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Precipitation Estimated by Remote Sensing in the Baixo São Francisco Physiographic Region: A Performance Analysis of TRMM (3B42) and CHIRPS

Luciano da Silva Alves[1] Marcus Aurélio Soares Cruz[2], Ricardo de Aragão[3], André Quintão de Almeida[4]

[1]Mestre em Recursos Hídricos pelo PRORH da Fundação Universidade Federal de Sergipe - FUFS. E-mail:luciano.eng@outlook.com – ORCID: https://orcid.org/0000-0002-9277-629X, [2] Doutor em Recursos Hídricos e Saneamento Ambiental pelo PPGRHSA da Universidade Federal do Rio Grande do Sul – UFRGS, Professor convidado do PRORH da Fundação Universidade Federal de Sergipe – FUFS, Pesquisador da Embrapa Tabuleiros Costeiros. E-mail:marcusascruz@gmail.com – ORCID: https://orcid.org/0000-0003-3725-0882, [3] Doutor em Engenharia pela Ehime University – EU Japão, Professor da Universidade Federal de Campina Grande – UFCG. E-mail: ricardo.aragao@professor.ufcg.edu.br – ORCID: https://orcid.org/0000-0001-7388-1310, [4] Doutor em Agronomia (Meteorologia Aplicada) pelo DEA/UFV da Universidade Federal de Viçosa, Professor da da Fundação Universidade Federal de Sergipe – FUFS. E-mail: andreqa@gmail.com – ORCID: https://orcid.org/0000-0002-5063-1762

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A B S T R A C T

The use of data estimated by Remote Sensing has become an alternative to make up for the deficit of meteorological/rainfall stations in Brazil. Therefore, this research aims to evaluate the performance of precipitation estimates from TRMM and CHIRPS products in the Baixo São Francisco (Baixo SF) physiographic region across different temporal scales, with the goal of providing rainfall data for areas not covered by weather stations, thereby contributing to water resource management. To this end, using the following statistical parameters: linear correlation coefficient (r), root mean square error (RMSE), relative bias percentage (PBIAS) and Nash-Sutcliffe efficiency (NSE), data from precipitation from 67 rain gauges with the respective values estimated by TRMM and CHIRPS, in the period from 2000 to 2015. With values of r = 0.88 and 0.87; RMSE = 31.01 and 144.98 and NSE = 0.76 and 0.71, CHIRPS performed better than TRMM on the monthly and annual scales. On the daily and decennial scales, neither product obtained significant results. In regions further away from the coastal zone, where altitudes range between 400 and 700 m, data from CHIRPS and TRMM had better accuracy. It is concluded that only the CHIRPS estimates, in the monthly and annual periods, have good accuracy to represent the rainfall in the Baixo SF in the studied period.

Keywords: Pluviometry, Accuracy, Deficit, Meteorological Stations.

Precipitação Estimada por Produtos de Sensoriamento Remoto na Região Fisiográfica do Baixo São Francisco: Uma Análise do Desempenho do TRMM (3B42) e do CHIRPS

R E S U M O

A utilização de dados estimados por Sensoriamento Remoto tem se tornado uma alternativa para suprir o déficit de estações meteorológicas/pluviométricas do Brasil. Sendo assim, esta pesquisa busca avaliar o desempenho da precipitação estimada pelos produtos TRMM e pelo CHIRPS na região fisiográfica do Baixo São Francisco (Baixo SF) em diferentes escalas temporais, com o objetivo de fornecer dados de chuva para áreas não cobertas por estações, contribuindo para a gestão hídrica. Para tanto, utilizando os seguintes parâmetros estatísticos: coeficiente de correlação linear (r), raiz quadrática do erro médio (RMSE), do percentual do viés relativo (PBIAS) e da eficiência de Nash-Sutcliffe (NSE), foram comparados os dados de precipitação de 67 postos pluviométricos com os respectivos valores estimados pelo TRMM e CHIRPS, no período de 2000 a 2015. Com valores de r = 0,88 e 0,87; RMSE = 31,01 e 144,98 e NSE = 0,76 e 0,71, o CHIRPS apresentou melhor desempenho que o TRMM nas escalas mensal e anual. Nas escalas diária e decendial, nenhum dos dois produtos obteve resultados significativos. Nas regiões mais distantes da zona costeira, cuja altimetria entre 400 e 700 m, os dados do CHIRPS e do TRMM tiveram melhor acurácia. Conclui-se que, apenas as estimativas do CHIRPS, no período mensal e anual, possuem boa acurácia para representar a pluviometria do Baixo SF no período estudado.

Palavras-chave: Pluviometria, Acurácia, Déficit, Estação Meteorológica.

Introduction

Due to its ability to support economic activities, water supply projects, drainage, disaster prediction, and more, precipitation is considered one of the most important variables in the hydrological cycle (Helmi & Abdelhamed, 2023). Despite its essential role in water planning, precipitation monitoring of river basins in Brazil remains a significant challenge. Generally, this issue arises from the lack of meteorological/rainfall stations and/or the insufficiency of consistent historical series (Amorim et al., 2020; Freitas et al., 2021).

According to data collected via the Hidroweb platform of the National Water and Sanitation Agency (ANA), the Baixo São Francisco (Baixo SF) physiographic region currently has about 149 rainfall stations. Given the Baixo SF area of approximately 30,377 km², there is only one rainfall station per 200 km². Considering the high spatial variation, the low number of rainfall stations directly affects the reliability of decision-making related to water planning (Medhioub et al., 2019; Macharia et al., 2020; Ma et al., 2020; Ghozat et al., 2022).

Therefore, the use of remote sensing data has shown to be a promising alternative to address the deficit in precipitation monitoring networks. Remote sensing products, such as the Tropical Rainfall Measuring Mission (TRMM) and the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), enable the acquisition of continuous (uninterrupted) and systematic monitoring data of climatic conditions over a significant portion of the globe (50ºN and 50ºS), including the entire Baixo SF region. These products can provide precise data on the spatial and temporal distribution of precipitation (Melo et al., 2015; Wang et al., 2017; Zhang et al., 2018; Silva et al., 2020; Alejo & Alejandro, 2021; Hsu et al., 2021; Yang et al., 2021). This information can be crucial for better understanding hydrological regimes, anticipating extreme events such as floods and droughts, and making informed decisions regarding water use (Melo et al., 2015; Wang et al., 2017; Amorim et al., 2020; Neto et al., 2021).

Studies in regions of Brazil and around the world have identified TRMM and CHIRPS as viable alternatives for acquiring and applying meteorological data, especially precipitation data, for watershed management. These tools can be used for filling historical gaps, hydrological models, water balance, drought monitoring, natural disaster management, and more (Oliveira et al., 2014; Melo et al., 2015; Paredes-Trejo et al.,2017; Santos et al., 2017; Wei et al., 2017; Bai et al., 2018; Rivera et al., 2018; Amorim et al., 2020; Macharia et al., 2020; Hsu et al., 2021; Alsalal et al., 2023; Du et al., 2023; Kibii & Plessis, 2023; Ning et al., 2023; Senjaya et al., 2023; Uma & Reshma, 2024).

Despite their great potential, climate studies based on remote sensing are still rarely adopted by public agencies responsible for Water Resources Management in Brazil (Neto et al., 2021). The Baixo SF physiographic region has a low density of rain gauges with long historical records, which limits hydrometeorological analysis (Alsilibe et al., 2023; Du et al., 2024). In this context, this study aims to assess the performance of precipitation estimates from TRMM and CHIRPS products across different temporal scales, with the goal of providing rainfall data for areas not covered by weather stations, thereby contributing to improved water resource management..

