Engenharia Agrícola

ISSN: 1809-4430 (on-line)

www.engenhariaagricola.org.br

Scientific Paper
Doi: http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v44e20240009/2024

REFERENCE FLOWS ESTIMATES USING DATA FROM REMOTE SENSING IN RIVER BASINS IN THE MATOPIBA, BRAZIL

Helio L. Araújo[1*], Sergio N. Duarte[1], Fernando C. Mendonça[1], Ronalton E. Machado[2], Marco A. Jacomazzi[3]

[1*]Corresponding author. Escola Superior de Agricultura "Luiz de Queiroz" - USP/Piracicaba-SP, Brasil.
E-mail: heliopiassaba@alumni.usp.br | ORCID ID: https://orcid.org/0000-0001-5762-519X

KEYWORDS

Water permits, satellite data, water balance.

ABSTRACT

The MATOPIBA, encompassing parts of the states of Maranhão, Piauí, and Bahia, as well as the entire state of Tocantins, is an expanding agricultural region characterized by water resource management challenges. The availability of water in the hydrographic basins of this region plays a fundamental role in sustaining agricultural activities and preserving local ecosystems. Remote sensing information was used to estimate the flow in 32 hydrographic basins sited in the MATOPIBA region. For this purpose, precipitation and evapotranspiration variables obtained from TerraClimate using the Google Earth Engine (GEE) platform, were considered to calculate monthly, annual, and long-term simplified water balances. To verify the performance of the remotely sensed flow data, the results were compared with those of the Agência Nacional de Águas e Saneamento Básico (ANA), using statistical performance parameters. The results showed that the estimates of long-term and annual mean flows were better than monthly ones. These findings reveal that the simplified water balance done long-term using remote sensing satisfactorily determines mean streamflow in the hydrographic basins of the study area.

INTRODUCTION

Water resource management consists of a set of actions aimed at guaranteeing a sustainable water supply to the population and its economic activities (Lopes et al., 2022). According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the frequency and intensity of precipitation events has increased since 1950, due to the escalating climate changes caused by human activity (IPCC, 2023). Fluvial water flow is an important component of the global hydrological cycle essential for understanding flood risks, water management, ecology and climate. However, the collection of observational flow data is a challenging and expensive task, which limits this information's availability in many regions. Remote sensing is a promising flow estimation tool, which can provide high-resolution spatial and temporal data (Dai et al., 2009).

The territorial delimitation of MATOPIBA was officialized by Federal Decree No. 8.447, June 6 of May 2015, by the Agricultural and Livestock Development Plan (PDA), also giving rise to the MATOPIBA Regional Development Agency by the Ministry of Agriculture, Livestock and Supply (MAPA). Digital Elevation Models (DEM) are powerful tools to estimate hydrographic parameters the latter being used in a variety of hydrological models. One of the main advantages of using GIS programs in hydrological analysis is the ability to estimate spatial connectivity between river basins (Bastawesy et al., 2009). Information obtained through the analysis of conventional maps or remote sensing data (such a photographs, satellite images and radars) reveal a close

[1] Escola Superior de Agricultura "Luiz de Queiroz" - USP/Piracicaba-SP, Brasil.
[2] Faculdade de Tecnologia – Unicamp/Limeira-SP, Brasil.
[3] Rasa (água, solo, ambiente)/Piracicaba-SP, Brasil.

Area Editor: Samuel Beskow
Received in: 1-17-2024
Accepted in: 10-1-2024

relationship between the hydrological pattern and the basins' physical characteristics, making knowledge of these elements very useful (Dixon et al., 2022).

The hydrological community has developed various methodologies for estimating fluvial water flow. Such methodologies use available data from river gauges to build hydrological models that simulate river basins flows (Belvederesi et al., 2022; Manke et al., 2022). Satellites can continuously estimate fluvial water balances under all climate conditions and provide long-term information with sufficient data sources to estimate flows (Lou et al., 2022).

This study aims to estimate the flow based on precipitation and evapotranspiration, extracted from data obtained through remote sensing, using the water balance equation in 32 hydrographic basins of MATOPIBA, at monthly, annual and long-term intervals.

MATERIAL AND METHODS

The research was conducted in the MATOPIBA region (a combination of the acronyms of the states of Maranhão, Tocantins, Piauí and Bahia) (Figure 1). The climate is humid tropical with winter dry *(Aw)*, according to the Köppen-Geiger classification, with monthly temperatures ranging from 25 to 27°C and with mean annual rainfall from 800 to 2.000 mm, spread over two seasons: the dry season (May to September) and the rainy season (October to April) Aquino et al. (2005).

The region encompasses the Cerrado (91%), Amazon (7.3%) and Caatinga (1.7%) biomes, with its natural vegetation cover formed predominantly by savannas (63.6%), transition areas (15%) and deciduous seasonal forest (10.7%). In terms of topography, 47.9% are flat areas (<3% slope) and the remaining 33.7% gently undulating (3% to 8%). Soil variety is considerable: predominantly Latosols (31.1%) and Argisols (12.8%), Petric plinthosols (8.7%), Quartzarenic oritic neosols (8.7%) and Lithic neosols (7.2%); with Argillic and Haplic plinthosols (3.9%), Gleissols (1.0%) and Planosols in the lower areas (0,9%) (Bolfe et al., 2016).

