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# Remote sensing and global databases for soil moisture estimation at different depths in the Pernambuco state, Northeast Brazil

## *Uso de sensoriamento remoto e bancos de dados globais para estimativa de umidade do solo em diferentes profundidades no estado de Pernambuco*

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## ABSTRACT

The present study aimed to apply and assess an exponential filter that calculates the root-zone soil moisture using surface data from the soil moisture and ocean salinity (SMOS) satellite, as well as to assess soil moisture simulated in land-surface models from global databases. The soil water index (obtained after application of the exponential filter) and soil moisture simulated using land surface models (GLDAS-CLSM, GLDAS-Noah, and ERA5-Land) from global databases were compared with *in situ* data to evaluate their efficiency in estimating soil water content at different depths. Surface measurements from the SMOS satellite allowed the estimation of soil moisture at depths of 20 and 40 cm by applying the exponential filter. At both depths, the application of the exponential filter significantly improved the estimation of soil moisture measured by the SMOS satellite. The GLDAS-Noah model had the best root mean square error values, whilst the GLDAS-CLSM and ERA5-Land models overestimated the soil moisture. Nevertheless, the seasonal variation was well represented by all land surface models.

**Keywords:** SMOS satellite; Semiarid; Northeast Brazil; Land surface models.

## RESUMO

O presente estudo teve como objetivo aplicar e avaliar um filtro exponencial que calcula a umidade do solo na zona da raiz usando dados de superfície do satélite soil moisture and ocean salinity (SMOS), assim como avaliar a umidade do solo simulada em modelos de superfície de bases de dados globais. O índice de água do solo (obtido após a aplicação do filtro exponencial) e a umidade do solo simulada com modelos de superfície terrestre (GLDAS-CLSM, GLDAS-Noah e ERA5-Land) de bancos de dados globais foram comparados com dados *in situ* para avaliar sua eficiência na estimativa do teor de água do solo em diferentes profundidades. As medições de superfície do satélite SMOS permitiram estimar a umidade do solo nas profundidades de 20 e 40 cm por meio da aplicação do filtro exponencial. Em ambas as profundidades, a aplicação do filtro exponencial melhorou significativamente a estimativa da umidade do solo medida pelo satélite SMOS. O modelo GLDAS-Noah apresentou os melhores valores de erro quadrático médio, enquanto os modelos GLDAS-CLSM e ERA5-Land superestimaram a umidade do solo. No entanto, a variação sazonal foi bem representada por todos os modelos de superfície.

**Palavras-chave:** Satélite SMOS; Semiárido; Nordeste do Brasil; Modelos de superfície.

## INTRODUCTION

As an essential climate variable, soil moisture has been used in many studies to investigate extreme hydrometeorological events. To investigate the occurrence of agricultural drought, estimation of soil moisture content is one of the most important parameters, considering that it directly affects crop growth and impacts the flux exchange of water and energy at the land-atmosphere interface through evapotranspiration (Xu et al., 2018). In addition, soil moisture is an important variable for forecasting other extreme climatic events, such as floods and landslides, and for providing information for water resource management, irrigation management, monitoring of the dynamics of vegetation, and agricultural production (Beck et al., 2021; Xu et al., 2018). Drought monitoring requires a comprehensive analysis to determine its characteristics, including frequency, spatial extent, intensity, magnitude, duration of the event, and the potential of occurrence (Mishra et al., 2014). The enhancement of monitoring tools facilitates the adoption of best management practices and attenuation of the vulnerability of the population to drought.

Soil moisture in the root zone is especially important in vegetated areas because of its direct influence on evapotranspiration and its fundamental role in plant growth (Ford et al., 2014), contributing to agricultural drought forecasting. Estimation of water content in the root zone can also contribute to the quantification of soil carbon content, which is essential for the analysis of future climate change (Tobin et al., 2017). The scarcity of precipitation over long periods is associated with high temperatures and produces an increase in water demand, thereby exhausting the root zone soil moisture, resulting in agricultural drought (Mishra et al., 2014).

An alternative to taking measurements at monitoring stations is to establish a relationship between the moisture on the surface and in the soil profile, as proposed in previous studies (Albergel et al., 2008; Wagner et al., 1999). The soil water index (SWI) applies an exponential filter on data estimated, for example, by the soil moisture and ocean salinity (SMOS) satellite and soil moisture active passive (SMAP) satellite (Ford et al., 2014; Pablos et al., 2018; Stefan et al. 2021). In addition, the soil moisture estimated with the filter can be used to evaluate the data simulated by hydrological and land-surface models. In comparison with *in situ* data, remote sensing and model products have some advantages, including fewer missing data, greater space coverage, and longer time series. This is particularly important in semiarid regions, such as Northeast Brazil, where the monitoring of hydrometeorological variables is useful for drought preparedness. The monitoring of agricultural drought, for example, requires daily data for application using soil moisture-based indices (Souza et al., 2021), a characteristic present in SMOS and SMAP data, and in land-surface models.

