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Evaluating Precipitation Estimates from Rfe2.0, Chrips Data in Semi-Arid Regions: Case Study Tekeze-Atbra Sub-Basin in Sudan

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Abstract
High quality precipitation data are critical to water resource management in particular for arid regions where rainfall controls important hydrological process and water resources. This research assesses the reliability of two satellite-based precipitation products, Rainfall Estimate- RFE 2.0 and Climate Hazards Group Infrared Precipitation with Station data - CHIRPS in Tekeze-Atbara sub-basin, Sudan; which is a semi-arid region with limited rain gauge measurements. We then evaluate the effectiveness of the two data sources by comparing their measured monthly accumulation, rainfall rates, and seasonal variations with observational data from local rain gauges between January 2015 and December 2020. Qualitative assessments of accuracy are determined using Statistical measures including Root Mean Square Error (RMSE), Mean Bias Error (MBE), Correlation coefficients (R^2). The study shows that, both RFE 2.0, and CHIRPS have high accuracy on a monthly scale with RFE 2.0 slightly outperforming CHIRPS in terms of accuracy in estimating extreme rainfall events on a seasonal scale. This evaluation provides insights on best-suited uses of each dataset for identifying patterns of precipitation within the Tekeze-Atbara sub-basin and offers implications for water resource management, flood hazard mapping, and agricultural planning in data-deficit semi-arid areas.

Keywords
Precipitation, RFE2.0, Remote sensing, CHRIPS

1. Introduction
Rainfall is one of the most crucial components of freshwater resources, making its accurate measurement essential. Precisely determining the location and temporal distribution of rainfall is key for the effective management of water resources, including rivers, lakes, irrigation systems, dam reservoirs, and weather forecasting. Additionally, rainfall estimation plays a critical role in scientific research, helping to assess the hydrological cycle, global water balance, and meteorological modeling (Babita Pal, Sailesh Samanta, 1996).

In regions with a low density and uneven distribution of meteorological stations, accessing reliable rainfall data can be challenging, and the available data often contain irregularities. These limitations hinder the accurate recording of environmental variables and restrict the ability to characterize spatial and temporal patterns, which are crucial for water management strategic plans and research.

Currently, numerous precipitation remote sensing products are available. Examples include the RFE2.0 (Rainfall Estimate) and Climate Hazards Group Infrared Precipitation with Station data (CHIRPS). However, these data are prone to errors and require evaluation and validation before they can be reliably used.

The objective of this study is to evaluate the precipitation estimates from both (RFE2.0), CHIRPS products compared to observed data from meteorological stations in the Atbra sub-basin, Sudan. The goal is to assess the applicability of these estimates in areas with low station density.

2. Study Area and Data

2.1 Study Area

The Atbara River is the last tributary of the Nile, joining the main river 322 km north of Khartoum, the capital of Sudan. It originates in Ethiopia at an elevation of 1,830 to 3,000 meters, approximately 50 km north of Lake Tana.

The Atbara River, like the Blue Nile, descends rapidly and transforms into a large, muddy river during the flood season, while shrinking to a series of pools during the dry season. Its average annual discharge is estimated at 12 billion cubic meters (BCM), contributing approximately 12% of the Nile's inflow at Aswan. The Tekeze Atbra sub-basin area is 23.51thosand square kilometer. Fig. 1 shows the boundaries of Tekeze Atbra sub-basin and location of observation stations. (Mr. Philip J. Akol, 2016).

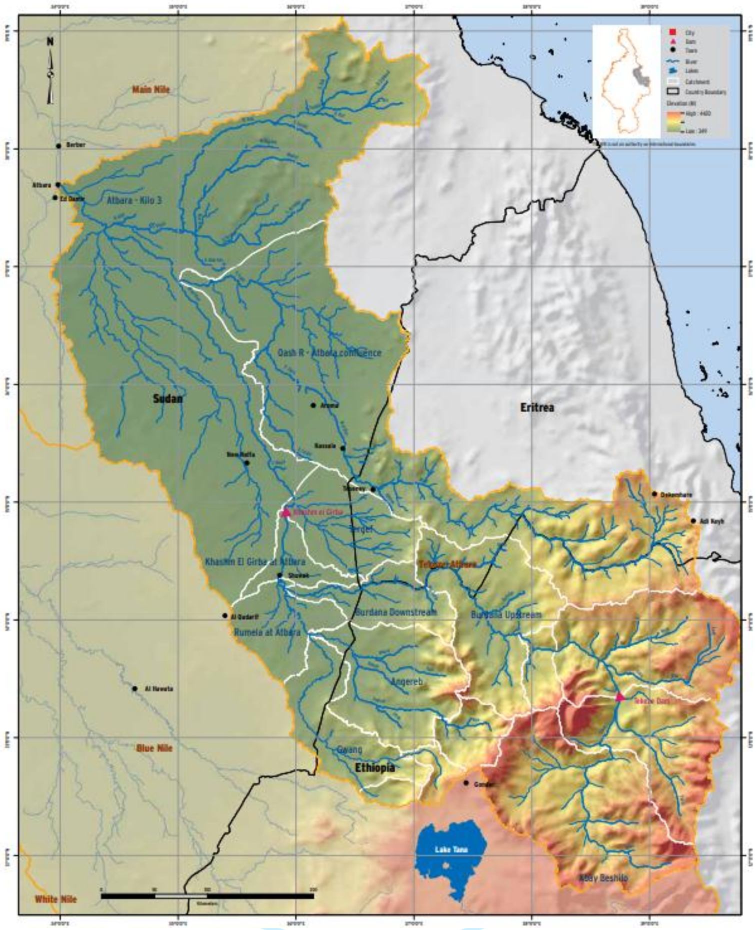


Fig. 2 Location of study area (Tekeze Atbara sub-basin), Source: Nile Basin Water Resources Atlas 2016

2.2 Data Description

2.2.1 Rain-Fall Estimate 2.0 (RFE2.0)

RFE2.0 Data Description

The input data for operational rainfall estimates RFE 2.0 come from four primary sources shown in Table 1.

Table 2 (1) RFE2.0 data sources and used techniques and coverage extent

Data Source	Techniques Used	Coverage Extent
GTS Rain Gauge Data (up to 1000 stations	Daily station data collection and merging with satellite estimates	Africa: 40°S to 40°N, 20°W to 55°E
AM SU Microwave Satellite Estimates	Precipitation estimates gathered up to 4 times per day, combined linearly with other sources	
SSM/I Satellite Rainfall Estimates	Precipitation estimates gathered up to 4 times per day, combined linearly with other sources	
GPI Cloud-top IR Temperature Estimates	Half-hourly IR-based precipitation estimates, merged with rain gauge data	

The three satellite-based estimate are weighted linearly with scaling coefficients determined prior to fusion with station data to provide the end product of rainfall estimates for Africa. The last output is daily binary and graphical files produced at approximately 3 pm Eastern Standard Time with daily grids of 0.1° and spatial domain of 40°S–40°N and 20°W–55°E. Accumulated daily data are compiled by additional datasets for 10-day, monthly and seasonal rainfall totals. Moreover, seven other daily binary output fields are generated using different combinations of the input data, though these are not considered operational and will be addressed later. The algorithm's functioning relies on the availability of these four data sources (Nicholas S. Novella, African Rainfall Climatology Version 2 for Famine Early Warning Systems, 2013).

