



Revista Brasileira de Geografia Física

Homepage: <https://periodicos.ufpe.br/revistas/rbgf>



Validation of the CHIRPS precipitation estimate in a Brazilian Savanna Basin

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Artigo recebido em 14/06/2023 e aceito em 18/09/2023

ABSTRACT

Measuring and understanding precipitation over space and time is essential for several human activities. Satellite remote sensing products are presented as an alternative to the low-density network of pluviometric stations. The objective of the present study was to evaluate precipitation estimates obtained by the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product, from 1981 to 2020, in the Rio Grande basin, Bahia state, Brazil. This watershed has about 75,000 km², is inserted in one of the most active agricultural frontiers in the world and has undergone significant changes in land use and occupation and changes in rainfall patterns. We compared data from 11 series of conventional and CHIRPS, derived surface stations on monthly and seasonal scales, using statistical metrics – relative bias (BIAS), correlation coefficient (R^2), mean error (ME), and mean squared error (RMSE) – and categorical – correct proportion (PC), probability of detection (POD), frequency bias index (FBI), false alarm (FAR). Results showed that the CHIRPS estimates provided good responses compared to the data observed – most values greater than: $R^2 > 0.9$; $NES > 0.86$; $PBIAS \pm 10$. The CHIRPS was accurate in detecting rainfall and estimated events, especially those at the pre and post rainy season and in the rainy season itself, according to the values of the correct proportion (PC ~ 1) and frequency bias index (FBI ~ 1). False alarms were detected in the dry season. The CHIRPS exhibits an adequate ability to represent space-time precipitation variation.

Keywords: precipitation products; validation; remote sensing.

Validação das estimativas de precipitação do CHIRPS em uma bacia hidrográfica do cerrado brasileiro

RESUMO

Medir e compreender a precipitação no espaço e no tempo é essencial para diversas atividades humanas. Os produtos de sensoriamento remoto por satélite apresentam-se como uma alternativa à baixa densidade da rede de estações pluviométricas. O objetivo do presente estudo foi avaliar as estimativas de precipitação obtidas pelo produto *Climate Hazards Group InfraRed Precipitation with Station data* (CHIRPS), de 1981 a 2020, na bacia do rio Grande, Bahia, Brasil. Esta bacia hidrográfica tem cerca de 75 mil km², está inserida em uma das fronteiras agrícolas mais ativas do mundo e tem passado por mudanças significativas no uso e ocupação do solo e alterações nos padrões de chuvas. Comparamos dados de 11 séries de estações de superfície convencionais com as estimativas do CHIRPS, em escalas mensais e sazonais, usando métricas estatísticas – viés relativo (BIAS), coeficiente de correlação (R^2), erro médio (ME) e erro quadrático médio (RMSE) – e categóricas – proporção correta (PC), probabilidade de detecção (POD), índice de polarização de frequência (FBI), alarme falso (FAR). Os resultados mostraram que as estimativas do CHIRPS forneceram boas respostas em comparação com os dados observados com a maioria dos valores superiores a: $R^2 > 0,9$; $NES > 0,86$; $PBIAS \pm 10$. O CHIRPS foi preciso na detecção de chuvas e eventos estimados, especialmente aqueles ocorridos antes e depois da estação chuvosa e na própria estação chuvosa, de acordo com os valores da proporção correta (PC ~ 1) e do índice de polarização de frequência (FBI ~ 1). Alarmes falsos foram detectados na estação seca. O CHIRPS apresentou capacidade adequada de representar a variação espaço-temporal da precipitação.

Palavras-chave: produtos de precipitação; validação; sensoriamento remoto.

Introduction

Precipitation is one of the most critical components in the global water and energy cycles. However, precisely measuring precipitation has been challenging due to its significant space-time variations (Tang et al., 2015). Correctly measuring precipitation is essential not only for meteorologists and climate scientists but also for many decision makers, including hydrologists, farmers, emergency managers, and industrialists.

Rainfall data is measured using rain gauges, weather radar, and satellite sensors. While the former provides accurate and timely data, the latter provides spatial data. Conventional rain gauge observations can usually provide the most direct and accurate measurements at a site (Duan et al., 2016; Sun et al., 2018; Salio et al., 2015). However, the global network of rain gauges needs to be adequately distributed (Kidd; Levizzani, 2011). Such instruments still provide punctual and faulty records, which limits their use, in addition to having low rainfall density, irregular station distribution, or even short-term records (Melo et al., 2015; Salio et al., 2015; Xavier et al., 2015; Xavier et al., 2015). Historical datasets from these rain gauges can also be problematic due to their varied availability, completeness, consistency, and availability for near real-time analysis (Kidd; Levizzani, 2011). Such factors limit the use of rain gauges, compromising the understanding of precipitation spatial and temporal & generating uncertain results (Camparotto et al., 2013). The World Meteorological Organization (2008) suggests minimum rainfall densities in various types of physiographic regions – for example, 575 km²/rain gauge for inland plains – and recommends that the number of missing rainfall observations in hydrological modeling should be below 10% in all historical series available.

Tan e Yang (2020) evaluated the impact of rainfall network density and data absence (failures) in hydrological simulations in a Malaysian basin. Among the main results, the distance between pluviometric and fluviometric stations has a considerable impact on modeling; a rate greater than 20% for missing rainfall values would significantly affect tropical flow simulation; lacking precipitation values during the high flow period impacts less than in moderate and low flow periods; having too many missing values in rainfall data would lead to errors in trend analysis.

Remote sensing products are alternative sources to pluviometer networks, as they are easily

accessible while enabling the detection of precipitation variability at high spatial and temporal resolutions (Xie e Xiong, 2011; Tang et al., 2015). However, such information contains non-negligible random errors and biases due to inadequate sampling, algorithm deficiencies, or simply the nature of the estimated data (Sun et al., 2018; Tapiador et al., 2012). For example, sampling and retrieval are the primary error source in satellite-based precipitation estimates (Tang et al., 2015). The sampling error for these authors arises from estimating precipitation for a continuous spatial and temporal domain with measurements in discrete space and time intervals. On the other hand, recovery errors are related to remote sensing procedures involved in converting satellite observations (brightness temperature) into rainfall rates. Recovery errors can be classified as systematic (predictable and consistent error behaviors associated with instrument or algorithm characteristics) and random (stochastic component whose magnitude directly determines the uncertainty).

Several gridded rainfall products have been used for hydrological simulation (Le et al., 2020; Le et al., 2020; Falck et al., 2015; Tuo et al., 2016; Singh Saravanan, 2020a; Singh e Saravanan, 2020b; Song et al., 2020; Strauch et al., 2011; Xue et al., 2013; Viana et al., 2021), drought and aridity studies (Bai, Wu e Wang, 2019; Brasil Neto et al., 2020; Brito et al., 2021; Santos et al., 2021), extreme event analysis (Seyyedi et al., 2015; Herold, Behrangi e Alexander, 2017; Fang et al., 2019), among others. For such applicability, it is necessary to assess whether precipitation Satellite estimates resemble the spatial and temporal variability of pluviometer observations and check their quality, uncertainty, and precision.

Studies have been carried out on the subject of evaluating the performance of spatial precipitation products from different sources and satellites, comparing them with rainfall networks, sometimes validating at least one product, sometimes validating and comparing different products at different spatial scales, such as quasi-global analysis (Sorooshian et al., 2000); West Africa (Satgé et al., 2020); South America (Salio et al., 2015); Latin America (Baez-Villanueva et al., 2018), China (Tang et al., 2018; Gao, et al., 2018; Liu et al., 2019; Sun et al., 2016); Iran (Sharifi et al., 2016; Darand et al., 2017); Indonesia (Liu et al., 2020); Malaysia (Tan e Santo, 2018); Italy (Duan et al., 2016); Pakistan (Arshad et al., 2021);

Ethiopia (Gebremedhin et al., 2021); South Sudan (Basheer e Elagib, 2019); Argentina (Rivera et al., 2018); Brazil (Melo et al., 2015; Cavalcante et al., 2020; Paredes-Trejo et al., 2017; Pereira et al., 2013; dos Santos et al., 2020).