Materials and methods

Study area

The São Francisco River basin, physiographically divided into four regions - Upper, Middle, Sub-Middle, and Lower (Figure 1) - spans the states of Minas Gerais, Bahia, Alagoas, Pernambuco, and Sergipe. It extends 863 km, has a drainage area of 639.219 km², and covers about 8% of the national territory, making it one of Brazil's 12 hydrographic regions (COMITÊ DE BACIAS HIDROGRÁFICAS DO RIO SÃO FRANCISCO - CBHSF, 2016).

Located between the geographical coordinates of latitude -8.31ºS to -10.63ºS and longitude -36.31ºW to -38.56ºW, with a drainage area of approximately 25.524 km² - 4% of the total basin área - the Baixo SF is the smallest physiographic region. Its drainage network measures 5.713 km and spans the states of Bahia, Pernambuco, Alagoas, and Sergipe. From west to east, from the city of Paulo Afonso (west) to its mouth (east), the river covers a distance of approximately 265 km (CBHSF, 2016).

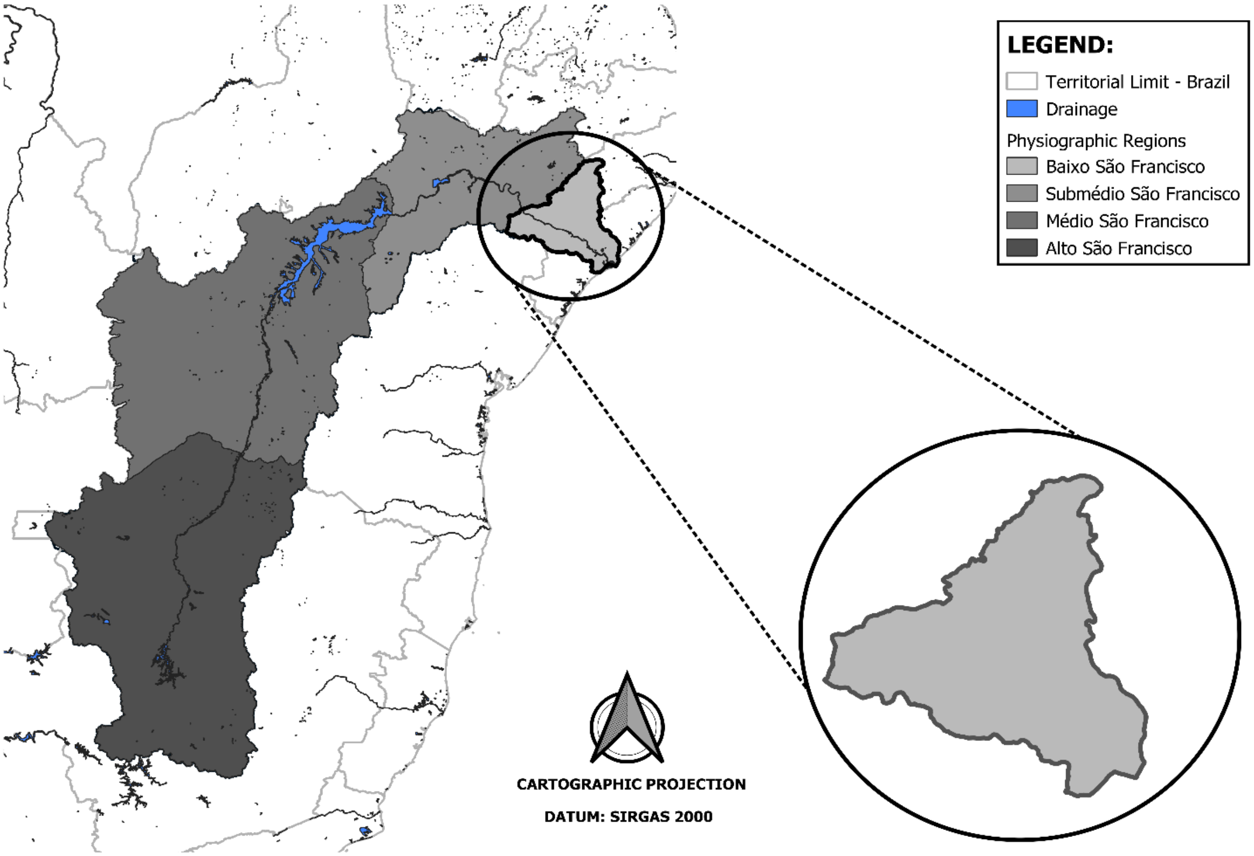

Figure 1. Location of the Baixo SF physiographic region. Source: Organized by the authors.

In terms of population characteristics, the Baixo SF region has about 1,412,500 in habitants spread across 90 municipalities, with 53.3% living in urban areas and 46.7% in rural areas (CBHSF, 2016). Economically, despite the growth of aquaculture, tourism, and leisure activities, riverside activities linked to agriculture and traditional fishing remain the primary sources of income in the Baixo SF (CBHSF, 2020).

The Baixo SF predominantly features the Caatinga biome, especially in the semi-arid region. However, along the coastal zone, there are patches of Atlantic Forest, identified by gallery and riparian forests. Due to the extensive agricultural activities, there is a trend toward the reduction of the Caatinga (CBHSF, 2016).

Regarding the multiple uses of water in the basin, according to the volumes granted and in force until July 2017, with 41.65 m³/s, the Baixo SF was the physiographic region with the lowest “demand” for granted water. The largest withdrawals are for irrigation, followed by public supply and animal watering. In percentage terms, water withdrawals for irrigation, urban public supply, and industrial consumption in each sub-basin of the Baixo SF are as follows: Curitiba 60% - 25% - 9%, Seco/Talhada 92% - 4% - 2%, Alto Ipanema 31% - 22% - 32%, Baixo Ipanema 54% - 13% - 9%, and Baixo SF 77% - 10% - 7% (CBHSF, 2019).

According to the Köppen Climate Classification (1936), the predominant climate in the Baixo SF physiographic region is AS (hot and humid, with winter rains). However, moving northwest, there are areas with Bsh characteristics, meaning semi-arid with a short rainy season in autumn/winter. According to CBHSF (2016), the Baixo SF physiographic region receives precipitation ranging from approximately 300 to 1300 mm/year and has an average minimum and maximum temperature of 20.8 ºC and 31.2 ºC, respectively. The highest rainfall occurs in April (90 mm), May (100 mm), and June (120 mm), while the lowest rainfall is in October (35 mm), November (30 mm), and December (37 mm).

Figure 2 shows the hypsometry of the Baixo SF region. Generally, elevation variations range from 0 to 1,150 m. The highest areas are located near the Sub-Middle region. As one approaches the riverbed and coastal zone, altitudes decrease. Approximately 80% of the Baixo SF has altitudes lower than 450 m. Elevation changes are not steep, resulting from the low slope, with 77% of the region having a slope parameter below 8% (CBHSF, 2016).

