Revista Científica
Vol. 36, No. 05 (Especial), pp. 63-74/Noviembre 2023

ISSN-E 1995-9516
Universidad Nacional de Ingeniería

http://revistas.uni.edu.ni/index.php/Nexo
http://dx.doi.org/10.5377/nexo.vXXiXX.XXXX

Validation of chirps gauge – satellite based rainfall dataset over Nicaragua, 2011 - 2021

Validación del conjunto de datos de precipitación chirps para Nicaragua, 2011 - 2021

Jassy D. Rivera Solís[1,*], Edwin. A. Ojeda Olivares[2], Francisco E. Chamorro Blandón[1]

[1] Facultad de Tecnología de la Construcción. Universidad Nacional de Ingeniería. Managua, Nicaragua.
[2] Universidad Nacional de Ingeniería. Sede Juigalpa. Juigalpa, Nicaragua.
[*]jdrs1988@gmail.com

(recibido/received: 15-mayo-2023; aceptado/accepted: 01-agosto-20223)

ABSTRACT

Rainfall is a key input for many weather and climate numerical models. Therefore the strong need to have a dense enough monitoring network for this parameter. Satellite-based rainfall products have emerged in recent decades as an alternative to the more expensive gauge stations. However, a proper validation of such satellite-based products against gauge data must be performed before using their data. This study presents a validation of CHIRPS dataset against gauge data for 17 stations across Nicaragua. The performance of the product was validated at different temporal scales (daily, pentadal, monthly and annual) by different error metrics. A total of six quantitative error metrics was assessed: Bias Percentage (PBIAS), Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Pearson's r and Nash Stucliffe Efficiency (NSE). A total three categorical indices were assessed at daily time scale: Probability of Detection (POD), False Alarm Ratio (FAR) and Critical Success Index (CSI). The results showed that CHIRPS dataset have better performance at monthly and annual time scales, while it is not capable of adequately represent the daily variability.

Keywords: Pentadal; NSE; POD; CSI.

RESUMEN

La precipitación es un dato de entrada clave para muchos modelos numéricos meteorológicos y climáticos. De ahí la necesidad de tener una red de monitoreo lo suficientemente densa para este parámetro. Los productos de lluvia basados en satélites han surgido en las últimas décadas como una alternativa a las estaciones de medición in situ que suelen ser más costosas. Sin embargo, se debe realizar una validación adecuada de dichos productos basados en satélites, con datos de medición antes de poder utilizar sus datos. Este estudio presenta una validación del conjunto de datos CHIRPS contra datos de estaciones in situ para 17 estaciones pluviométricas en Nicaragua. La validación se realizó a diferentes escalas temporales (diaria, pentadal, mensual y anual) mediante diferentes métricas de error. Se evaluaron un total de seis métricas cuantitativas de error: Porcentaje de sesgo (PBIAS), Error Medio (ME), Error Absoluto Medio (MAE), Error Cuadrático Medio (RMSE), r de Pearson y Eficiencia de Nash Stucliffe (NSE). Se evaluaron un total de tres índices categóricos a escala temporal diaria: Probabilidad de Detección (POD), Proporción de falsas alarmas (FAR) e Índice de Éxito Crítico (CSI). Los resultados mostraron que el conjunto de datos CHIRPS tiene un mejor rendimiento en escalas de tiempo mensuales y anuales, mientras que no es capaz de representar adecuadamente la variabilidad diaria.

Keywords: Pentadal; NSE; POD; CSI.

1. INTRODUCTION

Rainfall is a key component of the water cycle and one of the most important variables related to atmospheric circulation (Bras, 1996; Chris Kidd and Huffman, 2011). Therefore, it is a primary input when developing different climate and weather numerical models. Long enough records of this variable are necessary to carry out a wide range of studies in many water-related disciplines, such as water resources management, extreme events analysis, climate change, among others (Simpson et al., 2017; Tabari, 2020).

The conventional way to obtain such records is through the installation of rain gauge stations to measure at different time scales. Despite of being considered the most precise way to obtain rainfall records (Paredes-Trejo et al., 2021; Urrea et al., 2016), great challenges arise since reliability of data obtained in this way is especially limited by the spatial coverage given by the number and location of the gauge stations (Sun et al., 2018). In developing countries, particularly, budget limitations make even more difficult to have adequate weather monitoring services which in turn affects these countries' capacity to manage natural resources and related risks (Strigaro et al., 2019).

As an alternative in recent decades have emerged satellite-based monitoring missions which have much better temporal-spatial resolution and at a lower cost. Some of them are purely satellite-derived products, e.g. the Integrated Multi-satellite Retrievals for GPM dataset that is commonly known as IMERG dataset (NASA, n.d.). Others are gauge-satellite derived products which combines on ground station data with satellite-derived products. In the latest category can be mentioned the Climate Hazards group Infrared Precipitation with Stations dataset (CHIRPS), which provides information since 1981 to date (Funk et al., 2015).