Among the various datasets of precipitation estimated by satellites or from satellite data in association with other sources, we highlight the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), Tropical Rainfall Measuring Mission (TRMM), The Integrated Multi-satellite Retrievals for GPM (IMERG), Climate Prediction Center morphing method (CMORPH) and the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Sorooshian et al., 2000; Huffman et al., 2007; Sharifi, Steinacker and Saghaian, 2016; Joyce et al., 2004; Funk et al., 2015). CHIRPS stands out for its long data series, from 1981 to the present. CHIRPS is used for long-term trend analysis and supports the United States Agency for International Development Famine Early Warning System Network (Gao et al., 2018). It should be noted that CHIRPS is not a satellite or orbital sensor but a product generated from several data sources, including TRMM and surface stations (Funk et al., 2015). The results show that CHIRPS performs satisfactorily in almost all studies and better than other datasets in many cases (Cavalcante et al., 2020). However, the following limitations were identified in studies in Brazil: overestimation of low precipitation events and underestimation of extreme events (>100 mm/month), not being indicated for drought monitoring in some cases (Paredes-Trejo et al., 2017; Torres-Batló and Martí-Cardona, 2020; Cavalcante et al., 2020). The results of de Paredes-Trejo et al. (2017) also suggest that the CHIRPS performance depends mainly on the terrain features, biomes, and dominant convective precipitation systems. Carvalho (2020) also highlights limitations related to the non-continuous availability of anchor stations used in the calculation of the product due, for example, to instrument breakage and non-repairs, in addition to the fact that stations may no longer be maintained for political and/or budgetary reasons.

Paredes-Trejo et al. (2017) validated monthly rainfall CHIRPS data for Northeast Brazil using the 'point-by-pixel' technique and 21 rainfall station datasets from 1981 to 2013. The presented results show that CHIRPS data correlate well with the observations from all seasons. However, there is a tendency to overestimate low values and

underestimate high rainfall values above 100 mm/month. Among the evaluated biomes, the Cerrado presented the best overall performance.

Dos Santos et al. (2020) evaluated seven precipitation estimation methods in the Brazilian semiarid region from 1983 to 2013 on a monthly scale. First, they selected 560 rainfall stations in two subsets. The first subset modeled the spatial structure producing a continuous surface with a spatial resolution of 0.05° , and the second subset evaluated rainfall estimates. Three remote sensing products were used - CHELSA, CHIRPS, and PERSIANN - and four interpolation methods were applied to make rain gauge data continuous - Empirical Bayesian Kriging, Ordinary Kriging, and Inverse Weighted Distance (using powers 1 and 2 - IDW1 and IDW2, respectively). Results analysis used Pearson's coefficients (R), the Nash-Sutcliffe model efficiency (NSE), and the Mean Squared Error (RMSE). CHIRPS showed the best performance in estimating rainfall volumes, which is recommended for studies that use long-term monthly data for the Brazilian semiarid region.

Thus, the objective of this study is to evaluate CHIRPS estimates, on a monthly scale, from January 1981 to December 2020 in the Brazilian cerrado, specifically along the Rio Grande basin, Bahia state, Brazil. In addition, we aim to quantify its suitability to represent spatiotemporal precipitation patterns. Notably, the studies by Paredes-Trejo et al. (2017) and Dos Santos (2020) did not cover our study area. Although these researches allow spatial evaluation of large areas, they often need to prioritize the watershed as a territorial management unit. The relevance of understanding rainfall variability, intensity, and distribution, particularly in the Rio Grande basin, is due to being inserted in one of the world's most extensive active agricultural frontiers, with significant changes in rainfall patterns, land use, and cover.' The area experienced seven years of drought between 2010 and 2020 and, consequently, increased conflicts over natural resources - land and water (Dionizio e Costa, 2019; Pousa et al., 2019; Silva et al., 2021; Paredes-Trejo et al., 2021; Freitas et al., 2022)

Material and methods

Study area

The Rio Grande basin is located in the western part of Bahia state, Brazil, between coordinates $-10^\circ10'$ and $13^\circ20'S$ of latitude and $43^\circ08'$ and $46^\circ37'W$ of longitude. It is in the São Francisco River's middle course, covering an area

of approximately 75,000 km² (Figure 1). This basin is part of a broader region called MATOPIBA (an acronym formed by the states of Maranhão, Tocantins, Piauí, and Bahia), one of the most active agricultural frontiers in the world. The area has significantly increased rainfed, irrigated agricultural production and livestock activities (Dionizio and Costa, 2019).

The Rio Grande is one of northeastern Brazil's main São Francisco River tributaries. Its area includes the Caatinga and Cerrado biomes, with part of its territory in the Brazilian semiarid region. The basin waters are one of the central

regulators of the São Francisco River middle course flow rate, contributing to approximately 30% (rainy season) to 80% (dry season) of the Sobradinho reservoir effluent flow rates (PBHSF, 2016). The western region of Bahia is one of the most active agricultural frontiers worldwide. The cultivated and irrigated area has been increasing rapidly, as well as water conflicts due to its topographic characteristics and water availability on the surface and underground (Dionizio and Costa, 2019)

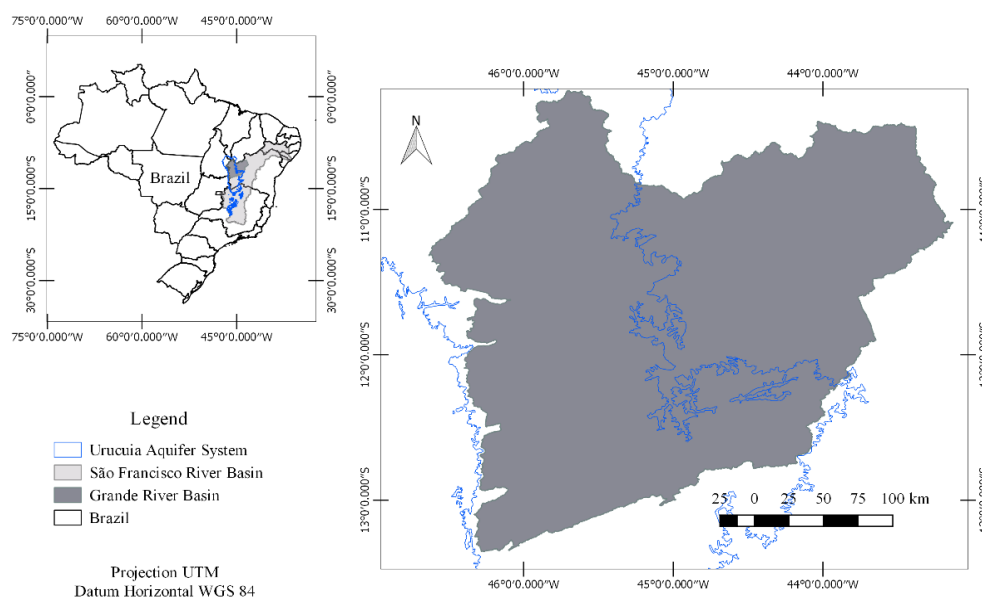


Figure 1 – The Rio Grande watershed location map, Bahia state, Northeast Brazil.

According to Thornthwaite's classification criteria, there are three predominant climate types: humid, in the basin extreme west, where rainfall rates can exceed 1,700 mm per year; subhumid, in the central basin; and semiarid, near the São Francisco River mouth where annual volumes below 800 mm year⁻¹ are observed (Moreira; David, 2010). Therefore, this basin presents significant spatial variability in annual precipitated volumes, especially from east to west. The Rio Grande basin is located within the scope of the Urucua Aquifer System (SAU), with a regime strongly influenced by groundwater's contribution, especially in drought. Its contribution is paramount

for maintaining the São Francisco River flow (Gonçalves et al., 2016).

Datasets

This section briefly describes the estimated rainfall data used in this study, derived from the Climate Hazards Group InfraRed Precipitation with Stations data version 2, CHIRPS, and the available rain gauge data in the Rio Grande basin.

In situ observation dataset

Rain gauge data were obtained from the National Water Resources Information System (SNIRH) through the HIDROWEB platform. Selected Rainfall stations presented a series with

daily data from 1981 to 2020 and failures equal to or less than 10%. The first criterion was established due to CHIRPS data availability, aiming to make series compatibility. Consistent data series was available from 1981 to 2019, the desired period. Therefore, raw data was used, and 11 stations met these criteria. Thus, data from these rain gauges were applied in this study as a reference for comparison with CHIRPS data.

Note that none of the stations selected from SNIRH are part of the stations used in the processing of the final CHIRPS product, available at https://data.chc.ucsb.edu/products/CHIRPS-2.0/diagnostics/list_of_stations_used/monthly/ in the file “global.stationsUsed.2023.04”.

