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VALIDATION OF THE SATELLITE PRODUCTS CAMS-RAD AND SOLCAST: A CASE STUDY FOR PETROLINA-PE, USING THE BRAZILIAN IRRADIANCE DATA FROM THE NATIONAL INSTITUTE OF SPATIAL RESEARCH

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Abstract. *Due to the increase of research efforts focused on improvements of solar energy utilization, there is in the last years an expressive relevance about the analysis and validation of the accuracy of irradiance data from satellite products. This occurs due to the advantages related to these satellite products services: the simple and easy access to the internet, the low-cost purchase (some of them are free data services) and the wide data availability for essentially the entire global territory. For these reasons, one can obtain radiation data without the need of expensive measurement equipment, thus reducing costs for academic or commercial purposes. In this sense, this study aims to validate the satellite products CAMS Radiation Service and Solcast by the comparison against the irradiance data for Global Horizontal Radiation (GHI) and Normal Direct Radiation (DNI) of a ground-based measurement station located in the city of Petrolina, Northeastern Brazil, under a tropical climate. The station belongs to the Brazilian National Institute of Spatial Research (INPE). In addition, this work has also the purpose of analyzing the causes of possible variability in the accuracy obtained, such as the effects of the seasons on the local climate. Furthermore, the accuracy verification of the satellite products is done by the calculation of the error metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R² correlation. The error metrics are applied on a solar radiation database for the years ranging from 2004-2018, with a 60-minute temporal resolution. As the first results, regarding the CAMS-RAD products, the RMSE values are 229,88 W/m² (GHI) and 409,43 W/m² (DNI). Similarly, the RMSE values of Solcast are 181,05 W/m² (GHI) and 397,89 W/m² (DNI). Previously, we can state that the DNI error is higher for both products, since the satellite modeling procedures about the clouds influence do not reach enough spatial resolution.*

Keywords: *solar energy, satellite products, solar radiation, Copernicus Atmosphere Monitoring Service, Solcast*

1. INTRODUCTION

The research efforts focused on improvements of solar power generation is passing by a consistent increase. There is, in the last years, an expressive attention on the analysis and validation of the accuracy of irradiance data from satellite products. Their bias estimation is usually made by a comparison against a data set from a ground-based measurement station.

Advantages related to these services justify the recent importance of this type of study: the simple and easy data access on the internet, the low-cost purchase (some of them are free services) and the wide availability for essentially the entire global territory (the poles are not well covered). For these reasons, one can obtain radiation data without the need of expensive measurement equipment that require frequent calibration and maintenance, thus reducing costs for academic or commercial purposes. Although, satellite data has modeling uncertainties and errors that come from insufficient spatial and temporal resolution.

Evaluation and development of satellite products are areas that remain on the rise even after decades of extensive publishing. This is justified by the appeal of solar energy production, which has enormous growth potential in the world due to sustainable development goals, energy transition and decarbonization. Ameen *et al* (2018), Bright (2019), Kamath and Srinivasan (2020), Yang (2018, 2021) and Yang and Bright (2020) have made similar studies.

Recent researches obtained a wide validation of various satellite products over the Earth territory in different study conditions. Yang and Bright (2019) made an hourly global validation of six satellite products (CAMS, NSRDB, SARAH-2, SARAH-E, CERES-SYN1deg and Solcast) using observational data of 76 locations, achieving a GHI nRMSE range from 8.91% to 58.8%. The same work concluded that metric errors can result misinterpretations. Validation accuracies vary according to region, climate, aerosol, sky condition, satellite resolutions and computational

models. High-resolutions (usually the native resolution of satellite observations period interval) have higher variability and higher errors, with GHI nRMSE >14% for 5-min time resolution over part of the Americas from 60ºN to 20ºS (Yang, 2021). On mid latitudes, these values are <10% for clear-sky and from 15% to 30% for all-sky conditions (Huang et al, 2019).

Despite this, a more detailed analysis of the Brazilian territory and its various climates is a gap in literature. In addition, Brazil has been interested in its enormous photovoltaic potential, especially when it comes to the Northeast, on account of the biggest solar energy potential in relation to other regions.