The SWI has been applied in a variety of studies, including validation of the root zone soil moisture per land cover type (Stefan et al., 2021), different climate regions (Gao et al., 2019; Zohaib et al., 2017), spatiotemporal trends (Zohaib et al., 2017), and comparison with other methods (Zhang et al., 2021; Gao et al., 2019), demonstrating its usability. On the other hand, recent studies have attempted to demonstrate the suitability of using soil moisture from remote sensing and land-surface models for drought monitoring (Zhang et al., 2021; Liu et al., 2019; Cammalleri et al., 2017). In general, these analyses were performed with surface soil moisture, which can be considered a limitation. Drought assessment using root zone soil moisture can lead to results more robust, and the combination of SWI and modeling has potential to enable this task. The study area chosen, the territory of Pernambuco state (Brazil), has heterogeneity (climate, soil type, and land cover) and size favorable to contribute for assessing issues regarding soil moisture monitoring.

This study aimed to apply and assess an exponential filter that calculates the root-zone soil moisture using surface data from the SMOS satellite, whose validation was conducted for Penambuco by (Souza et al., 2018). The performance of the filter was determined by comparing the soil moisture data with the *in situ* data. Furthermore, soil moisture simulated in land-surface models from global databases was assessed using *in situ* data.

## STUDY AREA

Pernambuco has an area of 98,068 km$^2$, of which 89% corresponds to a semiarid climate and the remaining to a humid and sub-humid climate (Asfora et al., 2017). This region has a low thermal amplitude, with annual temperature variation between 25 and 31 °C, and high space-time variability. The highest precipitation levels are recorded on the coast (annual average ranging from 1500 to 2500 mm) where a sub-humid climate prevails. In the westward direction, where the climate is semiarid, precipitation decreases and is concentrated in a few months of the year, resulting in a lower annual average precipitation (ranging between 500 and 800 mm). In the semiarid portion of the Northeast region, shallow soils prevail and tend to saturate after intense rainfall events and lose water during dry periods (Menezes et al., 2013). The territory of Pernambuco is divided into mesoregions, which have specific characteristics of land cover, soil type, and climate. Figure 1 illustrates the division of the territory into the mesoregions Sertão (aggregation of São Francisco Pernambucano and Sertão Pernambucano), Agreste, and Mata (aggregation of Mata and Metropolitan Region of Recife), the first two presenting a semiarid climate, and the third with sub-humid characteristics.

Rainfed and irrigated agriculture are important elements of the socio-economic development in Pernambuco, which are directly affected by recurrent drought events. The use of remote sensing products has shown the potential of these data for soil moisture assessment and monitoring in Pernambuco (Souza et al., 2021, Inocêncio et al., 2020).

## MATERIAL AND METHODS

After data acquisition, the exponential filter was implemented using SMOS data and then compared to the *in situ* soil moisture. Figure 2 shows the steps adopted in the filter application process, considering *in situ* data consistency, SMOS and model data acquisition, filter application, and statistical criteria calculation.

### Exponential filter

The assumption of hydrologic equilibrium in the soil profile enables the estimation of soil moisture in the root zone

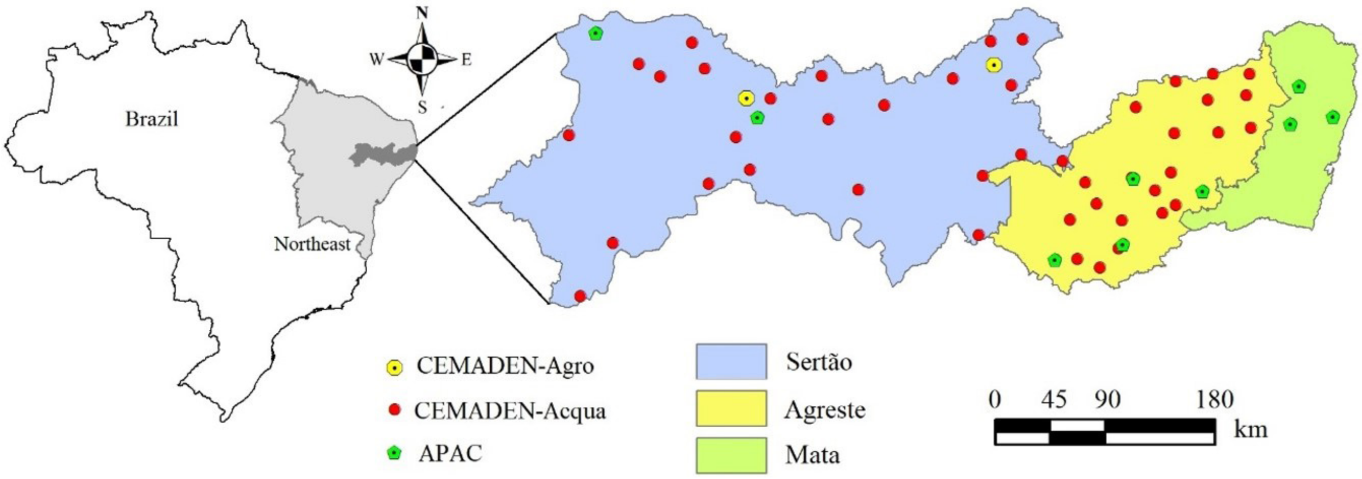


**Figure 1.** Location of the study area displaying the mesoregions in the Pernambuco state: Sertão and Agreste with semiarid climate, and Mata presenting sub-humid characteristics.

