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Performance of orbital data and indirect models of evapotranspiration estimation in the agreste region of Pernambuco, Brazil

Desempenho de dados orbitais e modelos indiretos de estimativa de evapotranspiração no agreste pernambucano, Brasil

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ABSTRACT

Accurate estimates of reference evapotranspiration (ET_0) are essential for water management and agriculture, especially in data-scarce regions such as the Brazilian semi-arid. In this context, the aim of this study was to evaluate the performance of indirect empirical methods for determining ET_0, Hargreaves–Samani, solar radiation, and Jensen–Haise, together with the MOD16A2 remote sensing product and the BR-DWGD gridded dataset. The methodology consisted of an analysis based on observed data from the municipalities of Garanhuns, Surubim, and Caruaru, in the Agreste region of Pernambuco, using the Penman–Monteith FAO-56 model as the standard reference. The results indicated that the solar radiation method achieved the best performance across all three municipalities, being classified as "excellent" (c > 0.85) in every case. The Jensen–Haise and Hargreaves–Samani models also performed well, with classifications ranging from "very good" to "excellent". In contrast, the MOD16A2 product showed limitations, with greater variability and lower accuracy among the evaluated sites. The BR-DWGD dataset, in turn, demonstrated strong performance, with low error margins and a high correlation with observed data. These results demonstrate that radiation- and temperature-based models are suitable for estimating ET_0 in the Agreste region, while also highlighting the need to improve remote sensing ET al algorithms in climatically heterogeneous environments.

Keywords: Penman–Monteith; Hargreaves–Samani; Jensen–Haise; validation; remote sensing; ODS.

RESUMO

Estimativas precisas da evapotranspiração de referência (ET_0) são essenciais para o manejo hídrico e agrícola, sobretudo em regiões com escassez de dados, como o semiárido brasileiro. Neste contexto, o objetivo deste estudo foi avaliar o desempenho dos métodos empíricos indiretos de determinação da ET_0, Hargreaves–Samani, Radiação Solar e Jensen–Haise juntamente com o produto de sensoriamento remoto MOD16A2 e a base em grade BR-DWGD. A metodologia consistiu numa análise utilizando dados observados dos municípios de Garanhuns, Surubim e Caruaru, na região do Agreste de Pernambuco, tendo o modelo Penman–Monteith (FAO-56) como referência padrão. Os resultados indicaram que o método baseado em Radiação Solar apresentou o melhor desempenho nos três municípios, sendo classificado como "excelente" (c > 0,85) em todos os casos. Os modelos de Jensen–Haise e Hargreaves–Samani também se destacaram, com classificações entre "muito bom" e "excelente". Em contraste, o produto MOD16A2 apresentou limitações, com maior variabilidade e menor precisão entre os locais avaliados. A base BR-DWGD, por sua vez, demonstrou elevado desempenho, com baixa margem de erro e forte correlação com os dados observados. Esses resultados demonstram que modelos baseados em radiação e temperatura são adequados para a estimativa de ET_0 no Agreste, ao mesmo tempo em que evidenciam a necessidade de aprimoramento dos algoritmos de ET por sensoriamento remoto em ambientes climaticamente heterogêneos.

Palavras-chave: Penman-Monteith; Hargreaves-Samani; Jensen-Haise; validação; sensoriamento remoto; ODS.

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Introduction

Evapotranspiration (ET) refers to the total quantity of water lost to the atmosphere through the combined processes of soil evaporation and plant transpiration (Ersi et al., 2025). It plays a pivotal role in agricultural water management, as it interconnects the terrestrial hydrological cycle, the surface energy balance, and the carbon cycle, while also influencing surface cooling, cloud formation, and precipitation generation (Lopes Sobrinho et al., 2024; Tang et al., 2024; Yu et al., 2024). Furthermore, the precise quantification of ET is essential for various purposes, including drought forecasting, efficient irrigation, plant productivity, water management, and understanding climate change processes (Claudino et al., 2025). Consequently, it is imperative to investigate methodologies that provide reliable estimates applicable across diverse agricultural and climatic realities (Allen et al., 1998).

Among the existing models, the Penman–Monteith model, recommended by the Food and Agriculture Organization (FAO), is recognized as the standard model for estimating reference evapotranspiration (ETo) and integrates multiple meteorological parameters (Shirmohammadi-Aliakbarkhani and Saberali, 2020). However, the application of this model may be constrained in areas characterized by a scarcity or low quality of climatic data, a reality common to numerous regions globally (Islam and Alam, 2021). In light of this, it is relevant to consider alternatives that require fewer input variables.

Simplified empirical models, such as those of Hargreaves–Samani, Makkink, Thornthwaite, and Jensen–Haise, emerge as viable alternatives, utilizing solely temperature or solar radiation information. Such approaches have been adopted in data-constrained scenarios; however, their performance may vary according to the climatic characteristics of the region (Turcato and Minuzzi, 2024). Thus, it is fundamental to investigate the accuracy of these models in comparison to the reference model, particularly in areas where the climate exhibits significant variability. Different models were evaluated by Moraes et al. (2023), Lopes Sobrinho et al. (2024), and Cabral Júnior et al. (2017), whose results demonstrated that performance varies with climate type (humid in MA and semi-arid in PE/BA), as the same model yielded different performances in each municipality.

The advancement of geotechnologies has enabled increasingly integrated environmental analyses, which, through remote sensing (RS) tools and techniques, provide continuous and precise access to information such as climatic variables and changes in land use and land cover. Remote sensing–based ET models offer an effective means of mapping ET across different spatial and temporal scales (Ouaadi et al., 2024; Yang, 2025). Moreover, global gridded ET datasets, with varying temporal coverages and categorized based on reanalysis, RS, machine learning, hybrid methods, and water balance, have been developed to complement in situ observations (Bu et al., 2024). Among these tools, the moderate resolution imaging spectroradiometer (MODIS) sensor, onboard the Terra and Aqua satellites, is notable for its use in estimating evapotranspiration, such as the MOD16A2 product, which is founded on the Penman–Monteith model and combines meteorological data with 500-m spatial resolution imagery at an 8-day frequency (Tito et al., 2020).

