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Sara Moreno-Tejera, Miguel Larrañeta, Isidoro Lillo-Bravo, and Manuel Silva-Pérez

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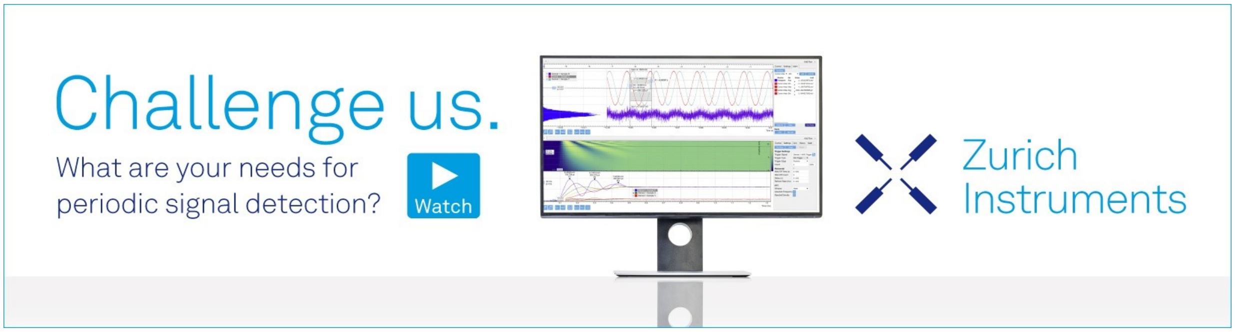

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A Normalized Variability Index of Daily Solar Radiation

Sara Moreno-Tejera [1, a)], Miguel Larrañeta [2], Isidoro Lillo-Bravo[1] and Manuel Silva-Pérez [1]

[1] *Department of Energy Engineering, University of Seville. Address: Camino de los Descubrimientos s/n. 41092, Seville, Spain.*
[2]*AICIA, Group of Thermodynamics and Renewable Energy. Address: Camino de los Descubrimientos s/n. 41092, Seville, Spain.*

a) Corresponding author: smoreno2@us.es

Abstract. The Variability Index (VI) is widely used to quantify the intra-day solar radiation variability. It compares the length of the global horizontal irradiance (GHI) or direct normal irradiance (DNI) profiles with the length of the corresponding clear sky GHI/DNI profiles. The VI is not a normalized index, it shows dependency on the day of the year, geographic location and time resolution. Thus, the quantification of the intra-day variability of the solar resource between different locations or different seasons could be mistaken. In this work, we propose a novel definition of the VI in order to normalize it (VI'). Moreover, we suggest a methodology to assess the dependencies of the intra-day solar resource variability quantifiers with the day of the year, geographic location and time resolution. We evaluate and compare the performance of both indexes in two different locations along two synthetic years and a measured annual dataset in different time resolutions.

INTRODUCTION

A good characterization of the solar resource is needed for the development of concentrated solar power and photovoltaics plants [1] and their integration in the electrical grid. One of the main drawbacks of this unlimited supply of energy is its intermittency. The solar energy is not steady along the day because of the Earth movement around the Sun and the atmosphere components, mainly the clouds. The consequences of the Sun-Earth relative position are commonly known and characterized by mean of the solar geometry equations. However, the impact of the atmosphere components on the solar radiation in anywhere in the Earth is difficult to characterize and even more to predict owing to its local behavior. There is a growing interest related to the characterization of the intra-day solar resource variability by means of different quantifiers [2-4]. The Variability Index (VI) [5] is a widely used quantifier [6-9]. It compares the length of the global horizontal irradiance (GHI) or the direct normal irradiance (DNI) profiles with the length of the corresponding clear sky GHI/DNI profiles. The VI is not a normalized index, it shows dependency on the day of the year, geographic location and time resolution. Thus, the quantification of the intra-day variability of the solar resource between different locations or different seasons could be misleading. Recent works are focused on selecting the best identifier of a type of day [9-10] but, the possible dependencies of these parameters with the day of the year, geographic location and time resolution, are hardly considered. In this work, we propose a novel definition of the VI with the aim of avoiding the dependencies identified, the normalized variability index, VI'. Moreover, we suggest a methodology to assess the dependencies of the intra-day solar resource variability quantifiers with the day of the year, geographic location and time resolution. The methodology evaluates and compares the performance of the indexes (VI and VI') in two different locations along two synthetic years and a measured annual dataset in different time resolutions. The dependencies of the VI and the VI' are tested by means of this methodology.