In this sense, this study aims to validate two satellite irradiation products, the Copernicus Atmosphere Monitoring Service Radiation Service (http://www.soda-pro.com/) and Solcast (https://solcast.com/), using the comparison against the data for Global Horizontal Irradiation (GHI) and Normal Direct Irradiation (DNI) of a ground-based measurement station located in the city of Petrolina, Northeastern Brazil, under a tropical climate. The station belongs to the Brazilian National Institute of Spatial Research (INPE).

CAMS Rad is an European Earth observation program that combines atmospheric modeling with Earth observation data to provide information services applying its most recent model that estimates irradiation at ground-level, Heliosat-4. CAMS Rad spatial extension is -66° to 66° (in both latitudes and longitudes) and temporal extension from 2004-02-01 up to 2 days ago. On the other hand, Solcast is a commercial company that produces global satellite products from satellite-derived and semi-empirical methodology. Solcast radiation data is available near globally with temporal extension from 2007-01-01 up to 7 days ago.

2. APPLIED METHODS

2.1 Data collection

Ground-based irradiance measurements data from Petrolina station (09º04'08" S, 40º19'11" W) was collected on the Brazilian National Institute of Space Research (INPE) site (http://sonda.ccst.inpe.br/). The radiation database has 1 minute temporal resolution and almost 14 years of temporal extension (2004 – 2018). Moreover, Global Horizontal Irradiation (GHI) and Direct Normal Irradiation (DNI) are given in W/m².

Database from the satellite-derived products CAMS Rad and Solcast were obtained on the following pages:
- CAMS Rad: http://www.soda-pro.com/web-services/radiation/cams-radiation-service
- Solcast: https://solcast.com/

CAMS Radiation offers temporal resolution of 1-, 15-, 60-min, daily and monthly data, whereas Solcast offers a 5-, 10-, 15-, 30- and 60-min data. Aiming to validate the products on the same temporal resolution and using the data "as is", the 60-min resolution was chosen and then the Petrolina-PE dataset was collected from the cited pages. To make a comparison of the satellite products CAMS Radiation Service and Solcast against ground-based GHI and DNI, the 1-min Petrolina data was aggregated to generate hourly irradiation by period average.

Finally, using hourly average is recommended by the author Bright. It occurs because geostationary satellites instantly readings are at intervals less than one hour (between 10- and 30-min), and models use these data to estimate one-hour values. Using instant values does not guarantee that the value is from the same time the satellite measured at that specific point. Also, Huang *et al* (2019) showed that the 3D effect of clouds affects the validation results. That effect decreases as the timescale of a satellite product increases, thus many authors recommended using a higher averaging interval (usually 60-min).

2.2 Data quality

Data quality assessment was done before the validation procedure, on which two results groups was compared to evaluate the low-sun effects on performance. Group I is composed of radiation prediction errors obtained by applying the performance metrics across all sun zenith angles. On the other hand, Group II evaluates the errors after discarding the low-sun irradiation data that corresponds the zenith angles (θ_Z) greater than 85º (Gueymard and Ruiz-Arias, 2016).

Group I can be considered for validation, since there are studies that use the entire database to assess the accuracy of products (Thomas *et al*., 2016a; Clarke *et al*., 2021). However, Group II is preferable, as it analyzes the performance of the satellite models for the moments when solar irradiation is useful (existing). This approach is generally used and recommended (Bright, 2019; Yang and Bright, 2020; Yang, 2021), and in this sense it is the focus of this work.

2.3 Error metrics

Error metrics are part of the distance-based analysis and allows the comparison between an estimated value obtained by a model and a real observation. There are innumerous performance metrics but, according to Bright (2019), some of the most used on validation works are the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Correlation coefficient (R²).

Equation (1) is the root mean squared error, the normalized root mean square error is represented in Eq. (2), the mean absolute error in Eq. (3) and R² in Eq. (4),

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}, \tag{1}$$

$$nRMSE = RMSE/\bar{y} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i|, \tag{3}$$

$$R^2 = 1 - \left[\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 / \sum_{i=1}^{N}(y_i - \bar{y}_i)^2\right], \tag{4}$$

where $\hat{y}_i$ is the estimated value (CAMS or Solcast) of the observed y_i irradiation (INPE), $\bar{y}$ is the INPE observation mean and N is the number of data points. The difference between RMSE and MAE is the weight that the first one puts on large errors. The correlation coefficient R² is a dimensionless measure, it is 1 if a model replicates precisely the observed values and 0 if not.