Several studies have demonstrated the potential of integrating RS and reanalysis data to comprehend the spatiotemporal dynamics of ET. Bu et al. (2024) assessed the capacity of solar-induced fluorescence (SIF) to estimate ET and its partitioning in a dual-source model within dryland areas representative of natural grassland biomes in semi-arid environments. Jaafar and Sujud (2024) analyzed ET trends utilizing a global monthly dataset based on Landsat imagery, spanning the period from 1990 to 2021, in addition to data from the ERA5-Land reanalysis product. Yang (2025) evaluated the performance of the PML_V2 model through validation using flux measurements and water balance-based ET estimates, comparing the results with those of other global products over China.

In Brazil, Antunes et al. (2024) utilized evapotranspiração data from the MOD16A2 product and other models based on RS and reanalysis techniques, such as PML_V2, TerraClimate, GLEAM, FLUXCOM, SSEBop, FLDAS, and ERA5-Land, to analyze how changes in land use and land cover influence actual evapotranspiration in the Xingu basin between 1985 and 2020. Oliveira et al. (2025) applied the Brazilian Daily Weather Gridded Data (BR-DWGD) base, developed by Xavier et al. (2022), to validate surface solar radiation (SSR) datasets extracted from sources such as CMIP6, ERA5, NCEP, ISCCP, and EUMETSAT for the period from 1983 to 2009.

The state of Pernambuco, in Northeast Brazil, is an example of a region with significant climatic diversity, which directly influences evaporation and transpiration processes (APAC, 2023). This heterogeneity renders the Pernambuco territory a conducive environment for comparative analyses of different empirical ETo estimation models and for the use of RS techniques, such as in the Agreste of Pernambuco (*Agreste Pernambucano*), a mesoregion representing a climatic transition between humid and semi-arid areas. Furthermore, RS data can strengthen water management by addressing the scarcity of in situ data, which is recurrent in semi-arid environments such as the Agreste of Pernambuco.

In this context, aiming to surmount the limitations associated with data availability for local and regional applications in semi-arid areas, the objectives of this study were i. to analyze the behavior of different indirect ETo estimation models, utilizing observed data distributed throughout the Agreste of the Pernambuco mesoregion and ii. to evaluate the behavior of ETo estimated by the MOD16A2 product and the BR-DWGD database, comparing them to the standard Penman–Monteith–FAO56 model, in order to identify which models prove most suitable for local climatic conditions.

Methodology

Characterization of the study area and data acquisition

The research centered on the Agreste of Pernambuco mesoregion, situated between the *Zona da Mata* (Forest Zone) of Pernambuco and the *Sertão* (Backlands) of Pernambuco, occupying 24.7% of the state's territory (IBGE, 2023). According to the Köppen classification, the Agreste region exhibits three climatic typologies: a tropical climate with autumn–winter rainfall (*As'a*), a tropical climate with summer–autumn rainfall (*Aw'a*), and a low-latitude and low-altitude semi-arid climate (*BSh*), with the latter being the predominant type (APAC, 2023). Consequently, owing to this climatic transition, the behavior of evapotranspiration was analyzed in three municipalities located within the mesoregion, as represented in Figure 1.

The Agreste of Pernambuco is situated within the drought polygon (*Polígono das Secas*). However, owing to its proximity to the coast and the Borborema Plateau, the climate is less arid than that of the *Sertão*. The relief influences the rainfall regime, temperature, and air humidity, with dry periods occurring between September and January, and the rainy season spanning from April to June (Andrade et al., 2018).

Data acquisition

Data on temperature, relative humidity, wind speed, atmospheric pressure, and solar radiation were obtained for the municipalities of Garanhuns, Surubim, and Caruaru, retrieved from the National Institute of Meteorology (INMET) database. Reference evapotranspiration estimation models were applied using available data for the period from 2009 to 2023, defined according to the availability of observed and orbital data. Information regarding the stations utilized is presented in Table 1.

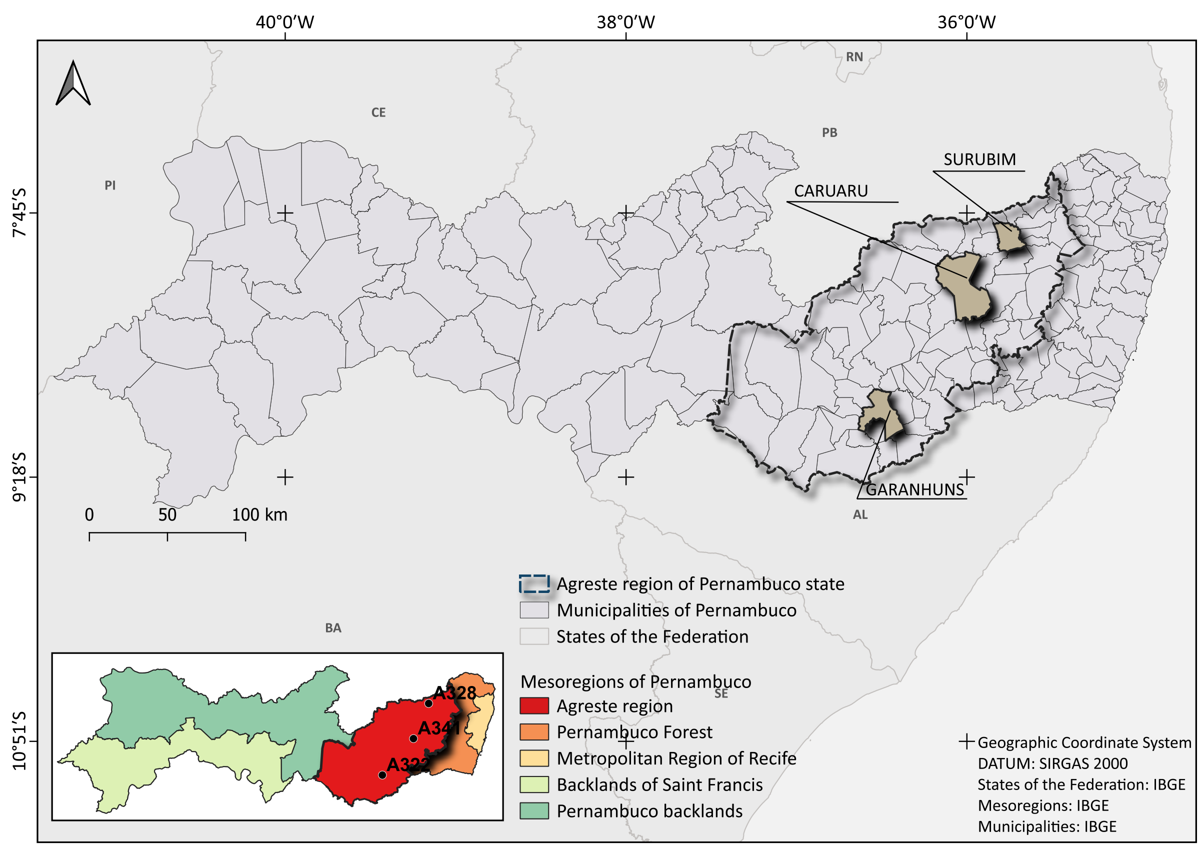

Figure 1 – Location of the study area.