While those satellite-based products usually offer a better temporal-spatial resolution when compared to gauge stations, they are prone to biases and systematic errors (Paredes-Trejo et al., 2021). Therefore, the need to validate them against gauge data before their usage for different applications. A first attempt to validate CHIRPS dataset for Nicaragua was made by Castaño et al. (2022), who compared around 100 gauge station data against CHIRPS dataset for the period from 1981 to 2010. However, their study didn't evaluate the satellite product's performance at pentadal and seasonal time scale. This study validates CHIRPS dataset again gauge stations for the period from 2011 to 2021, at daily, pentadal, seasonal, monthly, and annual time scales. A total of six quantitative error metrics and three categorical indices are used for the validation.

2. MATERIALS AND METHODS

2.1. Study area

Nicaragua is located between 11° and 15° North latitude, 83 and 88 West longitude. Some of the main meteorological systems in the country are the Zone of Intertropical Convergence (IZTC), tropical cyclones, El Niño – southern oscillation (ENSO), tropical waves, convection cells, troughs, sea breezes and mountains waves (INETER, n.d.).
Average annual rainfall ranges from 800 mm at some parts of the Pacific region to 5000 mm at the Atlantic region of the country. In the country, there are two well-defined weather seasons: the wet season, which

runs from May to October, and the dry season, from November to April. According to the Koppen classification, there are 11 subtypes or climatic zones in the country (INETER, n.d.).

The rain gauge stations selected for the study are distributed across the country, as depicted in Figure 1 (see also Table 1). It should be noticed that gauge density is very poor in the Caribbean region, when compared to the Pacific region of the country. Although there are many other stations all over the country, only 17 met the criteria of having a continuous record during the period here analyzed.

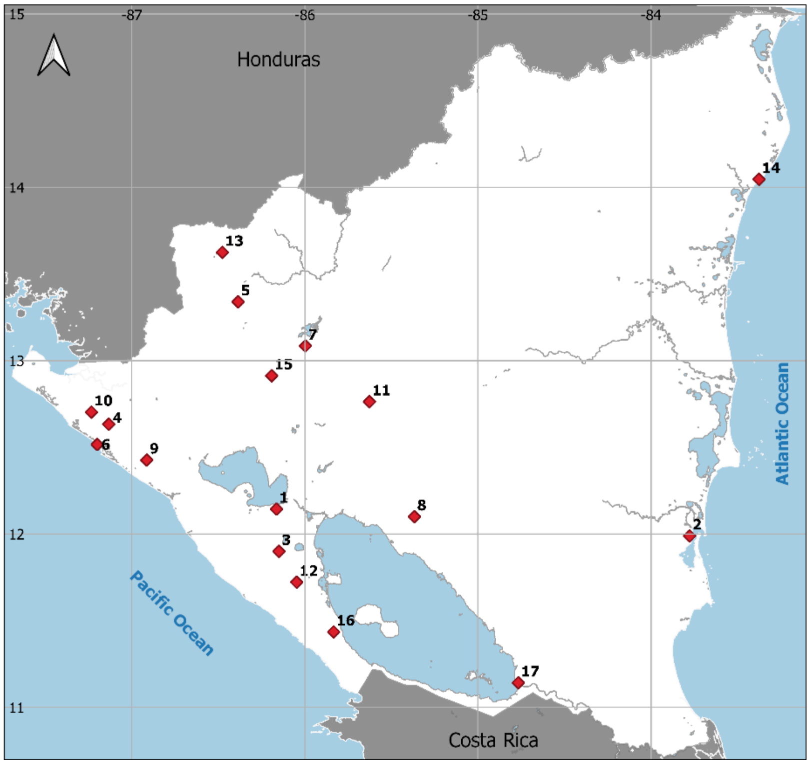

Figure 1. Study area and selected rain gauge stations.
Source: adapted from (Ojeda Olivares and Rivera Solís, 2022).

Table 1. Coordinates of the gauge stations used in this study.

