Evaluation of the solar irradiance variability in Brazil using satellite-based Variability Score

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Abstract

One of the main barriers to increase the solar energy share is its intermittency. In this work, we compared ground observations in different timescales (1-, 5- and 30-minutes) with satellite effective cloud cover coefficient variability, with 30-minutes time resolution. The smallest discrepancies happen when analyzing the same timescale (30-minutes), where the Pearson correlation for all sites was up 0.94. However, when the frequency of the solar irradiance measurements increased, the correlation decreased. A solution may be the use of downscaling methods, which may be a topic for future work. The most important result achieved in this study was the development of a simple methodology for evaluating the surface solar irradiance variability using only the cloud cover obtained from visible satellite imagery. The results denoted that the proposed methodology is an interesting alternative to evaluate the solar irradiance variability over large areas with satisfactory accuracy, where no ground data is available.

Keywords: Solar variability, cloud cover, satellite data

1. Introduction

Solar energy presents a high variability in different timescales driven mostly by the natural cycles and local typical weather conditions. The first one is precisely estimated by calculating the apparent motion of the Sun in the sky. On the other hand, the variability caused by weather and atmospheric conditions is mostly governed by clouds motion and weather systems, and it is much less predictable (Perez et al., 2016; Watanabe et al., 2016). The solar variability produces transients incompatible with the required power security standards expected for the electricity grid, e. g., voltage variability, imbalance between power generation and energy demand, and thermal stress of the devices (Ari and Baghzouz, 2011; Kazantzidis et al., 2012; Kleissl, 2013).

The different solar power technologies require data on different physical variables: global horizontal irradiance is relevant for PV technologies while the direct normal irradiance is relevant for concentrating technologies. To evaluate the incoming solar irradiance variability, it is important to use normalization parameters to avoid the influence of issues linked to the Sun-Earth position. For PV technologies, the clearness index, Kt (ratio between surface and the extraterrestrial global irradiances) and the clear sky index, Kt* (ratio of the measured solar data and the global irradiance in clear sky condition) are good parameters for meeting this criterion (Lave et al., 2017; Perez et al., 2016; Watanabe et al., 2016).

Furthermore, it is important to analyze the solar power variability in the correct context. Different timescales are relevant for different technologies and power plant sizes (footprint). For example, when we increase the footprint from a single location to a resource dispersed over a large region, the intermittency is reduced considerably. In this context, fluctuations below 30 minutes are not relevant for grid balancing of distribution system, while for single distribution systems and large centralized plants, one-minute fluctuations are important due to voltage control issues (Perez et al., 2016). Moreover, for concentrating technologies, one-hour data provides simplistic results about the prediction of a plant performance (Meybodi et al., 2017).

For this reason, it is important to quantify and investigate the solar variability in the correct spatial and temporal

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context. Watanabe et al. (2016) used the mean, standard deviation and sample entropy to evaluate the solar irradiance variability over Japan. Lave et al. (2015) proposed the Variability Score of solar irradiance ramp rates (RR) as a metric to quantify the local high-frequency variability based on their cumulative distribution functions. Perez et al.)2016) used used the RR, defined as the change in magnitude of the solar irradiance during a specific time-step as a metric to study the solar power variability.

Additionally, it is important to emphasize that ground-based measurements are useful only to understand the solar irradiance variability in small areas. Such limitation makes difficult to evaluate the impact of cloud variability in power plants located far away from the measurement sites. Satellite observations can help and provide useful data to analyze surface solar variability over large areas, however with coarser temporal and spatial resolutions (Lave et al., 2017; Luiz et al., 2018; Watanabe et al., 2016).

In this study we compare the monthly ground-based irradiance variability in different timescales (1- to 30-minutes) at three locations in Brazil with the satellite cloud cover variability obtained from 30-minutes time resolution satellite imagery. The study analyzes locations with different climate regimes in order to understand how the typical local climate can influence the temporal variability of the surface solar variability.