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THE NORMALIZED VARIABILITY INDEX

The Variability index was defined by Stein et al (2012) to identify periods and locations with high GHI variability. This index compares the length of the GHI profiles with the length of the corresponding clear sky GHI profiles, Eq (1)

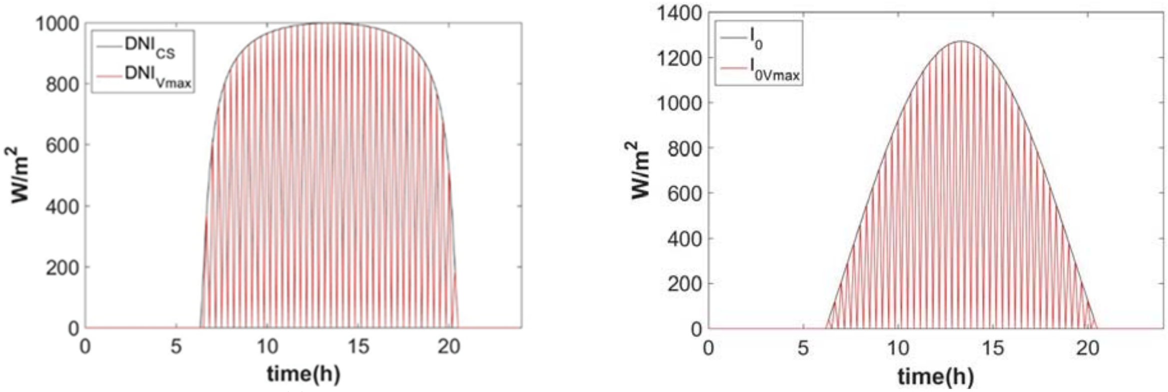
$$VI_{GHI} = \frac{\sum_{k=2}^{n}\sqrt{\left(I_{g0_k}-I_{g0_{k-1}}\right)^2+\Delta t^2}}{\sum_{k=2}^{n}\sqrt{\left(I_{g0,CS_k}-I_{g0,CS_{k-1}}\right)^2+\Delta t^2}} \qquad (1)$$

where I_{g0} is the measured GHI and $I_{g0,cs}$ is the maximum GHI clear sky at the corresponding interval of time (1min, 10min or 1h), Δt refers to the corresponding interval of time (1min, 10min or 1h), and n is the number of intervals of time of the considered day.

VI is also used to characterize the intra-day variability in DNI profiles by other authors [8-9]. In these cases, the index is defined as follows:

$$VI_{DNI} = \frac{\sum_{k=2}^{n}\sqrt{\left(I_{bn_k}-I_{bn_{k-1}}\right)^2+\Delta t^2}}{\sum_{k=2}^{n}\sqrt{\left(I_{cs_k}-I_{cs_{k-1}}\right)^2+\Delta t^2}} \qquad (2)$$

where I_{bn} is the measured DNI and Ics is the maximum DNI clear sky at the corresponding interval of time (1min, 10min or 1h), Δt refers to the corresponding interval of time (1min, 10min or 1h), and n is the number of intervals of time of the considered day. VI is not a normalized index since we do not find the length of the profile in the most variable day in the denominator but the clear sky length. In order to propose a new index definition we introduce the maximum variability day, for a given time resolution, as the profile that continuously alternates between the clear sky envelope value and 0 (Fig. 1).



(a)

(b)

FIGURE 1. (a) Example of clear sky DNI profile (DNI_{CS}) and maximum variability DNI profile (DNI_{Vmax}). (b) Example of extraterrestrial irradiance profile (I_0) and maximum variability extraterrestrial irradiance profile (I_{0Vmax}).

