Point

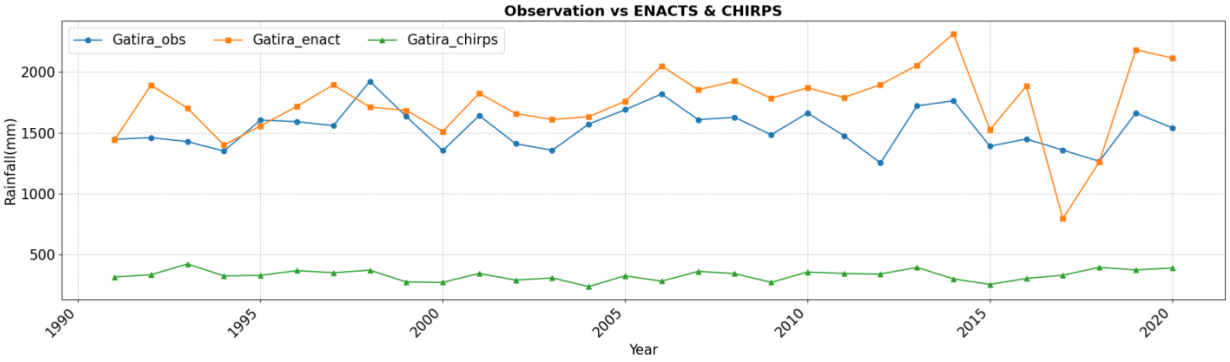
The annual time series precipitation analysis comparing ENACTS (Enhancing National Climate Services) and CHIRPS (Climate Hazards Group InfraRed Precipitation version 2) products with ground gauge station measurements reveals significant insights into their performance across various locations, as illustrated in Figure 4. The results indicate that ENACTS consistently outperforms CHIRPS version 2 at all evaluated stations, including Chira (a), Gatira (b), Jimma (c), Limugenet (d), and Sekoru (e), suggesting a higher accuracy in representing precipitation in these areas. Notably, both datasets exhibited similar performance at Sekoru (e) and Chira (a), indicating that their discrepancies may be minimized under certain climatic conditions. Conversely, CHIRPS version 2 displayed a marked underestimation of annual precipitation at Gatira, which can be attributed to the station's higher elevation relative to others. This highlights the critical influence of orographic effects on precipitation dynamics, where elevated regions often experience enhanced rainfall due to orographic lifting, which satellite-derived estimates may inadequately capture. The findings underscore the reliability of ENACTS as a superior precipitation data source while emphasizing the necessity of integrating ground station measurements, particularly in areas with significant topographical variation, to improve precipitation modelling accuracy and inform effective climate and water resource management strategies.


Observation vs ENACTS & CHIRPS
Chira_obs
Chira_enact
Chira_chirps
Rainfall(mm)
Year

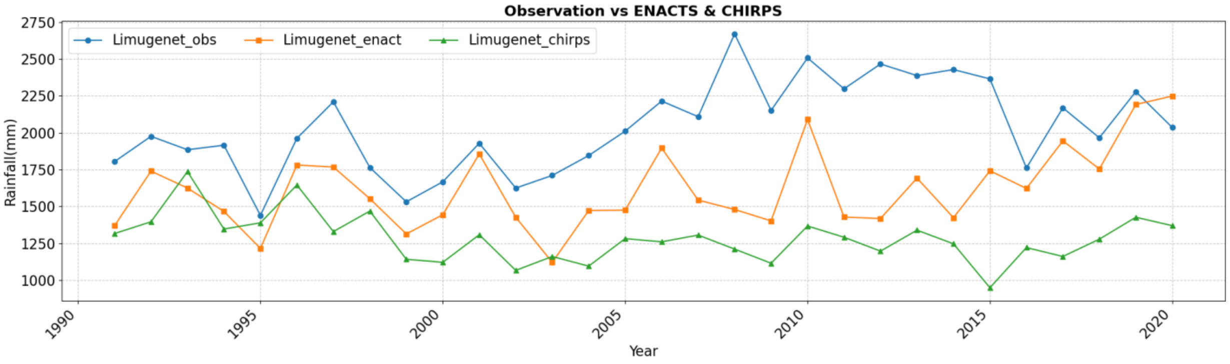
a)


Observation vs ENACTS & CHIRPS
Jimma_obs
Jimma_enact
Jimma_chirps
Rainfall(mm)
Year

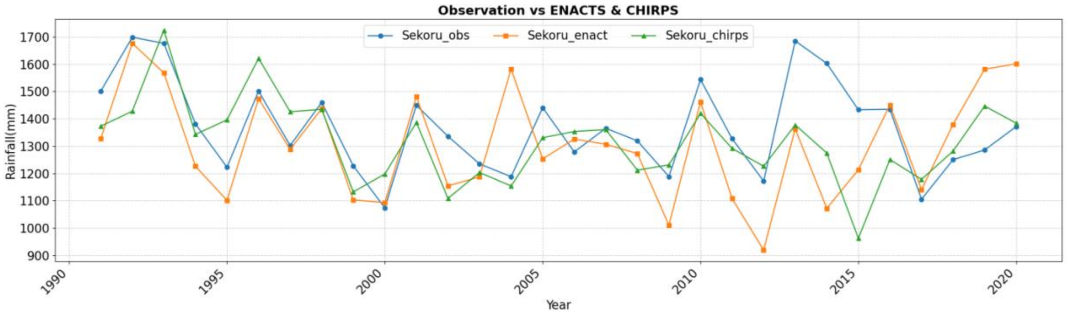
b)