ID	Code	Station	Latitude	Longitude	Elevation (m)
1	69027	Aeropuerto (A.C.S)	12.1433°	-86.1636°	64
2	61006	Bluefields	11.9889°	-83.7764°	9
3	69129	Campos Azules	11.8997°	-86.1497°	466
4	64018	Chinandega	12.6333°	-87.1333°	70
5	45050	Condega	13.3394°	-86.3853°	560
6	64034	Corinto	12.5167°	-87.2000°	4
7	55020	Jinotega	13.0850°	-85.9967°	1033
8	69034	Juigalpa	12.1000°	-85.3667°	85
9	64043	León	12.4267°	-86.9133°	73
10	64036	Monte Rosa	12.7033°	-87.2333°	40
11	55027	Muy Muy	12.7633°	-85.6267°	328
12	69033	Nandaime	11.7217°	-86.0467°	97

13	45017	Ocotal	13.6250°	-86.4767°	608
14	47002	Puerto Cabezas	14.0467°	-83.375°	17
15	69132	Raúl González	12.9133°	-86.1917°	471
16	69070	Rivas	11.4350°	-85.8333°	70
17	69090	San Carlos	11.1417°	-84.7661°	42

2.2. Gauge data preparation

The rain gauges dataset is managed by the Instituto Nacional de Estudios Territoriales (INETER). As a first step the dataset has been quality checked manually. This quality check included not only missing data imputation but also normality and homogeneity tests completion. Since the available variable in all cases was 24 hours accumulated rainfall, the pentadal, monthly and annual totals were determined by summing the daily rainfall values over the corresponding period.

Following the World Meteorological Organization (WMO) recommendations, missing data imputation was performed only when the total missing values was lower than 10 no consecutive days per month, or 5 consecutive days per month (World Meteorological Organization, 2017). The imputed missing values were then used to calculate either pentadal, monthly or annual totals, but they were excluded from the daily time series. Deletion is a valid missing value handling strategy, at the expense of a shorter sample without additional uncertainty associated with using estimated values (Longman et al., 2020).

After missing data filling, normality was examined through the Saphiro – Wilk test. The nonparametric Mann – Kendall trends test was used to verify the homogeneity of the sample, which is presented in (1) and (2). To determine any monotonic trend in a time series, the null hypothesis (H0) of the Mann-Kendall test is that there is no monotonic trend in the series. The alternative hypothesis (H1) is that the data follow a monotonic trend over time.

$$\mathbf{S} = \sum_{\mathbf{k=1}}^{\mathbf{n-1}} \sum_{\mathbf{j=k+1}}^{\mathbf{n}} \mathbf{sgn}(\mathbf{x_j} - \mathbf{x_k}) \tag{1}$$

$$\mathbf{sgn}(\mathbf{x_j} - \mathbf{x_k}) = \begin{cases} \mathbf{+1}, \mathbf{si}(\mathbf{x_j} - \mathbf{x_k}) > \mathbf{0} \\ \mathbf{0}, \mathbf{si}(\mathbf{x_j} - \mathbf{x_k}) = \mathbf{0} \\ \mathbf{-1}, \mathbf{si}(\mathbf{x_j} - \mathbf{x_k}) < \mathbf{0} \end{cases} \tag{2}$$

Where n is the sample size, j > k, k = 1,2, …, n – 1, and j = 2,3, …, n. For n > 8, the value of S is close to that of a normal distribution. Therefore, the variance of S (Var) is calculated as (3).

$$\mathbf{Var}(\mathbf{S}) = \frac{\mathbf{n(n-1)(2n+5)}}{\mathbf{18}} \tag{3}$$

2.2. Validation of CHIRPS dataset.

Group InfraRed Precipitation with Station data (CHIRPS V2.0) dataset was downloaded from the website https://app.climateengine.com/climateEngine. This gauge-satellite based dataset provides information from 1981 to present, with a spatial resolution of 0.05° x 0.05° (5.55 x 5.55 km^2), a quasi – global coverage (50° N – 50° S), and daily, pentadal and monthly temporal resolution (Funk et al., 2015). For every gauge station, its local coordinates were used for the extraction of the corresponding CHIRPS time series.
The temporal scales examined were daily, pentadal (including seasonal segmentation), monthly and annual. The validation was performed by comparing point to pixel statistical metrics, over the studied temporal scales. The six quantitative error metrics used for the validation are described next.

Percent BIAS (PBIAS): with a 0 optimum value, measures the average tendency of the simulated values (Si) to be larger (PBIAS > 0) or smaller (PBIAS < 0) than their corresponding observed ones (Oi). N is the total number of observations available.

$$\text{PBIAS} = 100\,\frac{\sum_{i=1}^{N}(S_i - O_i)}{\sum_{i=1}^{N} O_i} \tag{4}$$

Mean Error (ME): it is the averaged difference between the simulated vector and its corresponding observed vector (true values).

$$\text{ME} = \frac{1}{n}\sum_{i=1}^{n} S_i - O_i \tag{5}$$

Mean Absolute Error (MAE): with a 0 optimum value, can range from 0 to ∞. It measures the average magnitude of the errors in a set of simulated values without considering their direction.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |S_i - O_i| \tag{6}$$

Root Mean Squared Error (RMSE): with a 0 optimum value, can range from 0 to ∞. It is calculated as the standard deviation of the prediction errors (Si – Oi).