In order to avoid these dependencies a novel index is proposed, the normalized variability index, *VI'*. This index compares the length of the measured DNI profile to the length of the maximum variability DNI profile Eq (3), in the DNI case, and the length of the measured GHI profile to the length of the maximum variability GHI profile, in the GHI case, Eq (4).

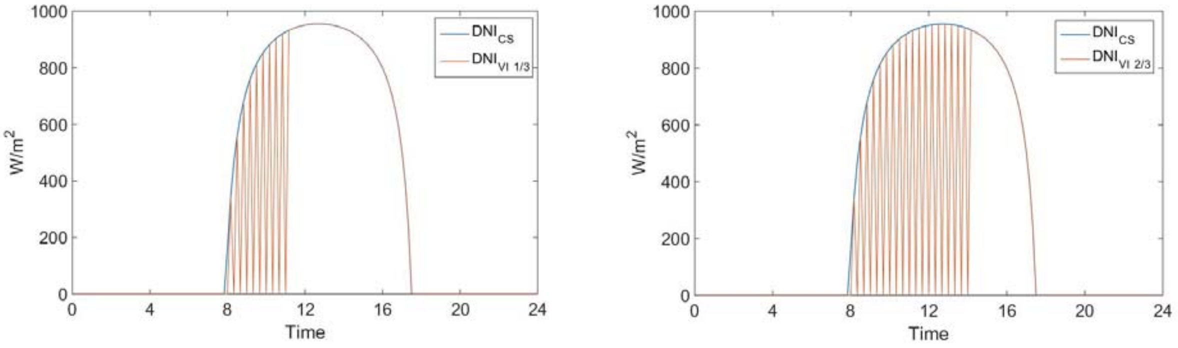
$$VI'_{DNI} = \frac{\sum_{k=2}^{n}\sqrt{\left(I_{bn_k}-I_{bn_{k-1}}\right)^2+\Delta t^2}}{\sum_{k=2}^{n}\sqrt{\left(I_{max_k}-I_{max_{k-1}}\right)^2+\Delta t^2}} \qquad (3)$$

$$VI'_{GHI} = \frac{\sum_{k=2}^{n}\sqrt{\left(I_{g0_k} - I_{g0_{k-1}}\right)^2 + \Delta t^2}}{\sum_{k=2}^{n}\sqrt{\left(I_{max_k} - I_{max_{k-1}}\right)^2 + \Delta t^2}} \tag{4}$$

where I_{maxk} is the maximum variability DNI/GHI of the instant k, Δt refers to the corresponding interval of time (1-min, 10-min or 1h), and n is the number of intervals of time of the considered day. In the case of GHI, the maximum variability GHI profile can also be defined by means of the extraterrestrial horizontal irradiance profile (I_0).

METHODOLOGY

The first step in assessing the seasonal, geographical and time resolution dependencies is knowing the value of these variability quantifiers in the maximum variability case. If no dependencies are found, the index should show similar results for any location, time resolution and day of the year. In this work, the values of these indexes are evaluated for an annual set of maximum variability daily profiles in 1 minute, 10 minute and hourly time resolution for two different locations, Seville (Spain) and Alice Springs (Australia). Moreover, to study the performance of the indexes in days with similar variability, two synthetic DNI/GHI datasets are generated in 1 minute, 10 minute and hourly time resolution for both locations. The days of the first dataset ($DNI_{VI\ 1/3}$ and $GHI_{VI\ 1/3}$) are built by dividing the daytime in three equal intervals and, then, considering that one third follows maximum variability DNI/GHI profile and the rest two thirds the corresponding clear sky DNI/GHI profile. Fig. 2 (a) represents an example of this type of days for the DNI component. The second synthetic dataset is similar to the first one but considering two thirds with maximum variability profile and one third with clear sky profile ($DNI_{VI\ 2/3}$ and $GHI_{VI\ 2/3}$) (see Fig 2 (b)). We also calculate the indexes for one year of measured data for both locations and different time resolutions. The days with maximum variability according to each index are identified and compared in the different time resolutions.