Table 1 – Meteorological stations studied.

Code	Station	Latitude	Longitude	Altitude	Data period	Percentage of missing data (%)
A322	Garanhuns	-8.9108	-36.493	827.78	07/2007-02/2025	13.3
A328	Surubim	-7.8397	-35.801	421.44	03/2008-04/2024	20.7
A341	Caruaru	-8.3653	-36.028	852	02/2008-02/2025	21.4

Orbital reference evapotranspiration (ETo) data from the MOD16A2 product (Collection 6) of the National Aeronautics and Space Administration (NASA) were obtained via a script in Google Earth Engine (GEE), for the period from 2009 to 2023. The product incorporates reanalysis and MODIS RS data, with a spatial resolution of 500 m and a temporal resolution of 8 days (Tito et al., 2020). Data from the MOD16A2 product were extracted as monthly totals for the coordinates of each station, while the observed ETo was converted to the monthly scale by summing the values estimated by the standard model throughout each month. Furthermore, the annual accumulation of the product was obtained for the entire state of Pernambuco for the years 2009, 2012, 2016, 2019, and 2022, with the aim of identifying changes in ETo behavior within the mesoregion over the years.

ETo from the BR-DWGD gridded climatic database was obtained via a GEE script for the coordinates of each station and for the years 2009, 2012, 2016, 2019, and 2022. The BR-DWGD is a gridded dataset resulting from the merger of data from 11,473 rain gauges and 1,252 meteorological stations, possessing a daily temporal resolution and a spatial resolution of 0.1 × 0.1°, covering the period from January 1961 to March 2024 (Xavier et al., 2022). The DWGD was evaluated on a daily scale, where existing gaps in the observed series (dates with missing data) were also removed from the gridded database series. Conversely, in the analysis of MOD16A2, months with no data or those containing significant daily gaps in the time series were excluded. The percentages of missing data for each series are presented in Table 1.

Estimation of Reference ETo

The estimation of evapotranspiration was carried out using three indirect models, which were subsequently compared with the standard FAO–Penman–Monteith (PM-FAO) model, as described below (Equation 1).

a) FAO–Penman–Monteith Model—ETo(PM)

$$ETo(PM) = \frac{0{,}408.\Delta.(R_n - G) + \gamma.\frac{900}{(T_{med} + 273)}.U_2.(e_s - e_a)}{\Delta + \gamma.(1 + 0{,}34.U_2)} \quad (1)$$

where ETo(PM) is the reference evapotranspiration by Penman–Monteith (mm/day); Δ is the slope of the saturation vapor pressure curve (kPa/°C); R_n is the net radiation (MJ/m²/day); G is the soil heat flux (MJ/m²/day); γ is the psychrometric constant (kPa/°C); T_{med} is the mean daily air temperature derived from the average of maximum and minimum air temperatures; U_2 is the wind speed at a height of 2 m (m/s); e_s is the saturation vapor pressure (kPa); and e_a is the actual vapor pressure (kPa).

b) Hargreaves–Samani Model — ETo(HS) (Equation 2)

$$ETo(HS) = 0{,}0023.R_a.(T_{max} - T_{min})^{0{,}5}.(T + 17{,}8) \quad (2)$$

where ETo(HS) is the reference evapotranspiration by Hargreaves-–Samani (mm/day); R_a is the extraterrestrial solar radiation (mm/day); T_{max} is the maximum daily air temperature (°C); T_{min} is the minimum daily air temperature (°C); and T is the mean daily air temperature (°C).

c) Solar Radiation or FAO-24 Radiation Model—ETo(RS) (Equations 3 and 4)

$$ETo(RS) = c_v.W.R_S \quad (3)$$

$$W = 0{,}483 + 0{,}01T_{med} \quad (4)$$

where ETo(RS) is the reference evapotranspiration by solar radiation (mm/day); c_v is an adjustment factor, determined as a function of the intervals of mean wind speed (m/s) measured at a height of 2 m and mean relative humidity (%); W is a weighting factor; R_s is the incident solar radiation (mm/day); and T_{med} is the mean daily temperature.

d) Jensen–Haise Model—ETo(JH) (Equation 5)

$$ETo(JH) = R_S.(0{,}0252T + 0{,}078) \quad (5)$$

where ETo(JH) is the reference evapotranspiration by Jensen–Haise (mm/day); T is the mean daily air temperature (°C); and R_s is the incident solar radiation (mm/day).

Performance Analysis of ETo Models

The statistical metrics applied to analyze the performance of the ETo estimation models were percent bias (PBIAS), Pearson correlation coefficient (r), coefficient of determination (R²), index of agreement (d), and performance index (c). The equations for determining these metrics are described below (Equations 6 to 10).

$$Pbias = \frac{\sum_{i=1}^{n}(O_i - S_i)}{\sum_{i=1}^{n}(O_i)} \times 100 \quad (6)$$

$$r = \frac{\sum(S_i - \bar{S}_i) \times (O_i - \bar{O}_i)}{\sqrt{\sum(S_i - \bar{S}_i)^2 \times \sum(O_i - \bar{O}_i)^2}} \quad (7)$$

$$d = 1 - \left[\frac{\sum(S_i - O_i)^2}{\sum(|S_i - \bar{O}_i| + |O_i - \bar{O}_i|)^2}\right] \quad (8)$$

$$R^2 = \left(\frac{\sum(S_i - \bar{S}_i) \times (O_i - \bar{O}_i)}{\sqrt{\sum(S_i - \bar{S}_i)^2 \times \sum(O_i - \bar{O}_i)^2}}\right)^2 \quad (9)$$

$$c = r.d \quad (10)$$

where O_i is the evapotranspiration estimated by Penman–Monteith–FAO; $\bar{O}_i$ is the mean of the data estimated by Penman–Monteith; S_i is the evapotranspiration estimated by the other indirect models; $\bar{S}_i$ is the mean of the estimated data; and n is the sample size.