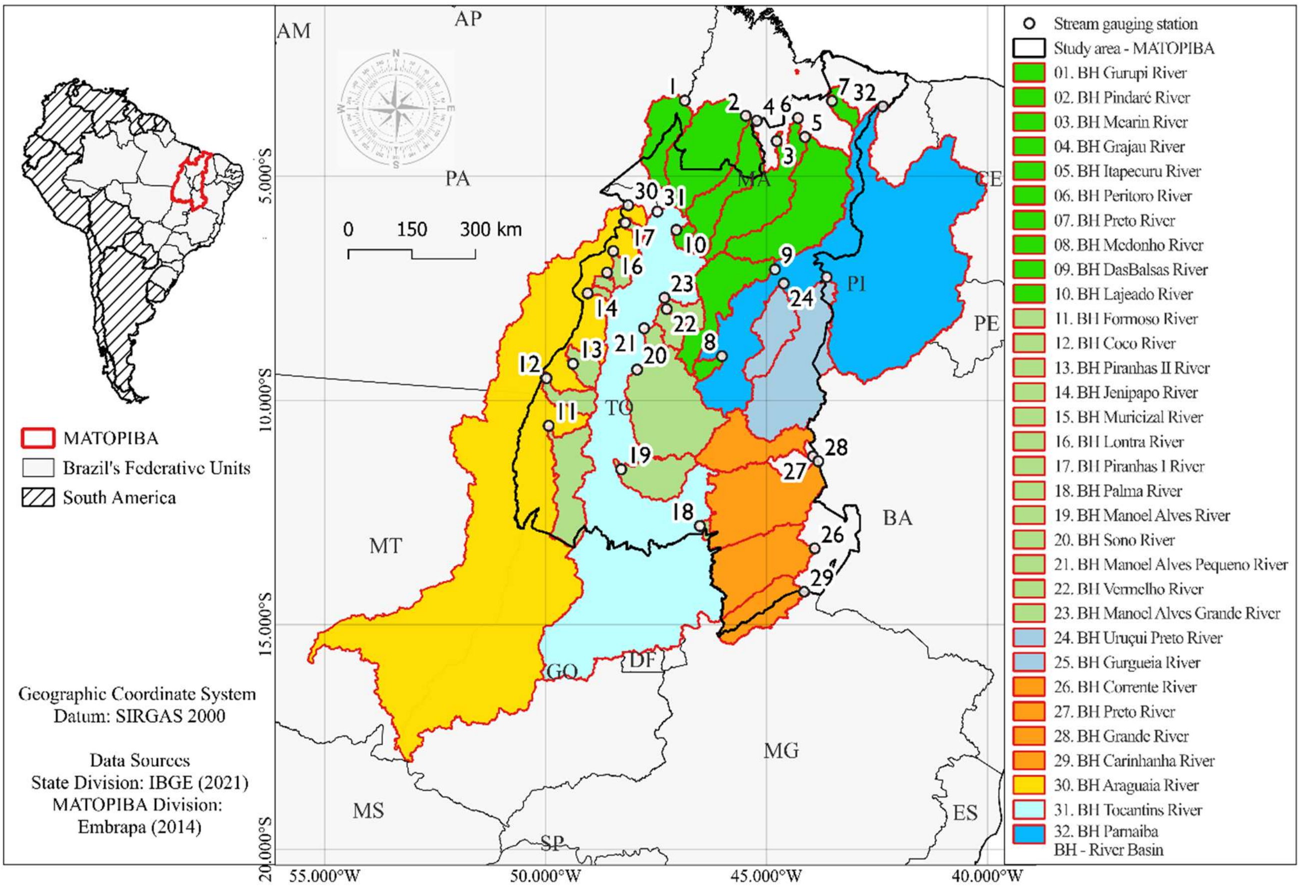


FIGURE 1. Study area location comprising 32 river basins within the MATOPIBA region.

All basins were separated within Earth Engine Apps (GEE), using the following criteria: availability of fluviometric data from the ANA at its mouth from 2001 to 2020 which was the period of the consistent and uninterrupted fluviometric series (Table 1).

TABLE 1. River basins characteristics estimated by remote sensing: elevation, basin area and actual evapotranspiration. Mean flow measured by ANA during the 2001-2020 study period.

Station code	Watershed	Elevation (m)		Basin area (km^2)	Mean rainfall (mm)	Mean actual evapotrans-piration (mm)	Mean flow ($m^3\ s^{-1}$)
		Min	Max				
32540000	1 - Gurupi River	59	451	16.088,37	140,85	89,37	26,26
33190000	2 - Pindaré River	6	469	35.122,93	116,40	87,23	32,49
33290000	3 - Mearin River	9	658	25.728,63	96,84	74,20	18,48
33380000	4 - Grajaú River	13	673	20.329,59	102,26	79,86	14,42
33630000	5 - Itapecuru River	26	612	43.758,01	105,16	78,54	36,93
33661000	6 - Peritoró River	17	174	3.083,02	122,72	93,43	2,86
33760000	7 - Preto River	25	126	4.037,46	141,48	92,80	6,23
34030000	8 - Medonho River	274	612	2.709,78	101,73	80,01	1,87
34170000	9 - Balsas River	174	643	24.584,55	97,23	79,70	13,67
23650000	10 - Lajeado River	166	650	2.541,60	110,13	84,94	2,03
26800000	11 - Formoso River	175	429	20.924,90	129,22	76,38	35,07
27110000	12 - Coco River	161	649	6.385,09	136,82	76,31	12,25
27380000	13 - Piranhas II River	161	622	5.550,69	141,03	78,86	10,94
27550000	14 - Jenipapo River	159	606	1.254,13	145,61	84,54	2,43
28150000	15 - Muricizal River	154	617	1.601,58	142,77	85,02	2,93
28240000	16 - Lontra River	153	499	3.470,13	138,62	85,17	5,88
28840000	17 - Piranhas I River	103	431	1.804,76	129,00	86,50	2,43
21750000	18 - Palma River	378	1048	1.271,76	111,22	77,30	1,37
22250000	19 - Manoel Alves River	222	953	14.940,51	116,42	79,02	17,72
22900000	20 - Sono River	185	874	43.940, 13	113,05	75,99	51,63
23150000	21 - Manoel Alves Pequeno River	185	497	2.490,43	124,19	80,68	3,44
23230000	22 - Vermelho River	186	624	4.777,84	101,88	78,78	3,50
23250000	23 - Manoel Alves Grande River	171	596	10.122,34	108,10	79,30	9,24
34090000	24 - Uruçuí Preto River	184	667	15.650,00	84,52	77,38	3,54
34270000	25 - Gurguéia River	143	820	47.030,50	74,64	68,33	9,41
45960000	26 - Corrente River	428	1013	31.075,05	82,56	71,40	11,00
46870000	27 - Preto River	416	899	22.121,37	84,76	72,51	8,60
46902000	28 - Grande River	411	1029	41.622,67	94,89	75,96	24,98
45260000	29 - Carinhanha River	440	960	4.777, 84	92,72	73,16	2,96
28850000	30 - Araguaia River	15	991	381.428,47	134,64	77,97	685,44
23700000	31 - Tocantins River	1	1629	297.122,59	120,39	78,48	394,81
34879500	32 - Parnaíba River	1	1021	298.305,55	78,72	66,42	116,40

The following input data (Table 2) was also used to prepare the study:

TABLE 2. Data used to conduct the work.

Satellite estimated data (SR) – rainfall and evapotranspiration			
Source	**Descriptions**	**Available data**	**Coverage**
Terra Climate	Generates monthly surface water balance datasets using a model that incorporates reference evapotranspiration, precipitation, temperature, and extractable soil water for plants (Abatzoglou et al., 2018)	Monthly from 01-01-1958. Available at GEE.	(1/24°, ~4 km) globally

Collected data were standardised to a spatial resolution of 4 km to enable comparisons. The original records were grouped into monthly, annual, and long-term mean series intervals. For comparison purposes, this series was limited to the period from 2001 to 2020. Finally, mean basin data were extracted for the 32 basins using their hydrological boundaries. These procedures were carried out in GEE, QGIS, and R.