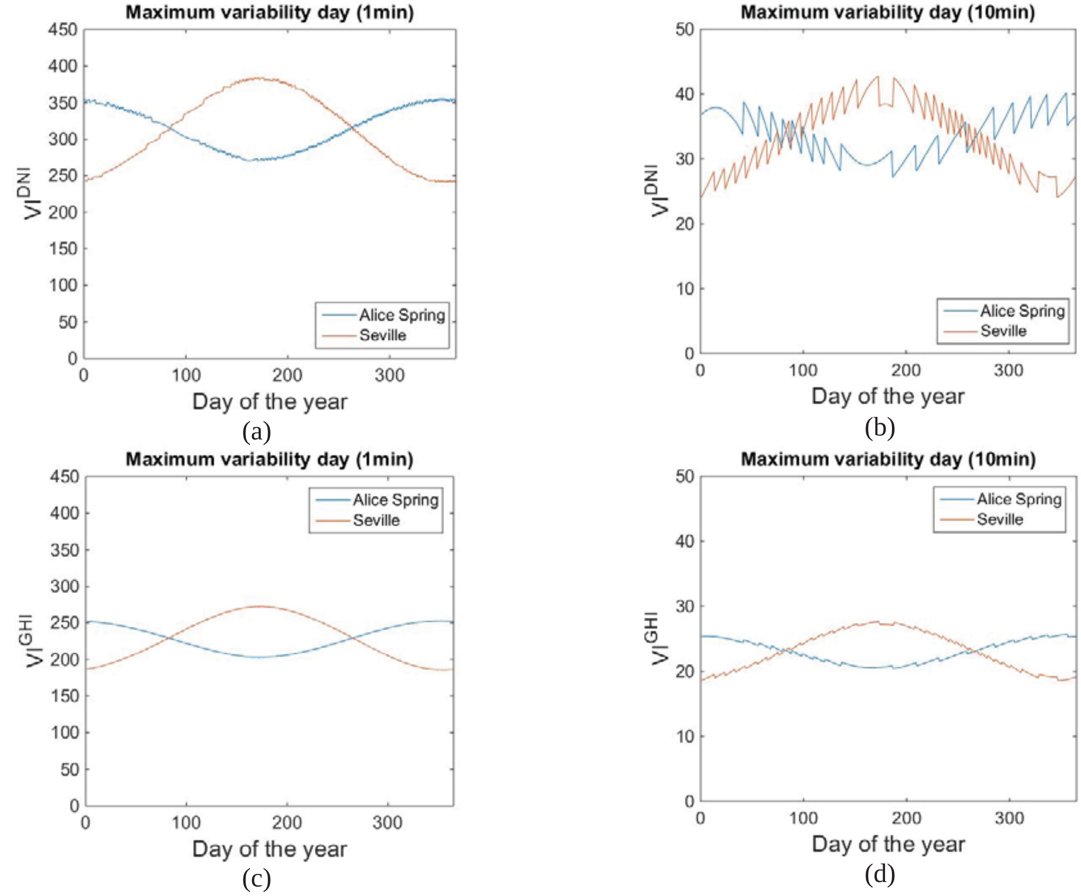
(a) (b)

FIGURE 2. (a) Example of one third of maximum variability DNI profile ($DNI_{VI\ 1/3}$) and its corresponding clear sky DNI profile (DNI_{CS}). (b) Example of two thirds of maximum variability DNI profile ($DNI_{VI\ 2/3}$) and its corresponding clear sky DNI profile (DNI_{CS}).

RESULTS

Figure 3 shows the VI_{GHI} and the VI_{DNI} of the maximum variability day from Seville and Alice Spring for the 365 days of the year in 1 min and 10 min time resolution. In both locations and for both components, the VI shows a clear dependence with the day of the year, more noteworthy for DNI, getting values, in the case of 1-min data, 32% higher in winter days (respect to the lowest value of summer days) for Alice Spring and 60% higher in summer days (respect to the lowest value of winter days) for Seville. In both locations the higher values are found in days with the higher number of sunlight hours. The dependence with the geographic location it is also shown in both cases, where the maximum values obtained for both resolutions and components are higher in Seville, the location with higher latitude and thus the location with days with higher maximum number of sunlight hour. Moreover, these figures also show the time resolution dependency since the range of VI values obtained from 1-min data in both locations are approximately

10 times higher than the VI values calculated from 10 min data for both components. By definition, the VI’ in a maximum variability day is equal to the unit for wherever location, whatever time resolution and day of the year.