Estimated data set – CHIRPS

CHIRPS is a rainfall dataset that supports the United States Agency for International Development Famine Early Warning Systems Network (FEWS NET). It was designed to monitor agricultural drought and global environmental changes over the Earth. It is based on high-resolution interpolation techniques; long precipitation estimates (from 1981 to present) at daily, pentadal, and monthly levels, with near-global estimates (50°S – 50°N, 180°E – 180°W); and primary spatial resolution of 0.05° (Funk et al., 2015). It is relevant to highlight that CHIRPS is not a satellite or orbital sensor. Instead, it is a product

of several data sources combination, including Climate Hazards Group Precipitation Climatology (CHPclim), satellite-only Climate Hazards Group Infrared Precipitation (CHIRP), Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis version 7 (TMPA product 3B42 v7), and terrestrial observations from different public and private sources.

In the present study, we use the daily CHIRPS product, which has a spatial resolution of $0.25^\circ \times 0.25^\circ$ and was acquired through the following website: <http://data.chc.ucsb.edu/products/>. This resolution was selected because it is sufficient to assess spatial precipitation patterns, considering the basin area. We chose this spatial resolution to the detriment of the study area's size (about 75000 km²) because we intend to use CHIRPS estimates in the future for hydrological simulations with a semi-distributed model. A model with a more refined resolution would imply an increase in computational effort and processing time, aspects that are relevant to the present research.

Figure 2 shows the CHIRPS grid, selected rainfall stations, and the elevation and slope of the Rio Grande watershed. Elevation and slope maps were obtained through the OBahia portal and are available at <http://obahia.dea.ufv.br/#/>.

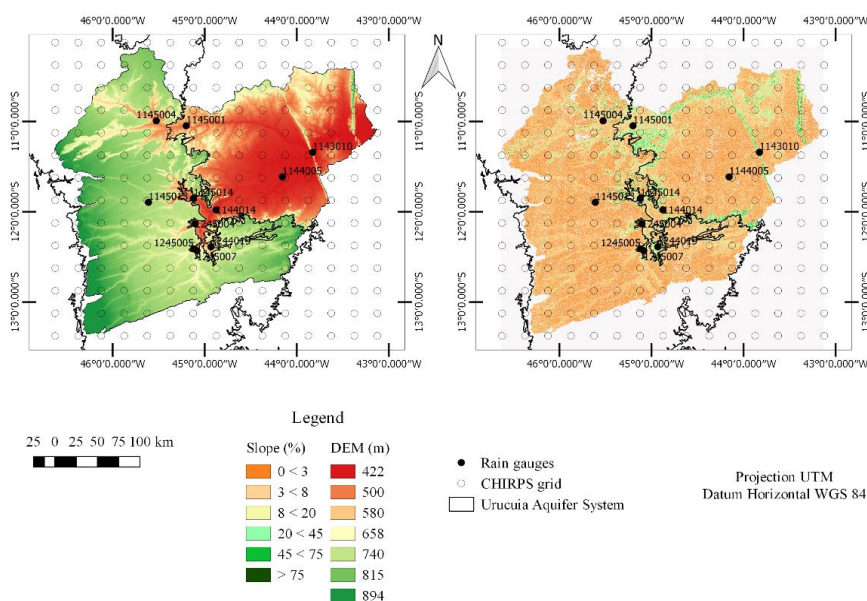


Figure 2 – Elevation, slope, selected rainfall stations, and the CHIRPS grid were used in this study. Source: <http://obahia.dea.ufv.br/layers>.

Validation of estimates

For data validation, the analysis technique known as 'point by pixel' was used, providing a reliable representation of the satellite-obtained product's performance in estimating the spatial precipitation variability (Reis et al., 2017). Cavalcante et al. (2020) claim this technique avoids errors of spatial interpolation of sparsely located and unequally distributed rain gauges. Baez-Villanueva et al. (2018) add that this technique implicitly assumes rainfall stations' representativeness concerning the respective product pixels.

The CHIRPS product validation was based on the general evaluation (continuous statistical metrics) and the ability to detect precipitation (categorical statistical metrics). Several authors have used these methods to validate precipitation products by satellites estimation; for example,

Duan et al. (2016), Gao et al. (2018), Liu et al. (2019), Liu et al. (2020), Abdourahamane (2021) and Wang et al. (2021).

In evaluating continuous statistical metrics, rain gauge, and CHIRPS data were compared monthly according to the statistical parameters presented in Table 1.

Where o_i is the precipitation value measured by the pluviometric station, e_i is the precipitation value estimated by CHIRPS; and $\bar{o}$ is the average precipitation value measured by the pluviometric station.

The R^2 and the r describe the degree of collinearity between the simulated and observed data. r values were then classified as proposed by Hopkins (2000), presented in Table 2.

Table 1 Information on the statistical indices used in this study.

Name	Formulas	Value Range	Perfect values	Unit
Mean error	$EM = \frac{\sum_{i=1}^n (o_i - e_i)}{n - 1}$	$(-\infty, +\infty)$	0	mm
Root Mean Square Error	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (o_i - e_i)^2}$	$[0, +\infty)$	0	mm
Percent Bias	$PBIAS = 100 \times \frac{\sum_{i=1}^n (e_i - o_i)}{\sum_{i=1}^n (o_i)}$	$[0, 1]$	0	%
Nash-Sutcliffe coefficient of efficiency	$NES = 1 - \left(\frac{\sum_{i=1}^n (o_i - e_i)^2}{\sum_{i=1}^n (o_i - \bar{o})^2} \right)$	$[0, 1]$	1	-
Determination coefficient	$R^2 = \left(\frac{\sum_{i=1}^n (e_i - \bar{e})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^n (e_i - \bar{e})^2} \sqrt{\sum_{i=1}^n (o_i - \bar{o})^2}} \right)^2$	$[0, 1]$	1	-
Correlation coefficient	$r = \frac{\sum_{i=1}^n (e_i - \bar{e})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^n (e_i - \bar{e})^2} \sqrt{\sum_{i=1}^n (o_i - \bar{o})^2}}$	$[-1, 1]$	-1, 1	-

Table 2 Classification of correlations according to the r coefficient.

Correlation coefficient "r"	Classes
0,9 - 1,0	Almost perfect
0,7 - 0,9	Very high
0,5 - 0,7	High
0,3 - 0,5	Moderate
0,1 - 0,3	Low
0,0 - 0,1	Very low

Source: Hopkins (2000)

In assessing the capacity of precipitation detection, five categorical statistical metrics were used: proportion correct (PC), probability of detection (POD), frequency bias index (FBI), and false alarm ratio (FAR). PC represents rain detection accuracy; POD stands for the rain detection probability and is described as the "hit" or "true positive" rate; FBI represents the degree of overestimation or underestimation of precipitation detection; FAR shows the proportion of events falsely reported by satellite-based precipitation products, referred as a "false alarm" or "false positive."

While 1 is the perfect value for PC, POD, and FBI, 0 is the perfect value for FAR. These metrics formulas are presented in the equations below:

$$PC = \frac{H+Z}{H+F+M+Z} \quad (\text{Equation 1})$$

$$POD = \frac{H}{H+M} \quad (\text{Equation 2})$$

$$FBI = \frac{H+F}{H+M} \quad (\text{Equation 3})$$

$$FAR = \frac{F}{F+H} \quad (\text{Equation 4})$$

$$\alpha = \frac{(H+M) \times (H+F)}{H+F+M+Z} \quad (\text{Equation 5})$$

Where Z and H are the hits of the CHIRPS estimates; F and M are the errors; F is a false alarm, as shown in the 2×2 contingency table (Table 3).

Table 3 Contingency matrix to assess CHIRPS rainfall detection frequency at monthly time intervals.