2.4 Distribution-based analisys

Relying only on the simple measure-oriented approach through error metrics is also not recommended (Yang and Bright, 2020). Data analysis works have extensive visual tools that investigates the data structure and behavior. These data visualization tools must provide clear illustrations in accordance to the purpose of the information. Thrun, Gehlert and Ultsch (2020) cited and studied some different approaches used to evaluate the data structure, such as histogram graphs, probability density functions, boxplots and ridgelines.

In order to complement the discussion, the results also exhibit a study of data distribution using the visual ridgeline tool. The Ridgeline plot was obtained through the function *geom_density_ridges*, available in the R package *ggridges* (https://wilkelab.org/ggridges/reference/geom_density_ridges.html). This function calculates densities of data that are mapped onto x-axis and aggregates the distribution curves along the y-axis through a categorization, thus not having a quantitative density axis. Consequently, the purpose of this type of plot is to allow a qualitative comparison of the density curves shapes between groups along the y-axis (Wilkie, 2019).

3. RESULTS AND DISCUSSIONS

The sun zenith angle effects are shown in Table 1. Results were obtained by firstly applying the error metrics on the all-zenith sun radiation data (Group I) and then on the high-zenith sun data, where $\theta_Z < 85°$ (Group II), for both satellite-derived products.

RMSE values for Group II were approximately 44% higher than the first group. For the second group the Mean Absolute Error (MAE) were at least 96% higher and all R² coefficients were lower. Evidently, these results illustrate that the low-sun irradiance data interfere with the accuracy, consequence of insignificant errors related to night set, which bias the global error to smaller values. Also, the DNI errors are higher for both products, since the satellite modeling procedures regarding the clouds influence do not reach enough spatial resolution to reduce modeling errors associated with the correction and adjustments of the different perspectives between the sun-satellite-cloud and sun-cloud-surface.

Table 1. Error metrics for the Group I and Group II, using 60 minutes temporal resolution of Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI) data. Results are for both CAMS Rad and Solcast.

Irradiance Component	Product	Group I				Group II			
		RMSE [W/m²]	nRMSE [%]	MAE [W/m²]	R²	RMSE [W/m²]	nRMSE [%]	MAE [W/m²]	R²
GHI	CAMS	125.83	55.2	77.54	0.85	181.06	37.6	154.75	0.66
GHI	Solcast	57.66	22.7	26.51	0.97	82.36	17.1	53.04	0.92
DNI	CAMS	219.66	124.8	114.20	0.58	313.31	85.6	224.02	0.35
DNI	Solcast	173.42	99.9	73.44	0.69	250.98	69.6	149.66	0.52

Thomas *et al.* (2016b) validated three satellite products (HC3v4, HC3v5 and CAMS) for GHI data over Petrolina (INPE) and other 41 stations in Brazil, using a temporal resolution of 60 minutes, obtaining a RMSE of 106.2 W/m² for CAMS model (against 125.83 W/m² from Table 1). The data qualification process may have originated this difference in results, since the authors used additional routines in the database. The authors concluded that, among the three

products analyzed, the CAMS had inferior performance results, with a tendency to overestimate the GHI. Additionally, Bright (2019) obtained a RMSE of 78.6 W/m² (GHI) from the Solcast validation at Petrolina station. It is noteworthy that the author used the Group II with data qualification recommended by Long & Shi (2006), what may explain the tiny but existent difference from our results. CAMS Hourly DNI estimates for Petrolina were validated in Salazar *et al.* (2020), the author used data of four years (2010-2014) with a rigid quality control onto Group II, reaching a RMSE value of 154.3 W/m² - CAMS model had the best performance over other four services. DNI validation works for Solcast and assessing works of satellite products derived GHI and DNI variability related to Brazilian climates are a literature gap.