The water balance model was used to estimate flows via remote sensing in river basins. This model was calculated by considering a system where rainfall (PPT) is the main water input, while flow (Q), evapotranspiration (ET), and positive water storage in the soil (Δs) constitute the water outflows in the watershed (Equation 1). On a monthly, annual, and long-term scale, changes in water storage (Δs) can be considered insignificant in river basins (Liu et al., 2015). To calculate the volume of the water balance for estimating Q, [eq. (2)]:

$$PPT = ET + Q + \Delta s \quad (1)$$

$$Q = PPT - ET \quad (2)$$

In which:

PPT = Rainfall (mm);

ET= Evapotranspiration (mm);

Q = Flow ($m^3\ s^{-1}$),

Δs = Water volume variation in the basin.

According to Willmott & Matsuura (2005), certain statistical methods are preferred for evaluating satellite data and are endorsed by the International Precipitation Working Group (IPWG). These include the coefficient of determination (R^2), Pearson correlation coefficient (r), mean absolute error (MAE), and root mean square error (RMSE). Additionally, Moriasi et al. (2007) recommend evaluations such as the Nash-Sutcliffe efficiency coefficient (NSE) and the percentage bias (pBIAS). The Willmott index (d) is also supported (Willmott, 1981). Table 3 presents a qualitative classification of the model's performance according to these indices.

TABLE 3. Qualitative classification of model performance, recommended for regionalization.

Parameters statistics	Performance			
	Very good	Good	Satisfactory	Unsatisfactory
R^2	>0,85	0,75< R^2≤ 0,85	0,60<R^2≤ 0,75	≤ 0,60
r	>0,85	0,75< r ≤ 0,85	0,60< r ≤ 0,75	≤ 0,60
NSE	>0,80	0,70< NSE ≤ 0,80	0,50< NSE ≤ 0,70	≤ 0,50
RMSE	<± 10	± 10≤ RMSE ≤ ± 20	± 20≤ RMSE ≤ ± 50	≥± 50
MAE	<± 5	± 5 ≤ MAE ≤ ± 10	± 10 ≤ MAE ≤ ± 15	≥± 15
pBIAS (%)	<± 5	± 5 ≤ pBIAS ≤ ± 10	± 10 ≤ pBIAS ≤ ± 15	≥± 15
d	>0,90	0,85< R^2≤ 0,90	0,70<R^2≤ 0,85	≤ 0,60

The aforementioned performance indices are metrics widely used in studies (Willmott, 1981; Willmott & Matsuura, 2005; Pereira et al., 2014) and are described in eqs (3) to (9).

$$R^2 = \left[\frac{\left[\sum_{i=1}^{n}(O_i - O)(S_i - S)\right]}{\left[\left(\sqrt{\sum_{i=1}^{n}(|O_i - O|)^2}\right)\left(\sqrt{\sum_{i=1}^{n}(|S_i - O|)^2}\right)\right]}\right]^2 \quad (3)$$

$$r = \frac{\sum_{i=1}^{n}(O_i - O)(S_i - S)}{\sqrt{\left(\sum_{i=1}^{n}(O_i - O)^2\right)\left(\sum_{i=1}^{n}(S_i - O)^2\right)}} \quad (4)$$

$$d = 1 - \frac{\sum(O_i - S_i)^2}{\sum(|S_i - O| + |O_i - O|)^2} \quad (5)$$

$$pBIAS = \left[\frac{\sum_{i=1}^{n}(O_i - S_i)}{\sum_{i=1}^{n}O_i} * 100\right] \quad (6)$$

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - S_i| \quad (8)$$

$$NSE = 1 - \frac{\sum(O_i - S_i)^2}{\sum(O_i - O)^2} \quad (9)$$

In which:

O_i – observed value;

O – mean of observed values;

S_i – estimated value;

S – mean of observed values, and

n is the number of observations.

RESULTS AND DISCUSSION

The long-term mean flows estimated by the satellite for the 32 river basins are graphically represented in Figure 2. Mean monthly and annual flows were also evaluated for all river basins. Estimates for river basins smaller than 5,000 km², with flows estimated by ANA at up to 100 $m^3\ s^{-1}$, include the Mearin River basin (3), Grajaú River basin (4), Preto River basin (7), Piranhas II River basin (12), and Gurguéia River basin (13). Larger basins, between 5,000 km² and 50,000 km², with flow ranges from 100 to 600 $m^3\ s^{-1}$, were also considered, as flow data in these basins were overestimated by satellite sensors. These variations in satellite-estimated flows were influenced by various factors, as the basins are located in regions with differing characteristics (altitude, terrain relief, Cerrado areas, flooded regions, transitions between the Cerrado and Amazon, among others), such as southern Piauí, central Maranhão, Bananal Island, and northern Tocantins.

As described by Salati et al. (2006), several factors contribute to these differences in flow, such as deforestation, which initially increases river flows due to higher surface runoff and reduced infiltration in compacted areas lacking vegetation. This decrease impacts the soil-plant system of the Amazon region, reducing evapotranspiration and affecting the components of the water balance. In addition, droughts in 1992, 1998, 2002, 2010, 2012, and 2015 in the North and Northeast regions of Brazil were characterised by significant annual variability, partly associated with the El Niño-Southern Oscillation (ENSO) phenomenon. Other drought periods were caused by the anomalous northward displacement of the Intertropical Convergence Zone (ITCZ) over the Atlantic, due to warming in the North Tropical Atlantic Ocean (Marengo et al., 2017). In their study, Aquino et al. (2005) found a mean annual discharge of 6,100 m³ s⁻¹ in the Araguaia River basin (the largest of the basins studied), which is the main fluvial system running through central Brazil.