According to Andrade et al. (2022), PBIAS analyzes the tendency of values and represents a better fit as the value approaches zero.

The result can be evaluated as "Very good" (PBIAS<±10), "Good" (±10<PBIAS<±15), "Satisfactory" (±15<PBIAS<±25), and "Unsatisfactory" (PBIAS>±25), in accordance with Moriasi et al. (2007).

The Pearson coefficient (r), which evaluates the linear relationship existing between two datasets, represents a better fit with a value close to 1, as the result varies between -1 and 1. The values of the r coefficient were interpreted according to Cunha et al. (2013), as presented in Table 2.

Willmott's index of agreement (d) ranges from 0 to 1, representing non-agreement between datasets when its value is close to 0 and perfect agreement when it is close to 1 (Pedreira Junior et al., 2021). Finally, the c-index, proposed by Camargo and Sentelhas (1997), indicates the performance of the models, with the interpretation criteria presented in Table 3.

Results and Discussion

The ETo estimated by the ETo(PM) model exhibited values ranging between 1,242 mm and 1,745 mm in Garanhuns, 1,317 mm and 2,262 mm in Caruaru, and 1,394 mm and 1,987 mm in Surubim during the period from 2009 to 2023, as represented in Figure 2.

The municipality of Garanhuns, characterized by an "As'a" climate type, presented the lowest ETo values. This is because, in addition to being located at higher altitudes, it experiences higher rainfall than Caruaru and Surubim, which possess a "BSh" climate type. According to Medeiros et al. (2021), the variability of evapotranspiration in the state across different seasons (spring, autumn, winter, and summer) is influenced by several variables, including solar radiation, wind speed, air temperature, relative humidity, and cloud cover.

Alvalá et al. (2017) identified that over the last 40 years, the Northeast has been marked by drought events, principally in the periods 1979–1983, 1992–1993, 1997–1998, and 2012–2017. As shown in Figure 2, the period from 2012 to 2017 exhibited the highest annual ETo values, indicating a greater atmospheric water demand. Furthermore, the years 2015 and 2016 were characterized by the presence of the El Niño-Southern Oscillation (ENSO), while the La Niña phenomenon occurred in 2012 (Marengo et al., 2017). Mousinho et al. (2024) characterized the rainfall in Caruaru over the last 50 years and identified significant variations in the peaks, including in 2019, with a value below the average of the analyzed period. Therefore, the high ETo rate in Caruaru in 2019 is attributed to the low rainfall regime during that year.

Table 2 – Classification of Pearson correlation index (r) values.

Correlation index (r)	Classification
0.0 to 0.1	Very Low
0.1 to 0.3	Low
0.3 to 0.5	Moderate
0.5 to 0.7	High
0.7 to 0.9	Very High
0.9 to 1.0	Almost Perfect

Source: Cunha et al. (2013).

Table 3 – Interpretation criteria for the performance index (c).

Performance index (c)	Performance
>0.85	Optimal
0.76 to 0.85	Very Good
0.66 to 0.75	Good
0.61 to 0.65	Average
0.51 to 0.60	Poor
0.41 to 0.50	Bad
≤0.40	Terrible

Source: Camargo and Sentelhas (1997).

Performance of Indirect ETo Models

Figure 3 presents the behavior of the monthly mean ETo for the period from 2009 to 2023, estimated by the ETo(PM), ETo(HS), ETo(RS), and ETo(JH) models for the municipalities of Garanhuns, Caruaru, and Surubim. It is noted in Figure 3 that, for the three municipalities, all models present the lowest values between the months of May and July, characterizing the rainy period or the winter season, with values below 4 mm/month, and the highest between October and March, characterizing the dry period or the summer season, with values above 4.5 mm/month. The behavior of the ETo estimated by the standard model was similar to the result of Cabral Júnior et al. (2017), where the ETo reached values around 5 mm/month.

The ETo(HS) model provided the closest approximation to the standard model in Garanhuns (Figure 3A), particularly during the wetter period. Conversely, for Caruaru (Figure 3B) and Surubim (Figure 3C), the model remained below the curve of the Penman–Monteith model, indicating

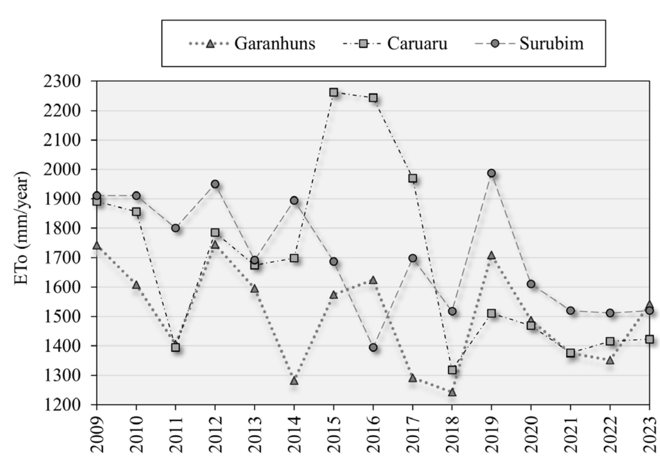

Figure 2 – Reference evapotranspiration (ETo) in municipalities of the Agreste of Pernambuco (Garanhuns, Caruaru, and Surubim).

