Revista Brasileira de Ciências Ambientais
Brazilian Journal of Environmental Sciences

The influence of weather on photovoltaic efficiency and solar mapping in Alagoas using the WRF-Solar model

Influência meteorológica na eficiência fotovoltaica e mapeamento solar em Alagoas utilizando o modelo WRF-Solar

Ewerton de Souza Muniz[1], *Rosiberto Salustiano da Silva Junior*[1], *Marcos Antonio Lima Moura*[1], *Ericka Voss Chagas*[1], *Roberto Fernando de Fonseca Lyra*[1], *Luana do Nascimento Vasconcelos*[1], *Luan Santos de Oliveira Silva*[1], *Geórgenes Hilário Cavalcante Segundo*[1,2]

ABSTRACT

Although the use of photovoltaic (PV) energy is a well-established strategy for the energy transition and climate change mitigation through the reduction of CO_2 emissions, the literature lacks studies that integrate real-world field operation data with atmospheric models to map generation potential in the region. Power generation efficiency is directly influenced by the inherent characteristics of PV systems and by installation losses, variables quantified by the Performance Ratio (PR). Considering this, the current study investigates the direct influence of meteorological variables and soiling on system efficiency. The results indicate high operational performance, with an average PR exceeding 80%. Statistical analysis revealed that the correlations of PR with solar radiation and air temperature are negative (−0.76 and −0.74, respectively). In contrast, relative humidity and precipitation exhibited moderate positive correlations (0.52 and 0.46–0.48, respectively), highlighting the efficiency gains generated by the cooling and natural cleaning of the modules. Using linear and multiple linear regression, an equation was developed to represent PV output. Applying this equation to the output data from the WRF-Solar atmospheric model allowed for the spatialization of PV potential. The mapping revealed a potential ranging from 2.4 kWh/kWp to 4.8 kWh/kWp in Alagoas, providing a robust methodological tool for local energy planning.

Keywords: photovoltaic energy; performance ratio; linear regression.

RESUMO

Embora a utilização da energia fotovoltaica (PV) seja uma estratégia consolidada para a transição energética e a mitigação das mudanças climáticas por meio da redução das emissões de CO_2, a literatura carece de estudos que integrem dados reais de operação em campo a modelos atmosféricos para mapear o potencial de geração na região. A eficiência da geração de energia é diretamente influenciada pelas características inerentes aos sistemas fotovoltaicos e pelas perdas de instalação, variáveis quantificadas pela Taxa de Desempenho (Performance Ratio - PR). Diante disso, este trabalho investiga a influência direta de variáveis meteorológicas e da sujidade na eficiência do sistema. Os resultados indicam um alto desempenho operacional, com PR médio superior a 80%. A análise estatística revelou que as correlações do PR com a radiação solar e a temperatura do ar apresentam correlação negativa (−0,76 e −0,74, respectivamente). Em contrapartida, a umidade relativa e a precipitação exibiram correlações positivas moderadas (0,52 e 0,46–0,48, respectivamente), evidenciando os ganhos de eficiência gerados pelo resfriamento e pela limpeza natural dos módulos. Por meio de regressão linear e regressão linear múltipla, foi obtida uma equação para representar a produção fotovoltaica. A aplicação desta equação aos dados de saída do modelo atmosférico WRF-Solar permitiu a espacialização do potencial fotovoltaico. O mapeamento revelou um potencial variando de 2,4 kWh/kWp e 4,8 kWh/kWp em Alagoas, oferecendo uma ferramenta metodológica robusta para o planejamento energético local.

Palavras-chave: energia fotovoltaica; taxa de desempenho; regressão linear.

[1]Federal University of Alagoas – Maceió (AL), Brazil.
[2]New York University Abu Dhabi – Abu Dhabi, United Arab Emirates.
Corresponding author: Ewerton de Souza Muniz – Av. Lourival Melo Mota, S/N, Tabuleiro do Martins - Cidade Universitária – Maceió (AL), CEP 57072-970, Brazil. E-mail: ewerton.muniz@icat.ufal.br

Received on: 11/14/2025. Accepted on: 09/08/2026.
https://doi.org/10.67790/rbciamb.026.2880

Introduction

The growing global demand for energy is closely linked to economic growth, particularly through key sectors such as industry, commerce, agriculture, and residential consumption. This demand has been further intensified by the rapid expansion of urban centers and the growing adoption of electric vehicles (EVs). Although the transition from internal combustion engine vehicles to EVs offers potential environmental benefits, the sustainability of this shift depends on the availability of renewable energy sources. Among these, solar energy stands out for its abundance, renewability, and sustainability (Rubbi et al., 2020).

In Brazil, renewable sources dominate the electricity mix, with hydropower accounting for 58.9%, followed by wind (13.2%) and solar (7%). According to the 2024 National Energy Balance (BEN), photovoltaic (PV) energy showed the highest growth rate, increasing by 68.1% between 2022 and 2024, driven mainly by residential solar installations. The Northeast region of Brazil (NEB) accounts for 62% of the country's installed solar capacity, making it Brazil's leading producer of PV energy. However, the state of Alagoas, the focus of this study, contributes only 4.86% of the national total, indicating significant potential for expansion. Findings by Pereira et al. (2017) highlight that NEB has high solar potential, with minimal annual variability in global solar radiation, ensuring greater stability in energy production.

A critical aspect of solar energy deployment is the accurate assessment of solar resources. Ideally, high-quality local measurements of solar radiation provide the most reliable basis for evaluating energy potential and determining the financial viability of large-scale projects. However, these measurements are often limited in terms of temporal and spatial coverage. As an alternative, pre-existing irradiance datasets derived from satellites or atmospheric models can be used. In recent years, satellite-based techniques have been increasingly used to estimate surface solar irradiance, yielding reasonable accuracy (Pereira et al., 2017; Letu et al., 2020; Vamvakas et al., 2020). However, solar irradiance data alone do not fully meet the needs of energy system operators, since actual production depends on various operational and environmental factors. Therefore, integrating meteorological data with energy performance models is essential to optimize system efficiency and improve forecast accuracy (Oliveira Silva et al., 2024).

Given the high capital investment associated with installing PV systems, it is essential to maximize energy production. The Performance Ratio (PR) is a widely used metric for evaluating the actual efficiency of PV installations relative to their nominal capacity (Bentouba et al., 2021). PR calculations, as standardized by IEC 61724-1, use daily or monthly data to assess performance. Although manufacturers guarantee the performance limits of the panels, actual energy production can vary due to environmental factors. For example, an increase in module temperature reduces efficiency, while soiling accumulation decreases light absorption and shortens the service life of the panels (Sharma et al., 2024). Additionally, installation issues, such as suboptimal tilt angles, inadequate cabling, and low-quality inverters, can impair performance. On the other hand, natural ventilation can increase efficiency by reducing module temperatures. Understanding and mitigating these factors is essential to ensure that the panels operate at maximum efficiency (Shaik et al., 2023).