2. Methodology

2.1. Study Area

Brazil has several distinct climate regimes mostly because of its large territorial extension. This study uses data acquired in three measurement sites located in different climate regions. The Cachoeira Paulista (CPA) site has an annual rainfall around 1500 mm and the region presents two distinct climate seasons – a wet season, from October to March (~190 mm/month) and a dry season, from April to September (~55 mm/month) (Climatempo, 2017). During the winter (dry season) is very common the occurrence of cold fronts, in summer (wet season) the region is affected by the South Atlantic Convergence Zone (ZCAS) and natural convection (Nunes et al., 2009). The São Martinho da Serra (SMS) site has annual rainfall around 1600 mm presenting monthly averages ranging from 120 mm to 160 mm, with low seasonal variability (Climatempo 2017b). The occurrence of different systems like cold fronts in winter and convective systems in summer explain the low rainfall variability during the year (Pereira et al., 2017). The Petrolina (PTR) site, a much dryer place, has annual rainfall around 580 mm with a wet season, from November to April (~87 mm/month) and a dry season, from May to October (~9 mm/month) (Climatempo 2017c). The main reason to the dry climate is the influence of the Walker's circulation, which is only broken from February to April because the Intertropical Convergence Zone (ITCZ) is in its southernmost position (Cavalcanti et al., 2009; Strang, 1972). Figure 1 presents the main climate regimes in Brazil and the location of the measurement sites.

2.2. Data

In this work, we calculated the clearness index Kt at the three measurement sites using global irradiance data with one-minute global solar irradiance. Additionally, we used the empirical correction, proposed by Perez et al. (1990), to remove the effects of the air mass at large zenith angles. Equation 1 presents the corrected value (Kt') where 'am' is the relative air mass.

$$Kt' = Kt/(1.031\exp(-1.4/(0.9 + 9.4/am)) + 0.1) \qquad \text{(eq. 1)}$$

Additionally, we used the moving average proposed by Kleissl (2013) as a definition to ramp rates in order to estimate the solar variability. The ramp rates of Kt', designated from now on as $RR_{\Delta t}^{Kt'}$ are defined in Equation 2, where Δt is the timescale of interest

$$RR_{\Delta t}^{Kt'} = \frac{1}{\Delta t}\left(\sum_{t}^{t+\Delta t} Kt' - \sum_{t-\Delta t}^{t} Kt'\right) \qquad \text{(eq. 2)}$$

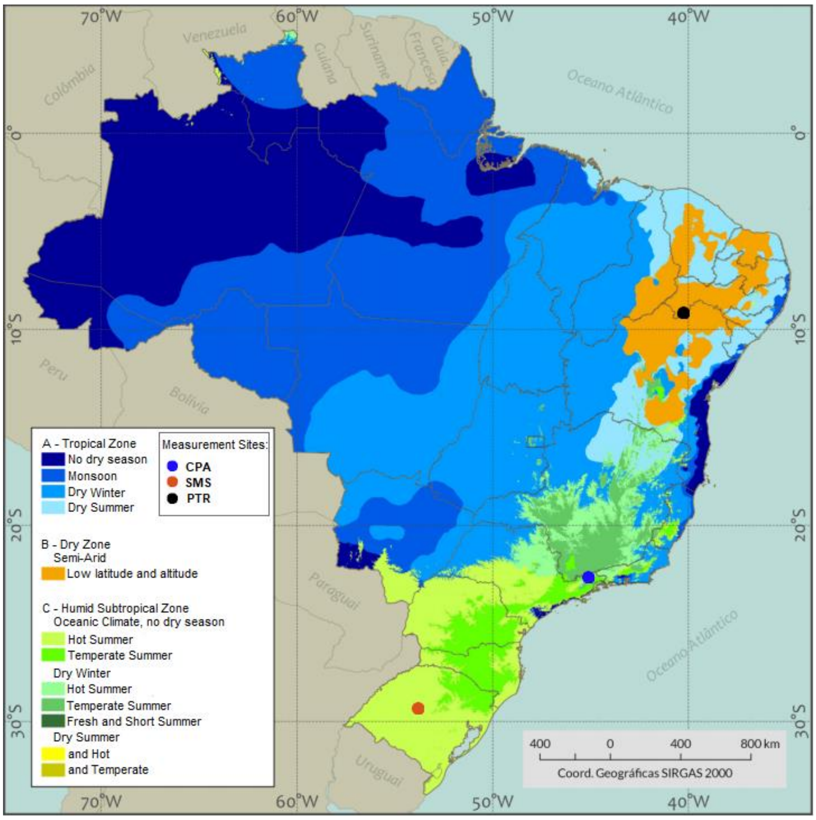

Fig 1. The typical climate zones in Brazil and the location of measurement sites used in this study. Adapted from Alvares et al. (2013).