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \tag{7}$$

Pearson correlation coefficient (Pearson's r): is the most common way of measuring a linear correlation, with its values ranging from – 1 to 1. It allows to measure not only the strength but the direction of the relationship between the simulated time series and its corresponding observed one. A r with a value of one indicates a perfect positive correlation.

$$r = \frac{\sum_{i=1}^{N}(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{N}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{N}(S_i - \bar{S})^2}} \tag{8}$$

Nash Stucliffe Efficiency (NSE): indicates how well the plot of observed versus simulated data fits a 45° line. Its values range from 1 to negative infinity, with a value of one indicating a perfect fit.

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{N}(O_i - S_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \tag{9}$$

In addition, the detection ability of CHIRPS dataset was also evaluated using three categorical indices (Table 1): the Probability of Detection (POD), the False Alarm Ratio (FAR) and the Critical Success Index (CSI). The POD measures the ratio of observed events correctly detected by the satellite product, i.e., CHIRPS. The FAR measures the ratio of events incorrectly detected by the satellite product that were not really observed. And the CSI is an overall measurement of the satellite product's ability to detect real rainfall events.

Table 2. List of categorical metrics used in this study.

Statistical Index	Formula	Range	Optimum value
Probability of Detection	$POD = \frac{A}{A+C}$	0 to 1	1
False Alarm Ratio	$FAR = \frac{B}{A+B}$	0 to 1	0
Critical Success Index	$CSI = \frac{A}{A+B+C}$	0 to 1	1

Source: (Rachdane et al., 2022)

In Table 1, A corresponds to a rainfall event detected by both the satellite product and the gauge station (hits), B corresponds to a rainfall event detected only by the satellite product (false positives) and C corresponds to a rainfall event detected by the gauge station and missed by the satellite product (misses). These categorical indices were calculated on a daily time scale. A threshold of 3.5 mm/d suggested by Funk et al. (2015) was used as a rain/ no rain threshold.

3. RESULTS AND DISCUSSION

3.1. Pentadal and Seasonal validation

The pentadal time scale is presented first because it is obtained directly from the statistical blending procedure, while the remaining time scales are obtained using the derived pentadal rainfall (Funk et al., 2015). Figure 1 shows a comparison between the pentadal rainfall for both, CHIRPS and Gauges data. It can be observed that the boxes and whiskers itself look very similar one to another, but differences are evident when it comes to the atypical values (maybe associated with extreme events pentads). A few stations show notable different boxes size, i.e., CHIRPS fails to adequately represent their variability. They are Stations 4, 6, 9 and 10, respectively. Such stations are all located over the northern part of the pacific coast of the country, all of them at low elevations (< 70 m).