	Precipitation measured in situ	No rainfall measured in situ
Rain detected by CHIRPS	H	F
No rain detected by CHIRPS	M	Z

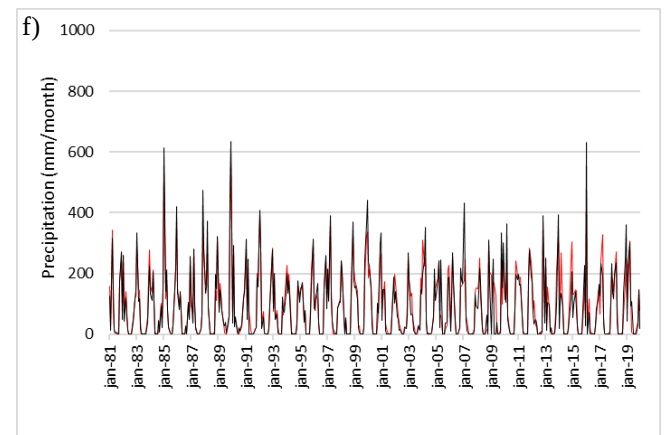
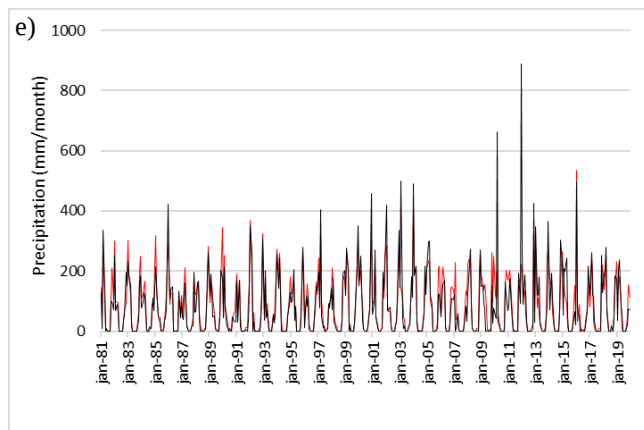
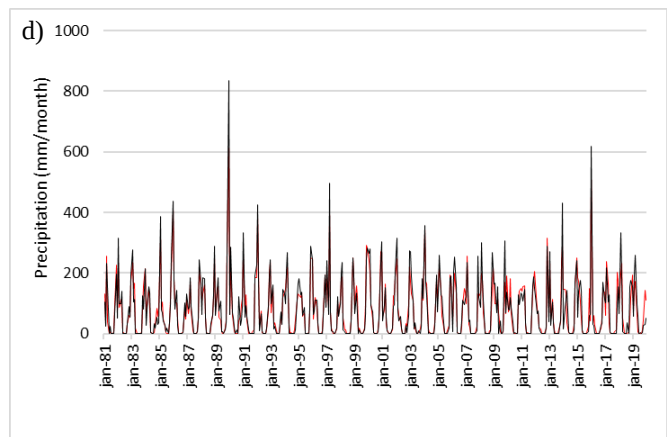
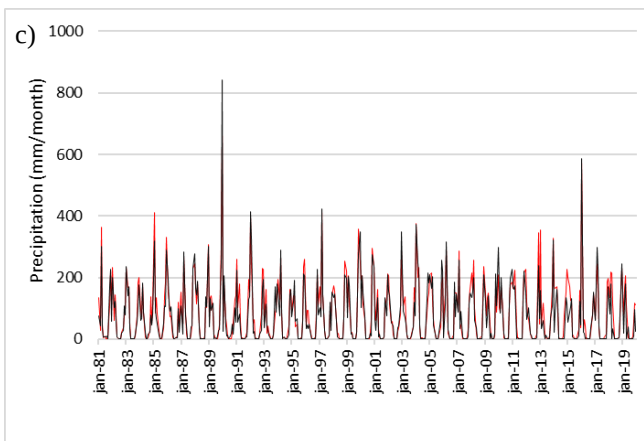
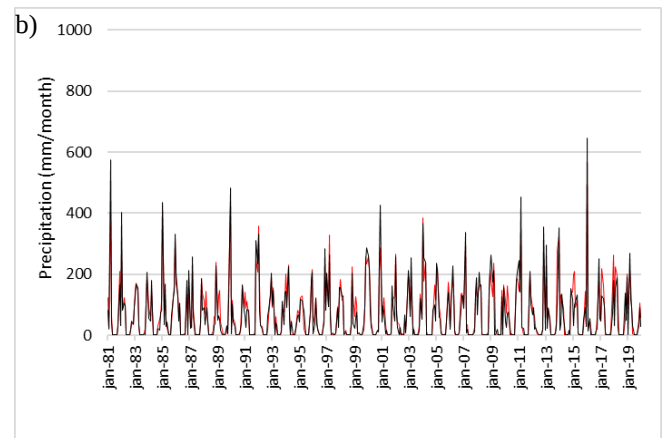
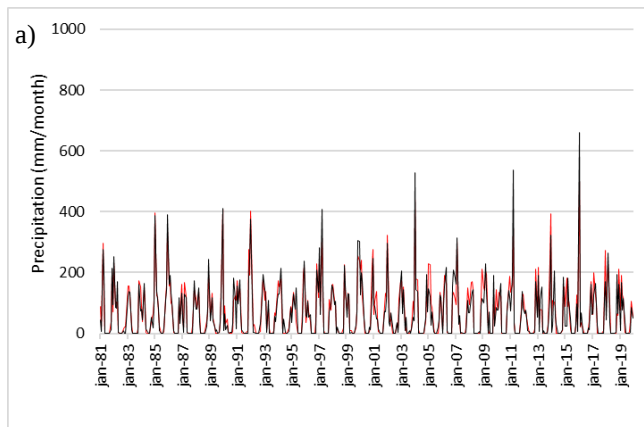
Interpolation of CHIRPS data

In order to spatially represent precipitation patterns along the basin, after validating the CHIRPS monthly precipitation estimates, the averages of 4 different periods were interpolated (1981 – 1990, 1991 – 2000, 2001 – 2010, and 2011 - 2020) using the Inverse Distance Squared Weighting (IDW) method. This method was selected to generate a more continuous spatial surface, allowing better visualization of precipitation in transition zones with different basin land uses.

Resultados e discussão

Statistical metrics

Daily precipitation data estimated by CHIRPS and rain gauges were grouped into monthly accruals. Time series from the rain gauges and CHIRPS estimates are shown in Figure 3. The estimated rainfall faithfully reproduced the seasonal variability, satisfactorily separating dry and rainy periods.



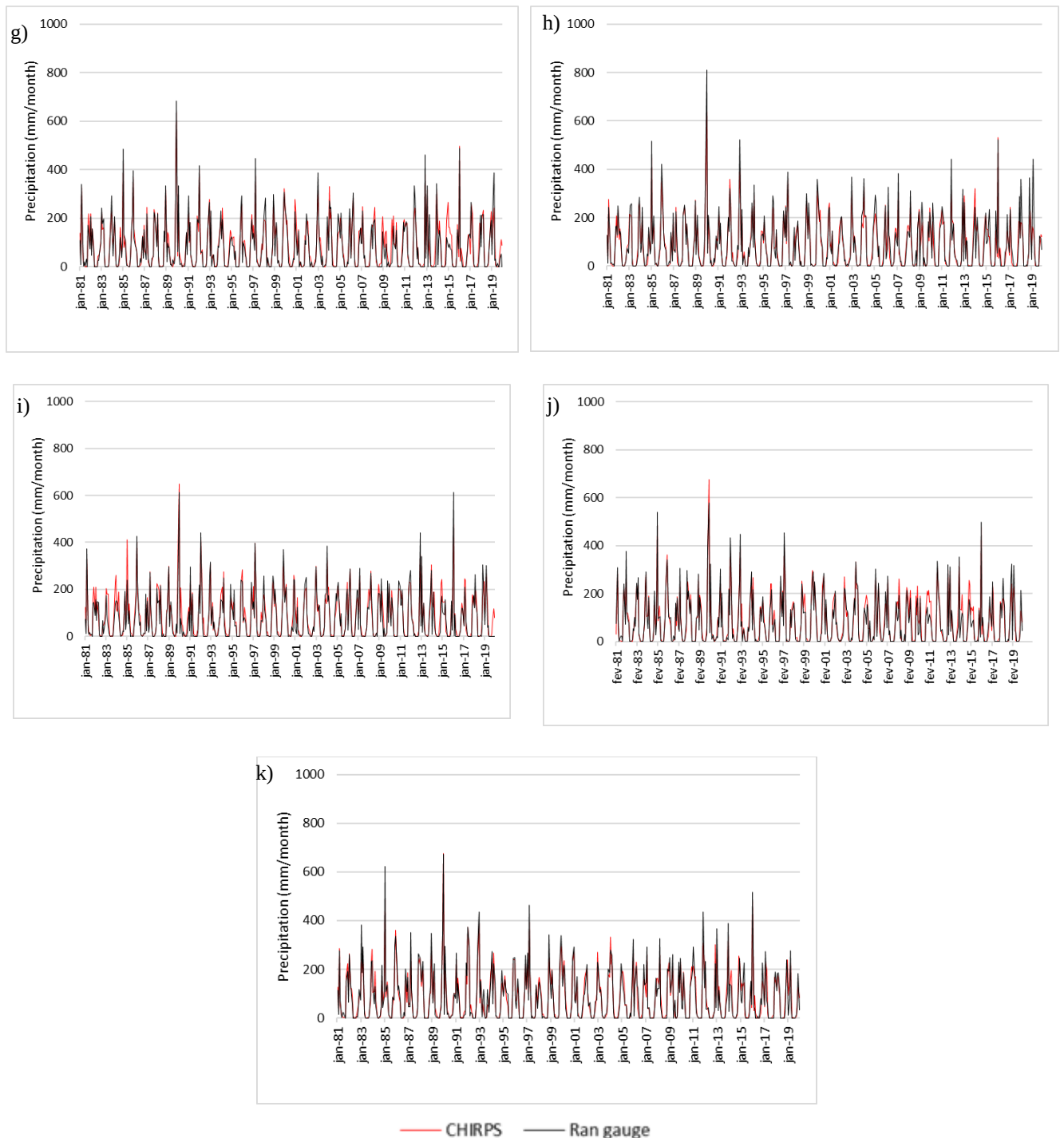


Figure 3 – Precipitation estimated by CHIRPS and observed by rainfall, on a monthly time scale, for the period 1981 - 2020. a) 1143010, b) 1144005, c) 1144014, d) 1145001, e) 1145004, f) 1145013, g) 1145014, h) 1244019, i) 1245004, j) 1245005, k) 1245007