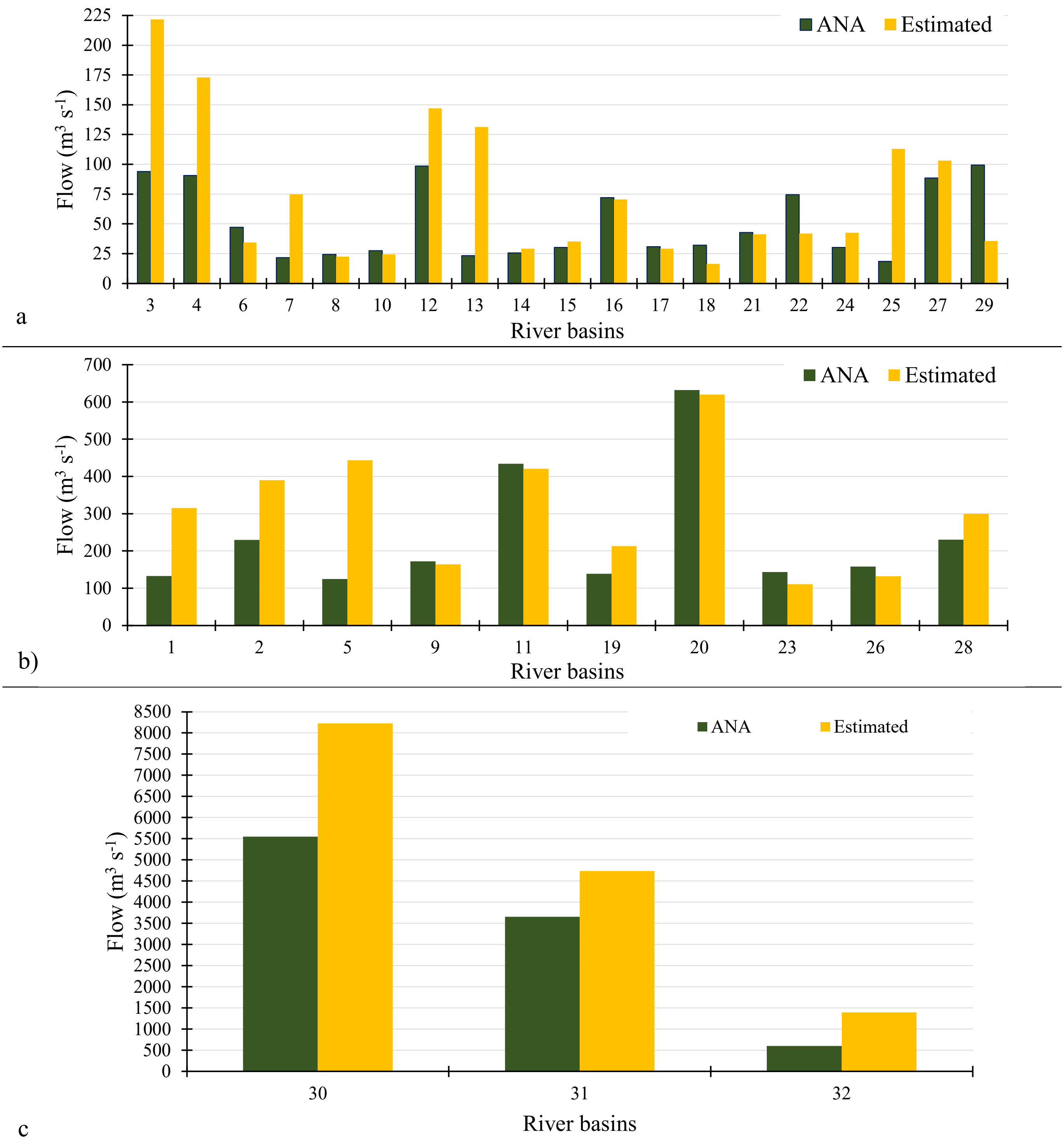
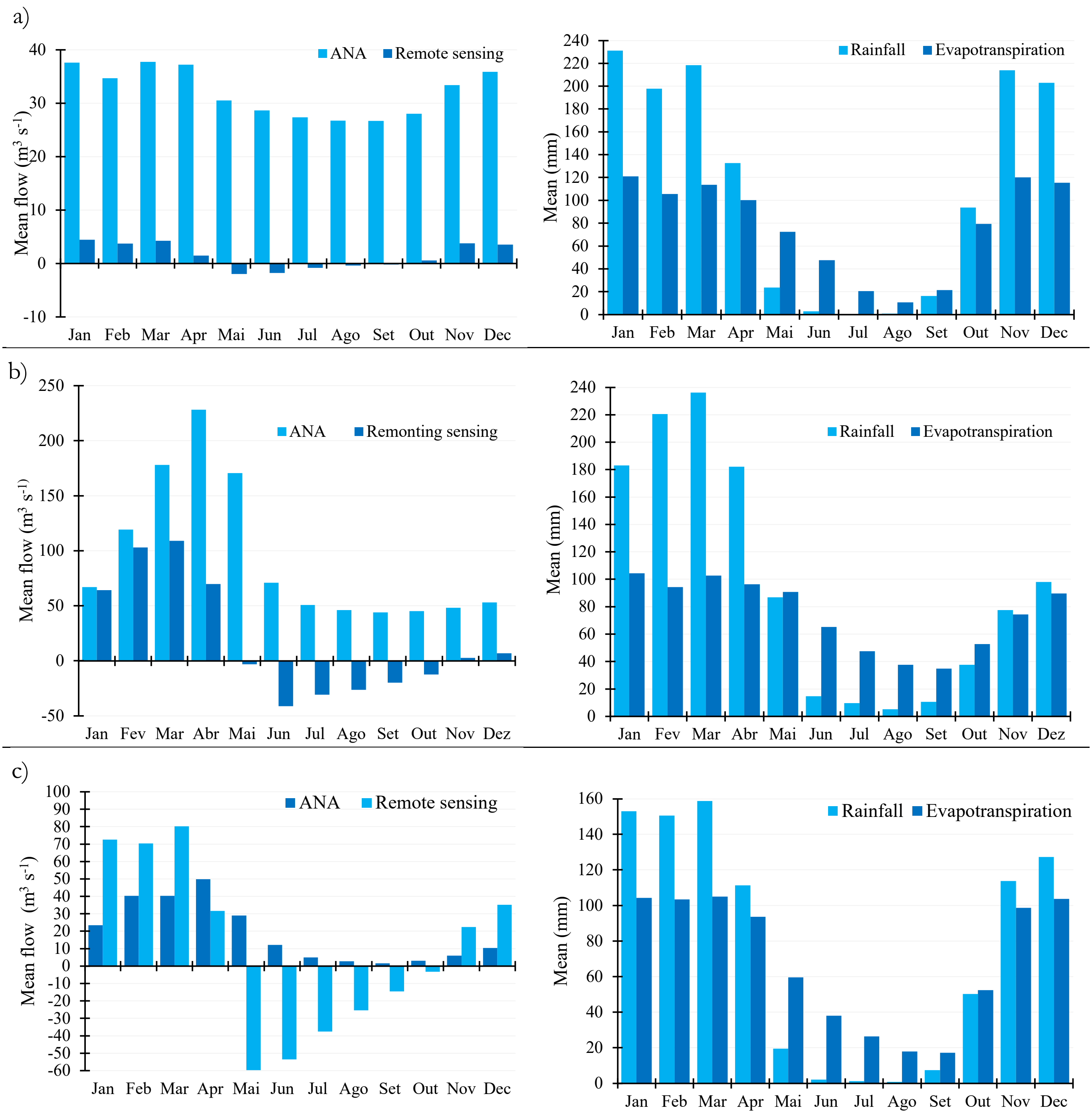


FIGURE 2. Long-period mean flows in the 32 river basins studied, a) basins smaller than 5.000 km^2, b) basins largest than 5.000 and smaller than 50.000 km^2 e c) basins larger than 50.000 km^2 considering the 20 years of data in the series, comparing ANA measurements with satellite estimates.