Table 3 shows the data sources, techniques used, and the spatial coverage for RFE 2.0 (Rainfall Estimation Version 2.0).

Table 4 RFE2.0 data sources and used techniques and coverage extent

Category	Used technique	Extent
Gauge	GPCC - atoll	Land – atoll
IR	GPI	40°South- 40° North
MW (Scattering)	Grody	Global land ocean
MW (Emission)	Chang	Global ocean
Model	ECMWF	Global land ocean

RFE2.0 Algorithm

To reduce the random error in satellite precipitation estimates, a linear combination of GPI, SSM/I, and AMSU data is performed using the Maximum Likelihood Estimation (MLE) method as (Pingping Xie, 1996) .The equation used for this combination is typically structured as follows:

$$Wi = \frac{\sigma i^{-2}}{\sum_{i-1}^{3} \sigma i^{-2}}$$

Where: Wi = weighting coefficient, σ^2 = random error

The weights of the different satellite data are derived from the random errors of the satellite-estimated precipitation with respect to the measured rain gauge data on a daily basis. After the weighting coefficients are computed, the outputs of the individual precipitation estimates are combined so as to yield a single estimate with lesser random uncertainty. Using the following equation:

$$S = \sum_{i-1}^{3} Wi\ Si$$

Where: S is the combined precipitation estimate, Si: individual satellite rainfall estimation techniques namely GPI, SSM/I and AMSU, and Wi: weighting coefficients determined using the random error of each satellite data source.

The second phase of merging is to compare the first step of precipitation estimates from satellite with the GTS rain gauge data to eliminate bias. This comparison enables correction of the systematic errors which might be present in the satellite data by comparing it with data obtained from stations.

In the last values of an appreciation of the precipitation, the values from the rain station gauges are directly inputted where existent. Whereas close proximity data relies on actual measurements through an instrument, the further away the estimate is from a rain gauge station the more reliance there is on satellite data. This approach makes it possible to obtain nearly-station estimates based on sequential measurements, while satellite data supplement distances further from the stations.

2.2.2 CHRIPS Data

CHRIPS Data Description

The CHIRPS stands for Climate Hazards Group Infrared Precipitation with Station is a rainfall dataset of more than 35 years quasi globally. Spanning from 50°S to 50°N and all longitudes, CHIRPS temporally records data from 1981 to the near contemporary period. It uses CHPclim climatology, spatial scale 0.05° latitude/longitude, temporal scale daily, 5-day and decadal and near-global coverage and in situ station data to generate high resolution gridded rainfall times series. It is regularly employed to study long term trends in rainfall and to assess current drought conditions (Chris Funk, Pete Peterson, et. al, 2015).

CHRIPS Algorithm

CHIRPS rainfall data is generated using an algorithm that combines several key data sources shown in table Table 5.

Table 6 CHRIPS data sources

Data Source	Description
Climate Hazards Group Precipitation Climatology (CHPclim)	Based on rain gauge data from the FAO and GHCN, used as part of the climatology for generating CHIRPS data.
Cold Cloud Duration (CCD)	Derived from thermal infrared data archived by the CPC and NOAA.
Rain Gauge Data	Collected from multiple sources, including FAO and GHCN, providing ground-based observations.
TRMM 3B42 Data (Version 7)	Satellite-based rainfall estimates, incorporated to improve spatial coverage in CHIRPS data
NOAA Climate Forecast System (CFS) Version 2	Provides atmospheric model rainfall fields to contribute to the CHIRPS data algorithm.
National Climate Data Center (NCDC)	Supplies additional climate data for generating rainfall estimates.

The process to derive the available CHIRPS data, as described (Chris Funk, Pete Peterson, et. al, 2015), can be summarized as follows:

1. ***Calibration of CCD Data***: Initial 5-day CCD-based precipitation estimates are derived from TRMM 3B42 data with which CCD data is properly adjusted.
2. ***Conversion to Fractions***: These estimates are then base on fractions of the long-term mean precipitation estimates.
3. ***Bias Removal Using CHPclim***: These calculated fractions are then multiplied by CHPclim data to ameliorate systematic biases in the precipitation estimate.
4. ***Blending with Rain Gauge Data***: CHIRPS data is combined with rainfall station data using a modified inverse distance weighting technique; increases spatial rain estimation in areas with station data.
5. ***Disaggregation to Daily Estimates***: Daily estimates of 5-day accumulated precipitation are derived from the 5-day CCD data and the 5-day CFS data by a direct mean redistribution method.
6. ***Final Data Output***: The final dataset generated through CHIRPS is available in raster form, which is suitable for easily accessible rainfall data for comparison with other studies.

Specifically for any given pixel, CHIRPS blending algorithm employs weighted average using ratios between the five neighboring stations and CHIRP information. This is expressed as follows:

$$b_{1\to5} = \frac{s_{1\to5} + \boldsymbol{\varepsilon}}{c_{1\to5} + \boldsymbol{\varepsilon}}$$

Where: **b** is a 5-element vector representing bias ratios, **s** is a 5-element vector containing station observations, **c** is a 5-element vector with CHIRP values, and **ε** is a small value added to both the numerator and denominator to avoid division by zero in cases where CHIRP values are zero or near zero.

Ratios exceeding three are capped at three. Bias ratios (**b**) for stations beyond the decorrelation distance are set to 1. (Chris Funk, Pete Peterson, et.al., 2015).

3. Methodology

3.1 Ground Data

In this study, observed data were collected at nine meteorological stations distributed within and around the Tekeze Atbra sub-basin, Sudan. Fig. 3 show the locations of meteorological stations.

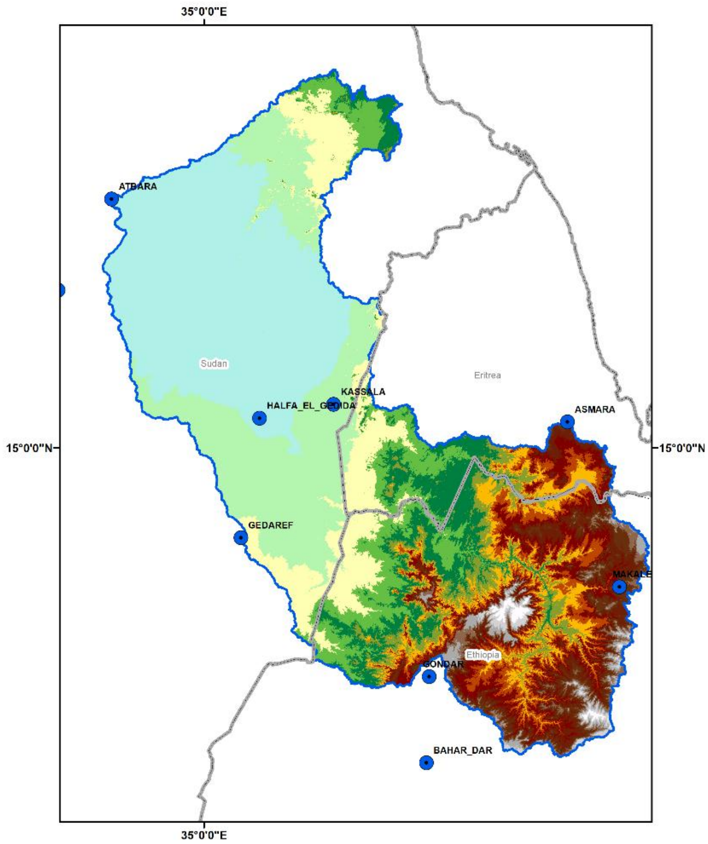


Fig. 4 Location of observation station over study area (Tekeze Atbara sub-basin)

The observed precipitation data source is WMO meteorological stations. These data were downloaded from Northern Illinois University web site: https://atlas.niu.edu/. Then downloaded data were decoded to extract the precipitation observation for each station. Table 7 summarize location of the meteorological stations and data availability.