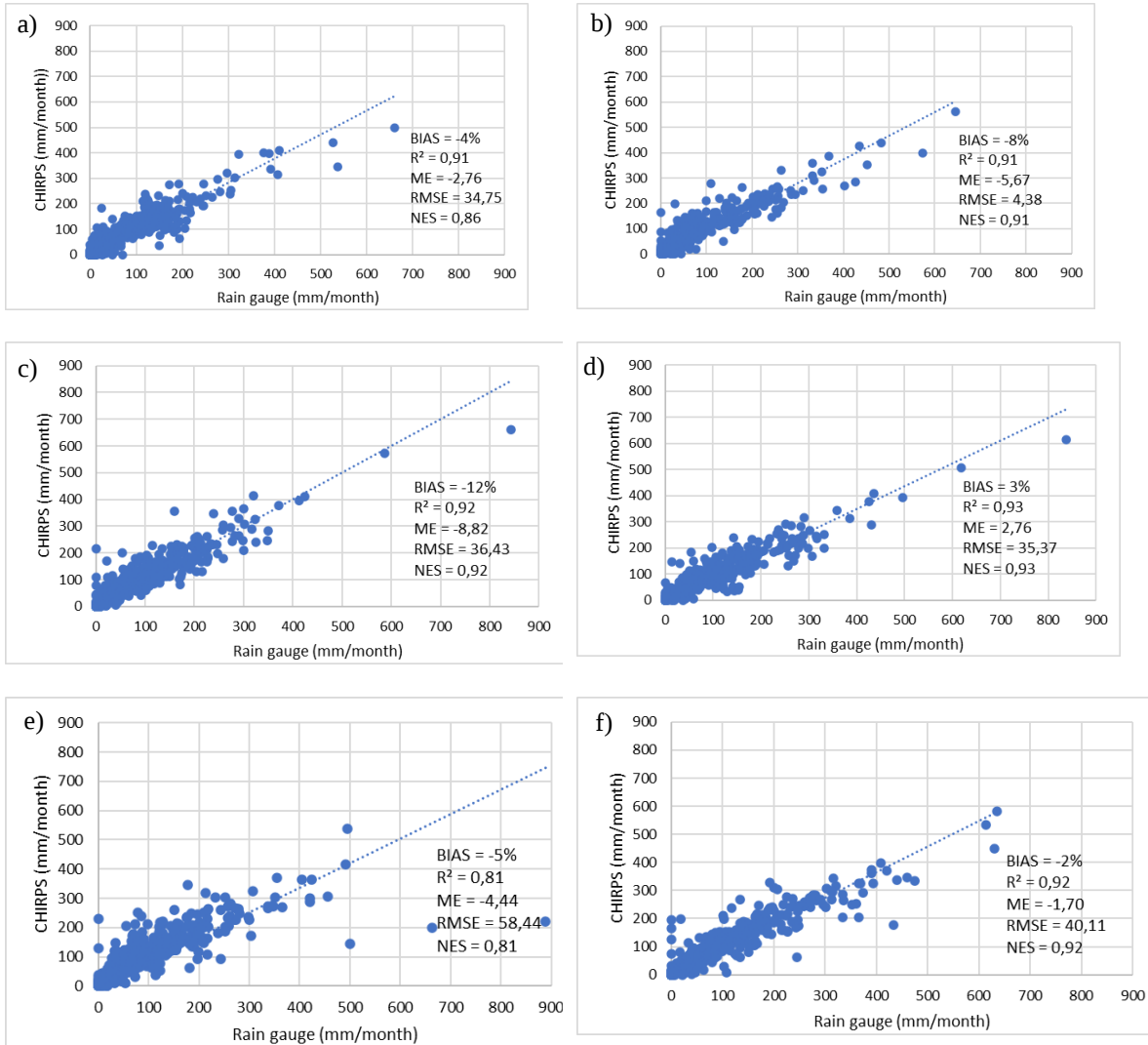
The precipitation values estimated by CHIRPS well represented rainfall behavior in the Rio Grande basin throughout the year under the following conditions: 1) pre and post of the rainy season in October and April, respectively, with

average precipitation volumes between 50 to 80 mm month⁻¹; 2) dry period between May and September with rainfall lower than 20 mm month⁻¹; and 3) rainy season between November and March with average rainfall between 100 and 200

mm month⁻¹ (Figure 4). These seasonality results of precipitation estimates are similar to those of Gonçalves et al. (2020) and Pousa et al. (2019). Furthermore, such studies were carried out in the three basins of western Bahia, including the Rio Grande basin. The results of statistical metrics are shown in Figure 2. Regarding R^2 , the results were greater than 0.90, except for station 1145004, where this value was 0.81, with r of 0.90. Thus, in all seasons, r values were greater than 0.90, classified as "almost perfect" by Hopkins (2000).

Therefore, CHIRPS data showed a strong linear correlation with rain gauge measurements.

In general, CHIRPS satisfactorily estimated precipitation compared to that observed in rain gauges. However, with PBIAS values lower than 10% and NES values greater than 0.75, this product slightly overestimated data in eight (1143010, 1144005, 1144014, 1145004, 1145013, 1145014, 1245004, and 1245005) stations and slightly underestimated in three (1245007, 1244019 and 1245007), according to ME values.