Plots for a distribution-based validation by the conditional probabilities are shown in Figure 1 and Figure 2. Each curve represents the conditional probability density function of observations given estimated values. In essence, it is the function $f(o|p)$, where "o" is the observation and "p" the predictions. For any set of estimates, the Expectation (concentration) of the observations is expected to be close to that prediction, or $E(o|p) = p$ (Yang and Bright, 2020).

Figure 1(a) presents the CAMS Rad conditional distribution of GHI observations given a GHI prediction and Figure 1(b) shows the conditional distribution of DNI observations given a DNI prediction. The same is done in Figure 2, but for Solcast.
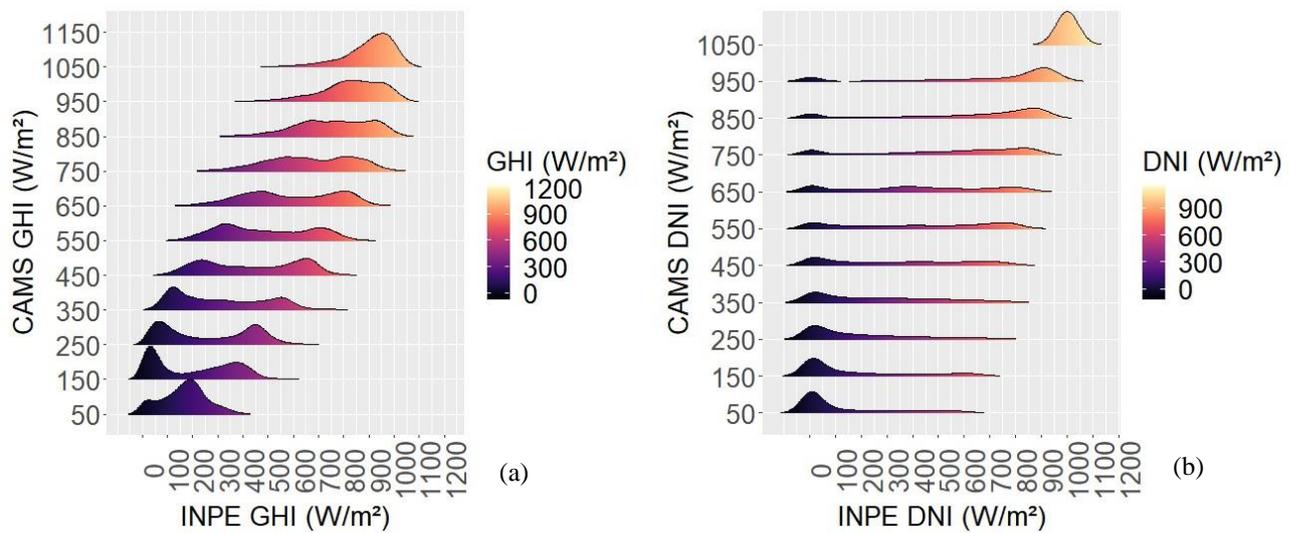