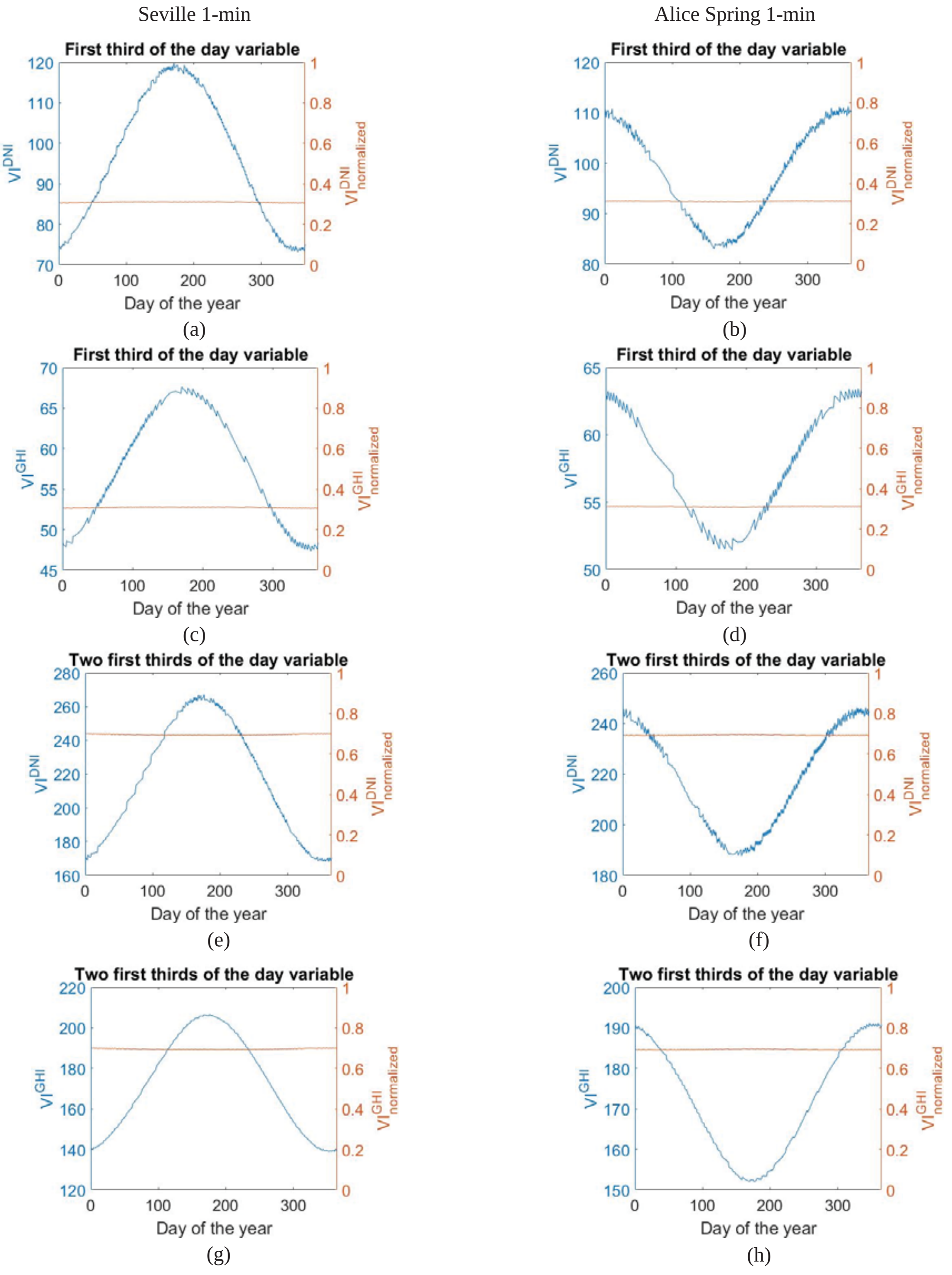


(a) (b)