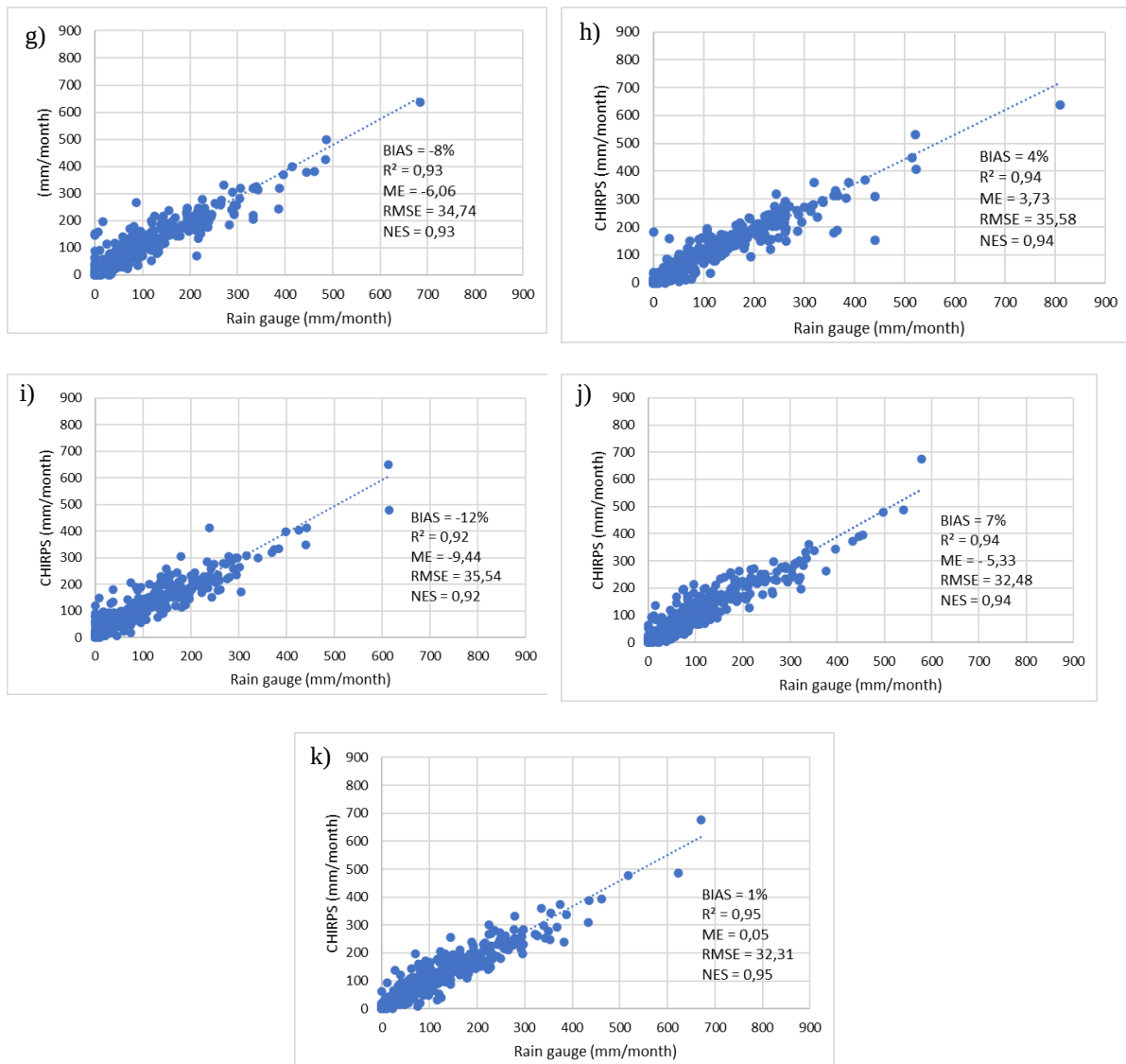


Figure 4 – Statistical metrics of estimated and observed precipitation data on a monthly scale from 1991 to 2019. a) 1143010, b) 1144005, c) 1144014, d) 1145001, e) 1145004, f) 1145013, g) 1145014, h) 1244019, i) 1245004, j) 1245005, k) 1245007.

The BIAS, ME, RMSE, and NES were analyzed in three distinct periods: dry (May to September), pre and post rainy season (October and April, respectively), and rainy (November to March), as shown in Figure 5. In general, the CHIRPS overestimated precipitation at the pre and post rainy season (negative EM values) and in the

rainy season itself. It also underestimated those in the dry period (positive EM values). However, relative differences between the estimated and observed data (BIAS values) for the dry season were higher than for other periods. Regarding the NES, the values were better (greater than 0.75) in the dry and rainy periods.

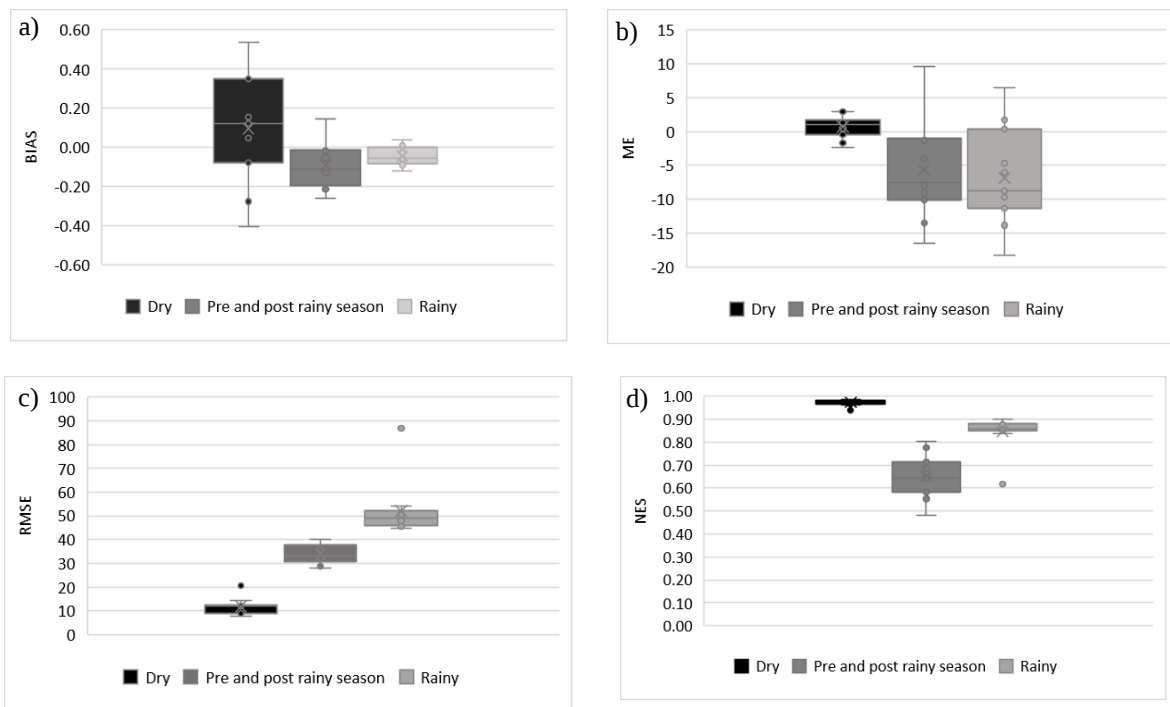


Figure 5 – Statistical metrics of CHIRPS precipitation estimates in the Rio Grande basin – BA. a) BIAS, b) ME, c) RMSE, d) NES.

Categorical metrics

The results of CHIRPS estimates of hits and misses are presented below (Tables 4 and 5). It is observed that this product was correct in just over 80% of the monthly precipitation estimates from 1981 to 2020. More than 80% of these hits were type H, which means it detected rain when there was rain. The other 20% of hits (Type Z, not detecting rain when there is no rain) were exclusively dry (May to September). Most type H hits were in the rainy season (60%), followed by the pre and post rainy season of the rainy season (20%), thus totaling more than 80% of type H hits.

Regarding errors (less than 20%), almost 90% were Type F (CHIRPS detecting rain when the rain gauge did not register it), all practically concentrated in the dry period. It is also noteworthy that the number of errors of this type in the month

before the rains (April) and after the rains (October) was similar – Figure 7. Type M errors (CHIRPS not detecting rain when the rain gauge recorded it) were exclusively in the dry period. Therefore, CHIRPS performed better in the rainy period and worse in the dry period. The highest BIAS values precisely in the dry period are another indication. The highest number of type F errors was observed in September, followed by June. In these two months, an average of 45% of the total type F errors occurred (Figure 6). Most errors occurred in the dry period when the most significant relative differences between estimated and measured values were recorded, as in the BIAS values (Figure 6).

Table 4 Percentage of correct and incorrect CHIRPS estimates.

Station	Hits	Misses	Hits		Misses	
	Z + H	F + M	Z	H	F	M
1143010	85%	15%	19%	81%	68%	32%
1144005	85%	15%	18%	82%	68%	32%
1144014	83%	17%	20%	80%	86%	14%
1145001	83%	17%	16%	85%	94%	6%
1145004	85%	15%	18%	82%	87%	13%
1145013	82%	18%	16%	84%	84%	16%
1145014	87%	13%	16%	84%	89%	11%
1244019	84%	16%	15%	85%	91%	9%
1245004	85%	15%	16%	84%	92%	8%
1245005	81%	19%	12%	88%	91%	9%
1245007	83%	18%	16%	84%	98%	2%

Z: Hit, rain not detected in the rain gauge, and CHIRPS

H: Hit, rain detected in the rain gauge and CHIRPS

F: error, rain detected only by CHIRPS (false alarm)

M: Error, rain detected only by rain gauge

Table 5 – Number of hits and misses of CHIRPS estimates by period.