Figure 1. Conditional probabilities of GHI observations given GHI predictions (a) and conditional probabilities of DNI observations given DNI predictions (b) for CAMS Rad.
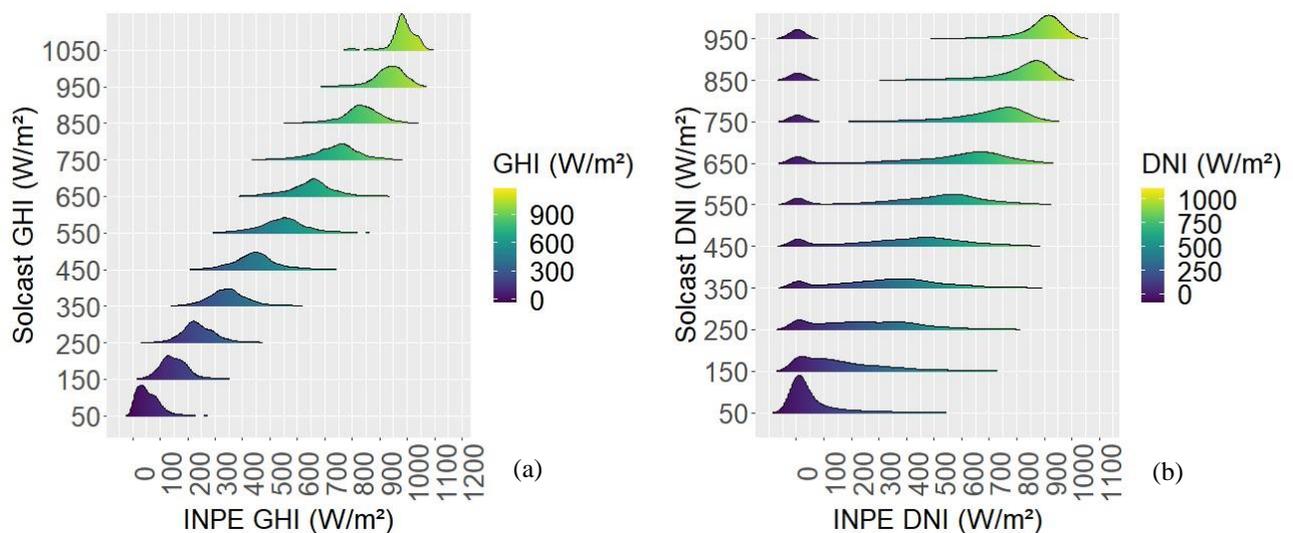

Figure 2. Conditional probabilities of GHI observations given GHI predictions (a) and conditional probabilities of DNI observations given DNI predictions (b) for Solcast.

As one can see, Figure 1 reveals that CAMS Rad tends to under and overestimate the GHI observations for all prediction groups between 150 W/m² and 750 W/m². In addition, for almost all estimated DNI groups between 150 and 950 W/m² it presents observations concentrated at zero value, attesting a deficient model performance. It means that even on days when there are no normal direct radiation measurements at the ground-based Petrolina station, the model can estimate values between 100 and 1000 W/m². Works in the literature (Nonnenmatcher, 2014; Gueymard and Ruiz-Ariaz, 2016; Bright, 2019; Yang, 2020) attest the possibility of clear-sky estimates when in fact there is cloudy-sky conditions. The complexity of satellite-derived DNI modelling is due to errors related to the spatial resolution and modeling errors that are responsible for the adjustments and correction of the different perspectives between sun-satellite-cloud and sun-cloud-surface.

Furthermore, from Figure 2(a) the Solcast model has a satisfactory performance in estimating GHI, since the density concentration of each group is situated close to the expected values. Figure 2(b) exposes that the DNI estimation have similar deviations like the CAMS-RAD model, but Solcast still has a better performance.

To analyze the possible variability in the accuracy as an effect of the seasons on the local climate, the error metrics obtained from seasonal data subset are shown in Table 2 for GHI values and in Table 3 for DNI values. The worst performance results are GHI estimates for summer and DNI for Spring, in both Solcast and CAMS Rad. Error metrics are lower for GHI and DNI estimates in autumn and winter, attesting the best performances.

Table 3. Error metrics for CAMS Rad and Solcast, GHI values per season (Group II).

Season	CAMS Rad (GHI)				Solcast (GHI)			
	RMSE [W/m²]	nRMSE [%]	MAE [W/m²]	R^2	RMSE [W/m²]	nRMSE [%]	MAE [W/m²]	R^2
Summer	199.32	39.0	168.56	0.61	100.00	19.6	63.38	0.89
Autumn	168.97	38.4	143.71	0.64	79.30	18.0	53.11	0.90
Winter	170.02	37.4	147.52	0.65	72.09	15.9	48.01	0.93
Spring	184.81	35.6	159.44	0.70	75.19	14.5	47.62	0.94

Table 4. Error metrics for CAMS Rad and Solcast, DNI values per season (Group II).