Observation vs ENACTS & CHIRPS
Gatira_obs
Gatira_enact
Gatira_chirps
Rainfall(mm)
Year

c)


Observation vs ENACTS & CHIRPS
Limugenet_obs
Limugenet_enact
Limugenet_chirps
Rainfall(mm)
Year

d)



e)

Figure 4. Time series annual time scale comparison with the ground gauge stations level Chira (a), Gatira (b), Jimma (c), Limugenet (c) and Sekoru (e).

Note: The gauge or observed station (obs) is indicated in blue, the ENACTS in dark red, and the CHIRPS in green. Additionally, the dots on the lines represent data points from the years 1991 to 2020.

3.2.5. Performance of ENACTS and CHIRPS During Wet Year

The standardized rainfall anomaly analysis of ground station precipitation data from 1991 to 2020, as illustrated in Figure 2, identifies the years 2014 and 1999 as the wettest and driest years, respectively. This classification serves to evaluate the performance of precipitation estimation products in the study area. In 2014, ENACTS exhibited a consistently higher correlation with ground station data across all months compared to CHIRPS. Notably, the months of July, October, and May showed the strongest correlations, with values of 0.81, 0.79, and 0.77, respectively, while February and March had the weakest correlations at 0.27 and 0.28. Conversely, CHIRPS performed relatively better in April and March, achieving correlation coefficients of 0.38 and 0.37, but struggled significantly in December and January, with correlations of 0.08 and 0.04 (Figure 4). On the other hand, Figure 5 shows that, in the very dry year of 1999, ENACTS maintained high correlations in July, October, and September (0.71, 0.70, and 0.62, respectively), while its lowest correlations occurred in February and November (both at 0.27). CHIRPS displayed similar low values during these months but peaked in June with a correlation of 0.44, and recorded notably low correlations in September, May, and August (approximately 0.05 to 0.06). Overall, the findings indicate that the ENACTS product consistently outperforms CHIRPS in estimating precipitation during both very wet and very dry years. ENACTS is particularly effective in capturing observed precipitation during wet conditions, while CHIRPS demonstrates better performance during dry years, highlighting the need for careful selection of precipitation products based on specific climatic conditions.

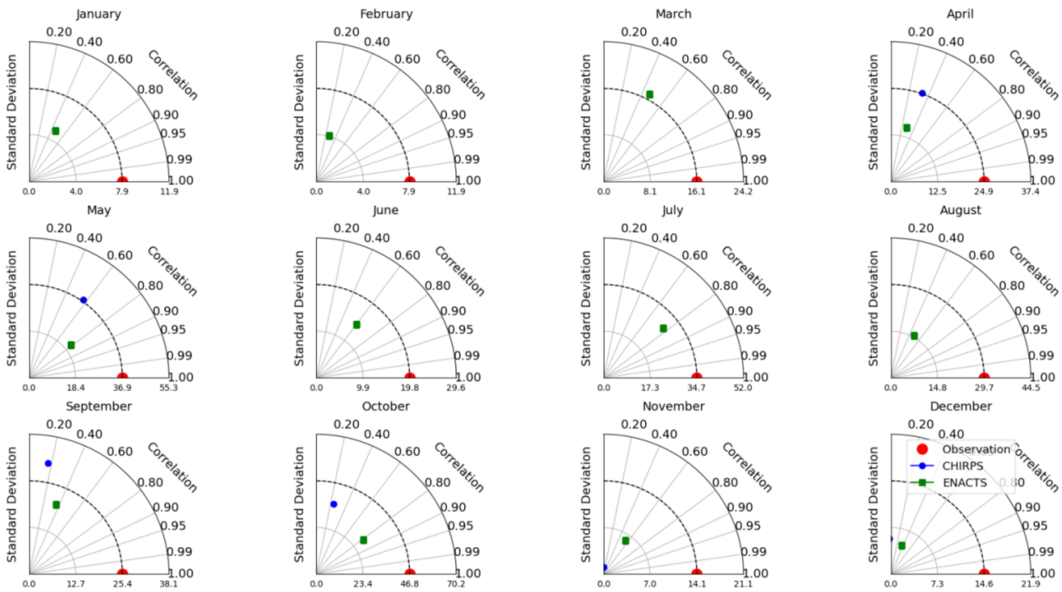


Figure 5. Performance of CHIRPS and ENACTS during selected wet year (2014).