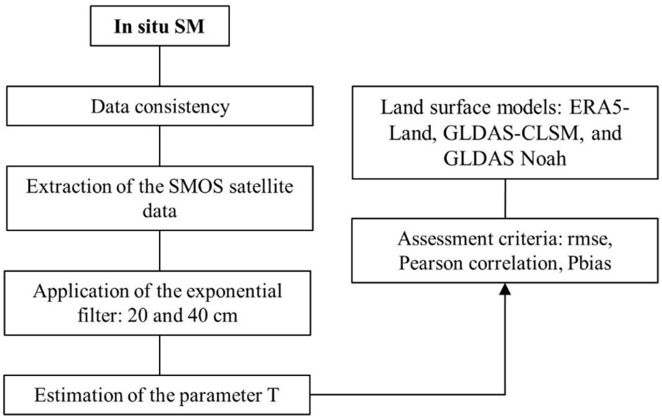


**Figure 2.** Flowchart displaying the procedures adopted for soil moisture measurements in the Pernambuco state.

using measurements on the soil surface (Tobin et al., 2017). For the conception of the exponential filter, a simple two-layer water balance model was proposed by Wagner et al. (1999).

These layers simulate the flow of water in the soil profile. The recursive formulation facilitates the application of the exponential filter, providing an estimation of soil moisture at time $t_n$ as proposed by Albergel et al. (2008):

$$SWI_n = SWI_{n-1} + K_n\left(m_s\left(t_n\right) - SWI_{n-1}\right) \tag{1}$$

where SWI is the soil water index, $m_s$ is the surface soil moisture estimation given by the SMOS data, the gain K varies between 0 and 1, and its value at time $t_n$ is:

$$K_n = \frac{K_{n-1}}{K_{n-1} + e^{\frac{-\left(t_n - t_{n-1}\right)}{T}}} \tag{2}$$

At the beginning of the simulation, the filter is initialized assuming $K_1 = 1$ and $SWI_1 = m_s\left(t_1\right)$. In addition to the previous values of SWI and K, only the $m_s\left(t_n\right)$ estimation and time interval of the last measure are required to update the SWI. As described by Albergel et al. (2008), the T parameter represents several processes, including the thickness of the soil layer, soil properties, evaporation, and runoff, and it represents the time scale of soil moisture variation in unit of days, the same time step of the input $m_s$.

Originally, the surface soil moisture $m_s$ was normalized between 0 and 1 before application of the filter (Albergel et al., 2008; Wagner et al., 1999). Later, other authors used volumetric unit ($m^3/m^3$) for $m_s$, resulting in the representation of SWI in $m^3/m^3$ as well (Pablos et al., 2018; Tobin et al., 2017; Zohaib et al., 2017).

## *In situ* and satellite Dataset

The soil moisture data for Northeast Brazil is relatively recent and is available on a large scale. This has stimulated interest in the scientific community and has led to extensive research focusing on drought. We used daily *in situ* soil moisture databases from the Pernambuco state water and climate agency (APAC) and the National Center for Monitoring and Early Warning of Natural Disasters (CEMADEN) (Zeri et al., 2020). The data covers the period between May 2015 and August 2019 for the APAC database, and between July 2015 and April 2019 for the CEMADEN database. Previous applications of these datasets in the Northeast Brazil can be found in Souza et al. (2021), Souza et al. (2018), and Zeri et al. (2018). The data consistency was verified according to the following criteria: minimum data availability of 30% of the days considering the total number of days in the period selected, removal of divergent values (negative or inconsistent with the soil characteristics of the region), and exclusion of stations with long periods of missing data. In total, 55 stations were selected: 9 from APAC and 46 from CEMADEN, distribution in the mesoregions detailed in Table 1 and Figure 1. APAC stations measured the soil moisture at depths of 10, 20, and 40 cm. The CEMADEN

**Table 1.** *In situ* stations that measure soil moisture at 20 and 40 cm depths.

| Region | CEMADEN-Acqua Stations | CEMADEN-Agro Stations | APAC Stations | Climate |
|---|---|---|---|---|
| Sertão | 23 | 2 | 2 | Semiarid |
| Agreste | 21 | 0 | 4 | Semiarid |
| Mata | 0 | 0 | 3 | Sub-humid |

stations are of two types, Acqua (that measure soil moisture at 10 and 20 cm depths) and Agro (that measure soil moisture at 10, 20, 30, and 40 cm depths). Herein, we used data from depths of 20 and 40 cm for the exponential filter application and 10, 20, and 40 cm for comparison with the land surface models.