In light of this, the study aims to quantify the PR of an actual small-scale PV power plant in Alagoas and investigate the influence of meteorological variables on energy production. As an extension of this analysis, equations are proposed to enable the mapping of the state's PV potential.

Methodology

Study area and data

Located in the NEB, the state of Alagoas is divided into three main mesoregions based on precipitation patterns: the East (coastal region), Agreste, and Sertão. An analysis of the average annual accumulated precipitation between 2002 and 2022, conducted using data from the Center for Weather Forecasting and Climate Studies (CPTEC) MERGE product, made it possible to map the spatial variability of rainfall, a key factor in PV power generation (since cloud cover reduces the amount of solar radiation). Rainfall distribution in the state shows a clear gradient: the East receives the highest volumes (1,000 to 1,800 mm annually), followed by agreste, a subhumid zone (800 to 1,000 mm) where rainfall is driven by the orographic effect of the Borborema Plateau. In contrast, Sertão is the driest region, with a slight increase in rainfall only in the higher-elevation areas in the far west (Figure 1).

Photovoltaic performance indicators

Table 1 presents the parameters used to evaluate the performance of the PV system, as defined by the International Energy Agency (IEA PVPS, 2014). These performance metrics are widely used in the literature to compare PV systems with different configurations, designs, and conversion technologies around the world (Oliveira Gonzalez and Martins, 2024).

The reference yield (Yr, Equation 1) quantifies the system's potential energy production by comparing the solar irradiation incident on the module surface (Hi) with the reference irradiance under Standard Test Conditions (GSTC = 1,000 W/m^2). The calculation of the reference yield follows IEC 61724-1, while the Standard Test Conditions are defined in IEC 60904-3. The final yield (Yf, Equation 2), or system yield, is the ratio between the alternating current (AC), energy output (Eac) and the nominal power (P_0) of the PV system, representing the equivalent number of hours the system operates at full capacity. The PR (Equation 3) is a widely accepted metric for evaluating the efficiency of grid-connected PV systems, incorporating optical,

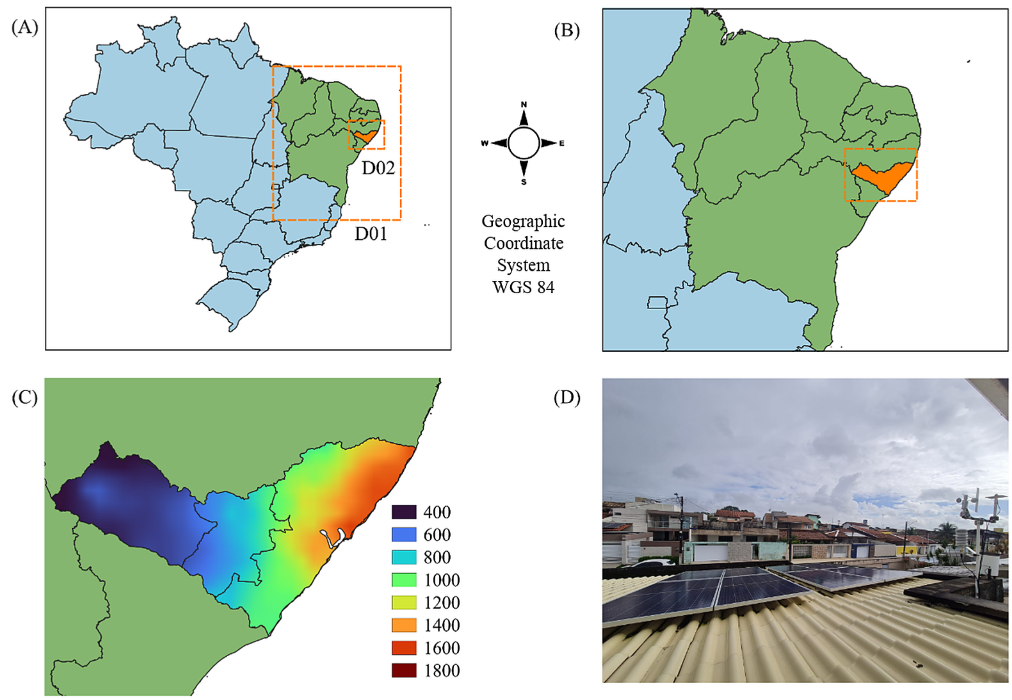

Figure 1 – (A) Spatial distribution of the domains used in the study simulations (D01 and D02); (B) study area; (C) annual mean accumulated precipitation between 2002 and 2022 based on the MERGE-CPTEC dataset; and (D) characterization of the Automatic Weather Station (AWS) and the panels.

Table 1 – Metrics used to evaluate the performance of the PV.

Metrics	Equation		Unit
Reference yield (Yr)	$Yr = Hi/G_{stc}$	(1)	kWh/kWp
Final yield	$Yf = Eac/P_0$	(2)	kWh/kWp
Performance Ratio	$PR = (Yf \times 100)/Yr$	(3)	%

thermal, and electrical losses to provide a normalized measure of system performance relative to available solar energy.

Automatic weather station (AWS)

To evaluate the efficiency of the PV system, an Automatic Weather Station (AWS) was installed near the system to assess the influence of weather conditions (solar radiation, air temperature, relative humidity, wind speed and direction, and precipitation) on energy production. All meteorological sensors were mounted 1.5 m above the height of the solar panels and microinverters, with the rain gauge positioned at the same level. For reference, the roof of the pilot residence is 2.30 m high. The data acquisition and management system used was the Campbell CR800, which took measurements at 10-minute intervals; these were subsequently aggregated and analyzed at one-hour intervals during the study period, from March 10, 2024, to August 9, 2024. For logistical reasons, rain-gauge measurements began one month later, and to complete the data series, the database from the National Institute of Meteorology (INMET A303), located at latitude -9.55° and longitude -35.77°, was used. The straight-line distance between the two stations is less than 5 km, a range within which the data are considered valid according to the guidelines of the World Meteorological Organization (WMO).

Atmospheric transmittance

Atmospheric transmittance (*Kt*) represents the fraction of solar radiation that reaches the Earth's surface, taking into account the attenuation caused by cloud cover and airborne particles. A *Kt* value less than 1 indicates increased atmospheric turbidity, which means a greater reduction in the solar radiation reaching the surface. On the other hand, a *Kt* value closer to 1 suggests minimal attenuation, where radiation levels at the surface are very similar to those in the upper atmosphere. The equation for *Kt* is defined as follows (Equation 4):

$$Kt = \frac{Rg}{Ra} \quad (4)$$

Where *Kt* is the ratio of the total solar radiation reaching the surface in W/m^2 (Rg) to that reaching the top of the atmosphere, which is approximately 1367 W/m^2 (Ra). The result indicates how much total solar radiation actually reaches the surface.