Hits and misses	Period	Types of hits and misses	1143010	1144005	1144014	1145001	1145004	1145013	1145014	1244019	1245004	1245005	1245007
Hits	Full time	Z	75	79	62	75	65	67	62	64	47	64	62
	Dry	Z	75	79	62	75	65	67	62	64	47	64	62
	Pre and post rainy	Z	0	0	0	0	1	0	0	0	0	0	0
	Rainy	Z	0	0	0	0	0	0	0	0	0	0	0
	Full time	H	333	321	338	334	329	349	340	343	341	332	340
	Dry	H	61	50	65	61	57	74	71	68	72	59	64
	Pre and post rainy	H	72	73	74	74	74	77	73	76	72	74	76
	Rainy	H	200	198	199	199	198	198	196	199	197	199	200
Misses	Full time	F	49	69	75	62	72	57	71	67	84	82	74
	Dry	F	41	60	68	55	64	52	60	62	73	75	70
	Pre and post rainy	F	8	7	6	6	6	3	7	4	8	6	4
	Rainy	F	0	2	1	1	2	2	4	1	3	1	0
	Full time	M	23	11	5	9	14	7	7	6	8	2	4
	Dry	M	23	11	5	9	14	7	7	6	8	2	4
	Pre and post rainy	M	0	0	0	0	0	0	0	0	0	0	0
	Rainy	M	0	0	0	0	0	0	0	0	0	0	0

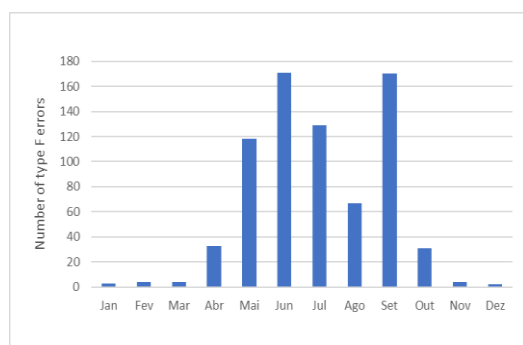
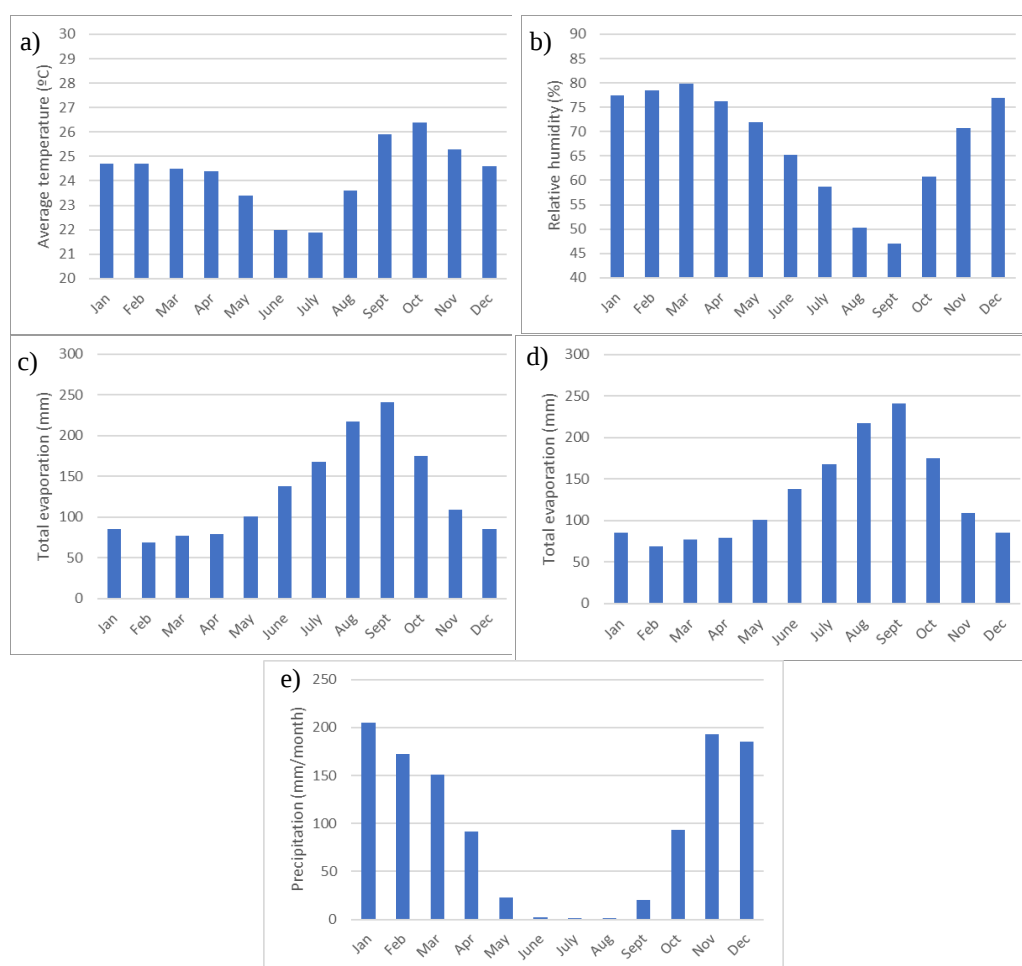


Figure 6 – Number of F-type errors over the months

Among the reasons for false alarms observed in the dry period, rain gauge precision in quantifying light rains stands out. Although the reason is that rain can evaporate from the collector or bucket, which can affect measurements concerning other instruments, they are also subject to other errors, such as lower uptake induced by wind, air temperature, and moisture loss (Adam

Lettenmaier, 2003; Tapiador et al., 2021; Tang et al., 2018).

The climatological normals of station 83236, managed by the National Institute of Meteorology (INMET) and located in Barreiras – BA, inserted in the Rio Grande basin, are presented in Figure 7. From May to September, we observed that the dry period presents increasing total evaporation values, higher values of atmospheric pressure, and the lowest relative humidity values, with higher temperatures registered in September and October. Precipitation is characterized by values below 25 mm/month between May and September, pre and post rains in October and April, respectively, with rainfall close to 100 mm/month and the rainy season between October and March with values between 100 and 200 mm. /month. Therefore, such climatological characteristics can affect measurements of rain gauges and thus justify false alarms identified by CHIRPS.



Source: National Institute of Meteorology Figure 7 – Climatological standards of the INMET station located in the city of Barreiras – BA: a) Monthly average temperature; b) Relative air humidity; c) total evaporation; d) Atmosphere pressure; e) Precipitation.

It is also essential to highlight errors resulting from estimating precipitation per area compared to those measured by pluviometers. Wood et al. (2000) compared weather radar estimates with a dense rain gauge network in the Brue catchment in Somerset, England. They observed that standard precipitation error based on a single rain gauge is about 33% at a grid pixel of 2×2 km, with rainfall rates of 4 mm in 15 minutes. Jensen and Pedersen (2005), when comparing the precipitation obtained using radar (500 x 500 m) with nine rain gauges spatially distributed in the pixel. The magnitude of variation in accumulated precipitation observed in these points was relatively high. Measured values indicate up to 100% variation between neighboring rain gauges within the pixel over four days. Villarini et al. (2008) suggested that more than 25 rain gauges are needed to reduce the average precipitation error to within 20% of the actual rainfall in a ~ 200 km²

pixel on the 15 min time scale. Therefore, the mismatch between the continuous accumulation of point-scale gauge observations and instantaneous satellite precipitation consistently impacts the assessment results.

Regarding categorical indicators, CHIRPS was accurate in detecting rainfall and estimated events, especially those at the pre and post rainy season and in the rainy season itself, according to the values of the correct proportion (PC ~ 1) and frequency bias index (FBI ~ 1), respectively (Figure 8). Furthermore, CHIRPS performed excellently in the probability of detecting rain, even in the dry period, with a POD value close to 1. However, the proportion of falsely reported events was significantly higher in the dry period, when FAR values were between 0.40 and 0.56. In the other periods, FAR values were lower than 0.1.

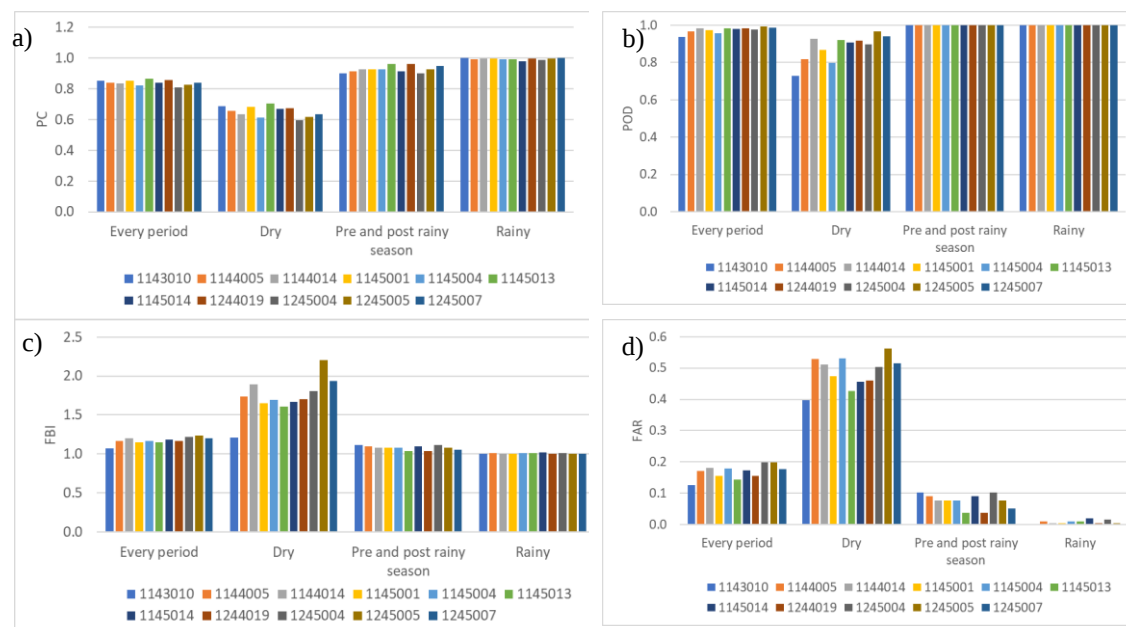


Figure 8 – Categorical metrics: a) correct proportion (PC), b) probability of detection (POD), c) frequency bias index (FBI), and d) false alarm rate (FAR).