The SMOS soil moisture data level L3 – v003, spatial resolution of 25 km and daily time resolution is provided by the SMOS Barcelona Expert Center (SMOS BEC) at http://bec.icm.csic.es/data/data-access/. The soil moisture was measured on the soil surface (~0–5 cm) with an accuracy of 0.04 $m^3.m^{-3}$. The SMOS data was validated using *in situ* time series (Souza et al., 2018) for the region of Pernambuco state, where it was verified satisfactory agreement between the satellite data and *in situ* soil moisture. For each of the 55 stations, the cells of the SMOS grid were identified to extract the soil moisture data for subsequent application.

## Soil moisture data from global databases.

The Global Land Data Assimilation System (GLDAS) applies observed and satellite data as inputs in surface modelling to generate variables associated with the hydrological components in the continents (Rodell et al., 2004). The GLDAS models are constructed using data on observed precipitation, products of incident radiation, and the best atmospheric data assimilation available (Chen et al., 2013). The GLDAS database comprises the surface models Noah, VIC, Mosaic, and Catchment Land Surface Model (CLSM); 1° and 0.25° spatial resolution; 3 hourly, daily, and monthly time resolution; and a period of simulation starting in 1948. The Noah and CLSM models are more suitable for use in this application because of their better spatial resolution (0.25°) and time step of the simulations (3 hourly for Noah and daily for CLSM).

The GLDAS-Noah model simulated the water content in four layers of the soil profile, 0–10, 10–40, 40–100, and 100–200 cm. The first two layers were considered for calculation of the depth 0-40 cm and comparison with the SWI and SMOS data. These datasets correspond to GLDAS-2.1 products, which is simulated with model and observation data from 2000 until the present.

The GLDAS-CLSM can simulate soil moisture at the surface depth (0–2 cm) and root zone (0–100 cm). The data covers the period from 2003 to the present, corresponding to version 2.2 of the GLDAS, and includes a main product from CLSM-F2.5 with assimilation of the Gravity and Climate Experiment (GRACE) data, which allows the simulation of terrestrial water and groundwater storage. In addition, meteorological data from the European Center for Medium-range Weather Forecasts (ECMWF) were used to force the simulations (Li et al., 2019).

The ECMWF Atmospheric Reanalysis version 5 (ERA5) utilizes weather forecast models to reproduce the observed data. Version 5 is characterized by atmosphere, continental surface, and ocean data from 1979 to the present day. The ERA5-Land version was obtained after a new simulation of the ERA5's terrestrial component. Each model was compared with the soil moisture from different depths: GLDAS-CLSM (0–2 cm) compared to the depth of 10 cm, ERA5-Land (0–28 cm) with 20 cm depth, and GLDAS-Noah (0–40 cm) with 40 cm depth.

## Statistic criteria and estimation of the T parameter

Three criteria were used to estimate the values of the T parameter and assess the performance of the exponential filter in determining moisture in the soil profile. First, Pearson's r coefficient measures the linear correlation between two series of data, where the closer the coefficient is to -1 or 1, the higher the correlation between the data. Second, the root mean square error (RMSE) is a measurement of the mean standard deviation that quantifies the accuracy between *in situ* and satellite values. Finally, Pbias represents the error of volume in percentage, giving a notion of over-or underestimation.

For each station, the equivalent pixel of the SMOS grid was identified, and the datasets were extracted. The stations and SMOS satellite had common data between 2015 – 2019. The T parameter was calculated for each station by applying the optimization nonlinear programming algorithm Generalized Reduced Gradient (GRG) available in the solver of Microsoft Excel. The objective function was based on Pearson's r and RMSE values. The GRG uses nonlinear programming to find the best values for the decision variable (T in this application). These calculations were made for the depth of 20 cm at all stations and 40 cm for the APAC and CEMADEN-Agro stations. To evaluate the efficacy of the filter, the soil moisture in the profile was also compared with the SMOS values without filter application.

# RESULTS AND DISCUSSIONS

The following sections present the estimation of the T parameter and the statistical criteria used for the assessment. Based on the analysis performed by Wagner et al. (1999), the maximum variation allowed for the T parameter was in the interval of 1–100.

## Estimation and sensitive analyses of T parameter

The analysis of T parameter was divided into two parts according to the soil depth. For depth of 20 cm, at the stations in the Sertão region, the T parameter varied between 3.9 and 100 days. To analyze the sensitivity of the exponential filter to changes in the T parameter, tests were performed by applying a unique value for all stations. The first value (8.5 days) was the average of all stations with T values lower than 20 days, the second value was 14 days obtained from Albergel et al. (2009), and the third value was 20, obtained by Wagner et al. (1999). The results showed small changes in the statistical criteria. Another test was conducted at six stations, where T varied between 52 and 100 days, replacing these values by 40 days. The limitation of T for 40 days did not change the results of the criteria, implicating the maintenance of this new limit in the determination of the T parameter. Figure 3 illustrates the improvement in the soil moisture estimation after the application of the exponential filter at four stations. The application of the exponential filter improved the estimation of soil moisture at all the stations evaluated. This can be verified by the increase in Pearson's r and the reduction in the RMSE values. On average, Pearson's r improved from 0.49 to 0.66, and the RMSE decreased from 0.080 to 0.060 $m^3.m^{-3}$.