Linear regression and multiple linear regression

In this study, linear regression (Equation 5) and multiple linear regression (Equation 6) were implemented using the sklearn library, one of the most popular machine learning libraries in Python.

$$y = b_0 + b_1 x \quad (5)$$

Where y is the output (target value) of the model, x represents the independent variable of the model, b_0 is the intercept of the line, and b_1 is the coefficient of the regression model, which indicates the slope of the line.

$$y = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_n x_n \quad (6)$$

Where y is the model's output (target); [x_1, x_2, ..., x_n] represent the model's independent variables; and [b_1, b_2, ..., b_n] are the coefficients of the regression model.

Statistical metrics

Pearson's correlation coefficient (*r*), calculated using Equation 7, was used to quantify the linear correlation between PR and each of the meteorological variables. In this equation, x_i and y_i represent the individual observations of variables *X* and *Y*, respectively, while $\overline{x}$ and $\overline{y}$ represent the sample means of *X* and *Y*, respectively. The symbol $\sum$ indicates the summation of observations, ranging from *i=1* to *n*, where *n* corresponds to the total number of observations (Yu and Hutson, 2024). The equation is defined as:

$$r = \frac{\Sigma_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{[\Sigma_{i=1}^{n} (x_i - \overline{x})][\Sigma_{i=1}^{n} (y_i - \overline{y})]}} \quad (7)$$

Other statistical metrics were calculated at this stage to assess the dispersion and correlation between the observed and estimated productivity data, including the mean error (bias) and the root mean square error (RMSE) (Paz-Ruza et al., 2025), as described in Equations 8 and 9, respectively:

$$bias = \frac{1}{N} \Sigma_{i=1}^{n} (x_i - y_i) \quad (8)$$

$$RMSE = \sqrt{\frac{1}{N} \Sigma_{i=1}^{n} (x_i - y_i)} \quad (9)$$

Atmospheric model (WRF)

The Weather Research and Forecasting (WRF) atmospheric model is a mesoscale numerical model used for weather forecasting and simulation, developed by the National Center for Atmospheric Research (NCAR). The version used in this study was created specifically to meet the needs of the solar energy sector and is called WRF-Solar (version 4.5). The simulation period runs from the beginning of March 10 to August 9, 2024, to cover the observation period. The parameterizations were selected based on previous tests, in which the Pearson correlation, bias and RMSE of each parameterization were compared with global solar radiation data; those that yielded the best results were chosen (Table 2).

In addition, the input data used to perform the simulations were the series produced by the National Centers for Environmental Prediction (NCEP) – Final Analysis (FNL) – with a spatial resolution of 1° × 1° (approximately 111 × 111 km) and a temporal resolution of 6 hours

NASA-POWER database

The database known as NASA-POWER (Prediction of Worldwide Energy Resources) is an improved and more comprehensive version of the former *Surface Meteorology and Solar Energy* suite of products and services developed by NASA. This tool provides various openly available meteorological variables, such as precipitation, surface temperature, solar radiation, wind speed, relative humidity, and

Table 2 – Configuration and parameterization schemes used in WRF-Solar.

WRF Parameters	
Microphysics	WSM6 (6-class, with hail) (Hong and Lim, 2006)
Cumulus	Grell-Freitas ensemble (Grell and Freitas, 2014)
Shortwave/longwave radiation	RRTMG (Iacono et al., 2008)
Surface boundary layer	Monin-Obukhov (Monin and Obukhov, 1954)
Planetary boundary layer	Mellor-Yamada-Janjic (Janjić, 1994)
Earth's surface model	NOAH LSM (Chen and Dudhia, 2001)

atmospheric pressure, and serves as an important data source for analyzing renewable energy resources on a global scale with a spatial resolution of 0.5°.

The NASA-POWER project is available at https://power.larc.nasa.gov/data-access viewer/, with a data period ranging from 1983 to the present. This database features a robust and up-to-date dataset, with hourly, daily, monthly, annual, and climatological time scales, enabling the analysis of trends, climate patterns, and variations in solar resources over decades.

Results and discussion

Relationship between PR and meteorological variables

This section presents evidence of PV generation efficiency and the relationship between meteorological variables and production. The Sertão region stood out, particularly the village of Poço Branco (Mata Grande), due to its low variability in solar irradiance, which promotes stable generation. According to the Solarimetric Atlas of the State of Alagoas (Eletrobras, 2008), solar irradiance in the area reached monthly averages ranging from 3.61 kWh/m2/day in winter to 5.11 kWh/m2/day in summer. In the present study, the accumulated daily average was 4.8 kWh/m^2/day. To ensure an independent analysis of the number and power of the panels, the data were normalized, revealing an average yield of 3.44 kWh/kWp and an average PR of 88.68%, indicating high operational efficiency. These results confirm the technical feasibility of distributed generation in the state, aligning with levels reported in the literature. For comparison, Oliveira Gonzalez and Martins (2024) recorded an average PR of 89.8% in Santos, São Paulo, under humid tropical conditions; Herbazi et al. (2022) observed 80.29% in Tangier (Morocco) under a semi-arid climate; and Alnaser (2023) found PR values ranging from 65.6% to 75.1%, with a yield of 3.82 kWh/kWp, in Bahrain.

Despite the high overall performance, significant variations associated with meteorological variables were observed (Table 3 and figure 2), corroborating the findings of Casula et al. (2020), who reported lower PR values at the beginning of the time series, a period coinciding with drought and high temperatures. Solar irradiance (average of 4.17 kWh/m^2/day) and air temperature (average of 26.3 °C) showed an inverse correlation with PR, confirming the negative impact of these variables. High temperatures can accelerate the degradation of electronic components when operating temperatures exceed the standard test conditions (STC), increasing conversion losses in the inverter and reducing module efficiency (Lima et al., 2023). Although Hashim and Hassan (2022) suggest that high irradiance may offset thermal effects in arid climates, in this study, the combination of high irradiance and high temperatures resulted in a reduction in PR, since high irradiance raises the operating temperature and thermal stress on the modules, as also observed by Al-Ghezi et al. (2022). In addition, the influence of Aerosol Optical Depth (AOD) was evidenced by the high correlation between the Kt index and global solar radiation (0.90). These factors, combined with cloud cover and soiling accumulation, severely affect system performance (Fatima et al., 2024). More broadly, Bamisile et al. (2025) point out that losses in PV generation are primarily associated with climatic variations and system degradation.