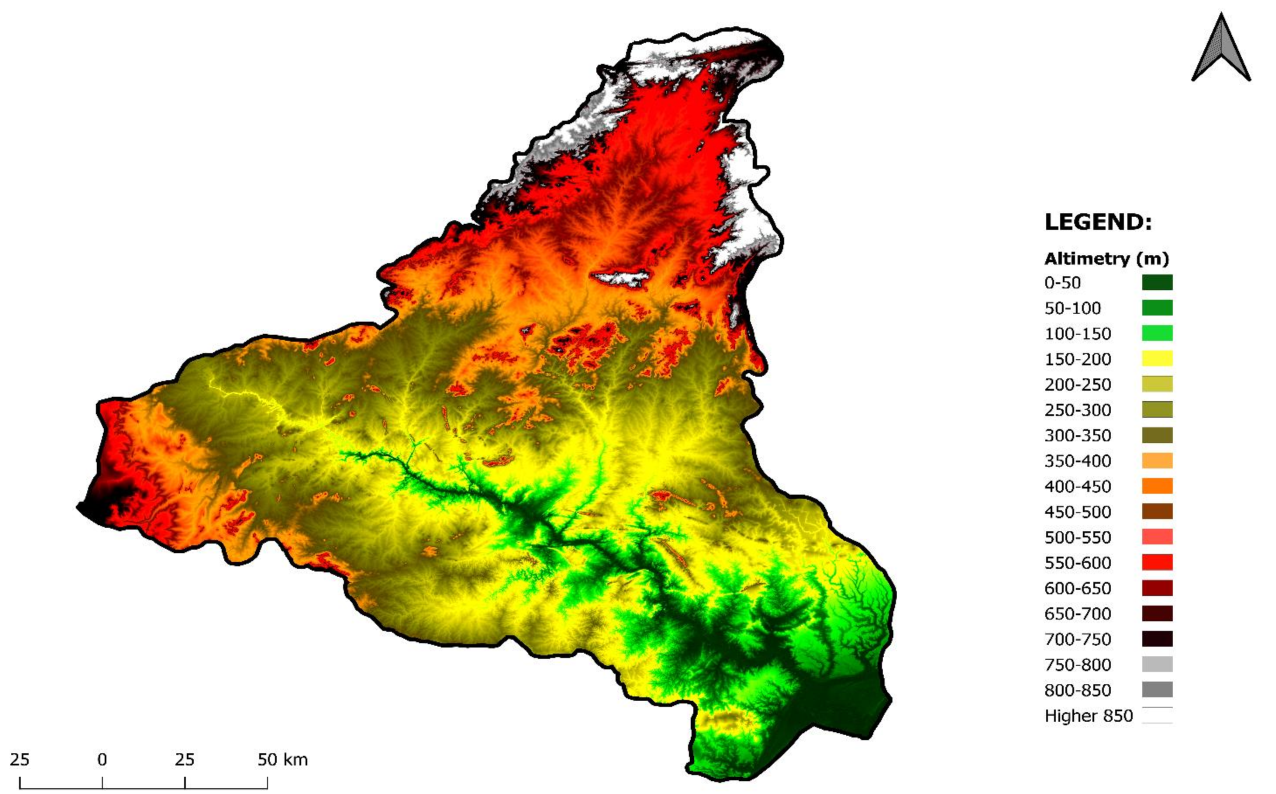

Figure 2. Hypsometry of the Baixo SF physiographic region. Source: Organized by the authors.

Acquisition of precipitation data from rainfall stations

Figure 3 presents the spatial distribution of the rainfall stations used in this research. Table 1 displays the data related to the selected stations. Initially, about 97 rainfall stations installed in the Baixo SF region were selected through the Hidroweb platform provided by ANA. Subsequently, using the acquired geographic positions, the rainfall stations were spatialized using the free software QGIS, Version 3.28.0 (QGIS Development Team, 2022). Given the proximity of some of them, the Thiessen polygon method was applied to filter based on areas of influence. Consequently, 67 rainfall stations were chosen for this research (Figure 3).

After the selection, the precipitation values for each rainfall station were validated using the database provided by Xavier et al. (2022). The authors provided already validated daily precipitation data from 11,473 rain gauges and 1,252 meteorological stations throughout Brazil. These data include those from the rainfall stations previously chosen for this research.

Acquisition of precipitation data from remote sensing products

Precipitation data from the remote sensing products TRMM (3B42) and CHIRPS were acquired through scripts developed in JavaScript on the Google Earth Engine - GEE (Google Earth Engine) remote sensing platform. The rainfall values of both products were extracted from the “Image Collection” at 3-hour intervals (TRMM 3B42) and daily (CHIRPS), respectively, for the period from 2000 to 2015, and exported in CSV format (Gorelick et al., 2017).

At this stage, the point-to-pixel approach was used, where, for each rainfall station, the respective precipitation series was extracted from the “Image Collection.” This methodology allows for a direct comparison of daily precipitation totals at each rainfall station with the respective values extracted from the pixel of the remote sensing products in which each station is located (Santos et al., 2017).

Both products were chosen based on the temporal compatibility of the available precipitation series, which justifies the period from 2000 to 2015, as well as on research by Melo et al. (2015), Paredes-Trejo et al. (2017), Santos et al. (2017) and Santos et al. (2018), which highlight the potential use of TRMM and CHIRPS precipitation data in the São Francisco River Basin.

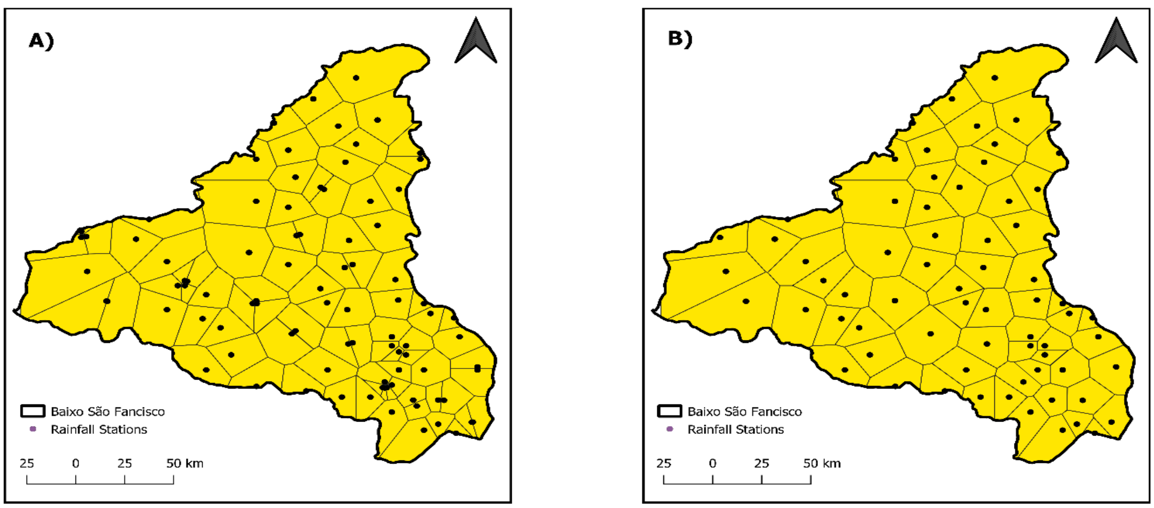

Figure 3. A) number of rainfall stations (97 stations) before filtering using the Thiessen polygon method; B) number of rainfall stations (67 stations) after filtering using the Thiessen polygon method. Source: Organized by the authors

Table 1. Data from the rainfall stations used in this research.

Nº Stations	Code	Longitude	Latitude	Nº Stations	Code	Longitude	Latitude
1	836029	-36.97	-8.5	35	937029	-37.67	-9.7
2	837045	-37.17	-8.62	36	937021	-37.43	-9.73
3	837002	-37.05	-8.77	37	937026	-37.27	-9.92
4	836053	-36.87	-8.73	38	937048	-37	-9.97
5	836019	-36.97	-8.87	39	936085	-36.8	-9.98
6	836057	-36.67	-8.92	40	936072	-36.73	-9.98