Figure 4 summarizes the frequency of classes with and without filter application for the RMSE and correlation statistics for all stations with a depth of 20 cm and T values obtained by optimization. All stations presented an increment of classification after filter application, resulting in a greater number of stations with a strong correlation. Similarly, for the RMSE, the prevalence of stations on the right side of the graph in Figure 4a corresponds to lower errors after filter application.

Considering the SMOS data without filter application, because of the deeper soil moisture, the correlation at a depth of 40 cm was lower than that at 20 cm (on average 0.54 and 0.60, respectively). The filter application also improved the statistics at 11 stations with measurements taken at a depth of 40 cm. Considering these 11 stations, on average, the correlation was greater at a depth of 20 cm (0.75) than at 40 cm (0.71), but the RMSE values were 0.062 (at 20 cm) and 0.063 (at 40 cm). However, when compared with the SMOS data without filter application, improvements were more evident at a depth of 40 cm. The correlation improved by 23.2% (at 20 cm) and 32.0% (at 40 cm), and the RMSE by 22.9% (at 20 cm) and 26.5% (at 40 cm), after filter application.

Figure 5 illustrates the spatial variability of the T parameter at two depths (20 and 40 cm). There is a trend in the Sertão region to present greater values of T compared to the Agreste region. This was especially evident for the 20 cm depth (upper Figure 5) because of the greater number of stations. A possible explanation for this may be that the low precipitation rates associated with high evapotranspiration rates caused less perturbation of the *in situ* soil moisture resulting in greater values of the T parameter. It is worth emphasizing that T was calculated iteratively for each station and soil depth.

## Comparison with land surface models

There was a trend of overestimation of the soil moisture simulated using the models, as shown in Figure 6. Table 2 lists the range and the average of the Pbias with positive values representing overestimation.

The GLDAS-Noah model had the best values for the RMSE criteria, followed by ERA5-Land and GLDAS-CLSM. As demonstrated in Figure 6, the GLDAS-Noah model satisfactorily

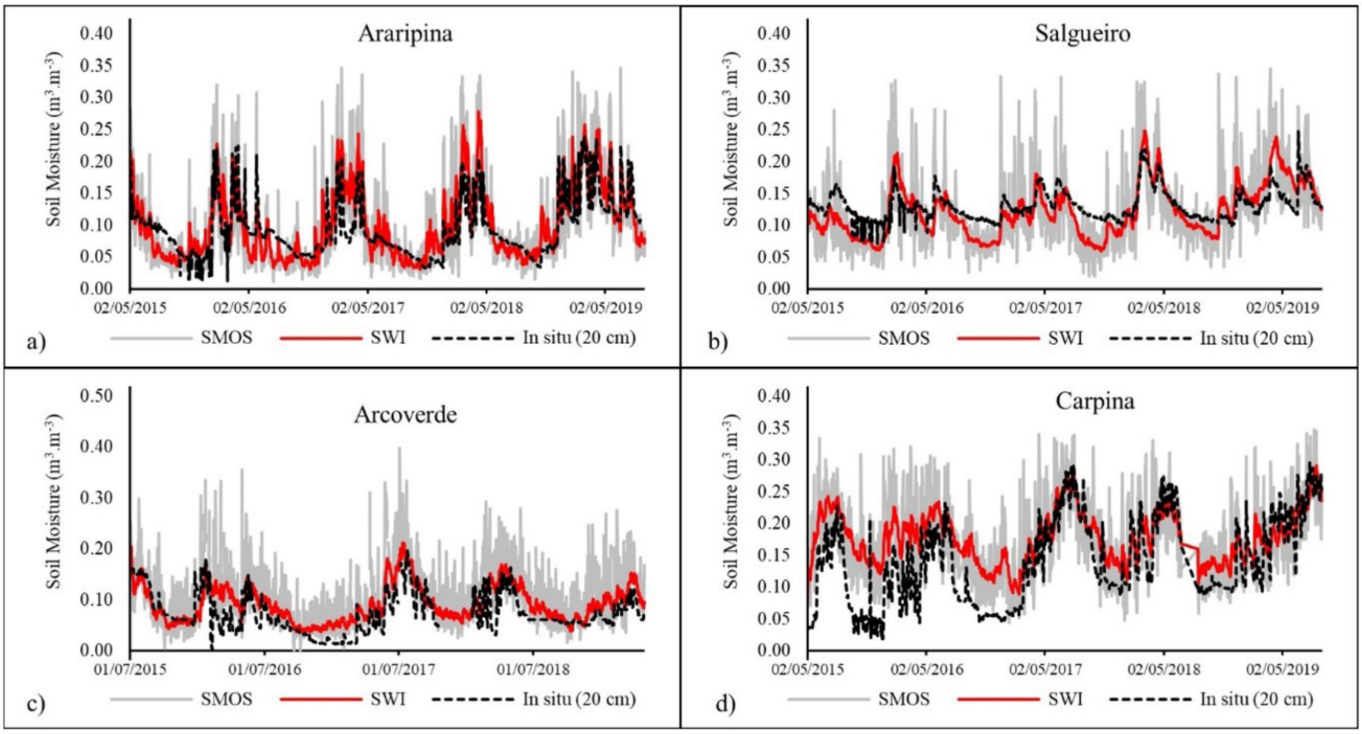


**Figure 3.** *In situ* soil moisture and soil water index (SWI) corresponding to 20 cm depth: Araripina-APAC (a), Salgueiro-APAC (b), Arcoverde-CEMADEN Acqua (c), Carpina-APAC (d).