In contrast, during the rainy season in the study area, which occurred from April to July (Silva Junior et al., 2022) and is associated with increased cloud cover, the highest PR values were recorded. This indicates that relative humidity and precipitation are positively correlated with increased efficiency (r = 0.52 and r = 0.46 to 0.48, respectively). A combined interpretation of these data suggests that precipitation and mild temperatures contributed to the cooling and natural cleaning of the PV modules. Although high humidity could theoretically facilitate the accumulation of sooiling (Gholami et al., 2023) and accelerate long-term degradation (Farou et al., 2025), the positive correlation of 0.52 demonstrates that the immediate benefits of cooling and cleaning outweigh the negative effects of humidity in the analyzed region.

Finally, wind speed positively influences the system by contributing to the cooling of the panels through increased ventilation (Hu et al., 2022) and aiding in the natural removal of dust. The effectiveness of reducing energy losses depends on the size of airborne aerosol particles, topography, and humidity (Stankov et al., 2024). Local interactions reveal that, even in high humidity scenarios, stronger winds are directly associated with greater efficiency in removing soiling adhered to the panels.

Estimated electricity generation

Since the sizes of PV systems vary depending on customers' purchasing power and the available area on the roof or property, the power output of each system was normalized according to its installed capacity before applying the regression methods. This normalization ensures that all values and errors are independent of system size, allowing for a direct comparison between meteorological variables and energy production efficiency. Based on this approach, two predictive equations were developed: one using the Linear Regression method (Equation 10) and the other using Multiple Linear Regres-

Table 3 – Pearson's correlation between PR and meteorological variables, where: Ir – Solar irradiance, At – Air temperature, Ws – Wind speed, Rh – Relative humidity, Prec - Precipitation and Kt – Atmospheric transmittance (per hour) from March 10, 2024, to August 9, 2024.

	Ir	At	Ws	Rh	Prec	Kt
AWS	–0.76	–0.74	–0.2	0.52	0.48	–0.68
INMET	-	-	-	-	0.46	-

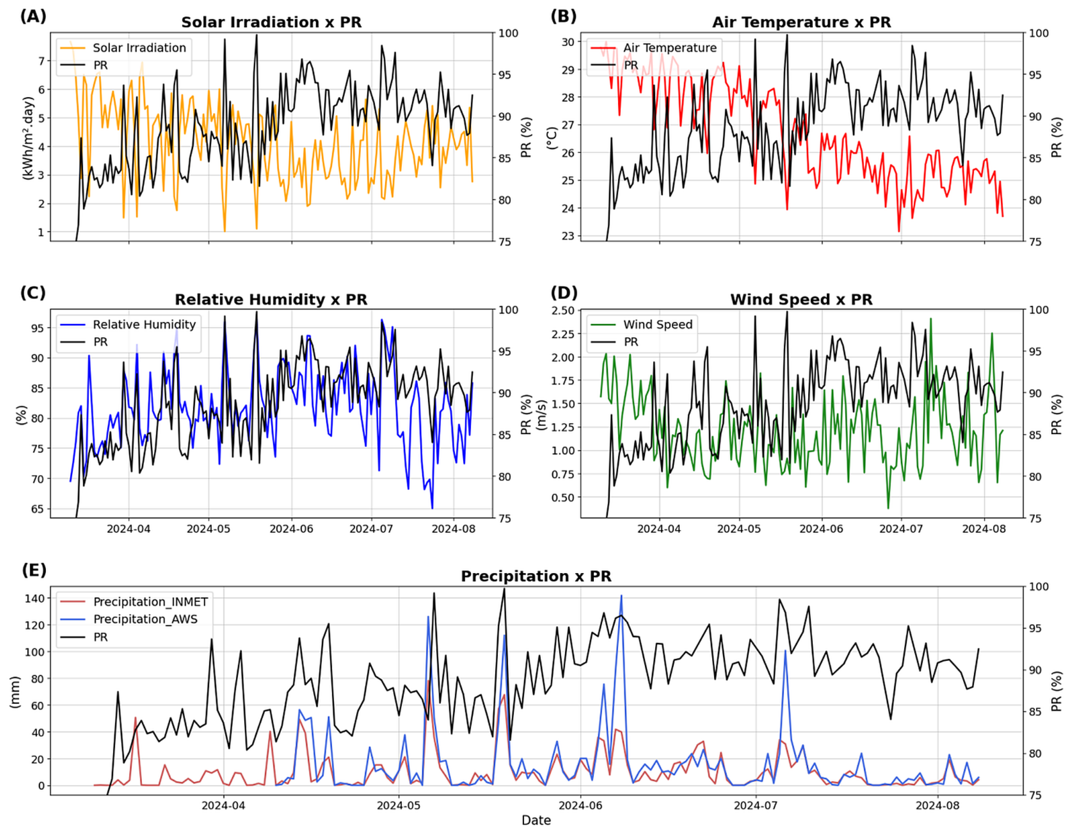

Figure 2 – Relationship between meteorological variables (solar radiation, temperature, relative humidity, wind speed, precipitation from the INMET station, and precipitation from the AWS) and PR, based on daily average values from March 10, 2024, to August 9, 2024.

sion (Equation 11). These models were derived from an analysis of the micro-power plant's solar energy production in relation to meteorological data from the AWS.

Where, in Equations 10 and 11, Ir represents solar irradiance ($kWh/m^2 \cdot day$), Ws represents wind speed at 10 meters (m/s), At represents air temperature at 2 meters (°C), Rh represents relative humidity (%), and Prec represents precipitation (mm). PV productivity is primarily influenced by solar irradiance, while air temperature plays a crucial role in determining efficiency. Wind speed helps regulate module temperature, improving system performance through cooling. The accuracy of performance estimates depends on the quality and representativeness of the dataset, making consistent data that capture temporal variations essential to improving model reliability.