7	837051	-37.35	-8.75	41	1036044	-36.73	-10.03
8	837019	-37.28	-8.9	42	936022	-36.51	-9.83
9	837015	-37.02	-8.97	43	938028	-38.25	-9.38
10	936009	-36.77	-9.12	44	938012	-38.22	-9.57
11	837024	-37.43	-8.95	45	938013	-38.13	-9.74
12	937002	-37.25	-9.05	46	937027	-37.85	-9.78
13	937031	-37.13	-9.11	47	937025	-37.68	-9.83
14	936007	-36.9	-9.18	48	937024	-37.6	-9.88
15	937012	-37.43	-9.18	49	1037027	-37.67	-10.12
16	937004	-37.28	-9.22	50	1037033	-37.55	-10.03
17	937032	-37.25	-9.37	51	A453	-37.43	-10.21
18	937011	-37	-9.4	52	1037016	-37.2	-10.23
19	936032	-36.87	-9.32	53	1037021	-37.1	-10.12
20	937005	-37.47	-9.47	54	1037056	-37.03	-10.27
21	937016	-37.28	-9.53	55	1036039	-36.9	-10.27
22	82991	-37.02	-9.55	56	1036009	-36.83	-10.18
23	936015	-36.78	-9.62	57	1036054	-36.8	-10.35
24	937010	-37.13	-9.67	58	1036043	-36.77	-10.12
25	936026	-37.1	-9.74	59	1036035	-36.7	-10.28
26	937040	-37.01	-9.78	60	1036023	-36.65	-10.45
27	82995	-36.77	-9.73	61	1036003	-36.65	-10.12
28	936066	-36.65	-9.75	62	1036005	-36.56	-10.29
29	936071	-36.8	-9.93	63	1036036	-36.58	-10.42
30	936065	-36.62	-9.8	64	1036038	-36.5	-10.47
31	937007	-37.93	-9.28	65	936020	-36.48	-9.93
32	907013	-37.99	-9.39	66	1036051	-36.4	-10.1
33	937017	-37.85	-9.52	67	1036008	-36.42	-10.41
34	A371	-37.77	-9.62				

Source: Organized by the authors.

Validation of precipitation estimated by remote sensing products

To verify accuracy and to compare precipitation data from remote sensing with in situ recorded data, statistical performance tests such as the root mean square error (RMSE), linear correlation coefficient (r), percent bias (PBIAS), and Nash-Sutcliffe efficiency (NSE) were used (Table 2). Similar research by Alsalal et al. (2023), Helmi and Abdelhamed (2023), Kibbi and Plessis (2023), and Ning et al. (2023) suggest that these indices are appropriate for accuracy verification. Table 2 describes the equations of the statistical parameters, the reference value, and the corresponding unit of measurement for each.

RMSE is used to measure the error between the in situ recorded rainfall and the rainfall estimated by remote sensing. The r helps to understand the degree of linear relationship between the comparisons. PBIAS allows for checking whether the value estimated by remote sensing is under- or overestimated, based on the values observed in the field (Melo et al., 2015; Amorim et al., 2020; Hsu et al., 2021).

Regarding Nash-Sutcliffe efficiency (NSE), it indicates how well the field-observed data match the data estimated by remote sensing products. According Amorim et al. (2020), NSE is understood as a normalized statistic that determines the relative magnitude of residual variance (“noise”) compared to the measured data (“information”). In theory, NSE is the metric that weights the relationship between the estimated precipitation and the average detected in the field (Paredes-Trejo et al., 2017).

The cross-referencing of precipitation recorded by rainfall stations and those estimated by TRMM (3B42) and CHIRPS was conducted on a daily, decennial, monthly, and annual scale for the period from 2000 to 2015. Similar to the extraction of precipitation values from the products, the comparison was also carried out using the point-to-pixel methodology mentioned earlier in this research.

Table 2. Statistical parameters used to compare in situ data with remote sensing product estimates.

Statistical Method	Equation	Reference value	Unit
Root mean square error	$RMSE = \sqrt{\frac{\sum_{I=1}^{n}(Pi - Oi)^2}{n}}$	0	mm
Linear correlation coefficient	$r = \frac{\sum_{i=1}^{n} (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^{n} (P_i - \bar{P})^2}}$	1	NA
PBIAS	$PBIAS = \frac{\sum_{i=1}^{n} (O_i - P_i)}{\sum_{i=1}^{n} P_i} \text{x}\, 100$	0	%
Efficiency of Nash-Sutcliffe	$NSE = 1 - \left[\frac{\sum_{i=1}^{n} (O_i - P_I)^2}{\sum_{i=1}^{n} (O_i - O)^2}\right]$	1	NA

Legend: NA - does not have a unit of measurement; $\bar{P}$ e $\bar{O}$ are the average of observed (field) and estimated (satellite) precipitation, respectively; P_i e O_i are the i^{th} observed (field) e estimated (satellite) precipitation, respectively, n representes the number of measurements.

Source: Organized by the authors.

Development of the index explaining the best relationships between precipitation values estimated by remote sensing products and those detected by rainfall stations

Following the evaluation of the statistics described in Table 2, based on Figueiredo et al. (2019), an index was developed to identify the best relationships between the precipitation recorded by rainfall stations and that generated by TRMM and CHIRPS, at daily, decennial, monthly, and annual temporal scales.

Initially, considering that the correlation coefficient (r), root mean square error (RMSE), percent bias (PBIAS), and Nash-Sutcliffe efficiency (NSE) have different units of measurement, critical points were determined, and the values were subsequently normalized according to the steps described below:

$$r_{critical} = \text{maximum value } (r_i) \quad (1)$$

$$RMSE_{critical} = \text{minimum}(RMSE_i) \quad (2)$$

$$PBIAS_{critical} = \text{minimum}(|PBIAS_i|) \quad (3)$$

$$NSE_{critical} = \text{minimum}(1 - NSE_i) \quad (4)$$

$$Norm\_r_i = \frac{r_i}{rcritical} \quad (5)$$

$$Norm\_RMSE_i = \frac{RMSE_{critical}}{RMSE_i} \quad (6)$$

$$Norm\_PBIAS_i = \frac{PBIAS_{critical}}{|PBIAS_i|} \quad (7)$$

$$Norm\_NSE_i = \frac{NSE_{critical}}{|NSE_i|} \quad (8)$$

After the steps specified above, the sum of the normalized values forms the Index. The higher the value of the index, the better the relationship between the precipitation detected at the rainfall station and that estimated by the remote sensing products. Since normalization standardizes the values in the range of 0 to 1, and considering the existence of four parameters, the best relationship between the precipitation values estimated by the remote sensing products and those detected by the rainfall stations is achieved when the resulting index value approaches four.

$$Index_i = Norm_{r_i} + Norm_{RMSE_i} + Norm_{PBIAS_i} + Norm\_NSE_i \quad (9)$$

Results and discussion

Descriptive statistics of precipitation measured in situ and by remote sensing products

Table 3 presents the descriptive statistics of precipitation measured in situ and estimated by remote sensing products on daily, decennial, monthly, and annual scales. For the daily period, the following results for mean and standard deviation were identified: Field (2.15 ± 5.37 mm/day), TRMM (0.48 ± 2.27 mm/day), and CHIRPS (1.99 ± 7.93 mm/day). These values indicate that CHIRPS estimates are closest to those recorded by rainfall stations.

Similar behavior was observed in the other temporal scales as described above. Specifically for the monthly and annual periods, the results are as follows: monthly equivalents to 65.46 ± 63.91 and P.75 = 92.72 mm/month (Field), 60.67 ± 57.44 and P.75 = 79.69 mm/month (CHIRPS); annual equivalents to 785.62 ± 267.72 and P.75 = 972.35 mm/year (Field), 728.6 ± 255.66 and P.75 = 869.9 mm/year (CHIRPS), indicating a good relationship between precipitation detected at rainfall stations and that generated by CHIRPS (Table 3).

In theory, the results for TRMM estimated precipitation averages (0.48 – daily, 4.89 – decennial, 14.91 – monthly, and 178.96 – annual) suggest a certain discrepancy between the rainfall values generated by the product and those recorded in Field (2.15 – daily, 21.52 – decennial, 65.46 – monthly, and 785.62 – annual) across all temporal scales (Table 3).

Table 3. Descriptive statistics of precipitation measured in situ and estimated by remote sensing products on daily,decennial, monthly and annual scales.