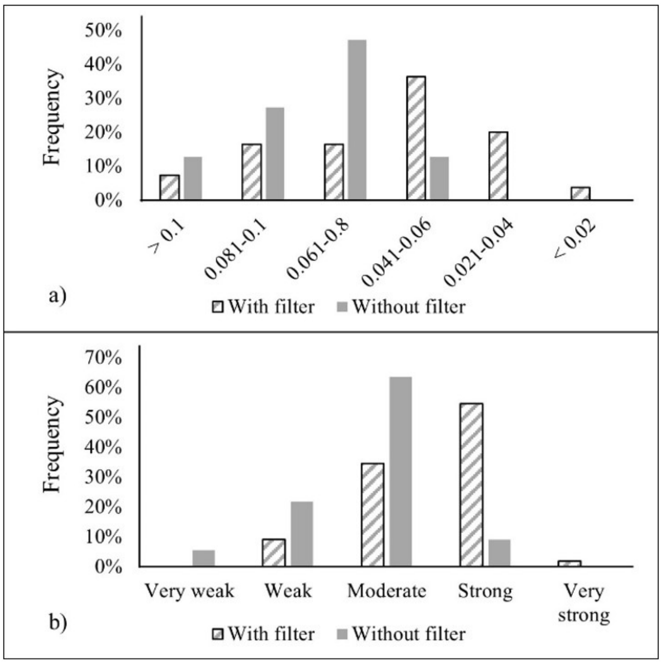


**Figure 4.** Frequency of occurrence of root mean square error (RMSE) (a) and Pearson's r correlation (b) with classifications of very weak (0–0.19), weak (0.20–0.39), moderate (0.40–0.69), strong (0.70–0.89), and very strong (0.90–1.0). Values correspond to all stations with depth 20 cm.

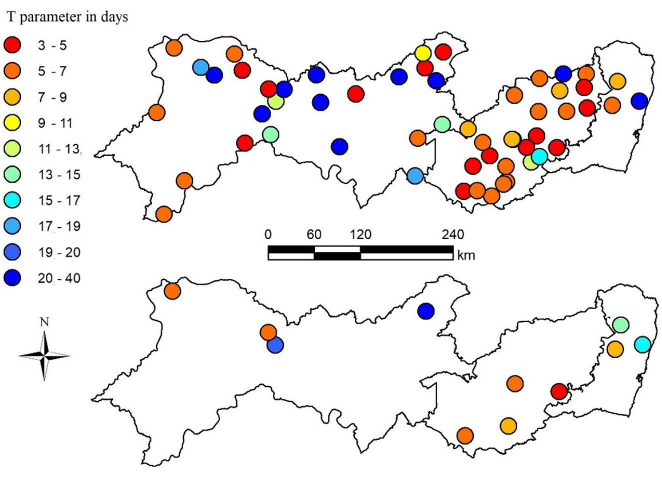


**Figure 5.** Spatial variability of the T parameter for the 20 cm (upper) and 40 cm (lower).

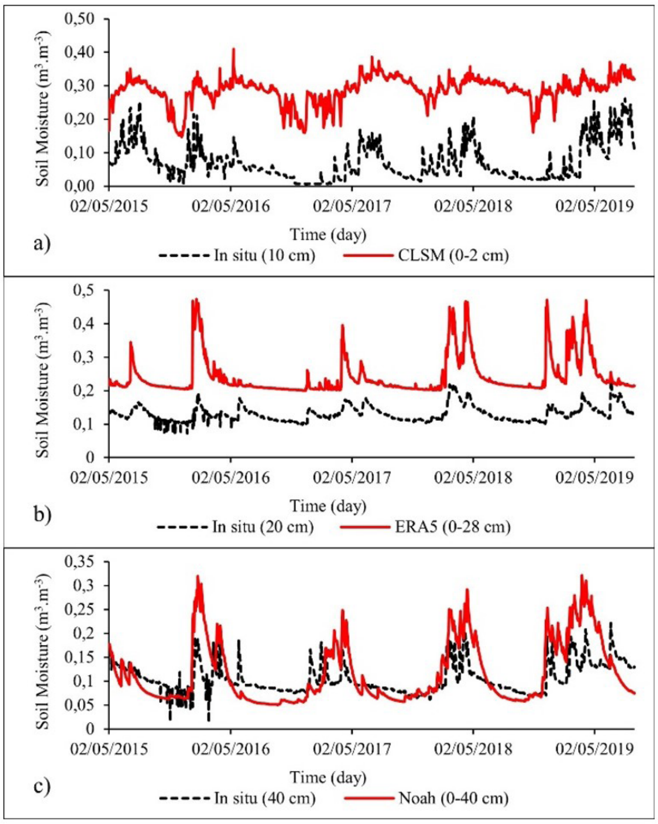


**Figure 6.** *In situ* soil moisture and GLDAS-CLSM at São Bento do Una (a), ERA5-Land at Salgueiro (b), and GLDAS-Noah at Araripina (c).