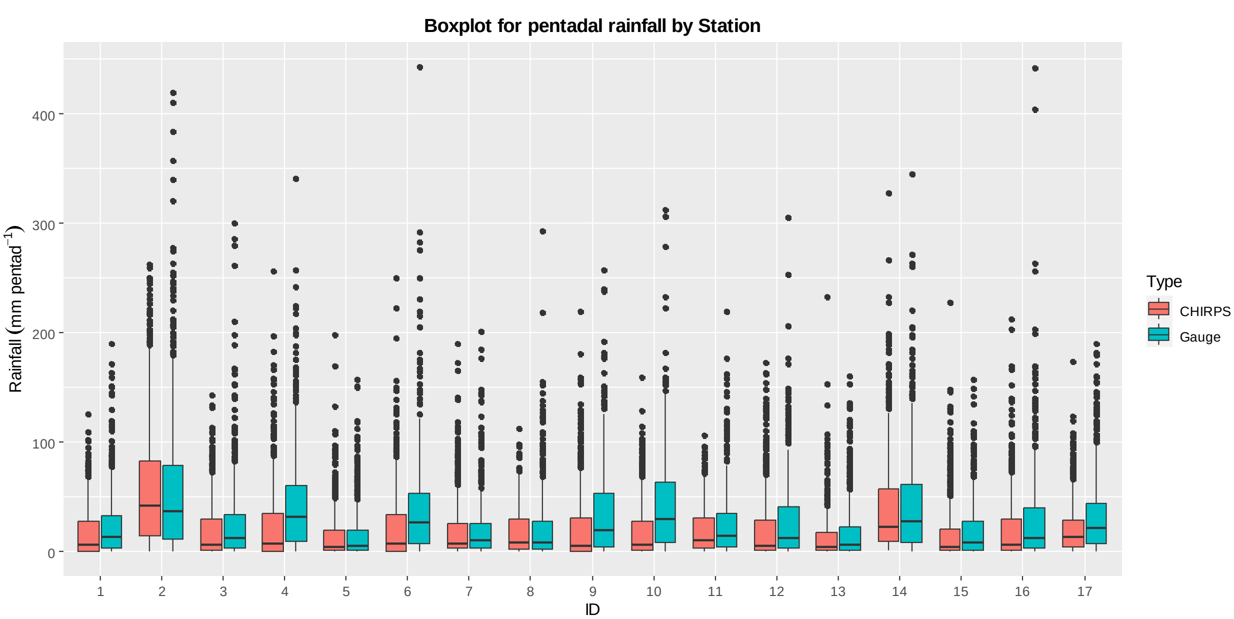

Figure 2. Boxplot comparison for CHIRPS and Gauges pentadal rainfall.

Figure 3 shows the spatial distribution of the quantitative error metrics used for the validation at pentadal scale. For the PBIAS and ME a diverging palette was used, i.e., the light color in the middle is the desired 0 value for these two metrics and the positive/negative extremes are emphasized with dark cold/warm colors. At pentadal time scale, CHIRPS tends to overestimate/underestimate rainfall in mountainous/low-lying coastal areas.

For the rest of the quantitative metrics, a sequential palette was used. Therefore, the light colors correspond to the lowest values of such metrics and the darkest cold colors correspond to their highest values. It can be observed (Figure 3) that the error tends to be higher in the two gauge-stations located at the Caribbean cost of the country (see table 1, IDs 2 and 14). With a tropical monsoon climate (Am type), that is the area of the country where the annual rainfall is maximum (above 4000 mm per year)(INETER, 2005).

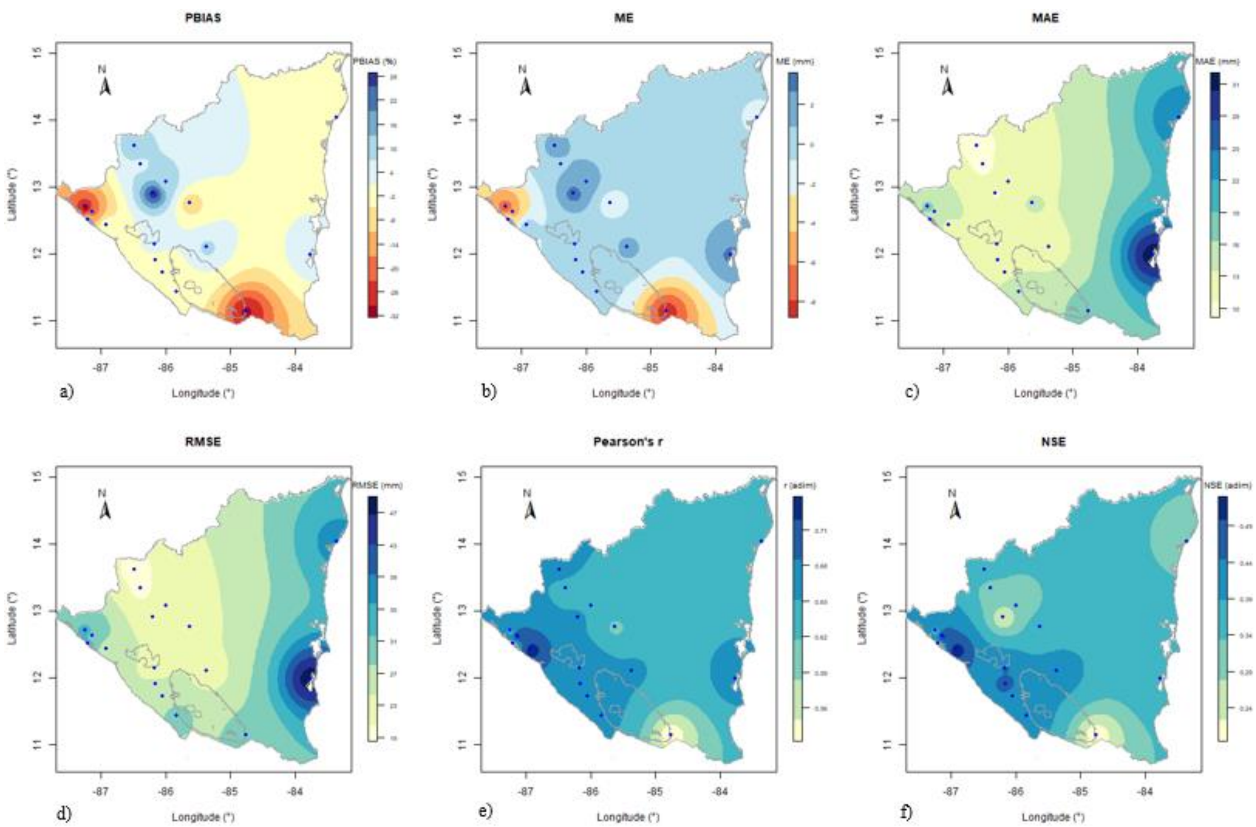

Figure 3. Spatial distribution of the quantitative error metrics at pentadal time scale. a) PBIAS, b) ME, c) MAE, d) RMSE, e) Pearson's r, f) NSE.