Data	Average	Median	Desv.Pad	Minimal	Maximum	P.25	P.75
Daily							
Field	2.15	0.1	5.37	0	147.2	0	1.9
TRMM	0.48	0	2.27	0	84.54	0	0
CHIRPS	1.99	0	7.93	0	435.69	0	0
Decennial							
Data	**Average**	**Median**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Field	21.52	11.6	28.05	0	342.2	1.8	30.9
TRMM	4.89	0.6	9.86	0	139.64	0	5.28
CHIRPS	19.92	10.16	29.84	0	472.25	0	26.91
Monthly							
Data	**Average**	**Median**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Field	65.46	48.2	63.91	0	558.6	17.77	92.72
TRMM	14.91	7.92	19.8	0	149.62	1.41	20.91
CHIRPS	60.67	44.41	57.44	0	657.17	21.12	79.69
Annual							
Data	**Average**	**Median**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Field	785.62	772.9	267.72	188.8	1657.6	589.87	972.35
TRMM	178.96	177.97	73.59	27.32	393.81	125.00	230.36
CHIRPS	728.6	678.08	255.66	223.61	1639.6	549.77	869.9

Source: Organized by the authors.

Performance of TRMM and CHIRPS on daily, decennial, monthly and annual time scales

Tables 4 and 5 show the statistical summary of the correlation coefficients (r), mean squared error (RMSE), relative bias (PBIAS) of the Nash-Sutcliffe Efficiency (NSE), which determine the performance of TRMM and CHIRPS in daily, decennial, monthly and annual time scales.

Overall, for the TRMM, regarding r, it is observed that as the time scales progress (daily, decadal, monthly, and annual), the coefficient shows better results and closer to 1 (Table 3). The average r values for each scale were 0.41, 0.65, 0.69, and 0.76. Similar behavior can be noted in the work of Xue et al. (2013), where it is believed that such occurrence is linked to the accumulation of precipitation volumes across the time scales, allowing for better agreement.

The daily TRMM statistics (Table 4) associated with RMSE and r found in this study were similar to those reported by Pinto et al. (2019) and Amorim et al. (2020). The authors found RMSE values ranging from 8 to 10 mm/day and r values between 0.2 and 0.3, respectively. Melo et al. (2015) report that the small magnitude of the error is related to the evaluated time scale and the low precipitation detected in the Northeast region.

Despite the values associated with RMSE, analyzing the other coefficients suggests that TRMM did not perform well on the daily scale (Table 4). It is assessed that even in the absence of 0 mm/day precipitation (Table 3), the product does not maintain estimation accuracy. Melo et al. (2015) emphasize that daily estimates are susceptible to systematic errors. Given the low accuracy at the daily scale, recent studies have shown a tendency to evaluate TRMM based on the monthly scale (Neto et al., 2021; Araújo et al., 2022; Souza et al., 2023).

Table 4. TRMM performance in the Baixo SF physiographic region on daily, decennial, monthly and annual scales.

Daily						
Coefficients	**Average**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Correlation Coeff	0.41	0.05	0.31	0.61	0.37	0.44
RMSE (mm)	5.05	1.07	3.7	7.46	4.23	5.73
PBIAS (%)	-76.33	4.26	-66.6	-82.7	-73.4	-79.95
NSE	0.06	0.06	-0.04	0.29	0.02	0.09
Decennial						
Coefficients	**Average**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Correlation Coeff	0.65	0.05	0.54	0.78	0.62	0.68
RMSE (mm)	27.38	7.64	17.63	43.64	21.01	31.82
PBIAS (%)	-76.33	4.26	-66.6	-82.7	-73.4	-79.95
NSE	-0.02	0.12	-0.24	0.22	-0.14	0.07
Monthly						
Coefficients	**Average**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Correlation Coeff	0.69	0.05	0.54	0.83	0.67	0.72
RMSE (mm)	69.86	20.87	41.88	111.77	54.94	82.25
PBIAS (%)	-76.33	4.26	-66.6	-82.7	-73.4	-79.95
NSE	-0.34	0.16	-0.67	0.04	-0.48	-0.21
Annual						
Coefficients	**Average**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Correlation Coeff	0.76	0.13	0.39	0.96	0.71	0.86
RMSE (mm)	620.44	189.17	393.52	1007.1	463.88	730.66
PBIAS (%)	-76.33	4.26	-66.6	-82.7	-73.4	-79.95
NSE	-14.25	9.07	-34.34	-4.01	-23.67	-6.98

Legend: Desv. Pad – standard deviation; Correlation Coeff - linear correlation coefficient; P.25 e P.75 represent the percentile 25 and the percentile 75, respectively.
Source: Organized by the authors.

Consequently, it can be stated that during the studied period, there was a considerable occurrence of positive anomalies, indicating the existence of extreme precipitation events (Table 2). In this sense, it is believed that such behavior contributed to the poor results found for the TRMM across all the studied time scales (Table 4). Ma et al. (2020) report that extreme precipitation events are difficult to detect by the remote sensing product, favoring the existence of errors in the estimates.

Regarding PBIAS (minimum = -66.6 and maximum = -82.7), the tendency to underestimate the precipitation series aligns with the results found by Souza et al. (2023). Melo et al. (2015) also highlight that, especially in the Northeast region of Brazil, where the Baixo SF is located, TRMM tends to show underestimations. The presence of a negative bias in the region suggests the possible influence of El Niño and La Niña phenomena on the total precipitation estimated by TRMM (Yan et al., 2020; Souza et al., 2023).

The research by Santos et al. (2018) evaluated the reliability of spatial-temporal trends for the Alto São Francisco Basin (ASF) using TRMM precipitation data. Despite having different climatic characteristics, it is worth noting that, as with the Baixo SF, the product did not show significant reliability for the ASF. The justification used by the authors can be applied to the Baixo SF, where it was verified that in regions affected by drought periods on different scales, the TRMM commonly presents negative trends (underestimation).

However, when compared with the research of Helmi and Abdelhamed (2022) and Zhang et al., (2022), it is possible to note that there is no well-determined pattern regarding the performance of the products, which can vary according to various aspects, such as time scale, analysis period, location, among others. In both studies, it is observed that the precipitation estimated by TRMM may present a tendency to under- or overestimate.

In theory, except for r, the other parameters did not improve significantly with the progression of the evaluated time scales. It was seen that throughout the entire period, the NSE maintained low values. The best result was obtained for the decadal period, NSE=0.22 (Table 4). This means that the estimates denote little accuracy. The NSE found for the Baixo SF can be considered unsatisfactory on all analyzed time scales. The magnitudes associated with each studied scale, the maximum annual RMSE equal to 1007.1 mm/year elucidates the product's poor performance (Amorim et al., 2020; Helmi & Abdelhamed, 2022).

Taking into account the research of Melo et al. (2015), Macharia et al. (2020), Amorim et al. (2020), Silva et al. (2020) and Almeida et al. (2021) it can be concluded that TRMM data were not adequate at the (daily, decadal, monthly, and annual) scales studied compared to field-measured data in the Baixo SF region.

Regarding CHIRPS data (Table 5), it can be verified that performance tended to improve with the progression of the time scales. Among the evaluated scales, the daily one was where the remote sensing product obtained the worst results. Works like those of Melo et al. (2015) and Silva et al. (2019) allow us to affirm that satellite estimates for the daily scale are likely to present low reliability when compared to decadal, monthly, and annual scales.

The statement by Melo et al. (2015) and Silva et al. (2019) is corroborated by Hsu et al. (2021). On that occasion, the authors identified that CHIRPS accurately represents medium- and long-term precipitation, meaning the accumulation forming decadal, monthly, and annual scales; however, for short-term precipitation (daily), it does not perform well.