**Table 2.** Range of variation and average Pbias considering the ten stations used for model assessment.

| Model | Range | Average |
|---|---|---|
| GLDAS-CLSM | 51.2%–487.7% | 161.09% |
| ERA5-Land | 33.0%–415.3% | 126.3% |
| GLDAS-Noah | -38.3%–640.0% | 91.5% |

simulated the seasonal variation in the soil moisture and the amplitude of the values. An exception occurred at station Serrita, where the *in situ* soil moisture was excessively low, resulting in a Pbias value of 640.0%. The Salgueiro station, located 18 km away from Serrita, had a Pbias of 54.7%, which could be an indication of the inconsistency of the data at Serrita.

The Pearson's r correlation for GLDAS-CLSM and ERA5-Land was greater than that for GLDAS-Noah, despite the latter having better RMSE values. Three stations are located in the eastern sub-humid parts and seven in the semiarid region. The results from ERA5-Land showed a remarkable difference between the stations within these two regions. In the sub-humid region (Mata region in Figure 1), the average RMSE was 0.226, and in the semiarid region was 0.119 (Sertão and Agreste regions in Figure 1). Figure 7 summarizes the values of correlation and RMSE for the data from SMOS, SWI, and the models compared to the *in situ* data. The lower the value of the RMSE, the better the performance (Figures 7a, 7c, 7e) with the SWI standing out, followed by SMOS data. For the correlation, the higher the value, the better the result (Figures 7b, 7d, 7f), and again the SWI stands out. This time, however, the models present correlation nearer the SMOS and SWI.

## Discussion

In general, T affects the behavior of the SWI curve as it increases its value, and consequently, the gain $K_n$ decreases in