The Pearson's r ranges from 0.54 to 0.73, meaning that there is a moderate positive linear correlation between CHIRPS dataset and gauge data. Regarding the NSE, Duc and Sawada (2023) suggest to choose NSE = 0 as a threshold to distinguish between acceptable and not acceptable simulated value. The NSE ranges from 0.19 to 0.53, i.e., it falls into the acceptable performance category.

3.1.1. Seasonal validation

The pentadal data were divided into two subsets per station, one for each of the two well defined seasons in the country. The wet season was defined from May to October, while the remaining months are considered as dry season. The same criteria were followed for all the gauge stations,

although some parts of the country typically have a longer wet season. A better performance of CHIRPS dataset was found during the dry season (
Figure 4 and Figure 5), when compared to the wet season and to the pentadal overall results (see 3.1).

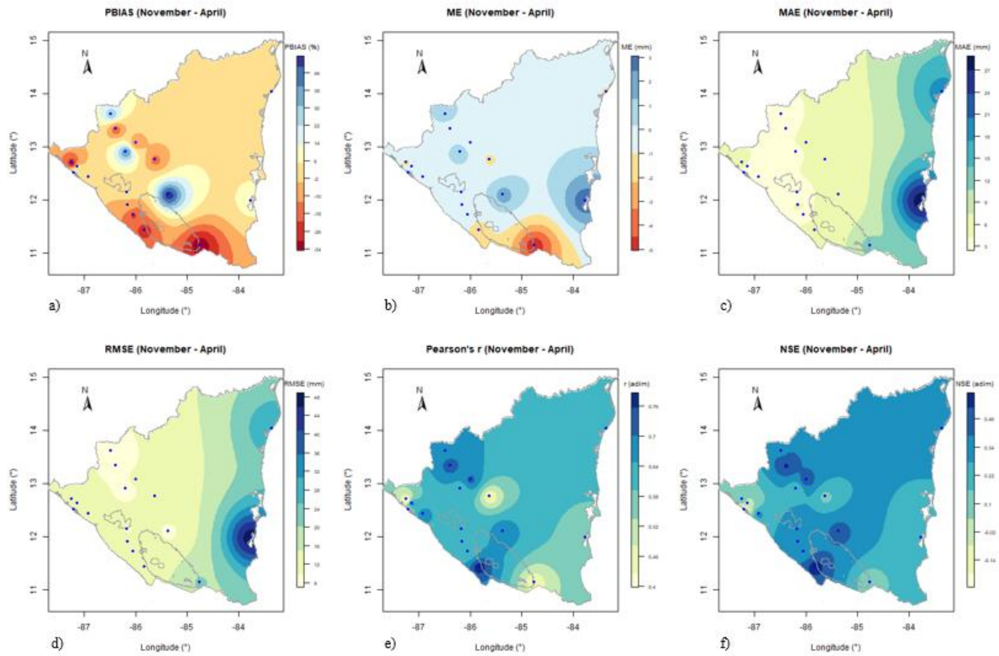

Figure 4. Spatial distribution of the quantitative error metrics at pentadal time scale for the dry season. a) PBIAS, b) ME, c) MAE, d) RMSE, e) Pearson’s r, f) NSE.