Figure 3 shows the measured and estimated mean monthly flows for the smallest basin, intermediate basin, medium basin and large basin and mean rainfall and mean evapotranspiration obtained from the remote sensing product. During the rainy season period (September to March) high flow values are observed due to the high rainfall which replenishes the water table. In the dry season (April to August) low flow values are registered. This is due to the lack of rainfall during this period and also to the high evapotranspiration rates in the region. Charles et al. (2022) found cumulative values of actual evapotranspiration using the Spatial Evapotranspiration Modelling Interface model (SETMI) for the soybean crop in MATOPIBA, which ranged from 394 to 538 mm per cycle. Whereas Lima's study (Lima, 2020) concluded that the vegetation reduction cover in MATOPIBA increased soil temperature and decreased humidity. According to this author, on the MATOPIBA's agricultural border, there's an interaction between environmental and climatic variables, and the vegetation cover reduction leads to decreased soil moisture, which in turn raises soil temperature and eventually a greater humidity drop.

Salviano et al. (2016), showed that in most of the Brazilian territory, evapotranspiration tendencies are directly related to mean temperatures, with a high percentage of positive trends. Salati et al. (2007) also showed positive trends in temperature and evapotranspiration throughout the Northeast region.



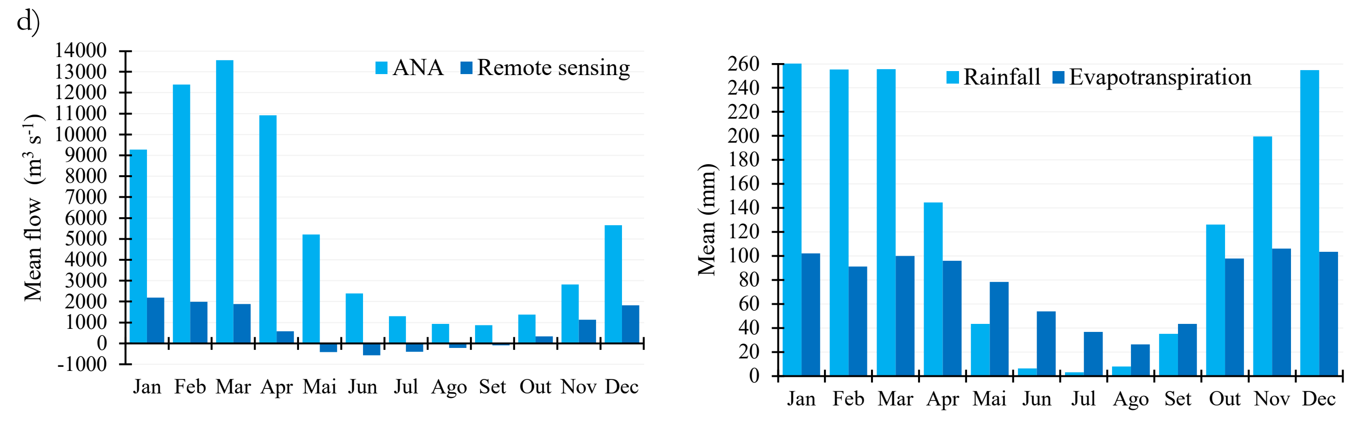


FIGURE 3. Mean monthly rainfall and evapotranspiration measured by satellite a) smallest basin (Rio Palma - 1,271.76 km^2); b) intermediate basin (Mearin River - 25,728.63 km^2); c) middle basin (Gurguéia River - 47,030.50 km^2); d) large basin (Araguaia River - 381,428.47 km^2)

One of the causes usually associated with the occurrence of dry years in the Northern and Northeastern Brazil relates to the presence of El Niño and ENOS, i.e., temperatures warmer than those normally observed in the Central Equatorial Pacific. According to some authors (Blanco et al., 2022), the determining factor for drought occurrence in the region from 2017 onwards, was the fact that the hottest temperatures observed on the North Atlantic's surface favored the migration of the Intertropical Convergence Zone (ITCZ) to a more northerly position than normal, thus drastically reducing the occurrence of precipitation in the regions mentioned. Also, in 2009, La Niña occurred, even if with a weaker signal (Marengo et al., 2017).