Table 8 summarize location of the meteorological stations and data availability

Station	Country	Latitude (^{0})	Longitude (^{0})	Altitude (M)	Precip	T Max	T Min	Wind Direction	Wind Speed
HALFA_EL_GEDIDA	Sudan	15.32	35.6	453	√	√	√	√	√
KASSALA	Sudan	15.47	36.4	507	√	√	√	√	√
SHENDI	Sudan	16.7	33.43	365	√	√	√	√	√
ATBRA	Sudan	17.7	33.97	348	√	√	√	√	√
GADAREF	Sudan	14.03	35.4	636	√	√	√	√	√
ASMARA	Ethiopia	15.28	38.2	2249	√	√	√	√	√
MALAKAL	Ethiopia	13.5	39.48	2119	√	√	√	√	√
BAHR_DAR	Ethiopia	11.6	37.4	1762	√	√	√	√	√
GONDAR	Ethiopia	12.53	37.43	1967	√	√	√	√	√

3.2 REF2.0 - CHIRPS Data Comparative Analysis

Daily precipitation data from RFE 2.0 and CHRIPS were accumlated on monthly basis for the location of the nine stations of Tekeze Atbra sub-basin for the period from 2015 till 2020.

In this analysis, the precipitation value from the ground station were matched directly to the value of the pixel that represents that point in RFE 2.0 and CHRIPS (point to pixel analysis). This is advantageous in a sense that the comparing data requires to be for the similar geographic location and area without distortion.

3.3 Assessment of RFE2.0 and CHRIPS data

To evaluate the discrepancies among precipitation products from RFE2.0, CHRIPS with stations measurements, we applied several statistical metrics: mean bias error (MBE), root mean squared error (RMSE), and percent bias (PB), as detailed in Table 9. Additionally, we included the coefficient of determination (R^2), the Nash-Sutcliffe efficiency (EFF) and Kling-Gupta Efficiency (KGE) to provide a more robust analysis of model accuracy (Ebert, 2007).

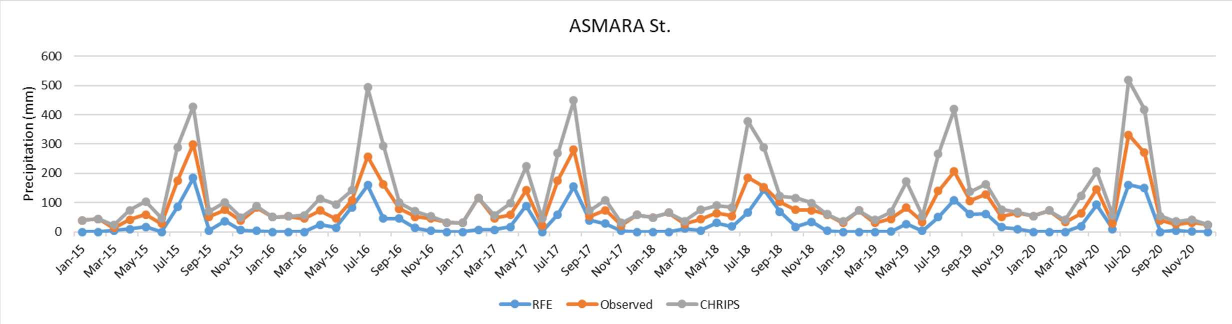
Table 10 Performance Measure Formulas

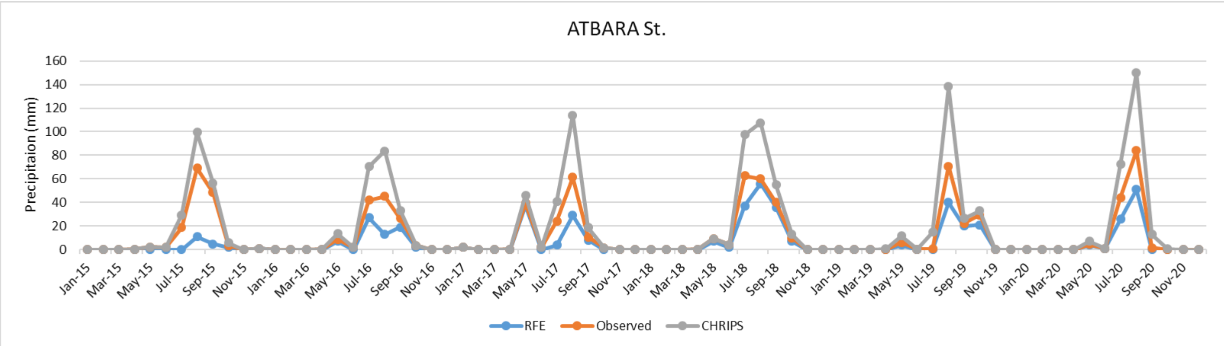
Statistical Metrics		
Name	**Formula**	**Limits**
Coefficient of determination (R^2)	$R^2 = \left(\frac{\sum_{i=1}^{N}(P_o-\overline{P_o})\times(P_i-\overline{P_i})}{\sqrt{\sum_{i=1}^{N}(P_o-\overline{P_o})^2}\times\sqrt{\sum_{i=1}^{N}(P_i-\overline{P_i})^2}}\right)^2$	0 to 1 (Ideal: Closer to 1, indicating a good fit)
Root mean squared error (RMSE)	$RMSE = \sqrt{\sum_{i=1}^{N}\frac{(Pi-Po)^2}{N}}$	0 to +∞ (Ideal: Lower values indicate better accuracy)
Relative root mean squared error (rRMSE)	$rRMSE = \frac{RMSE}{P_o}$	0% to +∞ (Ideal: Lower values indicate better performance; generally, values <10% excellent, 10–20% good, 20–30% fair, and > 30% indicate poor performance)
Average of errors - Bias (MBE)	$MBE = \sum_{i=1}^{N}\frac{(Pi-Po)}{N}$	-∞ to +∞ (Ideal: Close to 0, positive values indicate overestimation, negative values indicate underestimation)
Percent Bias (PB)	$PB = 100\,\frac{\sum_{i=1}^{N}(P_i-P_o)}{\sum_{i=1}^{N}P_o}$	-∞% to +∞% (Ideal: Close to 0%, positive values indicate overestimation, negative values indicate underestimation)
Nash-Sutcliffe efficiency coefficient	$EFF = 1 - \frac{\sum_{i=1}^{N}(P_i-P_o)^2}{\sum_{i=1}^{N}(P_o-\overline{P_o})^2}$	-∞ to 1 (Ideal: Closer to 1, values < 0 indicate poor performance)
Kling-Gupta Efficiency (KGE)	$KGE = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2}$	-∞ to 1 (Ideal: Closer to 1, values close to 0 or negative indicate poor performance)