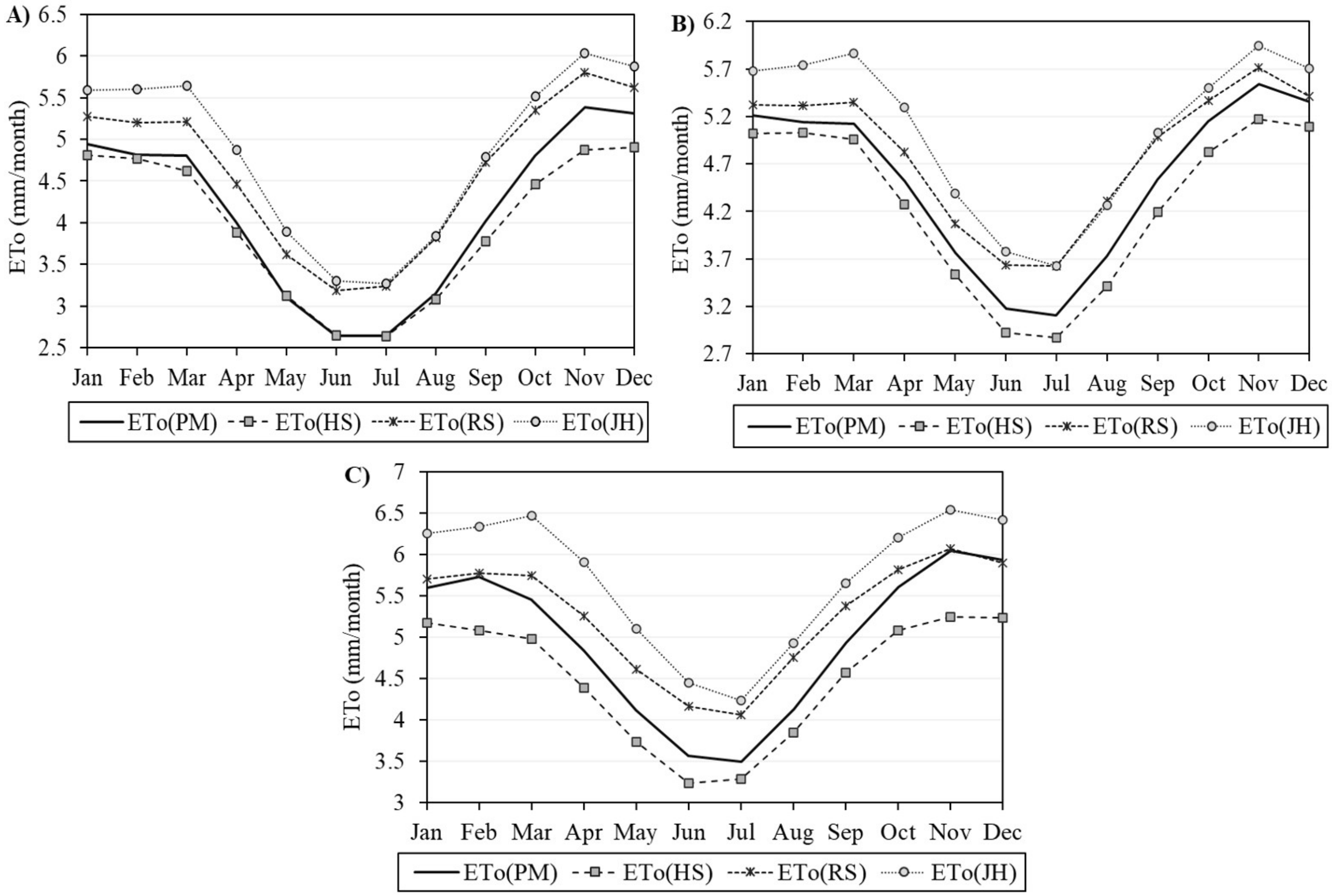

Figure 3 – ETo by ETo(PM), ETo(HS), ETo(RS), and ETo(JH) for the municipalities of A) Garanhuns, B) Caruaru, C) Surubim.

underestimation. The ETo(RS) and ETo(JH) models overestimated the entire seasonal variation of evapotranspiration for the three municipalities. However, the ETo(RS) model achieved values close to the standard in Caruaru and Surubim during the drier periods, where the monthly mean ETo exhibits higher values.

The metrics obtained for the models applied in Garanhuns, Caruaru, and Surubim are presented in Table 4. It is observed that, for the three municipalities, the ETo(HS) model achieved a PBIAS considered "very good" (PBIAS<±10), indicating a slight underestimation relative to the standard model. In turn, the ETo(RS) and ETo(JH) models presented PBIAS values indicating an overestimation of ETo; the performance of ETo(RS) was classified as "very good" in Caruaru and Surubim, and "good" (±10<PBIAS<±15) in Garanhuns. Finally, the ETo(JH) model exhibited a "good" PBIAS for Caruaru and a "satisfactory" rating (±15<PBIAS<±25) for Garanhuns and Surubim.

The coefficient of determination (R^2) indicated a good fit for all models, with particular emphasis on ETo(RS), which presented values exceeding 0.7 for all three municipalities. The Pearson correlation ranged from "very high" (0.7<r<0.9) to "almost perfect" (r>0.9)

Table 4 – Performance of indirect models for the municipalities of Garanhuns, Caruaru, and Surubim.

Metrics/Models	PBIAS (%)	R^2	r	d	c	Performance
Garanhuns						
ETo(HS)	4.96	0.83	0.91	0.92	0.83	Very Good
ETo(RS)	-11.33	0.92	0.96	0.95	0.91	Optimal
ETo(JH)	-16.50	0.89	0.95	0.92	0.87	Optimal
Caruaru						
ETo(HS)	4.76	0.72	0.85	0.90	0.76	Very Good
ETo(RS)	-6.17	0.90	0.95	0.96	0.91	Optimal
ETo(JH)	-11.55	0.90	0.95	0.94	0.89	Optimal
Surubim						
ETo(HS)	9.47	0.76	0.87	0.86	0.75	Good
ETo(RS)	-6.46	0.83	0.91	0.94	0.86	Optimal
ETo(JH)	-15.04	0.78	0.89	0.88	0.78	Very Good

for all evaluated models, with the highest value being obtained by the ETo(RS) model for the municipality of Garanhuns (r=0.96). The index of agreement exhibited behavior similar to "r" for the three municipalities, with the ETo(RS) and ETo(JH) models presenting performance classified as "optimal" (c>0.85), except in Surubim, where the ETo(JH) model obtained performance classified as "very good". The ETo(HS) model had a performance index between 0.75 and 0.85 for the three municipalities, resulting in "good" (c<0.76) or "very good" (0.75<c<0.86) performance.