In South America, the Geostationary Operational Environmental Satellite, GOES-13, managed by NOAA, provided images with a 30-minutes time interval during the study period. Equation 3 defines the effective cloud cover coefficient (C_{eff}) for each pixel of the satellite image in terms of the radiance (L_r) measured by the satellite in the visible channel. The clear-sky radiance (L_{clr}) and the radiance for overcast conditions (L_{cld}). The L_{clr} and L_{cld} values were obtained by composing clear and overcast images from satellite images acquired during a one-month period. In this step, we divided the reflectance by the cosine of the sun's zenith angle to avoid the influence of illuminance geometry in the radiance data observed by the satellite. According to Martins et al. (2008), C_{eff} is a dimensionless coefficient related to the cloud optical depth in each image pixel. The C_{eff} ranges in the 0 to 1 interval corresponding from the clear sky condition to a completely overcast sky with no direct solar irradiance reaching the Earth's surface.

$$C_{eff} = (L_r - L_{clr})/(L_{cld} - L_{clr}) \qquad \text{(eq. 3)}$$

In this study, we used the C_{eff} ramp rates as the difference between C_{eff} values in two consecutive satellite images at each pixel, as proposed by Luiz *et al.*, 2018, as a metric using satellite data. The C_{eff} ramp rates are designated from now on as RR_{30}^{Ceff} where the index 30 refers to the 30-minutes temporal resolution of the satellite images.

2.3. Variability Score

As a metric to study variability, we used the Variability Score (VS) proposed by Lave et al. (2015), which is based on the cumulative distribution functions of the RR values (Eq. 4), where RR_0 is the ramp rates magnitudes ranging from the minimum to the maximum value.

$$VS(\Delta t) = 100.\max[RR_0.P(|RR_{\Delta t}^{sm}| > RR_0)] \qquad \text{(eq.4)}$$

The VS is generally well correlated to the number of tap changes at a solar electric plant, however variables like the tracking setup, cloud velocity and geographic smoothing may lead to some erroneous evaluations and need to be better analyzed (Lave et al., 2015). The VS(Δt) value ranges from 0 (no variability) to 100 (all ramp rates presenting the maximum value). Larger VS (Δt) indicates more variability.