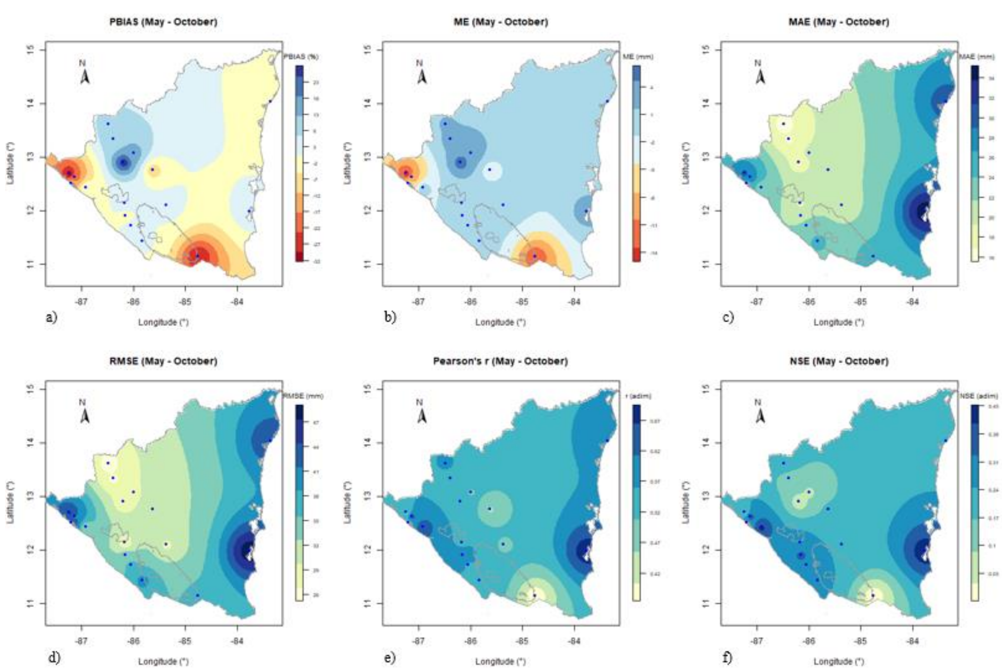

Figure 5. Spatial distribution of the quantitative error metrics at pentadal time scale for the wet season. a) PBIAS, b) ME, c) MAE, d) RMSE, e) Pearson’s r, f) NSE.

3.2. Daily validation

Table 3 shows the resulting error metrics per station at daily time scale. It can be observed that correlation decreases dramatically when compared to its value at pentadal scale. CHIRPS dataset has a weak positive linear correlation with gauge data, with Pearson's r ranging from 0.25 to 0.42. Again, the maximum errors correspond to Stations 2 and 14.

According to the categorical indices, the best value of POD corresponds to Station 2 (POD = 0.64) followed by Station 14 (POD = 0.59). In general, both POD and CSI have relative low values. The results show a median value of 0.46 for the POD and 0.35 for the CSI. The FAR had a median value of 0.41, with Station 7 and 14 having the worst performance for this metric.

Table 3. Error metrics per Station at daily time scale.

ID	**Lat (°)**	**Long (°)**	**PBIAS (%)**	**ME (mm)**	**MAE (mm)**	**RMSE (mm)**	**r (Ndd)**	**NSE (Ndd)**	**POD (Ndd)**	**FAR (Ndd)**	**CSI (Ndd)**
1	12.14	-86.16	4.00	0.12	4.02	10.17	0.33	-0.01	0.40	0.40	0.32
2	11.99	-83.78	5.30	0.57	12.44	25.04	0.36	-0.37	0.64	0.43	0.43
3	11.90	-86.15	-2.90	-0.11	4.69	11.87	0.36	0.05	0.47	0.42	0.35
4	12.63	-87.13	-19.10	-1.00	5.53	13.12	0.42	0.11	0.55	0.32	0.44
5	13.34	-86.39	6.50	0.17	3.52	8.79	0.33	-0.15	0.37	0.46	0.28
6	12.52	-87.20	-9.50	-0.42	5.17	12.85	0.38	0.06	0.48	0.32	0.39
7	13.09	-86.00	8.50	0.29	4.70	10.08	0.34	-0.30	0.44	0.52	0.30
8	12.10	-85.37	9.00	0.30	4.36	9.63	0.32	-0.05	0.42	0.33	0.35
9	12.43	-86.91	0.80	0.03	4.68	11.58	0.42	0.08	0.46	0.30	0.38
10	12.70	-87.23	-14.60	-0.74	5.50	12.92	0.39	0.06	0.52	0.32	0.42
11	12.76	-85.63	-9.80	-0.41	4.90	10.16	0.33	-0.05	0.51	0.47	0.35
12	11.72	-86.05	-0.10	0.00	5.01	12.58	0.32	-0.08	0.45	0.41	0.34
13	13.63	-86.48	10.60	0.25	3.41	8.89	0.30	-0.19	0.36	0.47	0.27
14	14.05	-83.38	-2.60	-0.21	9.31	18.99	0.34	-0.35	0.59	0.50	0.37
15	12.91	-86.19	28.40	0.69	3.65	9.06	0.33	-0.25	0.37	0.40	0.29
16	11.44	-85.83	-1.90	-0.07	4.91	12.07	0.40	0.06	0.44	0.40	0.34
17	11.14	-84.77	-30.30	-1.74	6.10	12.39	0.25	-0.11	0.57	0.44	0.39

Ndd: non-dimensional data

3.3. Monthly and Annual validation

CHIRPS dataset has a strong positive linear correlation at monthly and annual scale correlation (see Table 4 and Table 5). At monthly time scale, an outstanding improvement in r and NSE is found. The Pearson's r ranges from 0.74 to 0.91, while NSE ranges from 0.41 to 0.75.