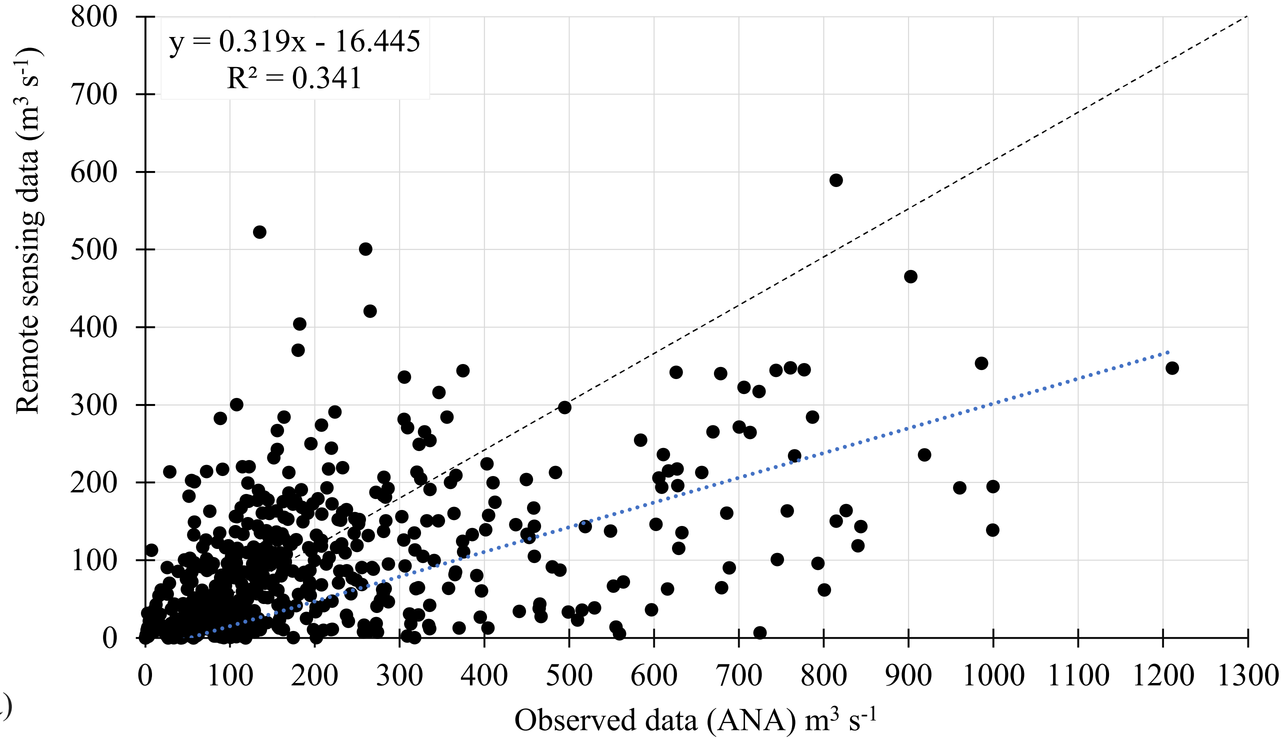
Based on the general summaries of the metrics used in this study (Figure 4 and Table 4) remote sensing performed best in estimating annual flow and the long-term mean flow compared to monthly flow. These performance indices reflect the quality of the fit between simulations and observations, as well as the degree of dependence between variables.

The R^2 and r values range from 0 to 1, with values closer to 1 indicating a better fit and lower error (Willmott & Matsuura, 2005). The high R^2 value (0.914) indicates a strong degree of explanation of the annual satellite products in relation to fluviometric data. A smaller accuracy is observed for monthly products (R^2=0.341), indicating a lower prediction degree of the satellite flow data in relation to the fluviometric stations. This is mostly due to the high rainfall variability and high evapotranspiration in the region. With a correlation coefficient (r) of 0.956, there was a strong positive correlation between the annual data from the SR and the ANA, these values suggest that as ANA values increase, so do SR values.

The NSE ranges from -∞ to 1, with values close to 1 indicating a good model performance and values close to 0 a poor one (Pereira et al., 2014). The NSE value ranged from 0.077 monthly, 0.603 annually and 0.869 in the basin's long-term mean, which is relatively good to satisfactory, and suggests that the model or relationship captured has a good efficient representation of observed data, with the exception of monthly data pBIAS measures bias average of the simulation, i.e., the difference between the simulated and the observed values; expressed in percentiles, values close to zero indicate good model performance. However, it is noteworthy that a pBIAS near zero does not guarantee that the model is accurate, as it can be influenced by random factors. It is therefore recommended to use pBIAS in conjunction with other statistical metrics (Moriasi et al., 2007). The NSE, R^2 and pBIAS statistical indices, resulting from the comparison between observed monthly, annual and long-period flows are shown in Table 4. According to these statistical indices, a good performance of the three hydrological models. R^2 values greater than 0.50 reveal the models' ability to explain most of the variation in the data observed. NSE values above 0.50 for the annual discharges during calibration periods, suggest that the models are appropriate for simulating annual flows in river basins. However, pBias values ranging from 81.20 to 43.20% indicate unsatisfactory performance. Comparatively, the effect of the adjustment of the observed and simulated values was better for the annual and long-term adjustments period when compared to the monthly ones.

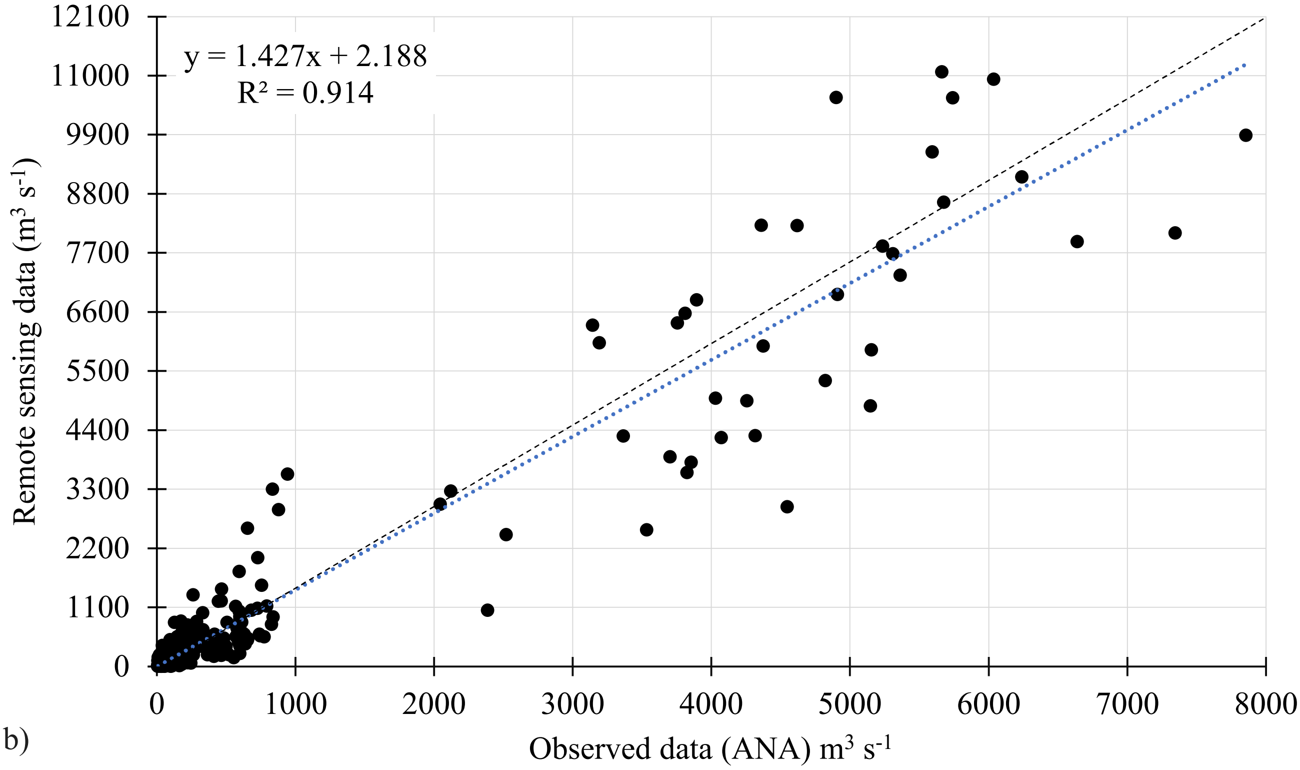
As for the errors, the monthly, annual and long-period estimates showed MAEs of 111.1; 232.1 and 191.98 respectively. This metric represents the errors' mean between the values observed and predicted; they indicate an average magnitude of the significant errors, RMSE of 164.7; 720.1 and 536.91 represent measures of dispersion of the errors between the values observed and estimated. These indicate an overestimation of the data flow as discussed above.