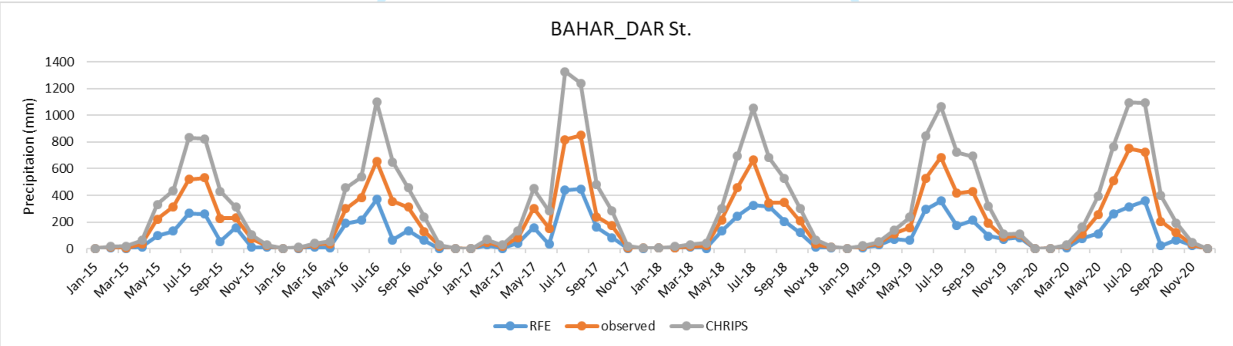
Where: Pi = estimated variable; Po = observed variable; $\overline{P_O}$ = average of the values observed at meteorological stations; N = total number of observations, r =Pearson correlation coefficient , α = term representing the variability of prediction errors, β = bias term

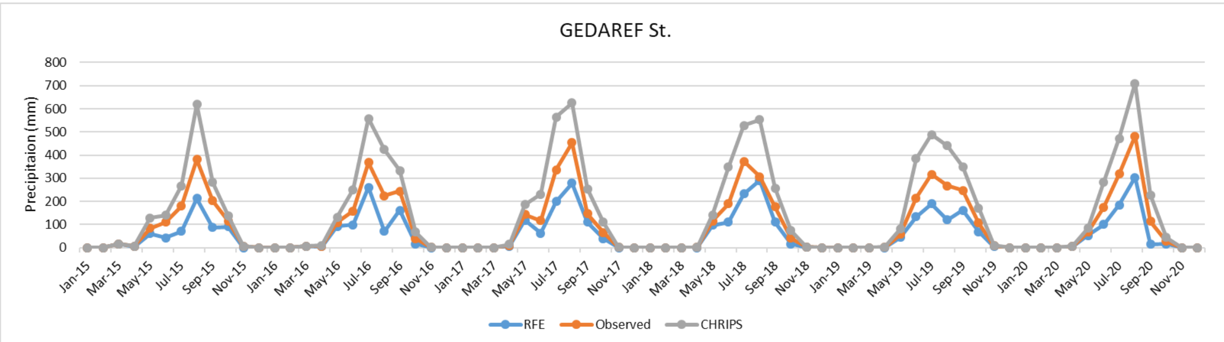
4. Results and Discussion

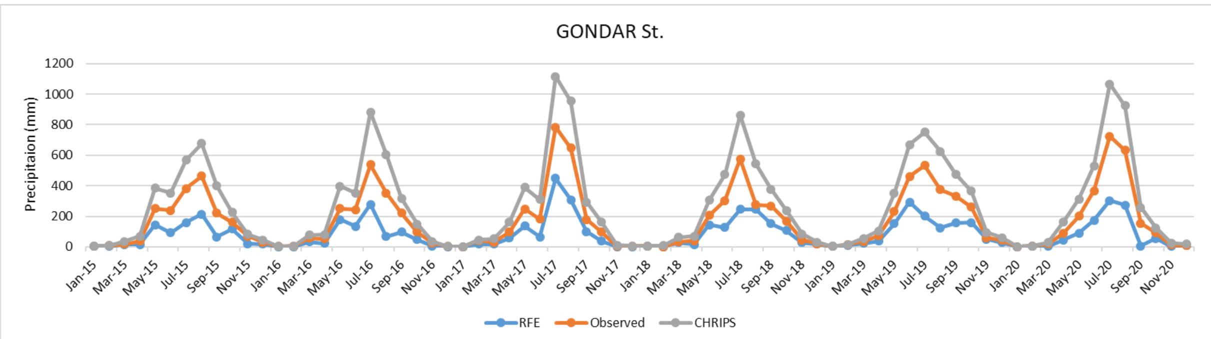
Fig. 5 show the monthly precipitation data from meteorological stations against detected and estimated RFE2.0 and CHIRPS from January 2015 to December 2020. The rainy season between June –September. On the other hand, the distribution patterns of precipitation in the RFE2.0 and CHIRPS estimates shown in this study resemble the station data at all the analyzed time periods.











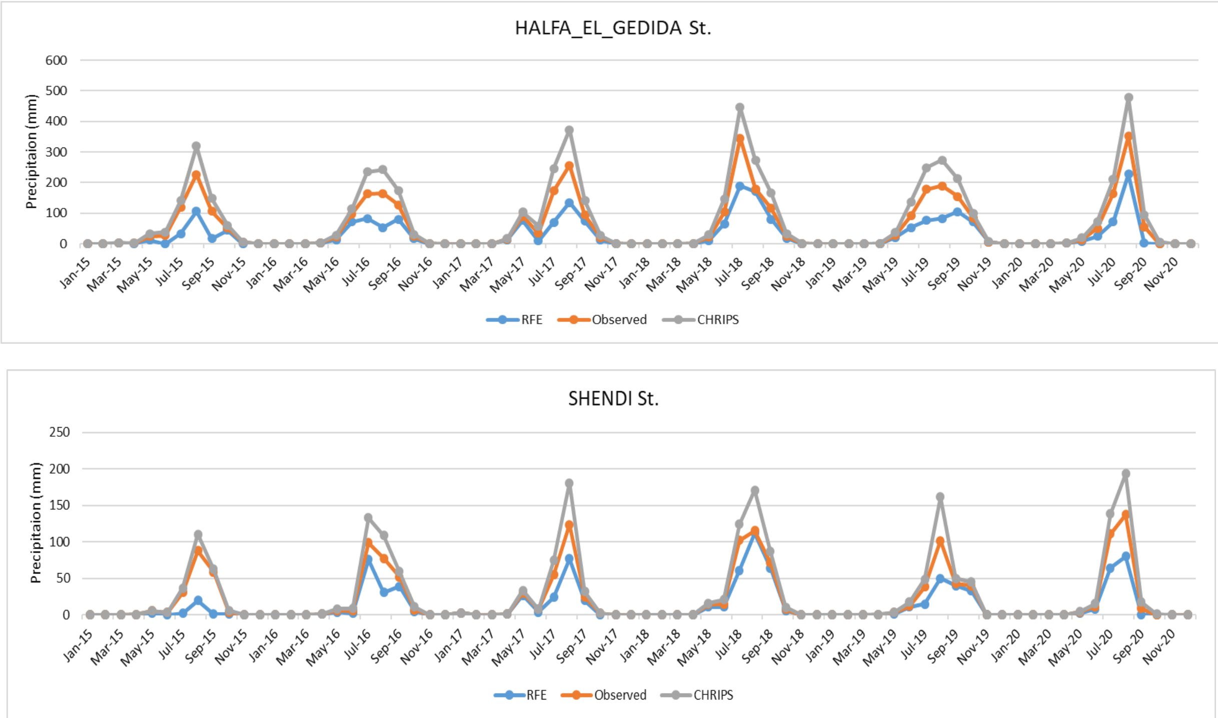


Fig. 6 Monthly precipitation data from 9 meteorological stations on (Tekeze Atbra sub-basin) against detected and estimated RFE2.0 and CHIRPS from January 2015 to December 2020.