The results obtained for Garanhuns corroborated those of Ongaratto and Bortolin (2021), who applied the ETo(HS) and ETo(JH) models in the municipality of São José dos Ausentes (RS), where performance varied between "good", "very good", and "optimal". Similarly, Silva et al. (2018) found results comparable to those obtained for Caruaru, applying the ETo(HS) and ETo(JH) models in the municipality of Jaíba, where ETo(HS) obtained a "d" coefficient equal to 0.94 and "good" performance (c=0.72), while ETo(JH) presented a "d" equal to 0.94 and "very good" performance (c=0.82). Lopes Sobrinho et al. (2024) achieved similar values for the Hargreaves–Samani method applied in Codó, MA, during the period from 2009 to 2013, obtaining a correlation of r=0.87 and a coefficient of R^2=0.75. Furthermore, the ETo(RS) model applied in Surubim showed performance similar to that reported by Moraes et al. (2023), in which the application in Imperatriz/MA obtained performance classified as "optimal" during the rainy season.

The results of this study are aligned with those of Monteiro et al. (2021), who, upon analyzing ETo estimation methods in Brazil over 38 years, identified better performance from the Hargreaves, Original Penman, and Stephens–Stewart methods in the Northeast. This pattern reinforces the climatic particularities of the region and explains the differences observed between the analyzed stations in Pernambuco, ranging from the hotter and drier conditions of Surubim to the milder and more humid climate of Garanhuns.

International studies confirm the good performance of indirect ETo estimation methods. Across 15 stations in Texas, Su et al. (2022) observed satisfactory performance of the Hargreaves–Samaní model, although they emphasized the necessity for local calibration, especially in transitional and drier regions. The Jensen–Haise model exhibited behavior similar to that found in this study, with overestimation in humid conditions, while maintaining a strong correlation with the Penman–Monteith model. Different indirect models have been applied in various regions, including China, Iran, Bangladesh, and Turkey, under diverse climatic conditions, such as semi-arid environments (Shirmohammadi-Aliakbarkhani and Saberali, 2020; Islam and Alam, 2021; Gharehbaghi and Kaya, 2022; Liu et al., 2025). Despite limitations and the need for calibration, indirect methods remain robust alternatives in data-scarce contexts (Alam et al., 2024; Mostafa et al., 2024).

Performance of orbital and gridded data

Figure 4 displays the ETo from the MOD16A2 product for the years 2009, 2012, 2016, 2019, and 2022. The image illustrates the climatic transition present in the Agreste, with high ETo rates toward the *Sertão* and lower rates toward the coast. In 2009, Garanhuns presented an annual ETo value of approximately 1,600 mm (yellow color), Caruaru presented 1,300 mm (a color transitioning from yellow to blue), and Surubim presented 1,000 mm (a more bluish hue). In 2012, the rates increased to 1,597 mm in Garanhuns, 1,668 mm in Caruaru, and 1,326 mm in Surubim. In 2016, the upward trend in rates continued for Garanhuns, which reached 1,663 mm, and for Caruaru, with 1,797 mm; conversely, Surubim decreased to 1,237 mm. In the image, these values for Garanhuns and Caruaru range between orange and yellow colors, while Surubim lies in the shade between yellow and blue. Rocha Júnior et al. (2020) noted that the drought events recorded between 2012 and 2018 in the Brazilian Northeast had a significant influence on evapotranspiration variability. In the analyzed product, the increase in ETo between 2012 and 2016 within the mesoregion was evident.

Garanhuns maintained high ETo rates in 2019 and 2022, with values ranging from 1,748 to 1,533 mm, respectively. Caruaru varied from 1,608 to 1,215 mm, and Surubim from 1,133 to 1,311 mm. According to INMET (2022), 2022 was considered the hottest year since 1961 and was marked by the presence of the La Niña climatic phenomenon; however, conversely, it presented a high rainfall regime, considered above average, in the North and Northeast regions. This shift in the rainfall regime explains the decline in ET indices between 2016 and 2022.

Table 5 presents the performance of the MOD16A2 product in relation to the ETo estimated by the standard ETo(PM) model.

The MOD16A2 product presented unsatisfactory PBIAS (PBIAS>±25) for all municipalities, indicating significant data overestimation. The municipalities of Garanhuns and Caruaru yielded low R^2 values, yet these were higher than that of the Surubim station (R^2=0.05). The Pearson correlation obtained a low classification for Surubim and a high classification for the other stations (0.5<r<0.7). Willmott's coefficient presented values above 0.5 for the Garanhuns station and below this threshold for the others. According to the "c" index, performance was terrible for all three municipalities. Tito et al. (2020) found similar R^2 values for six stations in Rio de Janeiro, where the coefficient presented a value close to 0. Similarly, Tang et al. (2024) evaluated 25 global terrestrial surface evapotranspiration datasets and noted that MOD16A2 was one of six RS products that consistently overestimated in situ observations. According to Srivastava et al. (2017), the poor performance of the MOD16A2 product is attributed to cloud cover and vegetation shading, underscoring the need for standardization of the product in relation to data from the PM-FAO model or lysimeters.

Figure 5 details the ETo from the BR-DWGD gridded database for the years 2009, 2012, 2016, 2019, and 2022.

As shown in Figure 5, the ETo image from the gridded database appears pixelated compared to the MOD16A2 product, likely due to the spatial resolution of the base, which is 0.1 × 0.1°. However, as observed in Figure 4, it is possible to note the transition in evapotranspiration variation within the Agreste of Pernambuco, with higher values near