Season	CAMS Rad (DNI)				Solcast (DNI)			
	RMSE [W/m²]	nRMSE [%]	MAE [W/m²]	R^2	RMSE [W/m²]	nRMSE [%]	MAE [W/m²]	R^2
Summer	308.91	89.8	227.52	0.33	235.86	68.9	146.47	0.53
Autumn	290.06	81.4	205.94	0.37	221.61	62.3	130.66	0.57
Winter	310.25	82.3	222.09	0.36	250.87	67.8	148.16	0.55
Spring	340.22	88.5	239.71	0.32	290.53	77.6	173.55	0.42

In Petrolina, according to Luiz *et al.* (2018), the rainy season occurs from November to April (spring and summer) and the dry season from May to October (autumn and winter). The sky condition depends directly on the local climate, the seasons, and it also varies during the day. Under cloudy-sky conditions it is expected higher irradiation prediction errors due to variability and modeling errors. Certainly, this effect is observed in the satellite-derived products, despite that the Solcast performs the best results. Figure 3 exhibits four 2D histogram plots of GHI estimated by CAMS versus the values measured by INPE for each season. The same is done for Solcast model in Figure 4. In 2D histogram the concentration of data points in each bin is colour-coded, here brighter colors represent higher occurrences of overlapping points.
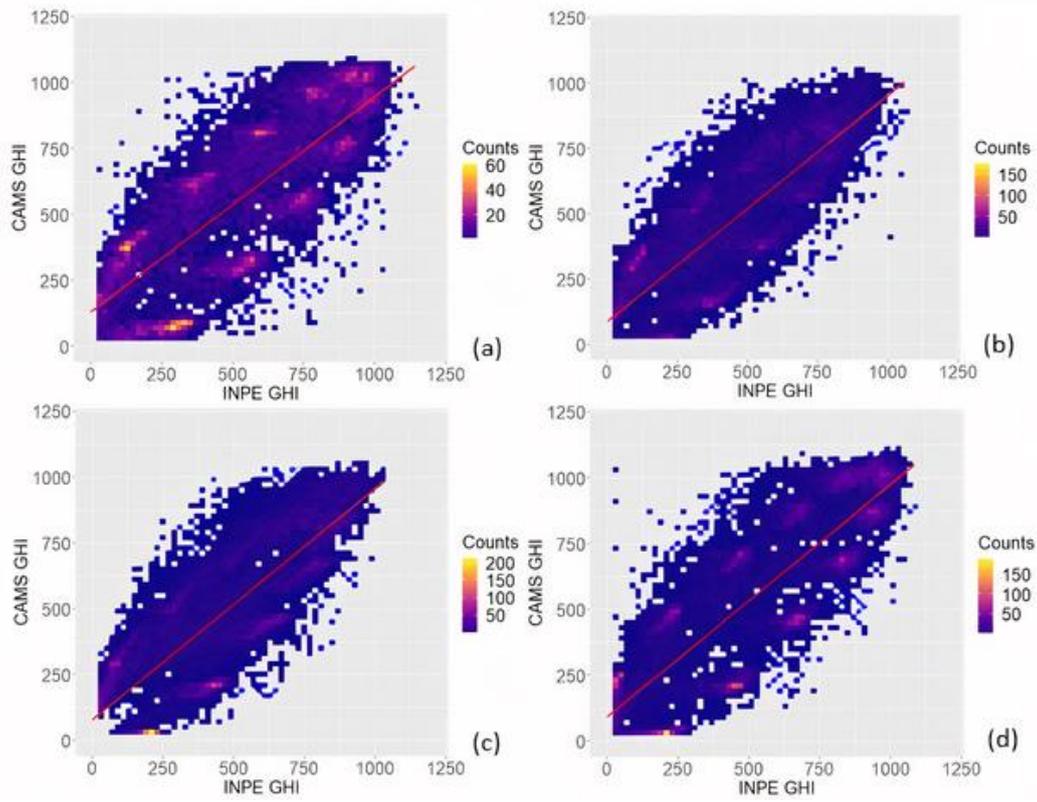
Figure 3. 2D histogram of Global Horizontal Irradiation (GHI) estimated by CAMS Rad model vs measured by Petrolina station (INPE), where (a) summer, (b) autumn, (c) winter and (d) spring. Brighter colors represent higher number of overlapping points.
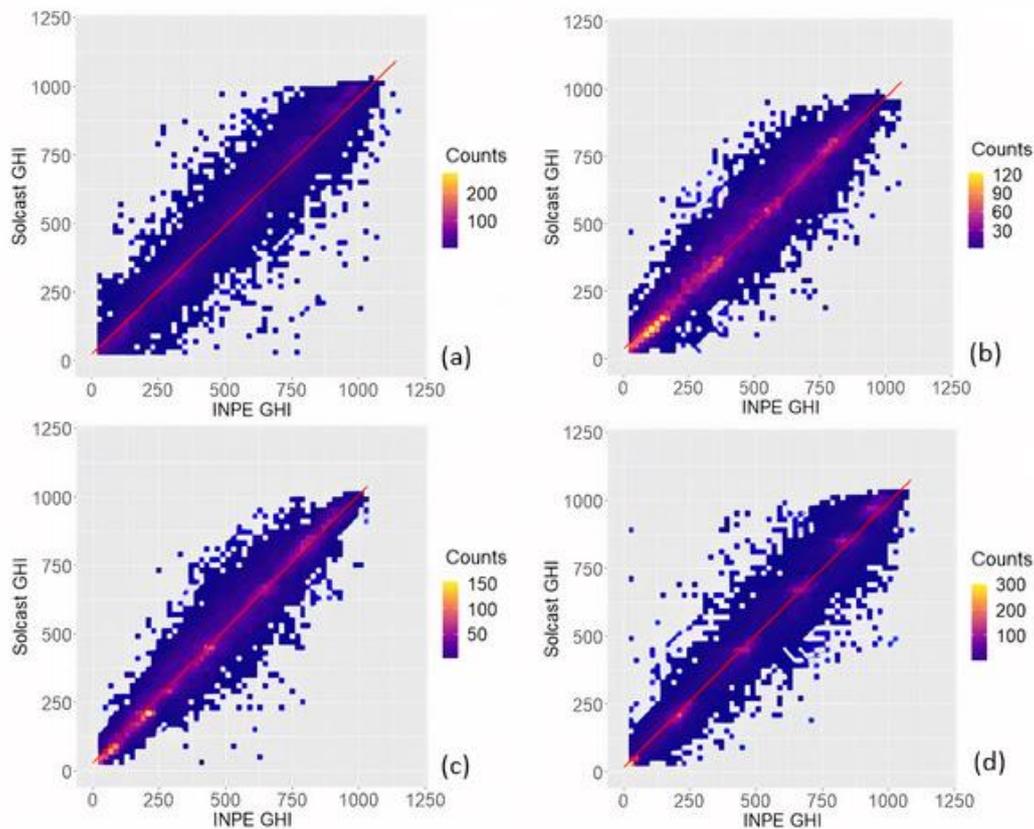
Figure 4. 2D histogram of Global Horizontal Irradiation (GHI) estimated by Solcast model vs measured by Petrolina station (INPE), where (a) summer, (b) autumn, (c) winter and (d) spring. Brighter colors represent higher number of overlapping points.