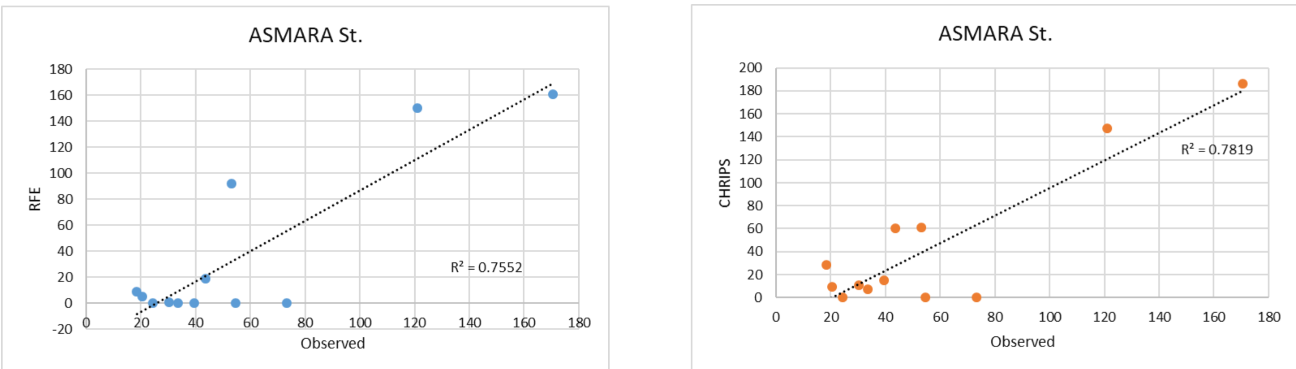
The precipitation distribution captured by RFE2.0 and CHIRPS data closely aligned with the variations observed in nine station data (over Tekeze Atbra sub-basin) throughout each analyzed period, demonstrating strong consistency in seasonal patterns.

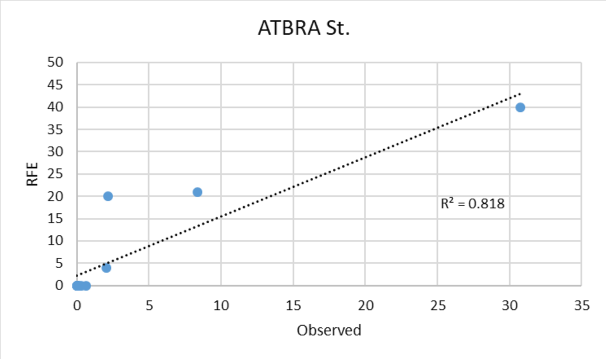
The coefficients of determination (R^2) varied according to the station and the year represented. The coefficients in the current analysis were ranged between 0.25 and 0.99, the highest coefficients were found in 2020 (R^2 = 0.99), whereas lowest coefficients were found 2016/ 2017 (R^2 = 0.25) 0. The worst performance in both RFE and CHIRPS was realized in the 2017. Table 11 list the values of (R^2) for the stations for both RFE and CHRIPS data for the years (2015-2020).

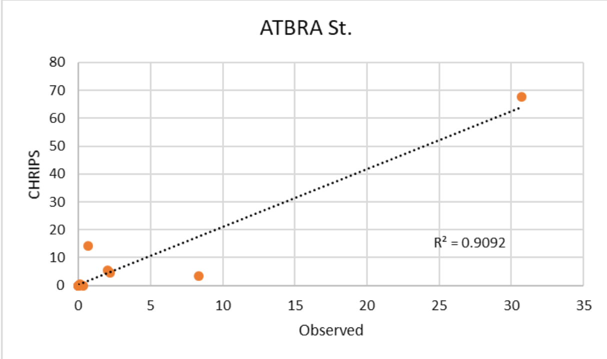
Table 12 the values of (R^2) for the stations for both RFE and CHRIPS data for the years (2015-2020).

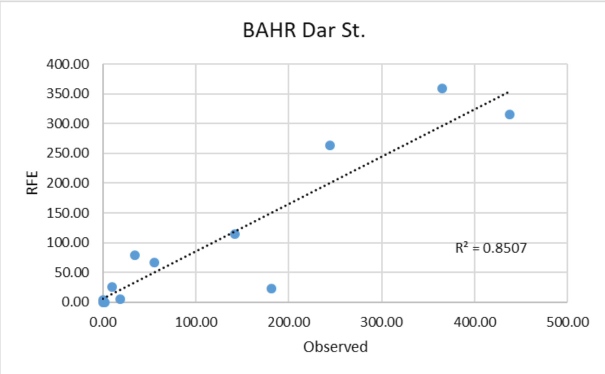
STATION -YEAR	2015		2016		2017		2019		2020	
	RFE	CHRIPS	RFE	CHRIPS	RFE	CHRIPS	RFE	CHRIPS	RFE	CHRIPS
ASMARA	0.65	0.58	0.22	0.62	0.35	0.41	0.52	0.77	0.76	0.78
ATBRA	0.84	0.84	0.43	0.93	0.25	0.91	0.82	0.91	0.99	0.97
BAHR_DAR	0.78	0.94	0.58	0.90	0.95	0.90	0.88	0.98	0.85	0.97
GADAREF	0.76	0.85	0.43	0.94	0.90	0.86	0.84	0.92	0.81	0.99
GONDAR	0.75	0.93	0.48	0.91	0.93	0.97	0.56	0.88	0.90	0.99
HALFA_EL_GEDIDA	0.58	0.82	0.59	0.97	0.66	0.92	0.63	0.94	0.77	0.90
KASSALA	0.61	0.91	0.63	0.94	0.60	0.93	0.55	0.95	0.82	0.97
MALAKAL	0.89	0.94	0.51	0.95	0.90	0.79	0.68	0.82	0.93	0.93
SHENDI	0.55	0.69	0.47	0.82	0.80	0.92	0.50	0.91	0.98	0.93

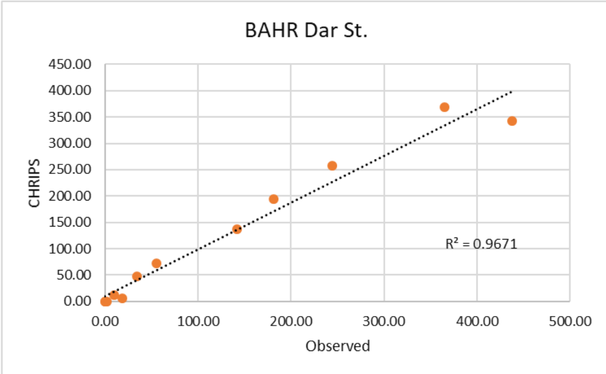
Figure (4) shows the relation between RFE and CHRIPS data compared with observed data for the years (2015-2020).