The d value is approximately 0.542; 0.935 and 0.961 for the monthly, annual and mean values period, respectively, indicating a good alignment between the observed and forecasted values.



y = 0.319x - 16.445
R² = 0.341
Remote sensing data (m³ s⁻¹)
Observed data (ANA) m³ s⁻¹
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300

a)



y = 1.427x + 2.188
R² = 0.914
Remote sensing data (m³ s⁻¹)
Observed data (ANA) m³ s⁻¹
0
1100
2200
3300
4400
5500
6600
7700
8800
9900
11000
12100
1000
2000
3000
4000
5000
6000
7000
8000

b)

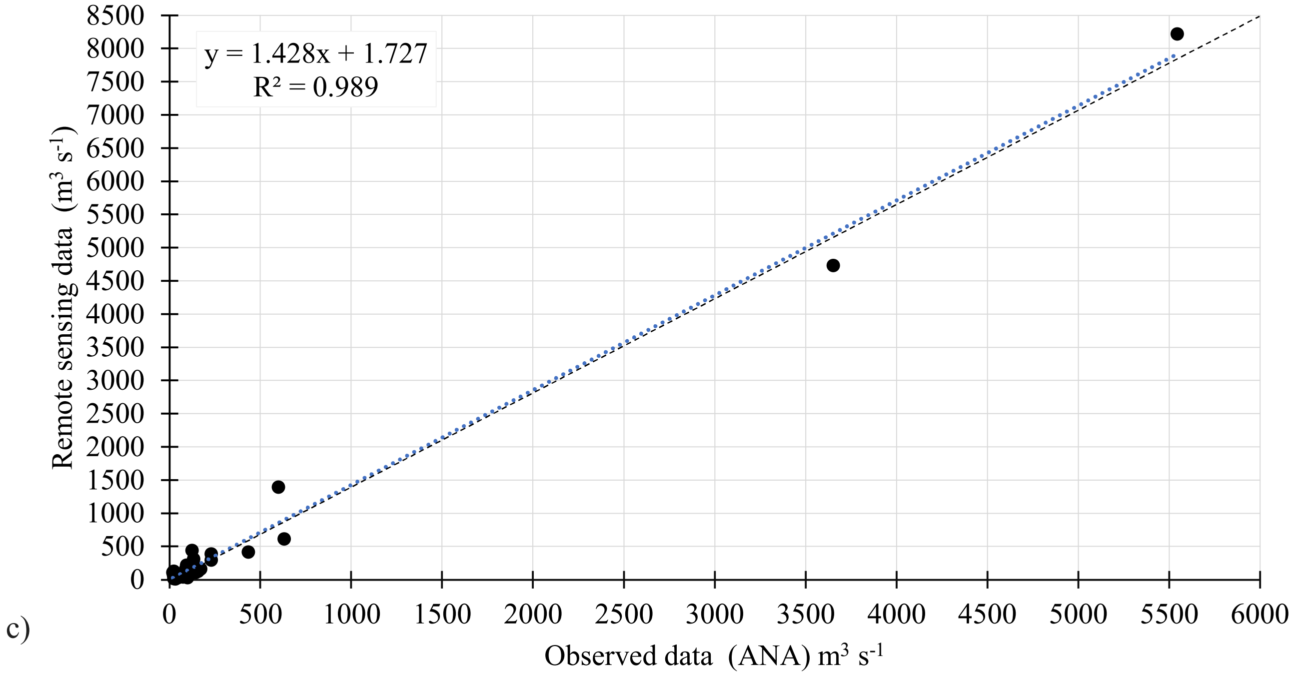


FIGURE 4. Comparison between the flow estimated by the TerraClimate satellite sensor and the data observed by the ANA using scales: a) monthly, b) annual and c) long-period mean.

In terms of its ability to estimate annual flow, the satellite performed very well, with R^2 equal to 0.914, r of 0.956, NSE of 0.603 and d of 0.935. The results indicate that both satellite products (monthly and annual) tend to overestimate observed rainfall e, consequently, the flow rate. On the other hand, the long-period mean flow fitted better.

TABLE 4. Quantitative performance indices of the model used.

Statistical parameters	Values		
	monthly	annual	long-term
R^2	0,314	0,914	0,989
r	0,584	0,956	0,995
NSE	0,077	0,603	0,869
RMSE (m^3 s^{-1})	164,7	720,1	536,9
MAE (m^3 s^{-1})	111,1	232,1	191,9
pBIAS (%)	81,20	43,20	30,89
d	0,542	0,935	0,961

Coefficient of determination (R^2), Pearson correlation coefficient (r), Nash-Sutcliffe efficiency coefficient (NSE), root mean square error (RMSE), mean absolute error (MAE), percentage bias (pBIAS) and the Willmott index (d).

CONCLUSIONS

The satellite data estimates were less effective in representing monthly data. This result is possibly due to the fact that, over a relatively shorter period, the assumption that the variation in the amount of water in the basin remains zero is not true, causing an error in the simplified volumetric balance equation.

On the other hand, the annual water balance was a satisfactory alternative for estimating reference flows in the study basins, when using remote sensing data and of GIS technology. The estimates found of annual flows through remote sensing, compared to the observed data from the ANA were good, although the satellite data led to a slight overestimation. In this way, the results presented can serve as a basis for future research and strategies for the sustainable management of water resources in the MATOPIBA region, after subsequent validation work.

Generally, flow estimation was better over long periods for all river basins, which showed similar behavior, but with slight flow overestimates. Since data is available for implementing other flow calculation techniques with products from other satellites, we recommend these data should be analyzed with different spatial resolution.