At annual time scale, Pearson's r still shows a strong positive linear correlation for most of the stations (r ranging from 0.46 to 1.00). But some negative values of NSE arise, meaning that those stations fall into the non-acceptable performance category.

Table 4. Error metrics per Station at monthly time scale.

ID	Lat (°)	Long (°)	PBIAS (%)	ME (mm)	MAE (mm)	RMSE (mm)	CC (Ndd)	NSE (Ndd)
1	12.14	-86.16	4.00	3.68	31.83	55.87	0.86	0.73
2	11.99	-83.78	5.30	17.43	117.29	162.74	0.74	0.48
3	11.90	-86.15	-2.90	-3.37	39.47	67.72	0.86	0.74
4	12.63	-87.13	-19.10	-30.35	55.84	91.31	0.88	0.74
5	13.34	-86.39	6.40	5.11	27.76	58.15	0.81	0.52
6	12.52	-87.20	-9.50	-12.81	50.50	97.74	0.80	0.62
7	13.09	-86.00	9.60	10.07	37.55	54.62	0.88	0.70
8	12.10	-85.37	8.70	8.83	40.56	56.71	0.86	0.73
9	12.43	-86.91	0.80	0.97	35.94	59.11	0.91	0.83
10	12.70	-87.23	-16.20	-23.84	47.62	82.49	0.89	0.77
11	12.76	-85.63	-9.80	-12.44	44.88	64.33	0.81	0.63
12	11.72	-86.05	0.60	0.70	46.97	75.57	0.84	0.68
13	13.63	-86.48	10.50	7.72	30.62	56.04	0.81	0.57
14	14.05	-83.38	-2.50	-5.86	78.72	110.52	0.74	0.41
15	12.91	-86.19	28.30	21.17	35.82	63.20	0.85	0.49
16	11.44	-85.83	-1.90	-2.28	43.01	73.68	0.87	0.75
17	11.14	-84.77	-30.30	-52.88	67.08	95.20	0.78	0.43

Table 5. Error metrics per Station at annual time scale.

ID	Lat (°)	Long (°)	PBIAS (%)	ME (mm)	MAE (mm)	RMSE (mm)	CC (Ndd)	NSE (Ndd)
1	12.14	-86.16	6.00	64.11	130.81	156.70	0.80	0.56
2	11.99	-83.78	5.30	209.11	381.19	450.19	0.70	-0.28
3	11.90	-86.15	-2.90	-40.45	207.73	260.12	0.69	0.46
4	12.63	-87.13	-18.80	-357.60	439.40	478.74	0.72	-1.05
5	13.34	-86.39	-2.60	-25.61	74.75	80.81	0.91	0.81
6	12.52	-87.20	-10.80	-172.24	262.93	332.61	0.79	0.39
7	13.09	-86.00	7.60	92.14	172.63	223.67	0.73	0.17
8	12.10	-85.37	10.10	114.15	164.79	208.90	0.71	0.27
9	12.43	-86.91	0.20	2.39	97.91	115.00	0.88	0.72
10	12.70	-87.23	-18.40	-394.80	394.80	395.38	1.00	-0.60
11	12.76	-85.63	-9.80	-149.33	221.36	280.21	0.62	-0.11
12	11.72	-86.05	-5.00	-67.47	194.76	205.08	0.71	0.40
13	13.63	-86.48	1.00	8.23	100.38	127.49	0.81	0.66
14	14.05	-83.38	-3.40	-97.00	385.26	532.67	0.46	-0.79
15	12.91	-86.19	31.60	282.40	282.40	316.08	0.88	-0.60
16	11.44	-85.83	-1.90	-27.35	154.69	191.26	0.90	0.78
17	11.14	-84.77	-30.30	-634.51	634.51	653.75	0.82	-4.63

4. CONCLUSIONS

CHIRPS dataset was validated against gauge stations at 17 different locations (stations) for Nicaragua. In terms of the different error metrics used for the study, the dataset showed a better performance at monthly and pentadal time scales. CHIRPS dataset's performance at daily time scale resulted poor, with low positive linear correlation against gauge data. While there was strong positive correlation between CHIRPS and gauge data at annual time scale, some stations appeared to have negative NSE values.

Regarding the pentadal seasonal validation, CHIRPS dataset showed better performance for dry season. No additional seasonal validation was performed, but it might be worth to further investigate it for the annual time scale as well.

Finally, CHIRPS dataset seems to be prone to underestimation in low-lying coastal regions and overestimation in mountain regions. It can be concluded that CHIRPS dataset might be useful for some applications at monthly and annual time scales, preferably at inland regions. Nevertheless, still further studies should be performed to better characterize the dataset's skill to fully represent the climate variability in Nicaragua.

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