Considering only statistical indices, CHIRPS performs better in the dry period (except for BIAS). However, categorical indices show this period as the worst performance. The lowest ME and RMSE values in dry period estimates occur because precipitation events are scarce and of smaller magnitudes, which leads to lower statistical errors and, consequently, higher NES values. High

precipitation values in the rainy season make errors more notable in the same proportion. On the other hand, categorical metrics measure hits and misses, not their magnitudes, thus highlighting the need for a joint analysis of statistical and categorical metrics.

Interpolation

Data from the average annual cumulative values of different periods (1981 – 1990, 1991 – 2000, 2001 – 2010, and 2011 – 2020) of the CHIRPS estimates were interpolated using the inverse squared distance (IDW) (Figure 9). A variability mainly distributed in the east-west direction was observed in all four periods. Higher

values of annual precipitation were detected in the west (typical values of the seasonally dry tropical climate) and lower values in the east (typical values of the semiarid climate). These results corroborate with those observed by Pousa et al. (2019), Montovani et al. (2019), Mutti et al. (2020), Vieira et al. (2021), Correia Filho et al. (2022).

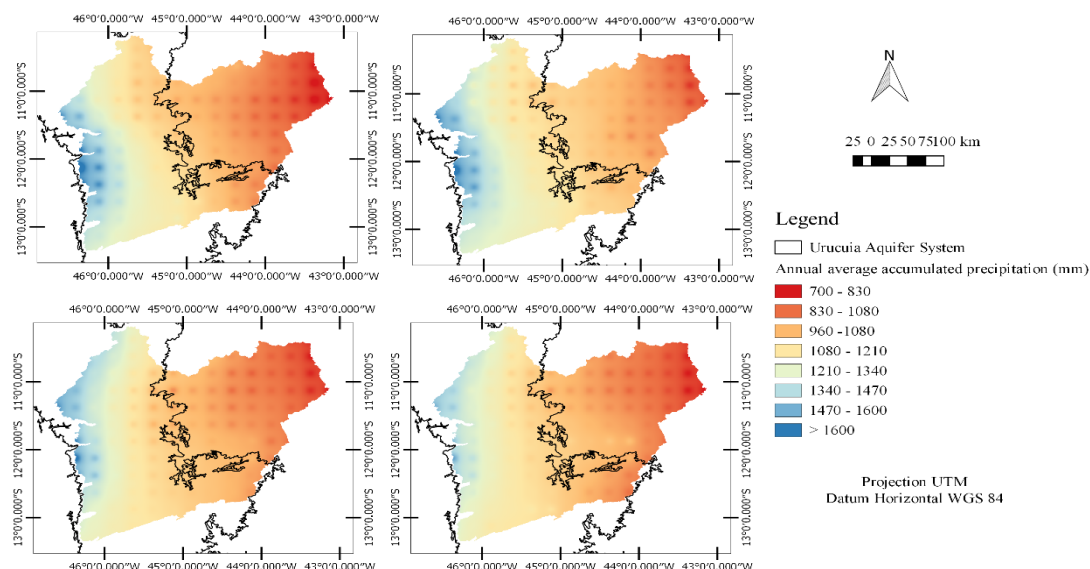


Figure 9 – Interpolation of CHIRPS precipitation estimates in the Rio Grande – BA basin for 1981 – 1990, 1991 – 2000, 2001 – 2010, and 2011 – 2020.

Like Pousa et al. (2019), CHIRPS estimates showed that precipitation isohyets move from east to west, detecting reductions in regional precipitation. Such authors evaluated the precipitation data of basins in the West of Bahia state from 1980 to 2015. They observed a rupture trend in 1992, with a statistically significant average reduction of about 12% (165 mm year⁻¹) from 1993 to 2015 compared to 1980-1992. The authors also observed reductions in river flows across the entire spectrum of the permanence curve, attributing such results to changes in watersheds due to anthropogenic effects, climate change, and low-frequency climate variability.

Silva (2020) evaluated rainfall from 1985 to 2017 and its relationship with deforestation in the MATOPIBA region. Regarding the historical precipitation series in the Rio Grande basin, a downward precipitation trend was observed in all historical series in the rainy and dry periods and the dry-rainy transition. The results also showed strong statistical significance and moderate correlation

between variables (change in land use, occupation, and seasonal precipitation trends) in more and less anthropized areas.

Mutti et al. (2020) validated rainfall data from the Climate Research Unit TimeSeries (CRU TS) over the São Francisco River basin. They evaluated its main climatological characteristics compared to observed data from rain gauges from 1942 to 2016. For the Sub-Medium region São Francisco, where the Rio Grande basin is located, the rainfall data estimated by the CRU TS were reliable, identifying significant decreasing trends in rainfall, with 2012 as the point of change in trend.

Vieira et al. (2021) evaluated trends in associations between atmospheric pressure variability and circulation patterns that occur over the Urucua Aquifer System (SAU) region and, therefore, over much of the Rio Grande basin. Precipitations from September 1973 to August 2006 were correlated with the Atlantic Multidecadal Oscillation (AMO), the El Niño South Oscillation (ENSO), and the Pacific Decadal

Oscillation (PDO). In addition, a correlation was observed between monthly and annual precipitation with the AMO index. The results were statistically significant, with no correlation between PDO, ENSO, and precipitation over the Sistema Aquífero Urucuia (SAU).

Changes in annual precipitation volumes detected by CHIRPS estimates and also observed by Pousa et al. (2019), Montovani et al. (2019), and Vieira et al. (2021), especially in the SAU area, may compromise recharges and alter surface water flows in the Rio Grande, São Francisco, and Tocantins river basins. The SAU is primarily responsible for maintaining the flows of the São Francisco River in the dry seasons. However, differences in duration and amplitude in pre-1980 cycles with significant changes in river baseflow thresholds indicate that such flows can change widely over time. In addition, a more significant contribution was detected in the western and central portions of its tributaries, where the greatest thicknesses of the aquifer system are found (Gonçavel et al., 2017).

The combined effects of possible changes in the rainfall regime, land use, occupation, and increased water demands, especially for grain production, intensified by climate change, may impact hydrological cycle components, compromise ecosystem services and intensify conflicts over water resources.

Conclusion

The present study focused on validating the Climate Hazards Group InfraRed Precipitation with Station data along the Rio Grande basin with monthly precipitation data for the recent 39-year years (1981 – 2020). Then, on a monthly scale, CHIRPS data from the $0.25^\circ \times 0.25^\circ$ grid were compared with data from rain gauges using the "point-by-pixel" technique.

Data from 11 rain gauges were selected and compared with CHIRPS values using statistical, categorical metrics and interpolating CHIRPS data using the IDW method. The correlation between the two precipitation datasets was rated "excellent" (R^2 greater than 0.81 and therefore r greater than 0.90).

The CHIRPS precipitation estimates provided good responses to rain gauge observed data. Additionally, CHIRPS was excellent at detecting the presence and absence of rain in the pre- and post-rainfall and also in the rainy season. However, in the dry season, it detected rain when not recorded by rain gauges, presenting a false

alarm exclusively in the dry season, mainly in June and September.

Therefore, CHIRPS accurately detected rain and presented a good probability of detecting these events, even in dry periods. In addition, CHIRPS exhibits an adequate ability to represent space-time precipitation variation, indicating a decrease in precipitation over the decades in the studied basin.

Acknowledgments

This study was supported by the Foundation for Science and Technology of the State of Pernambuco – FACEPE, through the postdoctoral fellowship of the second author (BFP-0044-3.01/20) and the National Council for Scientific and Technological Development – CNPq, through the Universal Announcement Project (431980/2018-7), BRICS project (442335/2017-2) and the fifth author's Productivity and Research grant (313392/2020-0).

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