ACKNOWLEDGEMENTS

Universidade de Sao Paulo (USP) – Escola Superior de Agricultura “Luiz de Queiroz” (ESALQ); Laboratório de Hidrologia do Departamento de Engenharia de Biossistemas (LABHA);

Fundação de Estudos Agrários Luiz de Queiroz (FEALQ);

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) - Finance Code 001.

REFERENCES

Abatzoglou JT, Dobrowski SZ, Parks SA, Hegewisch KC (2018) TerraClimate, a highresolution global dataset of monthly climate and climatic water balance from 1958–2015. Scientific Data 5(1): 1–12. https://doi.org/10.1038/sdata.2017.191

Aquino S, Stevaux JC, Latrubesse EM (2005) Regime hidrológico e aspectos do comportamento morfohidráulico do Rio Araguaia. Revista Brasileira de Geomorfologia 6(2): 29–41. https://doi.org/10.20502/RBG.V6I2.49

Bastawesy M El, White K, Nasr A (2009) Integration of remote sensing and GIS for modelling flash floods in Wadi Hudain catchment. Egypt. Hydrological Processes 23: 1359–1368. https://doi.org/https://doi.org/10.1002/hyp.7259

Belvederesi C, Zaghloul MS, Achari G, Gupta A, Hassan QK (2022) Modelling river flow in cold and ungauged regions: a review of the purposes, methods, and challenges. Environmental Reviews 30(1): 159–173. https://doi.org/10.1139/ER-2021-0043/ASSET/IMAGES/LARGE/ER-20210043F4.JPEG

Blanco LS, Portella DAPC, Santos JLA, Barbosa SCO, Dias JLR (2022) O projeto de modernização brasileira e suas consequências socioambientais no Matopiba. Boletim Paulista de Geografia 1(107): 121–136. https://publicacoes.agb.org.br/boletimpaulista/article/view/2162

Bolfe ÉL, Victória DC, Contini E, Bayma-Silva G, Spinelli-Araújo L, Gomes D (2016) Matopiba em crescimento agrícola Aspectos territoriais e socioeconômicos. Revista de Política Agrícola 25(4): 38–62. https://seer.sede.embrapa.br/index.php/RPA/article/view/1202

Charles TS, Lopes TR, Duarte SN, Nascimento JG, Ricardo HC, Pacheco AB (2022) Estimating average annual rainfall by ordinary kriging and TRMM precipitation products in midwestern Brazil. Journal of South American Earth Sciences 118: 103937. https://doi.org/10.1061/JWRMD5.WRENG-5771

Dai A, Qian T, Trenberth KE, Milliman JD (2009) Changes in continental freshwater discharge from 1948 to 2004. Journal of Climate 22(10): 2773–2792. https://doi.org/10.1175/2008JCLI2592.1

Dixon H, Sandström S, Cudennec C, Lins HF, Abrate T, Bérod D, Chernov I, Ravalitera N, Sighomnou D, Teichert F (2022) Intergovernmental cooperation for hydrometry – what, why and how? Hydrological Sciences Journal 67(16): 2552–2566. https://doi.org/10.1080/02626667.2020.1764569

IPCC (2023) Summary for Policymakers. In: Climate Change 2023: Synthesis Report. A Report of the Intergovernmental Panel on Climate Change. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Core Writing Team, H. Lee, & J. Romero, Eds.). https://www.ipcc.ch/ar6-syr/

Lima TP (2020) Dinâmica espaço temporal das alterações Geoespaciais na região do MATOPIBA, Brasil. Dissertação (Programa de Pós-Graduação em Conservação de Recursos Naturais do Cerrado) - Instituto Federal de Educação, Ciência e Tecnologia Goiano. Campus Urutaí.

Liu J, Duan Z, Jiang J, Zhu AX (2015) Evaluation of three satellite precipitation products TRMM 3B42, CMORPH, and PERSIANN over a subtropical watershed in China. Advances in Meteorology 2015: 1-13. https://doi.org/10.1155/2015/151239

Lopes TR, Folegatti MV, Duarte SN, Moster C, Zolin CA, Oliveira RK, Moura LB (2022) Economic value of the environment services for regulating flow and maintenance water quality in Piracicaba River Basin. Journal of Water resources Planning and Management 149(9): 05023008.

Lou H, Zhang Y, Yang S, Wang X, Pan Z, Luo Y (2022) A new method for long-term River discharge estimation of small- and medium-scale rivers by using multisource Remote Sensing and RSHS: Application and validation. Remote Sensing 14(8): 1-19. https://doi.org/10.3390/RS14081798

Manke EB, Teixeira-Gandra CFA, Damé R de CF, Nunes AB, Chagas Neta MCC, Karsburg RM (2022) Relações intensidade-duração-frequência obtidas sazonalmente para Pelotas, Rio Grande do Sul, Brasil. Revista Brasileira de Engenharia Agrícola e Ambiental 26(2): 85–90. https://doi.org/10.1590/1807-1929/AGRIAMBI.V26N2P85-90.

Marengo JA, Torres RR, Alves LM (2017) Drought in Northeast Brazil—past, present, and future. Theoretical and Applied Climatology 129(3–4): 1189–1200. https://doi.org/10.1007/S00704-016-1840-8/METRICS

Moriasi DN, Arnold JG, Liew MW, Van Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the ASABE 50(3): 885–900. https://doi.org/10.13031/2013.23153

Pereira DDR, Martinez MA, Almeida AQ, Pruski FF, Silva DD, Zonta JH (2014) Hydrological simulation using SWAT model in headwater basin in Southeast Brazil. Engenharia Agrícola 34(4): 789–799. https://doi.org/10.1590/S0100-69162014000400018

Salati E, Dos Santos AA, Klabin I (2006) Temas ambientais relevantes. Estudos Avançados, 20(56). https://doi.org/10.1590/S0103-40142006000100009

Salati E, Salati E, Campanhol T, Villa Nova N (2007) Caracterização do clima atual e definição das alterações climáticas para o território brasileiro ao longo do Século XXI. Relatório 4. Tendências de Variações Climáticas para o Brasil no Século XX e Balanços Hídricos para Cenários Climáticos para o Século XXI. 182p.

Salviano MF, Groppo JD, Pellegrino GQ (2016) Revista Brasileira de Meteorologia 31(1): 64-73. http://dx.doi.org/10.1590/0102-778620150003

Willmott CJ (1981) On the validation of models. Physical Geography 2(2): 184–194. https://doi.org/10.1080/02723646.1981.10642213.

Willmott CJ, Matsuura K (2005) Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Climate Research 30(1): 79–82. Available: www.int-res.com