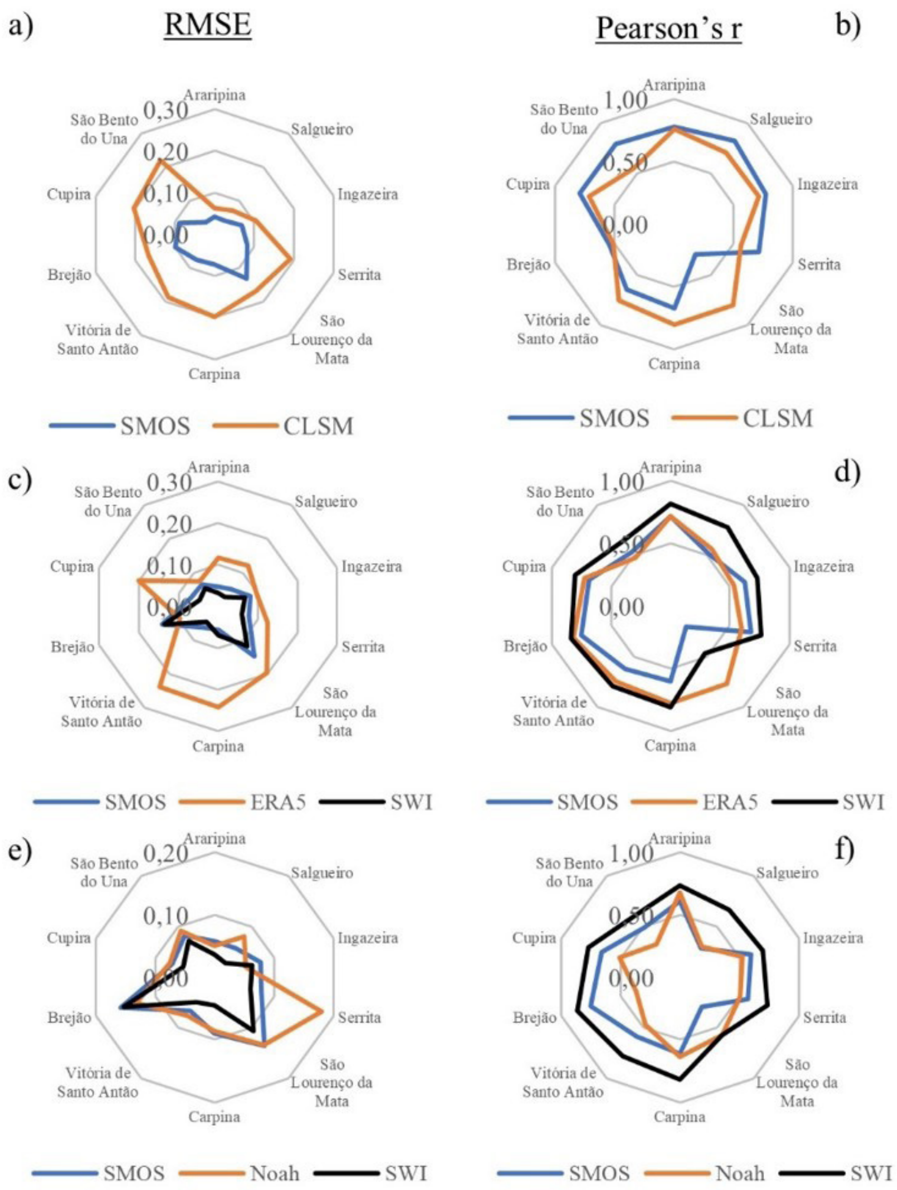


**Figure 7.** Root mean square error (RMSE) and Pearson's correlation for the comparison with *in situ* data: SMOS, SWI, and the models GLDAS-CLSM (a, b), ERA5-Land (c, d), and GLDAS-Noah (e, f). The *in situ* data used for comparison correspond to the depths 10 cm (a, b), 20 cm (c, d), and 40 cm (e, f).

Equation 2, making this equation less derivative, leading to smoother curves. Stations with fewer irregularities in soil moisture tend to have greater values of T. Wagner et al. (1999) concluded that T varying between 15 and 30 days can produce reasonable results. The relative insensitive of the method to T variation allowed to limit it in 40 days without loss for the results in Pernambuco. Studies have highlighted the importance of the soil moisture determination at the root zone (Stefan et al., 2021; Pablos et al., 2018; Tobin et al., 2017), especially, for agricultural applications. The data availability of root zone soil moisture is of great importance for hydrological processes and drought monitoring in the Northeast Brazil because of water scarcity arising from recurrent periods of drought. Besides the application of the exponential filter, this study presents an assessment of global databases which can be useful for soil moisture and drought monitoring in this region.

In Figure 7, three stations are located in the sub-humid Mata region (Vitória de Santo Antão, Carpina, and São Lourenço da Mata). The remaining seven stations are located in Sertão and Agreste (semiarid regions). GLDAS-Noah produced the best results in comparison with *in situ* data, regardless of the location of the stations. However, the GLDAS-CLSM and ERA5-Land models produced better results for the semiarid region. The soil moisture from GLDAS-Noah was compared with data from the European Space Agency's Climate Change Initiative project (ESA CCI SM), a multi-satellite surface soil moisture dataset (Liu et al., 2019; Zhang et al., 2021). These studies verified large discrepancies between the two databases, particularly in arid and semiarid regions. In contrast, the GLDAS-Noah dataset displayed greater potential for detecting drought occurrence. GLDAS-Noah also exhibited reasonable agreement between *in situ* and SMOS soil moisture in the Odra watershed in Central Europe (Zawadzki & Kędzior, 2016).

In relation to ERA5-Land and GLDAS-CLSM, there was a trend of overestimation, as shown in Figure 7a and 7b. Notwithstanding this behavior, the simulated soil moisture followed the seasonal variability well, which is reflected in the Pearson's correlation, registering values varying in the intervals of 0.55–0.81 and 0.48–0.82, respectively, for the GLDAS-CLSM and the ERA5-Land models. For the CLSM model, three stations had moderate correlations and seven had strong. For ERA5-Land, four and six stations had moderate and strong correlations, respectively. This level of correlation allows us to consider the application of bias-correction methods, as conducted by Liu et al. (2019).

The SWI was not calculated for 10 cm because we considered this depth to be equivalent to the surface soil moisture provided by the SMOS. Figures 7a and 7b show the results of SMOS and the GLDAS-CLSM model, both compared with *in situ* soil moisture at 10 cm. At depths of 20 and 40 cm, the SWI outperformed the other databases for both criteria and at all stations.

## CONCLUSIONS

This study evaluated global databases of soil moisture in the state of Pernambuco, demonstrating the capacity to represent the water content in the root zone. The application of the exponential filter significantly improved the soil moisture measured by the SMOS satellite. This was corroborated by the reduction in the RMSE and the increase in the Pearson's r correlation. The soil moisture simulated by the models tended to overestimate the *in situ* data, particularly for GLDAS-CLSM and ERA5-Land, a behavior similar to that observed in other studies.

Future studies should test the spatial interpolation of the parameter T to calculate the SWI in pixels of the SMOS satellite not covered by *in situ* stations. This procedure can be useful for estimating soil moisture in the root zone and for calculating indices for drought monitoring. Considering that the network of stations from CEMADEN is spread in the northeastern semiarid region, the interpolation coverage does not need to be limited to the territory of Pernambuco. The influence of environmental aspects (land cover, soil type, topography, and climate characteristics) can also be investigated to understand better the behavior of the soil moisture. The promising results of the models tested, mainly in terms of seasonal variability, demonstrated the potential of applying bias correction methods, which can improve the representation of the soil moisture.

## ACKNOWLEDGEMENTS

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Marcella Vasconcelos Quintella Jucá: Data curation, formal analysis, investigation, methodology, validation, visualization, writing-original draft.

Alfredo Ribeiro Neto: Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, validation, visualization, writing-original draft.

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