(c) (d)

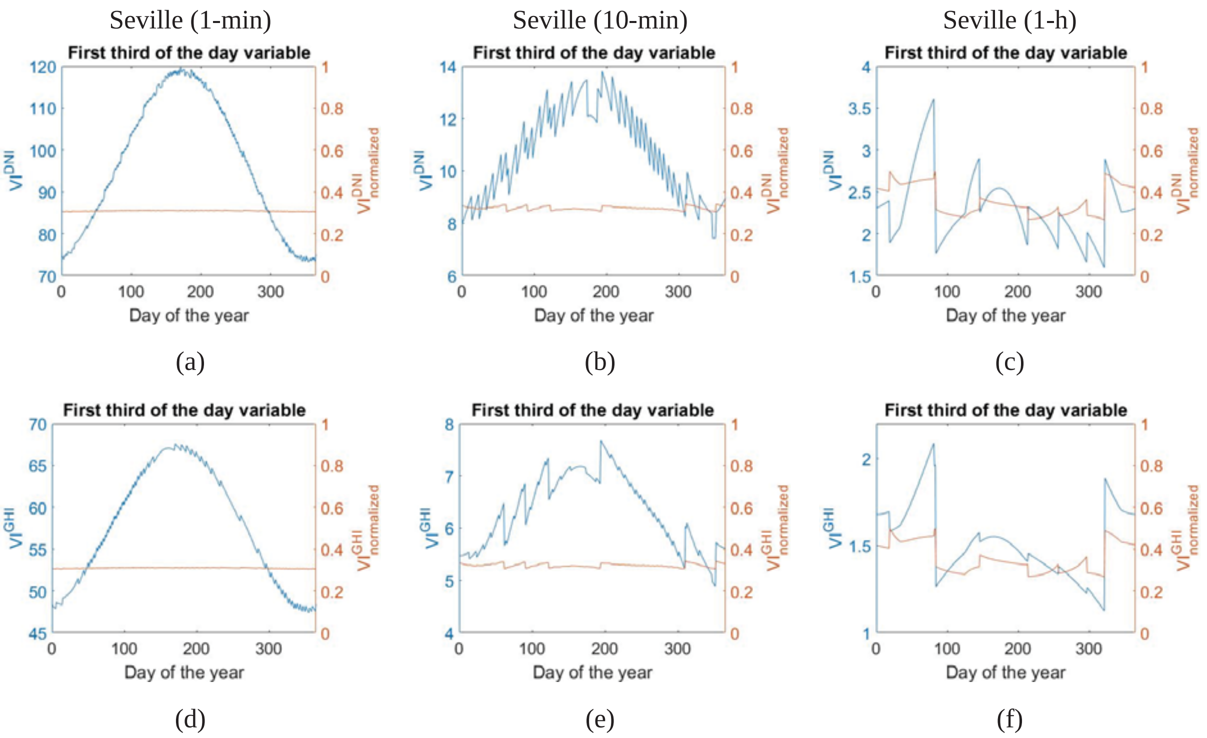
FIGURE 3. First row: VI of the maximum variability DNI annual dataset from Seville and Alice Springs in 1-min (a) and 10-min (b) time resolution. Second row: VI of the maximum variability GHI annual dataset from Seville and Alice Springs in 1-min (c) and 10-min (d) time resolution.

As shown Fig 4, when the proportion of the maximum variability holds constant and equal to one third or two thirds of the day for each day of the year and each location we obtain similar VI’ values, whereas VI is clearly dependent on both variables. So, VI’ avoids dependency on the day of the year and on the location. This behavior is also observed with the two thirds of maximum variability DNI datasets where VI’ reaches a steady value at around 0.67 in all cases, characterizing properly the proportion of the variability.