Similarly to TRMM, although CHIRPS did not yield favorable results for the daily scale, it also did not exhibit a high RMSE, with a maximum of 12.84 mm (Table 5), which is believed to be associated with the low precipitation found in the Baixo SF and the magnitude of the scale (Melo et al., 2015). Regarding the decadal, monthly, and annual RMSE, certain accuracy of the values was observed (Melo et al., 2015; Li et al., 2019).

The average values related to r (0.68 – 0.67 and 0.84) indicate a good correlation between the estimates made by CHIRPS and the rain gauge stations for the decadal, monthly, and annual scales (Bai et al., 2018; Anjum et al., 2022, Alsilibe et al., 2023.).

Regarding PBIAS, the results around -33.5 and 33.3 show that CHIRPS underestimates and overestimates the precipitation detected in the Baixo SF. Paredes-Trejo et al. (2017), when studying the performance of CHIRPS in the Northeast region of Brazil, found similar behavior, observing that the product tends to overestimate low rainfall volumes and underestimate high precipitation. Another factor noted by the authors is that during the transition period between dry and rainy seasons, the product tends to overestimate. In agreement with Paredes-Trejo et al. (2017), Bai et al. (2018) found that CHIRPS underestimated precipitation around 20 to 55 mm/day and overestimated rainfall below 5 mm/day.

Comparing the two remote sensing products, considering the average PBIAS (Tables 3 and 4), the results indicate that both products showed a tendency to underestimate the precipitation series measured in the field, particularly TRMM, with an average value of -76.33%, similar to what was found by Medeiros-Feitosa and Oliveira (2020). CHIRPS only underestimated by -7.05% (average value). The PBIAS value associated with CHIRPS is close to that explained by Mulungu and Mukama (2023), who detected an underestimation of -5.3%.

Considering the NSE results found for CHIRPS, except for the daily and decadal scales, the others presented relatively significant coefficients. The best NSE was obtained for the monthly and annual scales, with a minimum and maximum equivalent to 0.73 – 0.87 and 0.23 – 0.89, respectively (Table 5).

Table 5. CHIRPS performance in the Baixo SF physiographic region on daily, decennial, monthly and annual scales.

Daily						
Coefficients	**Average**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Correlation Coeff	0.34	0.05	0.26	0.51	0.3	0.37
RMSE (mm)	7.58	2.36	4.65	12.84	5.76	8.46
PBIAS (%)	-7.05	12.2	-33.5	33.3	-14.55	-0.3
NSE	-1.08	0.62	-2.72	-0.02	-1.45	-0.62
Decennial						
Coefficients	**Average**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Correlation Coeff	0.68	0.4	0.56	0.77	0.65	0.71
RMSE (mm)	22.35	6.5	13.57	38.82	17.08	26.26
PBIAS (%)	-7.05	12.2	-33.5	33.3	-14.55	-0.3
NSE	0.31	0.15	-0.07	0.55	0.22	0.42
Monthly						
Coefficients	**Average**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Correlation Coeff	0.87	0.03	0.77	0.93	0.86	0.9
RMSE (mm)	30.25	6.83	18.84	45.21	25.28	34.89
PBIAS (%)	-7.05	12.2	-33.5	33.3	-14.55	-0.3
NSE	0.73	0.06	0.53	0.87	0.7	0.77
Annual						
Coefficients	**Average**	**Desv.Pad**	**Minimal**	**Maximum**	**P.25**	**P.75**
Correlation Coeff	0.84	0.06	0.68	0.97	0.79	0.9
RMSE (mm)	137.96	56.13	55.65	332.27	95.42	165.49
PBIAS (%)	-7.05	12.2	-33.5	33.3	-14.55	-0.3
NSE	0.23	0.69	-3.15	0.89	0.14	0.6

Legend: Desv. Pad – standard deviation; Correlation Coeff - linear correlation coefficient; P.25 e P.75 represent the percentile 25 and the percentile 75, respectively. Source: Organized by the authors.

In general, according to Dembélé and Zwart (2016), Paredes-Trejo et al. (2017), Rivera et al. (2018), Wahyuni et al. (2021) and Medina et al. (2023), considering the coefficients presented for CHIRPS, particularly NSE, on the monthly and annual scales in the Baixo SF region, the performance of the remote sensing product can be considered satisfactory, meaning the estimates are close to the observations detected in the field.

Spatial distribution of TRMM and CHIRPS results in the Baixo SF physiographic region on monthly and annual time scales

Figures 4 and 5 present the spatial distribution of the Correlation Coefficient (r), Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), and Relative Bias (PBIAS) at monthly and annual time scales for the TRMM and CHIRPS remote sensing products in the physiographic region of Baixo SF.

In general, for both products, across both time scales, the results tend to improve as the stations move away from the coastal zone. Specifically for the monthly and annual scales, it is observed that, for CHIRPS, the results are similar. A "homogeneous" distribution of good values for r, RMSE, and NSE can be noted throughout the Baixo SF region. TRMM had the worst results associated with r, RMSE, and NSE near the mouth area, with progressive improvement of the coefficients from the center towards the Sub-Middle (Figures 4 and 5).

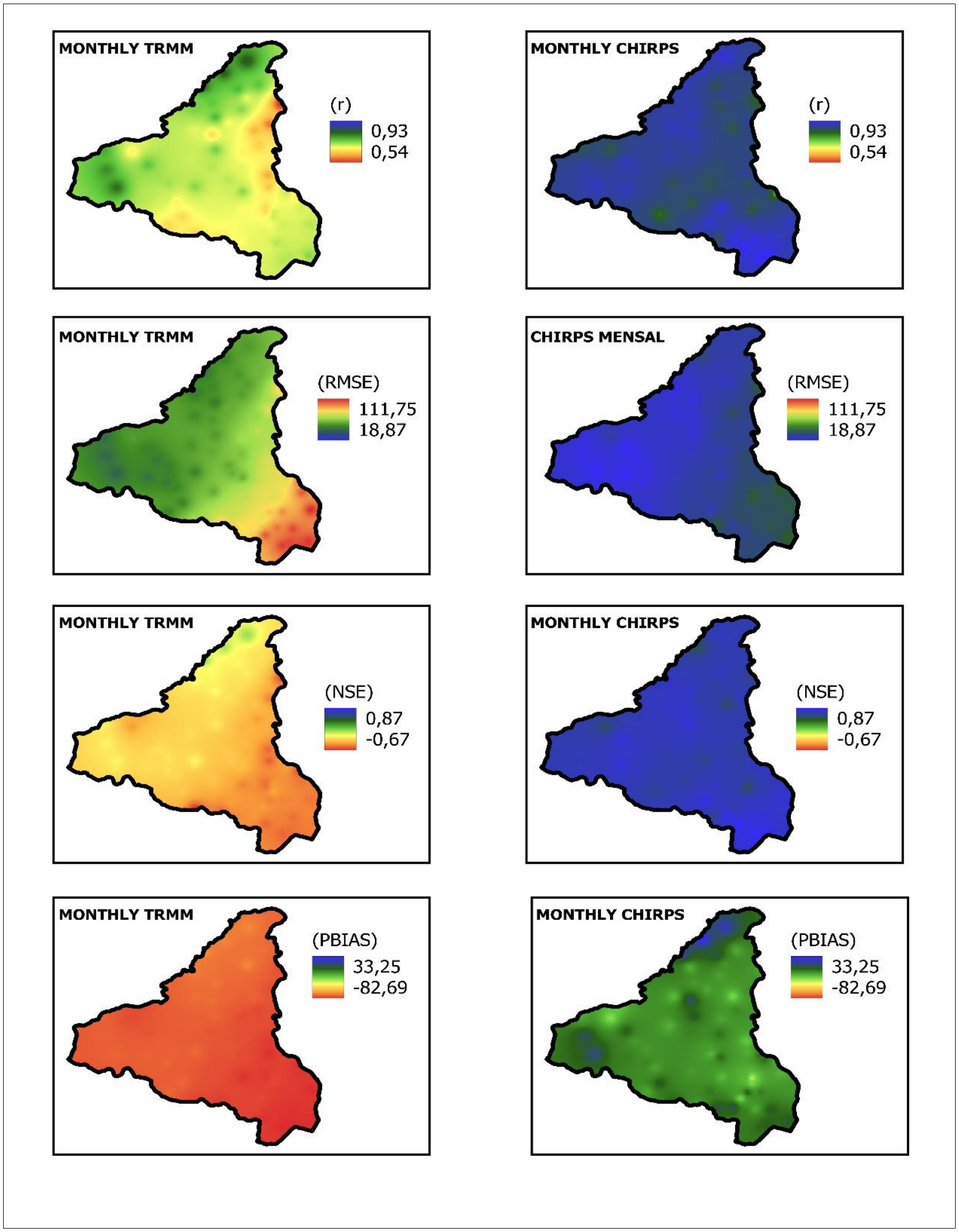

Figure 4**.** Spatial distribution on a monthly scale of the results found for TRMM an CHIRPS.