Figure 3 compares the productivity recorded by the small-scale PV plant (black line) with the estimates from the Linear Regression (LR, green line) and Multiple Linear Regression (MLR, red line) models. The results indicate that the LR overestimates solar energy production, while the MLR provides more accurate estimates. This discrepancy arises because the LR considers only solar radiation, assuming maximum system efficiency, whereas the MLR takes into account additional factors such as high temperatures, reduced wind speed, and low relative humidity, which negatively affect performance. These conditions lead to cable heating, reduced power transmission, and decreased microinverter efficiency, especially when module temperatures approach the manufacturer's limits (65 °C to 85 °C). Furthermore, soiling accumulation on the panels and the solar radiation sensor can further affect system performance. This highlights the importance of incorporating multiple variables into predictive models, given that soiling was not physically measured but merely analyzed via *Kt*.

$$Yf = 2.2\ Ir + 0.837 \quad (10)$$

$$Yf = 0.777\ Ir - 0.0002\ Ws - 0.0517\ At - 0.006\ Rh - 0.0011\ Prec + 2.414 \quad (11)$$

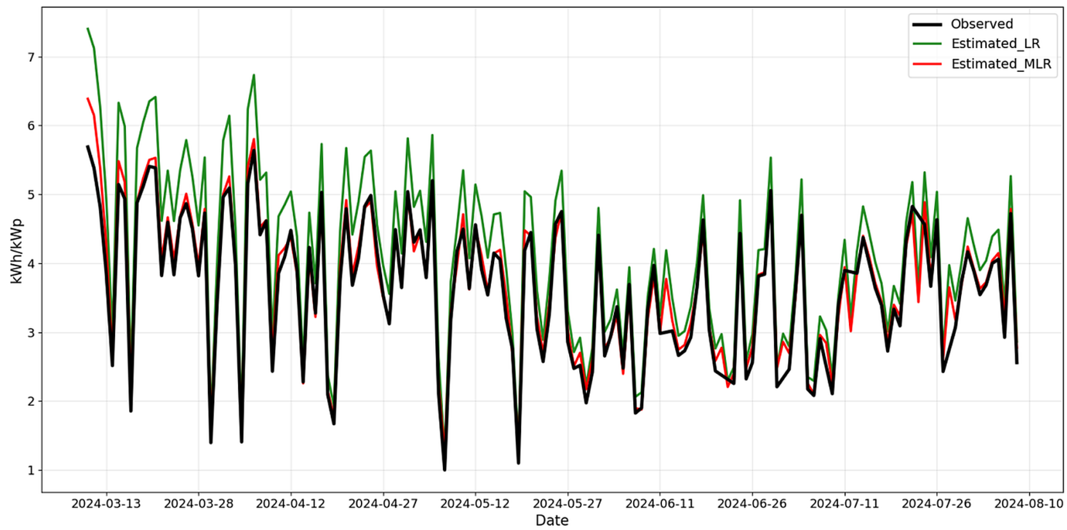

Figure 3 – Comparison between observed and estimated productivity, where the green line represents Equation 10 derived from LR, while the red line represents Equation 11 derived from MLR.

Figure 4 shows the scatter plot and statistical metrics comparing estimated productivity with observed energy production. Both models closely follow the performance trends, but the MLR model demonstrates superior accuracy, with a near-perfect correlation (r = 0.97), minimal bias (0.08), and a root mean square error (RMSE) of 0.17, indicating a highly reliable estimate. These results suggest that MLR is the most suitable model for the spatial estimation of PV energy production when meteorological data are available. In scenarios with limited access to measurements, LR remains a viable alternative, albeit less accurate.

Solarimetric mapping

Based on established methods, simulations were conducted using the WRF-Solar atmospheric model to spatially assess the solar potential of the state of Alagoas, incorporating adjustments derived from the micro-power plant's generation data and AWS measurements. To assess the accuracy of the datasets, a statistical comparison was performed between the NASA-POWER and WRF-Solar simulations against the observed data. The analysis yielded correlation (r), bias, and RMSE values, respectively: 0.88, 0.08 kWh/m^2/day, and 0.89 kWh/m^2/day for NASA-POWER, compared to 0.61, 0.11 kWh/m^2/day, and 0.82 kWh/m^2/day for WRF-Solar.

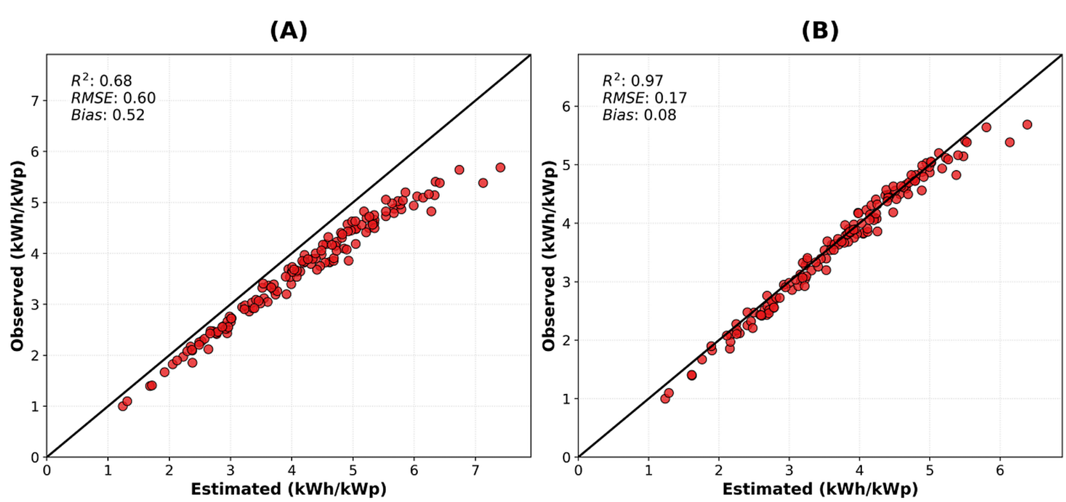

Figure 4 – Statistical metrics (correlation, bias, and RMSE) obtained from the micro-power plant measurements and resulting estimates from the (A) LR and (B) MLR models.

Although NASA-POWER demonstrated superior statistical performance in point-wise temporal correlation, WRF-Solar's sensitivity to high-frequency variability is expected during the rainy season, a period when dynamical models often struggle to accurately simulate transient cloud cover. Crucially, the NASA-POWER model relies on a coarse 0.5° grid (approximately 55 km). This low spatial resolution severely limits its ability to capture local meteorological systems, topography, and land use, factors that heavily influence photovoltaic (PV) energy generation, as demonstrated by Bamisile et al. (2025) and illustrated in Figure 5. Therefore, despite the lower temporal correlation, WRF-Solar's high-resolution spatial representation strongly justifies its use for mapping the regional solar potential of Alagoas.

As shown in Figure 5, the WRF-Solar estimates present irradiance values consistent with those reported by Atsbeha et al. (2025), who identified 5.5 kWh/m²/day in model estimates and 6.1 kWh/m²/day in measured radiation as indicative of strong PV potential. These results confirm the high solar energy potential of Alagoas, particularly in the Sertão and Agreste regions. This availability is largely driven by lower precipitation rates in these areas (as seen in Figure 1C), which are directly associated with reduced cloud cover and the continentality effect. radiation.