(a) (b) (c) (d) (e) (f) (g) (h)

FIGURE 4. First row: VI and VI’ ($\mathrm{VI}_{\mathrm{normalized}}$) of the one third of maximum variability DNI 1-min annual dataset from Seville (a) and Alice Springs (b). Second row: VI and VI’ ($\mathrm{VI}_{\mathrm{normalized}}$) of the one third of maximum variability GHI 1-min annual dataset from Seville (c) and Alice Springs (d). Third row: VI and VI’ ($\mathrm{VI}_{\mathrm{normalized}}$) of the two first thirds of maximum variability DNI 1-min annual dataset from Seville (e) and Alice Springs (f). Fourth row: VI and VI’ ($\mathrm{VI}_{\mathrm{normalized}}$) of the two first thirds of maximum variability GHI 1-min annual dataset from Seville (g) and Alice Springs (h).



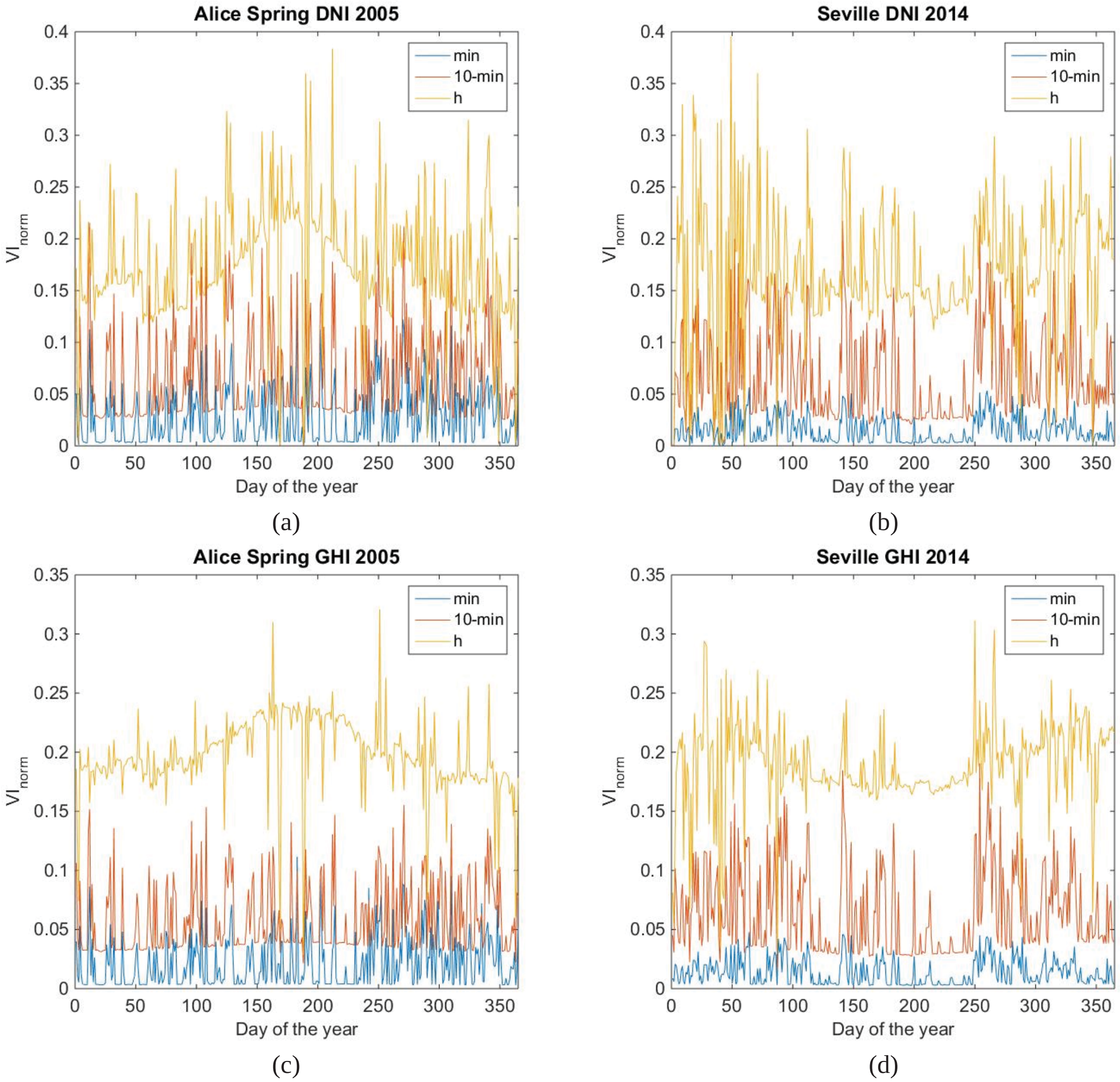
(a) (b) (c)