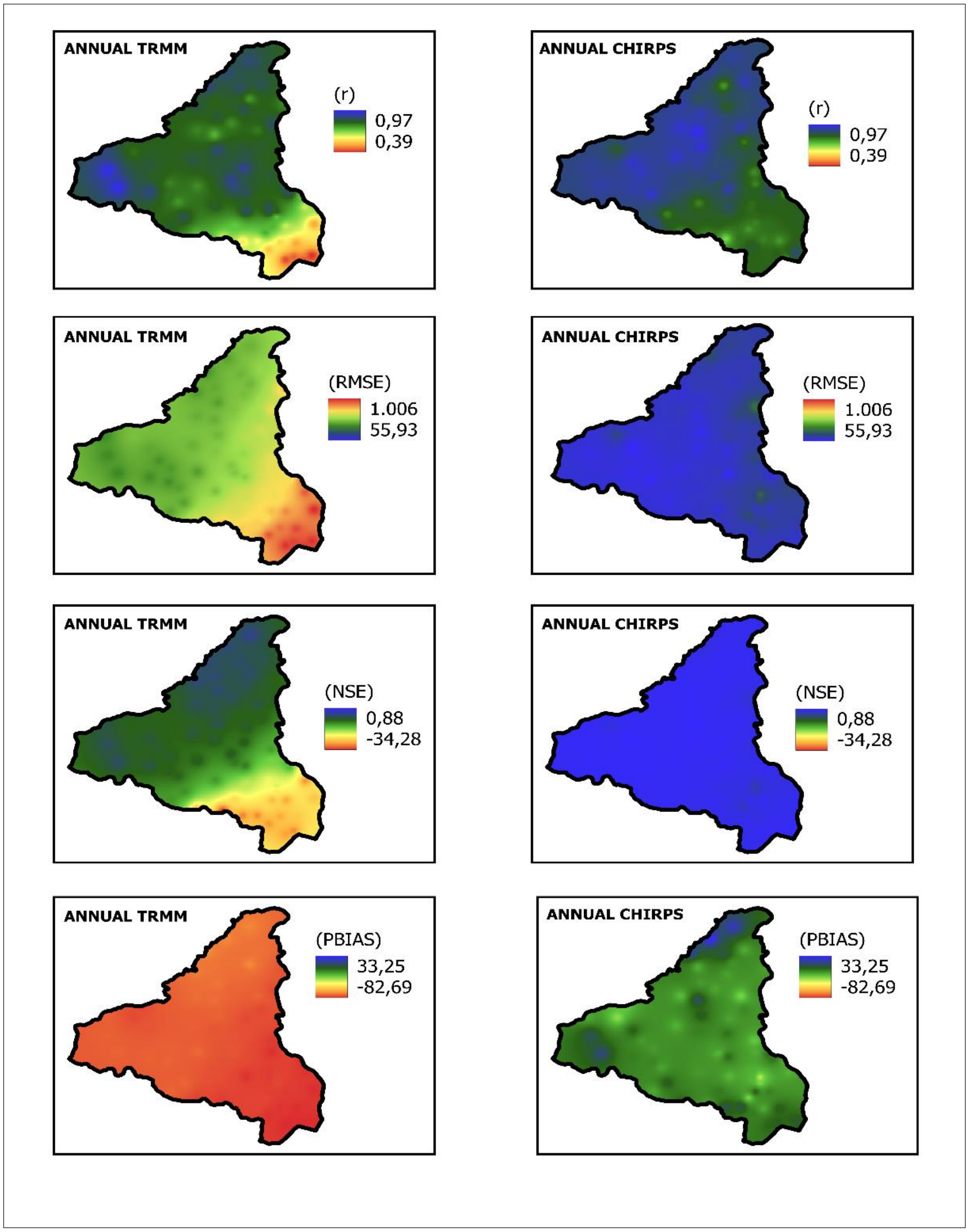

Figure 5**.** Spatial distribution on a monthly scale of the results found for TRMM an CHIRPS.

Regarding PBIAS, TRMM shows a tendency to underestimate, while CHIRPS shows a tendency to both under- and overestimate the evaluated precipitation series. Concerning the spatial distribution, it is observed that TRMM has PBIAS associated with underestimation throughout the physiographic region. For the CHIRPS parameter, the aforementioned variation is identified, but with a notable overestimation in a small portion to the northwest and southwest near the border with the Sub-Middle (Figures 4 and 5). Medhioub et al. (2019) found PBIAS results similar to those of this research. Particularly for TRMM, the authors observed

TRMM's potential for underestimation near the coastal zone, a condition that, according to Figure 6, extends to CHIRPS in some rain gauge stations near the mouth (light green points). As in Yuan et al. (2017) and Amorim et al. (2020), for both TRMM and CHIRPS, although the accumulation of precipitation estimates for the decadal, monthly, and annual scales contributed to the positive oscillation of r, it did not alter the magnitudes associated with PBIAS (Figures 4 and 5).

According to Medhioub et al. (2019), the variation in the spatial distribution of r, RMSE, PBIAS, and NSE is believed to be linked to the high variability of precipitation in time and space, and in the case of Baixo SF, where in some cases, given the orographic influence, the propensity of coefficient improvement towards the Sub-Middle (moving away from the coastal zone) can be verified.

Another factor related to the precision and accuracy of remote sensing product estimates is the topographic characteristics (Saeidizand et al., 2018; Lópes-Barmeo et al., 2022). As previously mentioned in this research, the topography of the Baixo SF river basin ranges from 0 to 1,150 m in altitude and presents a slightly accentuated relief (Figure 2). It is considered that the topographic aspect has contributed to the variability of results within the physiographic region (Medhioub et al., 2019; Ma et al., 2020).

Cross-referencing the information from Figures 2, 4, and 5, it is noted that, in general, the profile found for TRMM and CHIRPS indicates a progression of results from the proximity to higher areas of Baixo SF. The best coefficients for both products were obtained for areas with altitudes ranging from 400 to 700 m, extending to regions above 800 m in altitude. The performance partially agrees with the findings of Helmi and Abdelhamed (2022), whose analysis in arid regions of Arabia indicated that CHIRPS and TRMM performed better at altitudes between 500 and 750 m, while also pointing out that very high areas may contribute to the formation of warm clouds or the evaporation of precipitation before reaching the surface, affecting the performance of remote sensing products.

The results described in the previous paragraph disagree with Karaseva et al. (2012) and Li et al. (2013), who expected that due to the "low" variation in rainfall in less elevated regions, the estimates from remote sensing products would be more accurate and precise. Based on the discussion about the region's topography mentioned in this section, it is believed that this discrepancy is associated with the existence of terrain with a low degree of inclination (slightly accentuated).