Photovoltaic mapping

The PV map (Figure 6) was generated using estimates from the MLR model (Equation 11), which showed the best statistical performance. The Sertão region of Alagoas has the highest solar energy productivity, consistent with its high levels of radiation, as shown in Figure 5. Consequently, this region has the greatest potential for PV production. Lindig et al. (2021) note that production values of approximately 954.9 kWh/kWp/year, roughly 2.62 kWh/kWp/day, with an annual average PR of 76.7%, are associated with good operational performance under real-world conditions. Given these conditions, the municipalities located in the Sertão region of the study area could effectively contribute to solar power generation, since they achieve values greater than 3 kWh/kWp/day. Logistical feasibility studies remain essential prior to large-scale installations.

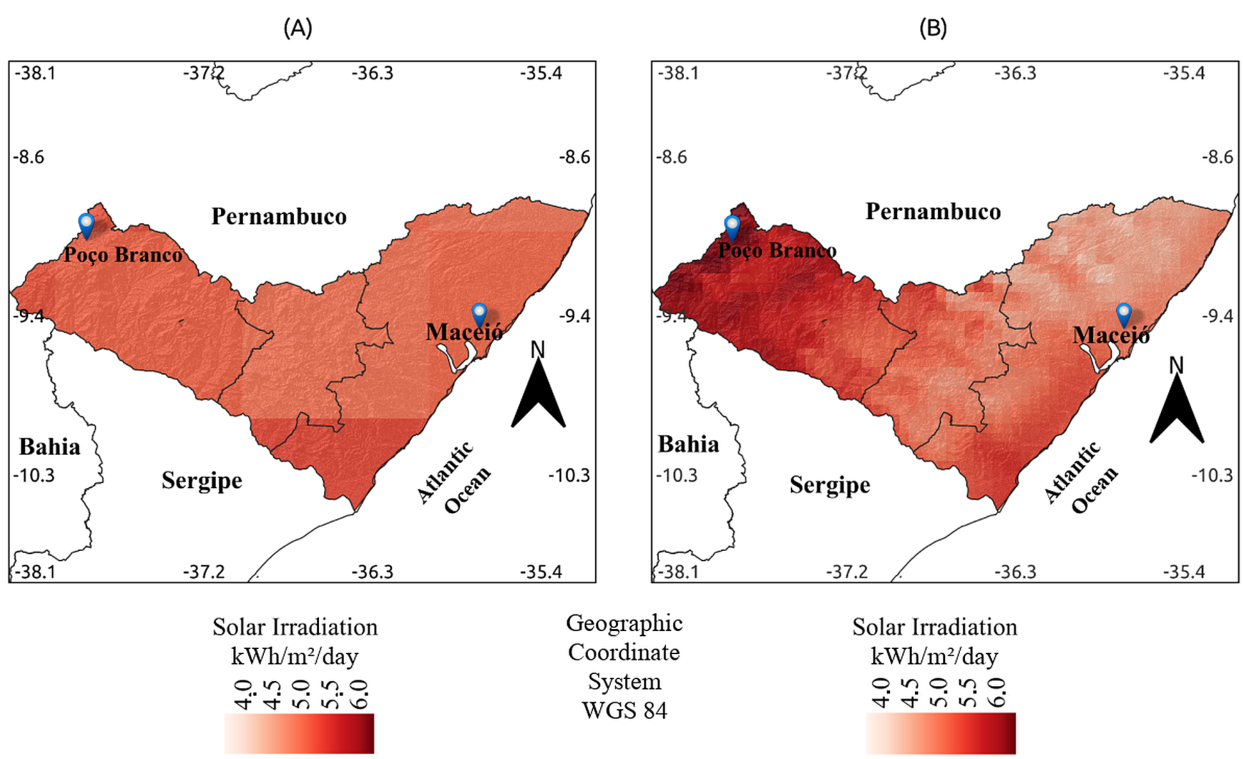

Figure 5 – Solar irradiance map using the (A) NASA-POWER and (B) WRF-Solar models, highlighting the region with the highest irradiance index, located near the village of Poço Branco in the municipality of Mata Grande.

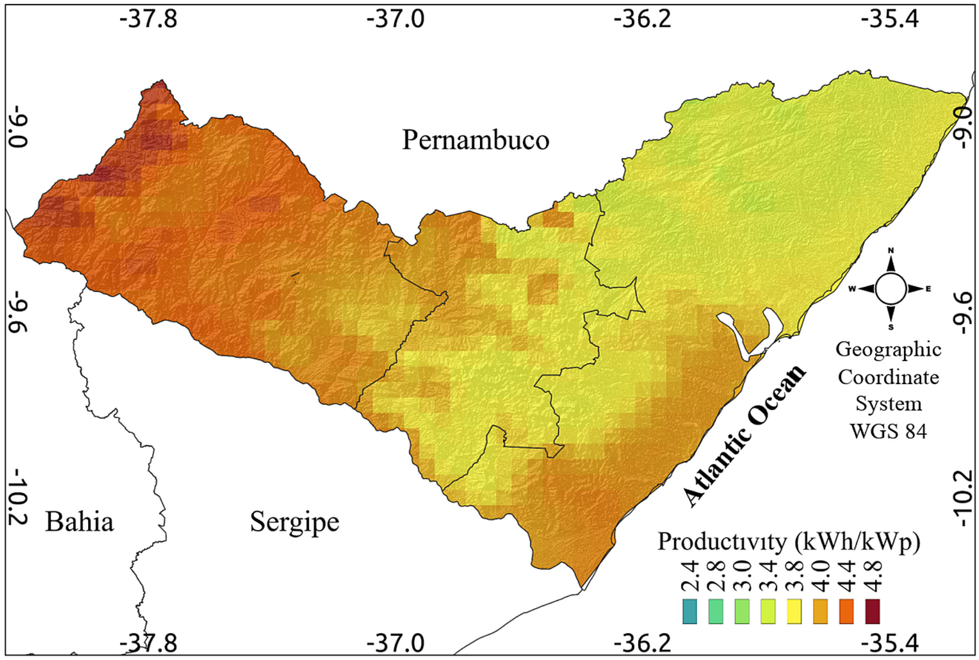

Figure 6 – PV map of the state of Alagoas using the equation proposed by the MLR model.

Conclusion

This study highlights the significant influence of meteorological variables on the efficiency of solar energy production. Strong correlations were observed between the PR and environmental factors such as air temperature (−0.74), relative humidity (0.52), and solar irradiance (−0.76). These results indicate that, although high irradiance increases gross energy production, it also causes PV components to overheat, leading to efficiency losses. In contrast, precipitation had a positive effect on the PR (0.46 to 0.48), contributing to the natural cooling and cleaning of the panels, which improves system performance. Regarding the system design, the PV panel was installed at a tilt angle of 8.53°, slightly below the ideal value based on the site's latitude (9.59°). Even so, the micro-power plant achieved solid operational results, with PR values above 85%, exceeding the 80% efficiency guaranteed by the microinverter manufacturer. It is recommended to adjust the tilt angle in future projects to further optimize solar capture.