(d) (e) (f)

FIGURE 5. First row: VI and VI' (VI$_{normalized}$) of the one third of maximum variability DNI 1-min (a), 10-min (b) and hourly (c) annual sets from Seville. Second row: VI and VI' (VI$_{normalized}$) of the one third of maximum variability GHI 1-min (d), 10-min (e) and hourly (f) annual sets from Seville.

As shown in Fig 5, when we compare VI' values with the same proportion of variability ((first third of the day variable) but different time resolutions, some differences are observed. These differences are higher between 10-minute and hourly values. Although, compared to VI, the dependency on the time resolution decreases. In order to identify the origin of this drawback, we analyze the VI' values calculated from an annual set of observed data in the three time resolutions for both locations and each component in Fig. 6.

Figure 6 shows a different tendency between VI' calculated from hourly and minute values. The days with maximum VI' value are not the same for the different time resolutions. The maximum variability day of Alice Spring according to the hourly VI'$_{DNI}$ is the day 212. In this day, the 1 min VI'$_{DNI}$ value is one third of 1 min VI'$_{DNI}$ value in the maximum variability day, located the day 183. These differences are also observed between 1-min and 10 min values, although the differences are lower. Moreover the maximum variability days according to the VI' are coincident for both components when the 1 min data are used in both location. But this is not true when we use 10 min or hourly values, when we average solar radiation data, the intra-day variability of the DNI/GHI can be modified. We also can observe that VI' values from 1 min data are very low in all cases.



(a) (b)

(c) (d)

FIGURE 6. First row: VI' ($VI_{normalized}$) calculated from 1-min, 10-min and hourly DNI data of a yearly measured set from Seville (a) and from Alice Spring (b). Second row: VI' ($VI_{normalized}$) calculated from 1-min, 10-min and hourly GHI data of a yearly measured set from Seville (c) and from Alice Spring (d).

CONCLUSIONS

In this work, we propose a methodology to assess the dependencies of a solar radiation variability quantifiers on day of the year, location and time resolution. This is a complementary and necessary study to ensure a proper characterization of the intra-day variability of the solar radiation and the global applicability of the selected indexes. This methodology is used to evaluate the dependencies of the well-known VI index applied to GHI and DNI data. Two locations, with different latitudes (Seville and Alice Spring), are selected for this purpose. In both locations and for both variables, the VI shows a clear dependency with the day of the year getting differences up to 60% between days with maximum variability in the case of 1-min DNI data of Seville. The dependency with the geographic location it is also shown in both cases. This dependency is related to the number of sunlight hours. Locations with higher latitude present days with higher maximum number of sunlight hours, therefore, they show a higher range of VI values for both components. Moreover, the study also reveals the time resolution dependency of the VI index since the range of 1-min VI values obtained are approximately 10 times higher than the VI values of 10 min data for both components and locations. In order to avoid these dependencies, we introduce the VI’ index. The VI’ shows similar values, proportional to the degree of variability, for any location and day of the year, showing no seasonal and no spatial dependency. However a certain time resolution dependency is observed. This dependency is more noteworthy between hourly and 10-minute data. We also calculate the daily VI’ index for one year of observed DNI and GHI data in different time resolution for Seville and Alice Spring concluding that the VI’ values calculated from data in the hourly time resolution show different tendency than for lower time resolutions. Calculating the solar radiation intra-day variability in the hourly resolution entails a great loss of information. We also observe that for real days, VI’ values are in general very low.

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