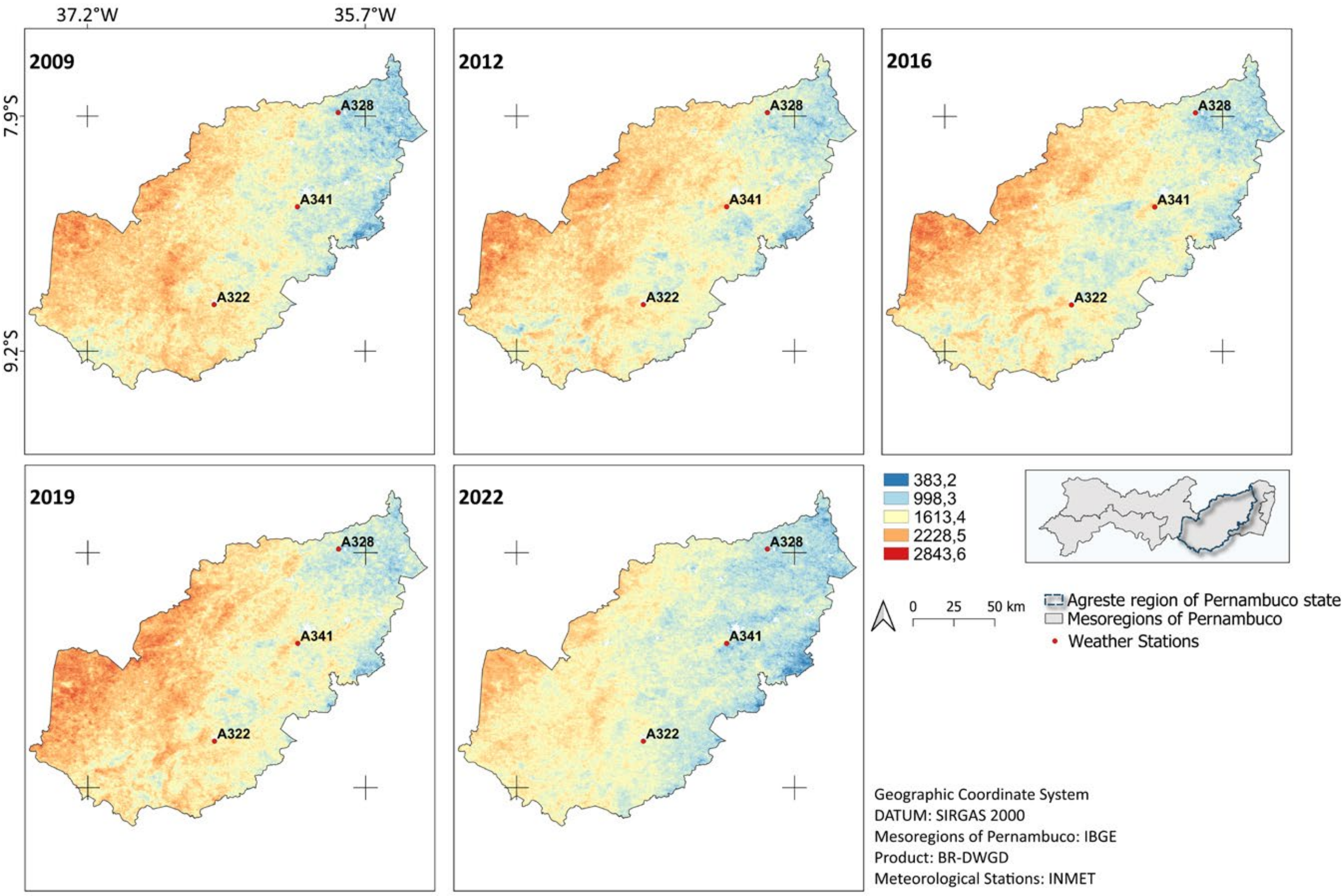

Figure 4 – ETo from the NASA MOD16A2 product for the years 2009, 2012, 2016, 2019, and 2022.

Table 5 – Performance of the MODIS MOD16A2 product in relation to ETo estimated by PM-FAO.

Station	PBIAS (%)	R^2	r	d	c	Performance
Garanhuns	-49.90	0.45	0.67	0.53	0.35	Terrible
Caruaru	-48.67	0.30	0.55	0.47	0.26	Terrible
Surubim	-26.22	0.05	0.21	0.47	0.10	Terrible

the *Sertão* of Pernambuco and lower values near the *Zona da Mata*. Furthermore, in general terms, values varied in relation to relief and climatic typology, where Garanhuns, situated partly on the Borborema Plateau, presented lower values than Surubim, which possesses a more arid climate. In 2009, Garanhuns presented an annual value of around 1,394 mm, Caruaru between 1,394 and 1,556 mm, and Surubim a value between 1,556 and 1,717 mm. In 2012, the Garanhuns and Caruaru stations presented an increase in ETo rates, with values around 1,600 mm, and Surubim also experienced a slight increase, with a value above 1,717 mm. In 2016, it was observed that Surubim experienced notable growth, presenting a value of around 1,736 mm. In 2019, a reduction in evapotranspiration rates was observed, with Garanhuns and Caruaru presenting values of approximately 1,394 mm, and Surubim presenting values between 1,556 and 1,717 mm. In 2022, declines were also noted at the three stations, with values ranging from 1,394 to 1,556 mm.

Table 6 presents the performance of ETo from the BR-DWGD database in relation to the ETo estimated by the standard ETo(PM) model.

The BR-DWGD climatic database presented optimal results for all stations, obtaining a "very good" PBIAS, indicating slight underestimation, a coefficient of determination above 0.7, Pearson correlation ranging from "very high" to "almost perfect", Willmott's coefficient with values close to or exceeding 0.9, and performance oscillating between "very good" and "optimal". This behavior of the database results from the interpolation of observed data, and owing to its high accuracy, numerous studies utilize climatic variables from the BR-DWGD as baseline data in their research (Monteiro et al., 2021; Barbosa et al., 2024; Dalcol et al., 2024; Freitas et al., 2024). Rasera et al. (2023) observed good results and correlations for the BR-DWGD base, highlighting its efficiency in filling gaps and providing data for modeling. Perleberg et al. (2025) also analyzed the BR-DWGD in Mato Grosso do Sul and identified it as the climatic database with the best performance