The analysis of atmospheric transmittance (*Kt*) confirmed that PR does not depend exclusively on solar irradiance, but is strongly influenced by temperature and operational inefficiencies. The two proposed equations demonstrated high predictive accuracy. The MLR model provided the most reliable estimates for the Alagoas region, while the LR model remains a viable tool in contexts where only radiation data are available.

Mitigating energy losses, reflected in an increase in the PR, directly impacts the techno economic viability of PV systems. Understanding the dynamics among meteorological variables allows for the optimization of system sizing. Such data provide scientific support for the adoption of cooling technologies and guide financial planning, such as reducing the levelized cost of energy for distributed generation in the state.

Finally, it should be acknowledged that the extrapolation of PV potential for the entire state is based on the calibration of models using data from a single micro-power plant over a five-month observation period. This spatial and temporal limitation restricts the ability to capture the full range of seasonality, such as heat stress during the peak of summer. However this study establishes a robust methodological framework and serves as proof of concept for solarimetric mapping. For future research, we suggest expanding monitoring networks to include multiple operational plants distributed across the East, Agreste, and Sertão regions, thereby enabling cross-validation of the atmospheric model under different microclimates and technical configurations.

Authors' Contributions: Muniz, E.S.: Conceptualization, Investigation, Methodology, Data curation, Formal analysis, Visualization, Writing–original draft, Writing–review & editing; Silva Junior, R.S.: Conceptualization, Methodology, Supervision, Validation, Writing–review & editing; Chagas, E.V.: Writing–review & editing; Lyra, R.F.F.: Resources; Moura, M.A.L.: Writing–review & editing; Vasconcelos, L.N.: Writing–review & editing; Silva, L.S.O.: Writing–review & editing; Cavalcante Segundo, G.H.: Writing–review & editing.

Conflicts of interest: The authors declare no conflicts of interest.

Funding: All authors gratefully acknowledge UFAL (Federal University of Alagoas) and CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior) for their support. G.H. Cavalcante thanks CNPq (National Council for Scientific and Technological Development) for the Research Fellowship (Grant: 306370/2023-9). G.H. Cavalcante was supported by funding from the Mubadala Foundation under the NYUAD Research Institute grant CG009 to Mubadala ACCESS.

Declaration on the use of generative artificial intelligence: The authors declare that they did not use artificial intelligence (AI) tools in the preparation of this manuscript.

References

Al-Ghezi, M.K.; Ahmed, R.T.; Chaichan, M.T., 2022. The Influence of Temperature and Irradiance on Performance of the Photovoltaic Panel in the Middle of Iraq. International Journal of Renewable Energy Development, v. 11 (2), 501-510. https://doi.org/10.14710/ijred.2022.43713

Alnaser, N.W., 2023. The performance of four domestic rooftop 7.8 kW PV in the Kingdom of Bahrain: toward low building emission. Renewable Energy and Environmental Sustainability, v. 8, 6. https://doi.org/10.1051/rees/2023002

Atsbeha, A.K.; Gebremariam, G.G.; Gebru, K.G. et al., 2025. Assessment of solar resource potential and estimation of direct and diffuse solar irradiation from sunshine hours data for Eastern Zone of Tigray, Northern Ethiopia. Sustainable Energy Research, v. 12 (1), 16. https://doi.org/10.1186/s40807-025-00162-2

Bamisile, O.; Acen, C.; Cai, D.; Huang, Q.; Staffell, I., 2025. The environmental factors affecting solar photovoltaic output. Renewable and Sustainable Energy Reviews, v. 208, 115073. https://doi.org/10.1016/j.rser.2024.115073

Bentouba, S.; Bourouis, M.; Zioui, N.; Pirashanthan, A.; Velauthapillai, D., 2021. Performance assessment of a 20 MW photovoltaic power plant in a hot climate using real data and simulation tools. Energy Reports, v. 7, 7297-7314. https://doi.org/10.1016/j.egyr.2021.10.082

Casula, L.; D'Amico, G.; Masala, G. et al., 2020. Performance estimation of photovoltaic energy production. Letters in Spatial and Resource Sciences, v. 13 (3), 267-285. https://doi.org/10.1007/s12076-020-00258-x

Centrais Elétricas Brasileiras (Eletrobras), 2008. Atlas Solarimétrico do Estado de Alagoas. Relatório técnico. Eletrobras, Maceió.

Chen, F.; Dudhia, J., 2001. Coupling an advanced land surface–hydrology model with the Penn State–NCAR MM5 modeling system. Part I: Model implementation and sensitivity. Monthly Weather Review, v. 129 (4), 569-585. https://doi.org/10.1175/1520-0493(2001)129<0569:CAALSH>2.0.CO;2

Farou, M.; Djellad, A.; Chiheb, S.; Lalaymia, H.; Rekik, B.; Logerais, P.-O., 2025. Quantification of the impact of irradiance, heat, humidity, and cyclic temperature on the aging of photovoltaic panels: a case study in Algeria. Energy Reports, v. 13, 642-652. https://doi.org/10.1016/j.egyr.2024.12.025

Fatima, K.; Minai, A.F.; Malik, H.; García Márquez, F.P., 2024. Experimental analysis of dust composition impact on photovoltaic panel performance: A case study. Solar Energy, v. 267, 112206. https://doi.org/10.1016/j.solener.2023.112206

Gholami, A.; Ameri, M.; Zandi, M.; Gavagsaz Ghoachani, R.; Jafarzadegan Gerashi, S.; Kazem, H.A.; Al-Waeli, A.H.A., 2023. Impact of harsh weather conditions on solar photovoltaic cell temperature: Experimental analysis and thermal-optical modeling. Solar Energy, v. 252, 176-194. https://doi.org/10.1016/j.solener.2023.01.039

Grell, G.A.; Freitas, S.R., 2014. A scale and aerosol aware stochastic convective parameterization for weather and air quality modeling. Atmospheric Chemistry and Physics, v. 14 (10), 5233-5250. https://doi.org/10.5194/acp-14-5233-2014

Hashim, S.M.; Hassan, R.I., 2022. Impact of high temperature on PV productivity in hot desert climates. Green Technology, Resilience, and Sustainability, v. 2 (1), 9. https://doi.org/10.1007/s44173-022-00009-9

Herbazi, R.; Amechnoue, K.; Khouya, A.; Chahboun, A.; Diani, M.; Louzazni, M.; Addou, M., 2022. Performance evaluation and analysis of polycrystalline photovoltaic plant located in Northern Morocco. International Journal of Ambient Energy, v. 43 (1), 1262-1268. https://doi.org/10.1080/01430750.2019.1694985

Hong, S.-Y.; Lim, J.-O.J., 2006. The WRF single-moment 6-class microphysics scheme (WSM6). Asia-Pacific Journal of Atmospheric Sciences, v. 42 (2), 129-151.