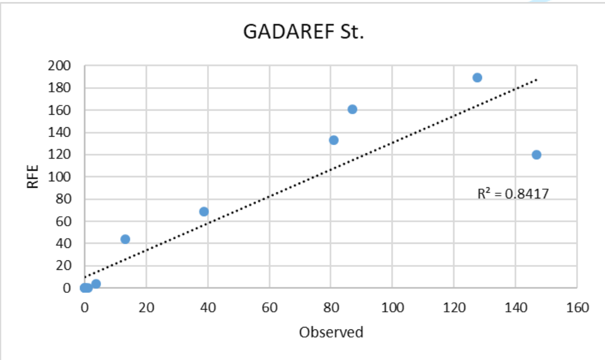


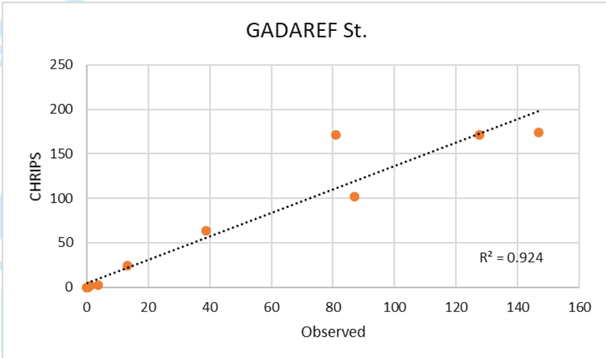

ATBRA St.
RFE
Observed
R² = 0.818

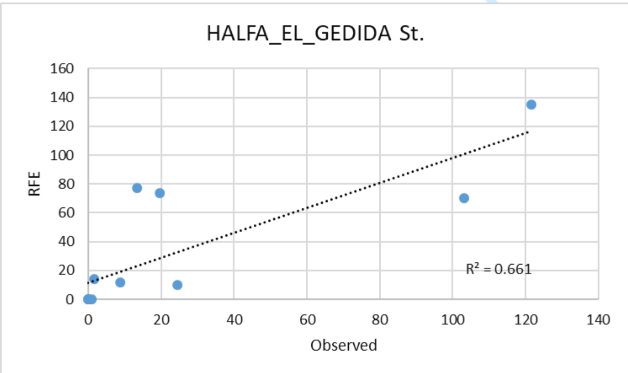

ATBRA St.
CHRIPS
Observed
R² = 0.9092

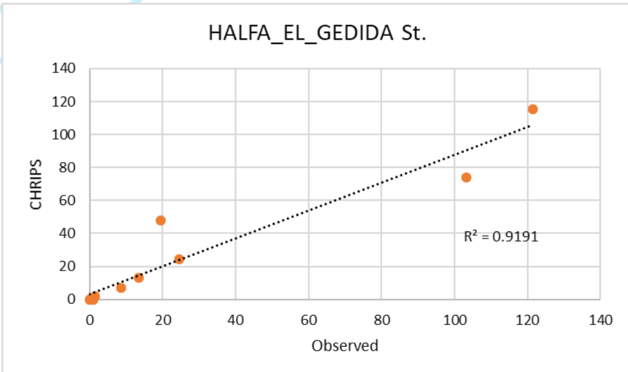

BAHR Dar St.
RFE
Observed
R² = 0.8507

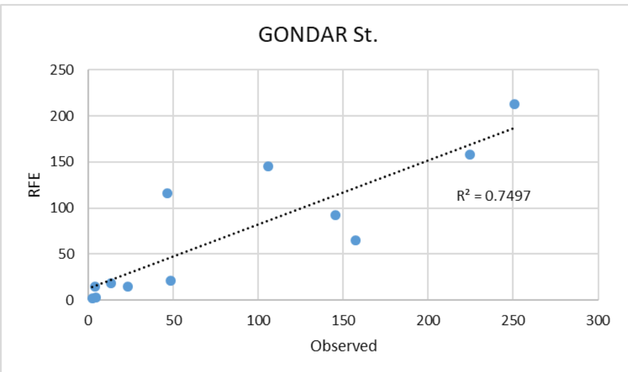

BAHR Dar St.
CHRIPS
Observed
R² = 0.9671

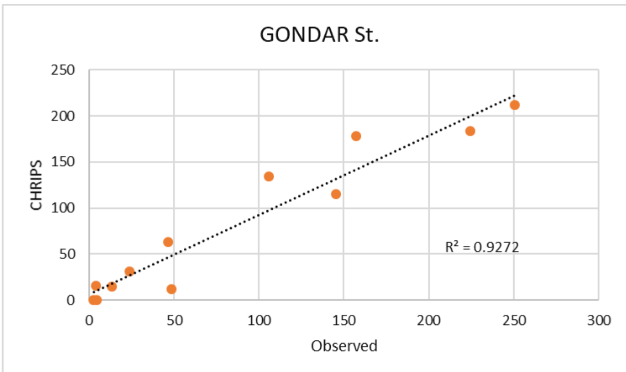

GADAREF St.
RFE
Observed
R² = 0.8417


GADAREF St.
CHRIPS
Observed
R² = 0.924


HALFA_EL_GEDIDA St.
RFE
Observed
R² = 0.661


HALFA_EL_GEDIDA St.
CHRIPS
Observed
R² = 0.9191


GONDAR St.
RFE
Observed
R² = 0.7497


GONDAR St.
CHRIPS
Observed
R² = 0.9272

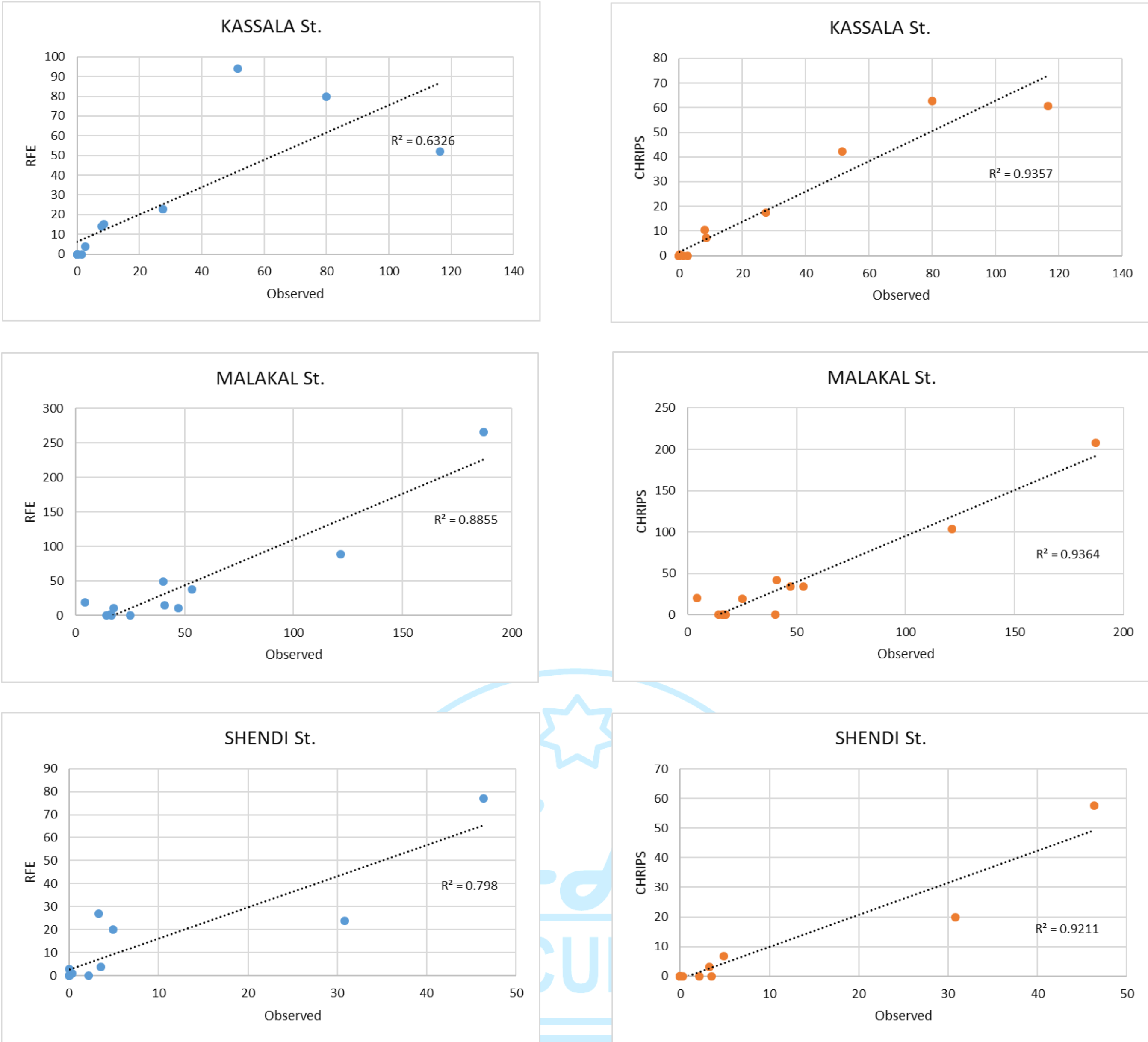
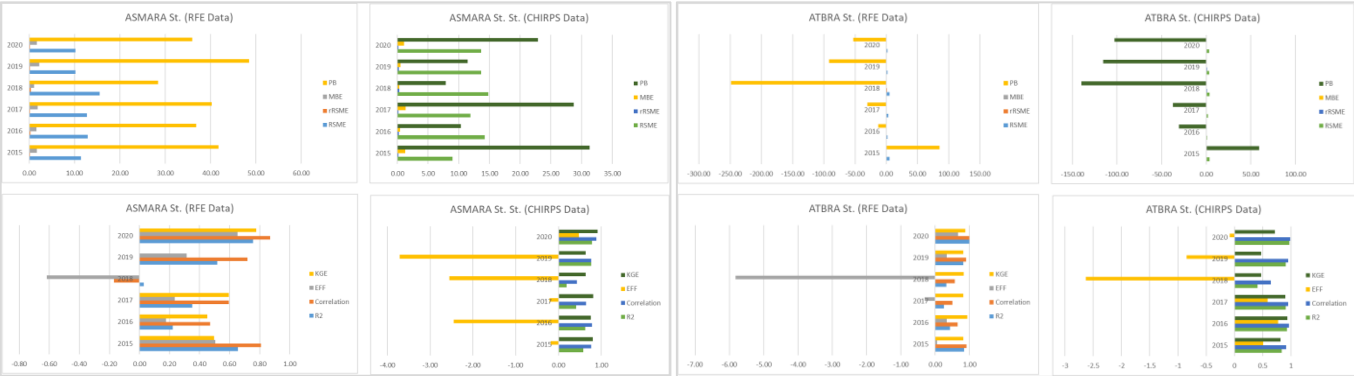


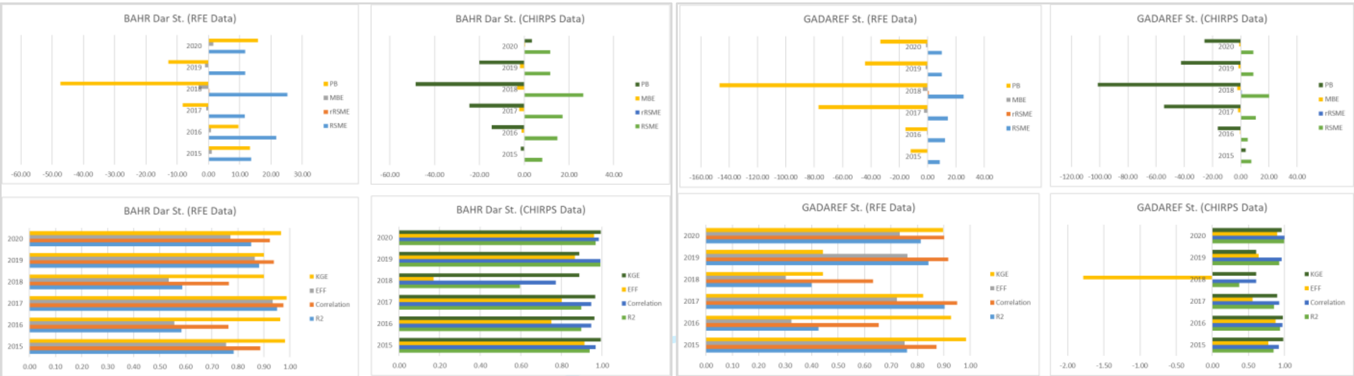
Fig. 7 monthly precipitation data observed meteorological stations on (Tekeze Atbra sub-basin) against detected and estimated RFE2.0 and CHIRPS from January 2015 to December 2020

Concerning the performances, CHIRPS yields higher values of correlation coefficients as well as R-squared relative to MAE and RMSE indicating better agreement with the observed rainfall data across station. For instance, when comparing the two indices in Gondar CHIRPS was, attained a value of 0.93 while the RFE attained 0.82, showing that the CHIRPS is had a close estimate of the observed rainfall fluctuations.

CHIRPS had statistically significant higher R^2, which measures the amount of the actual rainfall patterns that could be explained by the datasets. For example at Gondar the CHIRPS could account for 87 % of the rainfall in stability compared to RFE that could account for 68%.

The analysis of performance measures metrics showed that the values of precipitation data through CHIRPS and RFE proved that CHIRPS identified and aligned much better with observational ground data. In particular, CHIRPS was shown to be more accurate in representing real values of rainfall than RFE as shown in Fig. 8 and Fig. 9. This result is consistent with the structure of CHIRPS, using a merging between IR satellite data with in-situ station data which shall provide greater rainfall accuracy across the study area boundaries and seasons compared to RFE.