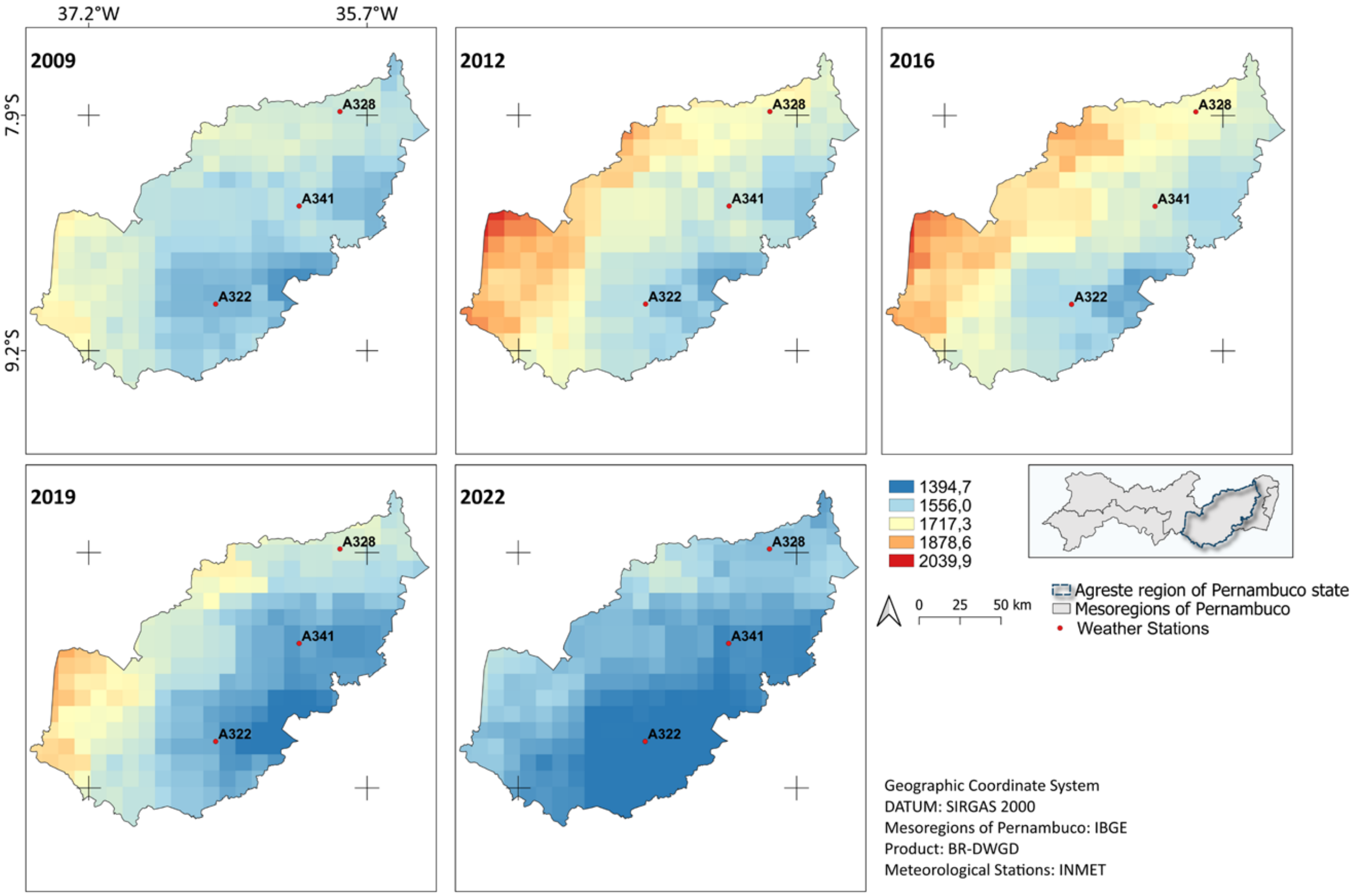

Figure 5 – ETo from the BR-DWGD base for the years 2009, 2012, 2016, 2019, and 2022.

Table 6 – Performance of the BR-DWGD base in relation to ETo estimated by Penman–Monteith–FAO.

Metrics/Models	PBIAS (%)	R^2	r	d	c	Performance
Garanhuns	3.42	0.89	0.94	0.96	0.91	Optimal
Caruaru	6.69	0.81	0.90	0.92	0.83	Very Good
Surubim	9.89	0.80	0.89	0.88	0.79	Very Good

in relation to the ERA5 (5th Generation of European Reanalysis) base. Therefore, in view of the results of the evapotranspiration metrics, the gridded climatic database presented good performance for use in the state of Pernambuco as a substitute for observed data.

This study demonstrated that the climatic conditions prevailing in each municipality led to variations in the performance of the studied models, which may be attributed to the dynamics of solar radiation, temperature, and other climatic variables present in each locality. Furthermore, the spatiotemporal behavior of MODIS and BR-DWGD allowed for the verification of variations in ETo rates throughout the Agreste, which relates to the region's physiographic, climatic, and environmental characteristics.

Conclusions

This study analyzed the performance of different indirect models for estimating reference ETo using orbital data and gridded data for three stations located in the Agreste of Pernambuco, comparing them to the standard Penman–Monteith–FAO 56 model. Regarding the indirect models, the solar radiation model was notable for its robustness, consistently presenting superior performance across all stations. The Hargreaves–Samani and Jensen–Haise models also demonstrated good applicability in the studied municipalities, proving to be viable alternatives in data-limited contexts.

The MOD16A2 product presented limitations in estimating evapotranspiration in the Agreste of Pernambuco, exhibiting unsatisfactory bias (PBIAS) and performance considered terrible for the three stations. The BR-DWGD climatic database demonstrated consistent performance, with low errors, very high correlations, and excellent statistical fit, demonstrating its suitability for applications in the Agreste of Pernambuco, particularly in hydrological and climatic studies. Thus, the study contributes to efficient water management in semi-arid regions, offering technical support for model selection and reinforcing the importance of regional calibrations to enhance the precision of estimates.

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Authors' Contributions

Silva, A.P.G.: Conceptualization, formal analysis, methodology, validation, visualization, writing — original draft, writing — review & editing. **Jovino**, E.S.: conceptualization, methodology, writing — original draft, writing — review & editing. **Moraes**, J.F.S.: conceptualization, visualization, writing — original draft, writing — review & editing. **Menezes**, R.B,G.G.: conceptualization, writing — original draft, writing — review & editing; **Silva Junior**, U.J.: conceptualization, visualization, writing — original draft, writing — review & editing. **Santos**, S.M.: formal analysis, methodology, supervision; visualization, writing — review & editing. **Oliveira**, L.M.M.: formal analysis, methodology, supervision; visualization, writing — review & editing.

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