Hu, W.; Li, X.; Wang, J.; Tian, Z.; Zhou, B.; Wu, J.; Li, R.; Li, W.; Ma, N.; Kang, J.; Wang, Y.; Tian, J.; Dai, J., 2022. Experimental research on the convective heat transfer coefficient of photovoltaic panel. Renewable Energy, v. 185, 820-826. https://doi.org/10.1016/j.renene.2021.12.090

Iacono, M.J.; Delamere, J.S.; Mlawer, E.J.; Shephard, M.W.; Clough, S.A.; Collins, W.D., 2008. Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. Journal of Geophysical Research: Atmospheres, v. 113 (D13). https://doi.org/10.1029/2008JD009944

International Energy Agency Photovoltaic Power Systems Programme (IEA PVPS), 2014. Monitorização analítica de sistemas fotovoltaicos ligados à rede. Relatório IEA-PVPS T13-03. IEA PVPS.

Janjić, Z.I., 1994. The step-mountain eta coordinate model: Further developments of the convection, viscous sublayer, and turbulence closure schemes. Monthly Weather Review, v. 122 (5), 927-945. https://doi.org/10.1175/1520-0493(1994)122<0927:TSMECM>2.0.CO;2

Letu, H.; Yang, K.; Nakajima, T.Y.; Ishimoto, H.; Nagao, T.M.; Riedi, J. et al., 2020. High resolution retrieval of cloud microphysical properties and surface solar radiation using Himawari-8/AHI next-generation geostationary satellite. Remote Sensing of Environment, v. 239, 111583. https://doi.org/10.1016/j.rse.2019.111583

Lima, G.P.; Ribeiro, A.C.; Lemos, F.V.E.; Silveira, J.P.C.; Barros, T.A.S.; Villalva, M.G., 2023. Comparing temperature derating test in the laboratory with commercial photovoltaic inverter datasheet. In: 2023 IEEE 8th Southern Power Electronics Conference and 17th Brazilian Power Electronics Conference (SPEC/COBEP). IEEE, pp. 1-7. https://doi.org/10.1109/SPEC56436.2023.10407835

Lindig, S.; Ascencio-Vásquez, J.; Leloux, J.; Moser, D.; Reinders, A., 2021. Performance analysis and degradation of a large fleet of PV systems. IEEE Journal of Photovoltaics, v. 11 (5), 1312-1318. https://doi.org/10.1109/JPHOTOV.2021.3093049

Monin, A.S.; Obukhov, A.M., 1954. Basic laws of turbulent mixing in the surface layer of the atmosphere. Contributions of the Geophysical Institute, Academy of Sciences of the USSR, v. 151, 163-187.

Oliveira Gonzalez, J.; Martins, F.R., 2024. Performance study of a photovoltaic system operating on the southeastern coast of Brazil. IEEE Latin America Transactions, v. 22 (5), 410-417. https://doi.org/10.1109/TLA.2024.10500721

Oliveira Silva, L.S.; Silva Junior, R.S.; Lyra, R.F.F.; Martins, F.R.; Moura, M.A.L. et al., 2024. Avaliação da complementaridade entre os recursos eólico-solar e considerações sobre estabilidade no setor elétrico. Revista Brasileira de Geografia Física, v. 17 (3), 1942-1960. https://doi.org/10.26848/rbgf.v17.3.p1942-1960

Paz-Ruza, J.; Alonso-Betanzos, A.; Guijarro-Berdiñas, B.; Cancela, B.; Eiras-Franco, C., 2025. Beyond RMSE and MAE: Introducing EAUC to unmask hidden bias and unfairness in dyadic regression models. IEEE Transactions on Neural Networks and Learning Systems. https://doi.org/10.1109/TNNLS.2025.3593059

Pereira, E.B.; Martins, F.R.; Gonçalves, A.R.; Costa, R.S.; Lima, F.J.L.; Rüther, R. et al., 2017. Atlas Brasileiro de Energia Solar. INPE, São José dos Campos. https://doi.org/10.34024/978851700089

Rubbi, F.; Habib, K.; Saidur, R.; Aslfattahi, N.; Yahya, S.M.; Das, L., 2020. Performance optimization of a hybrid PV/T solar system using soybean oil/MXene nanofluids as a new class of heat transfer fluids. Solar Energy, v. 208, 124-138. https://doi.org/10.1016/j.solener.2020.07.060

Shaik, F.; Lingala, S.S.; Veeraboina, P., 2023. Effect of various parameters on the performance of solar PV power plant: a review and the experimental study. Sustainable Energy Research, v. 10 (1), 6. https://doi.org/10.1186/s40807-023-00076-x

Sharma, S.; Malik, P.; Sinha, S., 2024. The impact of soiling on temperature and sustainable solar PV power generation: A detailed analysis. Renewable Energy, v. 237, 121864. https://doi.org/10.1016/j.renene.2024.121864

Silva Junior, R.S.; Gama, M.C.C.; Silva, E.H.L.; Mariano, G.L.; Oliveira Junior, J.F.; Silva, L.S.O.; Cardoso, K.R.A., 2022. Avaliação de eventos extremos de precipitação, associados a desastres naturais. Revista Brasileira de Geografia Física, v. 15 (6), 2755-2767. https://doi.org/10.26848/rbgf.v15.6.p2755-2767

Stankov, B.; Terziev, A.; Vassilev, M.; Ivanov, M., 2024. Influence of Wind and Rainfall on the Performance of a Photovoltaic Module in a Dusty Environment. Energies, v. 17 (14), 3394. https://doi.org/10.3390/en17143394

Vamvakas, I.; Salamalikis, V.; Benitez, D.; Al-Salaymeh, A.; Bouaichaoui, S.; Yassaa, N.; Guizani, A.; Kazantzidis, A., 2020. Estimation of global horizontal irradiance using satellite derived data across Middle East-North Africa: The role of aerosol optical properties and site adaptation methodologies. Renewable Energy, v. 157, 312-331. https://doi.org/10.1016/j.renene.2020.05.004

Yu, H.; Hutson, A.D., 2024. A robust Spearman correlation coefficient permutation test. Communications in Statistics – Theory and Methods, v. 53 (6), 2141-2153. https://doi.org/10.1080/03610926.2022.2121144