ASMARA St. (RFE Data)
ASMARA St. St. (CHIRPS Data)
ATBRA St. (RFE Data)
ATBRA St. (CHIRPS Data)
PB
MBE
rRSME
RSME
KGE
EFF
Correlation
R2


BAHR Dar St. (RFE Data)
BAHR Dar St. (CHIRPS Data)
GADAREF St. (RFE Data)
GADAREF St. (CHIRPS Data)
PB
MBE
rRSME
RSME
KGE
EFF
Correlation
R2


GONDAR St. (RFE Data)
GONDAR St. (CHIRPS Data)
HALFA_EL_GEDIDA St. (RFE Data)
HALFA_EL_GEDIDA St. (CHIRPS Data)
PB
MBE
rRSME
RSME
KGE
EFF
Correlation
R2


KASSALA St. (RFE Data)
KASSALA St. (CHIRPS Data)
MALAKAL St. (RFE Data)
MALAKAL St. (CHIRPS Data)
PB
MBE
rRSME
RSME
KGE
EFF
Correlation
R2

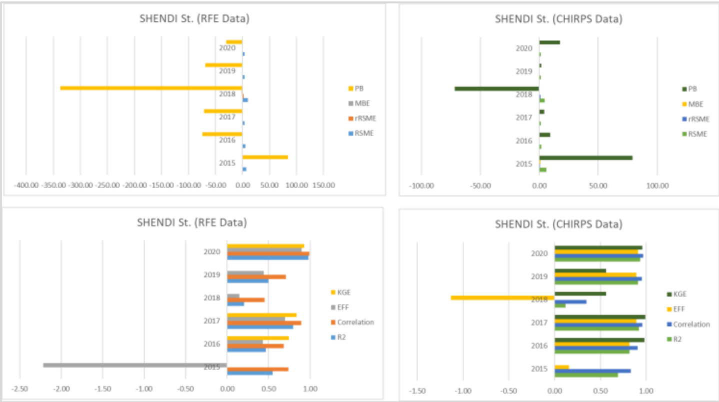


Fig. 10 performance measures metrics (R2, RMSE, rRMSE, MBE, PB, EFF, KGE) for observed meteorological stations against detected and estimated RFE2.0 and CHIRPS from January 2015 to December 2020.

The analysis of CHIRPS and RFE rainfall data across different stations, based on statistical performance metrics such as RMSE (Root Mean Square Error), rRMSE (relative RMSE), MBE (Mean Bias Error), PB (Percent Bias), R^2, correlation, EFF (Efficiency), and KGE (Kling-Gupta Efficiency), the values of performance metrics are listed in Table 13 .

Table 14 statistical performance metrics for the stations for both RFE and CHRIPS data against the observed data for years (2015-2020).

STATION	PRODUCT	RSME	RRSME	MBE	PB	CORRELATION	EFF	KGE
ASMARA	RFE	12.15	0.24	1.70	38.62	0.55	0.21	0.58
	CHRIPS	12.86	0.23	0.83	18.76	0.71	-1.44	0.76
ATBRA	RFE	3.32	0.66	-0.11	-58.55	0.76	-0.79	0.85
	CHRIPS	2.89	0.61	-0.15	-61.10	0.90	-0.28	0.72
BAHR_DAR	RFE	15.98	0.17	-0.25	-4.93	0.88	0.74	0.95
	CHRIPS	0.77	0.88	0.74	0.95	0.93	0.74	0.95
GADAREF	RFE	13.44	0.39	-1.61	-54.81	0.82	0.60	0.75
	CHRIPS	10.33	0.27	-1.16	-39.43	0.90	0.33	0.84
GONDAR	RFE	17.83	0.20	0.27	1.65	0.82	0.52	0.93
	CHRIPS	10.88	0.13	-0.15	-4.02	0.93	0.83	0.97
HALFA_EL_GEDIDA	RFE	8.78	0.38	-0.48	-26.92	0.79	0.51	0.82
	CHRIPS	4.84	0.20	0.33	13.99	0.92	0.79	0.95
KASSALA	RFE	9.56	0.37	-0.37	-25.20	0.80	0.52	0.81
	CHRIPS	5.31	0.23	0.54	22.81	0.91	0.71	0.81
MALAKAL	RFE	11.84	0.23	0.64	12.25	0.79	0.60	0.85
	CHRIPS	12.25	0.23	-0.01	-1.71	0.86	0.28	0.86
SHENDI	RFE	5.57	0.74	-0.34	-82.81	0.75	0.07	0.84
	CHRIPS	2.78	0.35	0.14	6.70	0.83	0.42	0.81

- ✓ In different stations, RMSE of CHIRPS in general is relatively lower than RMSE of RFE showing less difference with the observed values. For instance, while the RMSE of Kassala is as 5.31 of CHIRPS and 9.56 of RFE, shows the closeness of CHIRPS with observed data.
- ✓ Lower values of rRMSE in many places are evidence of the improved accuracy of CHIRPS which is highlighted in table (5).
- ✓ Similarly, the absolute mean bias error (MBE) of the CHIRPS product is lower in most cases as well and therefore is less biased in estimating rainfall. This can likely be seen in the stations such Gadaref, and Malakal where the percent bias plots indicate that CHIRPS has a lower systemic error than that determined by using the MBE.
- ✓ The (PB) usually proves CHIRPS is more accurate, for example in Kassla station (PB) values in CHIRPS = 22.81 against RFE = -25.20, which demonstrating how CHIRPS has a less spill more often than not, with little propensity for under- or overestimating, than true rainfall.
- ✓ Efficiency scores also confirmed that CHIRPS provided a better estimate of observed rainfall, compared to RFE. In Halfa El Gedida, the predictive efficiency of CHIRPS was higher at 0.79 while that of RFE was 0.51.
- ✓ The KGE values was scored slightly higher for CHIRPS than for RFE. For example, when applied to the data of the Gadaref station, CHIRPS gave the maximum value of 0.84, whereas RFE reached 0.75. This goes in further support of the fact that CHIRPS is the more suitable dataset for rainfall estimation.

5. Conclusion

- ✓ The results from this study confirm that CHIRPS dataset would offer a better estimate of rainfall than the RFE dataset for most of the stations used in this analysis. The accuracy and reliability of CHIRPS was better than RFE in most of the station compared to the observed measurements.
- ✓ CHIRPS had significantly lower error rates, less bias and showed realism closer to the observed rainfall data than RFE. The higher KGE scores for CHIRPS confirm that CHIRPS is a reliable dataset, especially in areas where few in situ observations are available. It is indicated that RFE is good for quick and initial identification of climate and rainfall conditions while CHIRPS is more superior for accurate climatic and rainfall analysis.

6. Recommendation

- ***Rainfall Assessments***: The results of analysis in this study showed that CHIRPS is given higher accuracy which should be prioritized in different applications requiring accurate rainfall data, such as agricultural planning, water resource management, and flood forecasting, where accurate estimations directly impact decision-making.
- ***Real-time Monitoring***: While CHIRPS is recommended for accuracy, RFE can still be useful for real-time tool for monitoring precipitation. In certain scenarios, RFE can provide an initial estimate, with CHIRPS used for subsequent validation and more accurate analysis for specific study area.
- ***Further Validation Studies***: in order to enhance the reliability of satellite-based precipitation products, it is recommended to conduct further validation using ground-based data, especially in regions with high rainfall variability. This would allow for continued enhancement for both CHIRPS and RFE data.
- ***Integration with Newer Technologies***: Enhancing and updating the satellite technologies, along with using artificial intelligence and machine learning algorithms with CHIRPS would provide more accurate and less bias results, and make it even more beneficial for climate change adaptation, resource management practices.

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