Especially for the monthly and annual scales, the estimates made by CHIRPS demonstrated significantly better precision and accuracy than those made by TRMM. Authors like Katsanos et al. (2016) and Yuan et al. (2017) attribute the performance to the superiority of CHIRPS's spatial resolution (0.05º) compared to TRMM (0.25º). On the other hand, Dembelé and Zwart (2016) and Gupta et al. (2020) found that a product with better spatial resolution does not always perform better, due to variations in algorithms, location, climate, topography, and temporal scale. In theory, the opposing examples cited for topography and spatial resolution highlight the absence of pre-established patterns, making it clear that remote sensing products should be primarily tested before any hypothesis is made.

Index of relationships between precipitation values estimated by remote sensing products and those detected by rain gauges

Figure 6 shows the index of precipitation estimates from remote sensing products and those detected at rain gauge stations at daily, decennial, monthly, and annual time scales. It allows for a spatial understanding of the regions with the best correlations between the precipitation detected at the rain gauge stations and the estimates from remote sensing products at the corresponding point (point-pixel). It is noted that, given the difference in the magnitude of precipitation across the respective time scales used in this study, a good correlation does not always indicate good statistical performance.

Upon analysis, in line with the spatial distribution of results presented in the body of this research (Figures 4 and 5), it is noted that for both TRMM and CHIRPS, across all temporal scales, the comparison of estimated precipitation with that recorded by rain gauge stations tends to achieve better performance and homogeneity from the central region of Baixo SF towards the northwest (Figure 6).

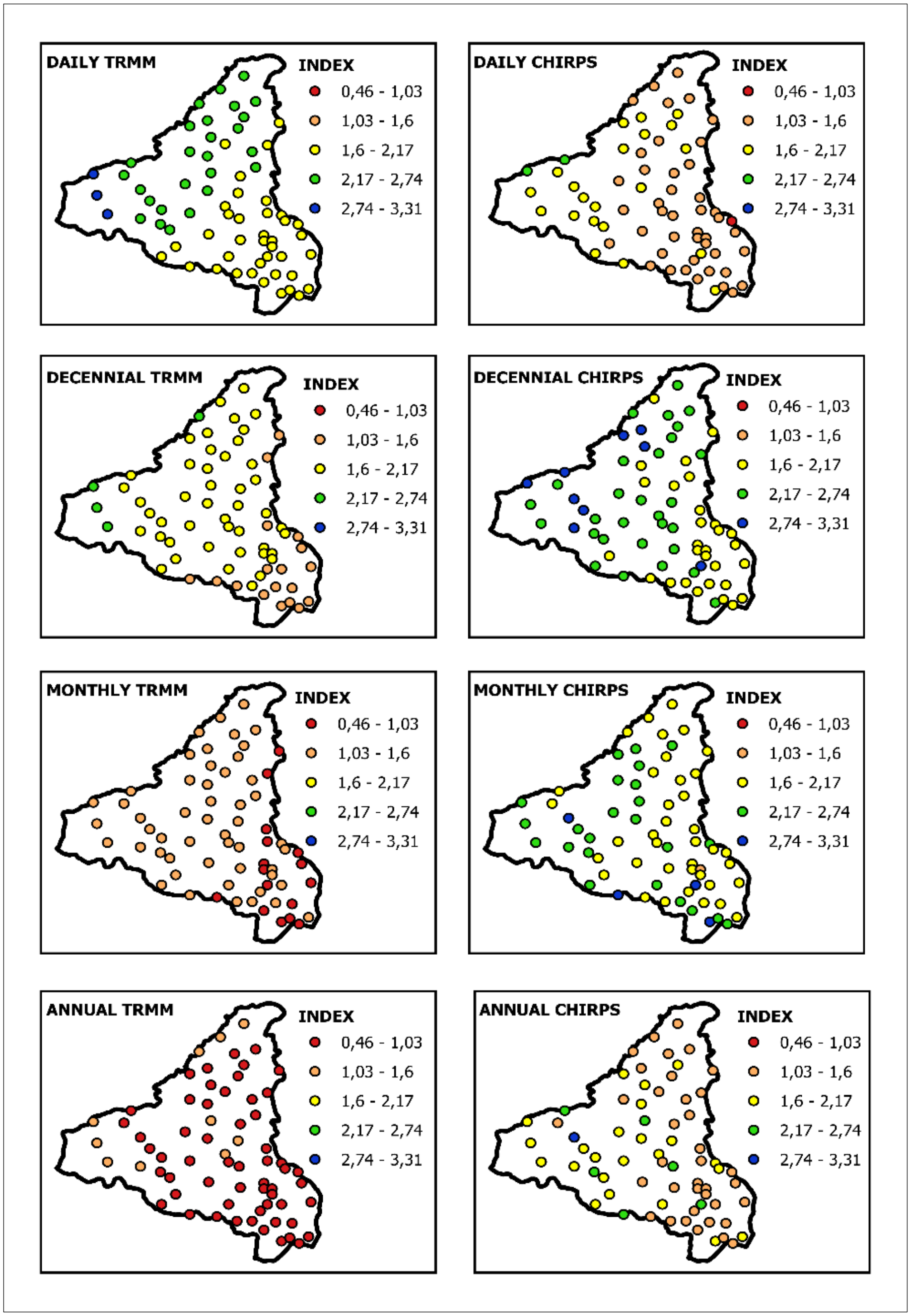

Figure 6**.** Spatial distribution of the index of precipitation estimates relationships between remote sensing products and those detected at rain gauge stations at daily, decadal, monthly, and annual time scales

The best indices, ranging from 2.74 to 3.31 (represented by the color blue), were found at the following rain gauge stations: stations 43, 44, and 45 (daily TRMM); stations 8, 11, 12, 31, 33, 34, 43, 46, and 58 (decadal CHIRPS); stations 33, 51, 58, and 60 (monthly CHIRPS); and station 33 (annual CHIRPS).

Indices lower than 1 (worst correlations, represented by the color red) were found at: station 42 (daily CHIRPS); stations 6, 10, 23, 27, and 42 (monthly TRMM); and stations 4, 5, 6, 8, 10, 13, 14, 15, 16, 18, 19, 20, 21, 23, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 47, 48, 49, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, and 67 (annual TRMM). The coordinates and codes of the aforementioned rain gauge stations can be found in Table 1.

The index also allows for identifying the existence of poor and/or good relationships between nearby rain gauge stations that persist across daily, decadal, monthly, and annual periods. This condition is better observed through the coloration of the rain gauge stations. Based on the works of Li et al. (2013), Dinku et al. (2018), Bai et al. (2018), Li et al. (2019), Ma et al. (2020), and Helmi and Abdelhamed (2023), it is estimated that such a factor is due to the characteristics associated with the temporal and spatial oscillation of precipitation distribution. In this context, it is noted that the area near the coast, where higher precipitation is observed, has the worst relationships for both TRMM and CHIRPS (Figure 6).

Conclusions

According to the results presented in this research, regarding the performance of the estimated precipitation, the TRMM did not perform well at any of the studied time scales. On the other hand, with r=0.88, RMSE=31.0, and NSE=0.76 (monthly scale), and r=0.87, RMSE=144.96, and NSE=0.71 (annual scale), the precipitation estimates generated by CHIRPS were representative for the Baixo SF region.

Regarding underestimations and overestimations, both products exhibited variations in space and time. With PBIAS ranging from -66.6 to -82.7, the TRMM underestimated the precipitation series. For CHIRPS, the PBIAS results (-33.5 and 33.3) indicated both underestimations and overestimations.

From a spatial distribution perspective, the best results for both TRMM and CHIRPS were found towards the boundary of the Submédio region (northwest), while the worst results were identified in the area near the coast. Concerning the topographical aspect, the products performed better at altitudes ranging from 400 to 700 m.

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