3.2.6. Performance of ENACTS and CHIRPS During Dry Year

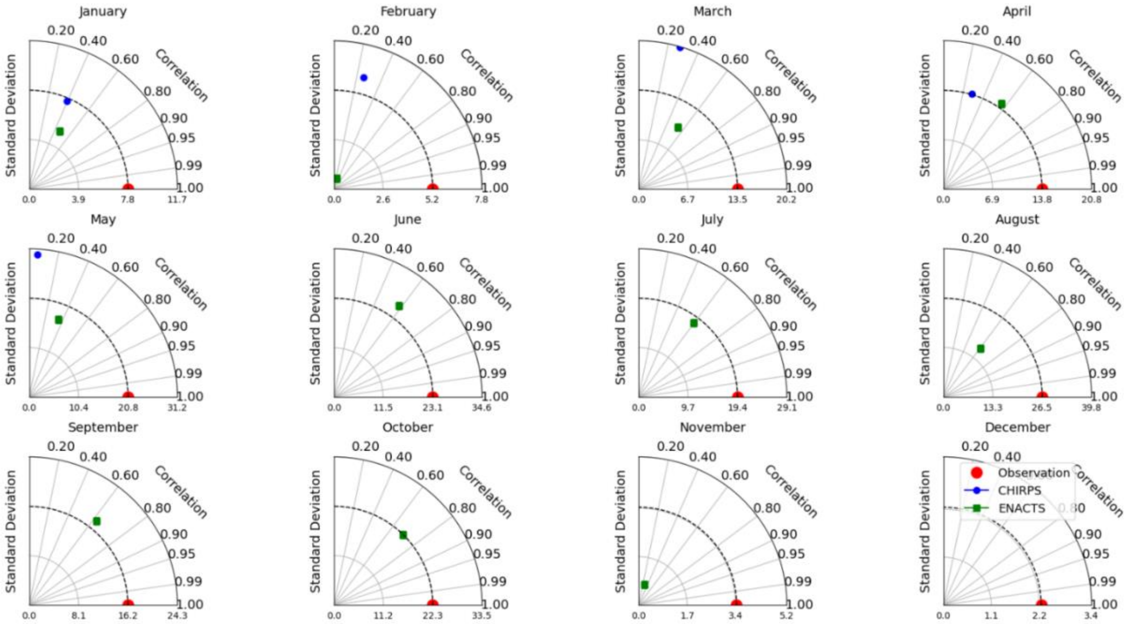


Figure 6. *Performance of CHIRPS and ENACTS during selected wet year (1999).*

4. Conclusion

In this study, the Enhancing National Climate Services (ENACTS) and Climate Hazards Group Infrared Precipitation (CHIRPS) version 2 were statistically evaluated using correlation coefficient (CC), root mean square error (RMSE), mean absolute error (MAE), and percentage bias (PBIAS) against gauge data from ground stations in Jimma zone, Ethiopia. The evaluation encompassed daily, monthly, seasonal, annual and selected very wet and dry years.

At the daily level, ENACTS consistently outperformed CHIRPS in terms of correlation with observed data and predictive accuracy. The higher RMSE for CHIRPS indicates its reduced reliability for precipitation estimation in this region. On a monthly scale, ENACTS again demonstrated superior performance, with a higher CC and lower RMSE, MAE, and PBIAS, affirming its reliability for precipitation estimation in the southwestern zone. The findings for very wet and dry years further emphasize ENACTS's capacity to provide a more reliable representation of seasonal precipitation, particularly during the long rainy season, where CHIRPS showed significant shortcomings.

The analysis of correlation coefficients, RMSE, and MAE reveals that ENACTS outperforms CHIRPS in capturing rainfall patterns across different months. ENACTS shows moderate correlation in January and a strong correlation in November, indicating its effectiveness in accounting for climatic factors influencing rainfall.

The findings highlight that while ENACTS provides a more reliable representation of seasonal precipitation in Jimma Zone, CHIRPS falls short, particularly in the long rainy season, indicating a need for improved methodologies or calibration for this product to enhance its predictive capabilities. While both the ENACTS and CHIRPS are more effective at the monthly scale than at the daily level, ENACTS remains the more accurate product across all time scales in the Jimma zone.

Overall, the results underscore the importance of selecting appropriate products for rainfall estimation, as the ability to accurately represent temporal variability can have significant implications for water resource management, agricultural planning, and understanding climate patterns in the Jimma zone.

Abbreviations

CC	The Correlation Coefficient
CCD	Cold Cloud Duration
CHIRPS	Climate Hazards Group Infrared Precipitation with Stations
EMI	Ethiopian Meteorology Institute
ENACTS	Enhancing National Climate Services
IQR	Interquartile Range
IRI	International Research Institute
MAE	Mean Absolute Error
Obs	Observed Station
PBIAS	Bias Percentage Calculation
r	Pearson Correlation
RMSE	Root Mean Square Error

SRA Standardize Rainfall Anomalies

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https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/p05/ at no costs.

Author Contributions

Endeshaw Shewangizaw Gebremedhin is the sole author. The author read and approved the final manuscript.

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Data Availability Statement

The relevant data that support the findings of this study are available from the corresponding author on the online repository link.

Conflicts of Interest

The author declares no conflicts of interest.

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