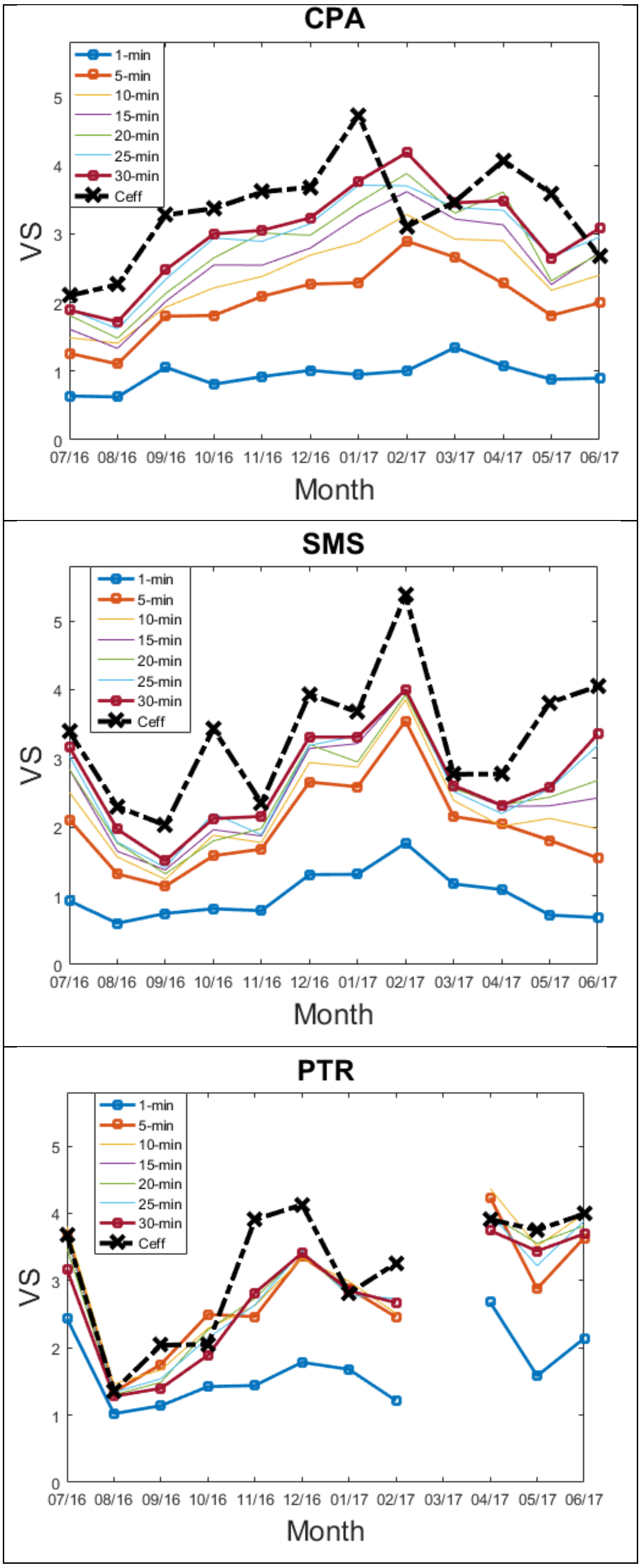

Fig. 2: Annual cycle of the monthly average of variability scores for Kt' in timescales from 1 to 30 minutes, and for Ceff in 30 minutes timestep for all 3 measurement sites: CPA, SMS and PTR.

3. Results

The Pearson correlation between the monthly VS(30) from the C_{eff} and the Kt' data were found as 0.94, 0.88 and 0.71 for PTR, SMS and CPA respectively. Fig. 2 presents how the monthly VS changes in different timescales during the year at the three sites. As we can see in the three graphs, the monthly average of the Kt' VS(ΔT) changes gradually, and its highest variability occurs in months with large precipitation (i.e., large nebulosity). Furthermore, regarding the comparison between the Kt' VS(ΔT) and Ceff VS(30), we can see that the smallest difference happens for the same timescale (30-minutes).

In most cases, the annual cycle of Kt' VS(ΔT) is well represented by the Ceff VS(30). Exceptions occur in October/2016 at SMS and in February/2017 at CPA. In the second case, the C_{eff} VS varies in opposite direction of the Kt' VS variation. This odd condition may be the reason to the lower CPA correlation, and it will be a subject for further investigation.

4. Conclusion

The incoming solar irradiance variability on three climate regions of Brazil was investigated using the Variability Score (VS). The determination of the VS values used one-year of the effective cloud cover (Ceff) estimated from satellite visible images. The local ground-irradiance data for the same period was the reference information to evaluate the uncertainties and the reliability of the method.

The results pointed out that the Variability Score (VS) using only visible satellite information can be an interesting alternative to study the solar irradiance variability over large areas with no ground data available. Besides that, we proved to be possible to get reliable information on solar irradiance variability without using radiative transfer models that demand larger computational resources than the proposed methodology. The Ceff values, obtained only using the visible geostationary satellite imagery, proved itself to be enough to characterize the solar resource variability on surface with the required accuracy.

The major limitation of the methodology is the temporal resolution of 30-minutes of satellite images. Even though, the information in 30-minutes timescale is useful for grid balancing of the PV power systems in the distribution grids, it cannot deliver the required accuracy to deal with the voltage control issues by operators of large solar PV power plants.

The future work will focus on the improvement of the methodology to evaluate the relationship between the high frequency variability (1-min or 5-min) of the incoming solar irradiance, with the cloud cover variability observed by geostationary satellites.

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