Figure 3(a) shows that the weakest performance of the CAMS Rad model is on summer. In addition, CAMS Rad results present a large spread of the data points in all four seasons when compared to Solcast model (Figure 4). In fact, one of the models used by Solcast (REST2v5) is ranked among the top three in terms of global performance (Sun *et al*., 2019). In this sense, Solcast data presents in the conditions evaluated in this work a higher accuracy and has a better representation of the real irradiation data structure of distribution.

4. CONCLUSIONS

Although the CAMS best performance over other satellite services (Salazar *et al.*, 2020), in comparison with Solcast, the second one has better skills to make GHI and DNI estimates for Petrolina climate, with lower errors and a satisfactory representation of observed data distribution. In addition, both services are reliable, so that they have been widely used around the world. However, when using this type of service, it must to keep in mind that there are associated uncertainties and that these uncertainties must be taken into account for any project that uses the data.

Furthermore, it is noteworthy that in Petrolina the dry season has a monthly cloud cover fraction of 50% and 60% in the wet season (Luiz *et al.*, 2018). This fact may explain why autumn (dry) has the best estimates and summer (wet) the worst estimates for both products.

More effort should be done in future works about distribution-based validation of geostationary satellite services, in order to conclude which model are more accurate to represent the observed data structure.

5. ACKNOWLEDGEMENTS

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7. RESPONSIBILITY NOTICE

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