SPATIAL AND TEMPORAL VARIABILITY OF THE SOLAR RESOURCE IN THE UNITED STATES

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ABSTRACT

The measurement of solar radiation to characterize the solar climate for renewable energy and other applications is a time-consuming and expensive operation. Full climate characterization may require several decades of measurements—a prospect that is not practical for an industry intent on rapid deployment of solar technologies. This study demonstrates that the consistency of the solar resource in both time and space varies widely across the United States. The mapped results here illustrate regions with high and low variability and provide readers with quick visual information to help them decide where and how long measurements should be taken for a particular application. The underlying data that form these maps are also available from the National Renewable Energy Laboratory to provide users the opportunity for more detailed analysis.

1. INTRODUCTION

The characterization of the solar resource is often considered only in terms of magnitude—how much solar energy is available at an area of interest over a specific time period. But a complete characterization includes the variability of available solar radiation over time, whether it is on the scale of one second to the next, one day to the next, one season to the next, or even one decade to the next. One can also consider variability of the solar resource in space—how it varies over distance. Both of these realms are driven by climate and its myriad complexities—primarily the amount and type of clouds and how they vary. Atmospheric forces and constituents have a strong impact on the solar radiation absorbed, reflected, or otherwise prevented from reaching the surface of the earth, and as the climate varies, so does the solar radiation available for a solar energy venture.

Knowledge of this variability is important for improving the design of a system (by adding properly sized storage capabilities, for instance) and understanding the performance of a solar conversion system (e.g., understanding how the extremes can enhance or degrade system performance or during which season they occur most frequently). Still, long before that, knowledge of the resource variability could provide critical information for determining *how long* and *where* to conduct a measurement campaign to provide data. That concept is the focus of this paper.

For solar energy applications, the literature is currently very limited on the topic of solar irradiance variability at the regional or continental scale, and it is usually limited even further to global horizontal irradiance (GHI). See, for example, [1–5]. This provided the impetus for the research described here. In a previous phase of this investigation [6], these authors showed that the resource in direct normal irradiance (DNI) is always substantially more variable than that in GHI, thus corroborating other reports (e.g., [7] and [8]). An important finding of that phase of the study showed that the long-term annual average GHI could be estimated within ±5% after only one or two years of local measurements. In contrast, a similar approximation of the long-term annual average DNI could take 10–15 years. Furthermore, if a single year of DNI measurement is by chance performed during the climatological best period, the annual DNI can be typically too optimistic by about 8% to 15%, depending on location. Similarly, if it is performed by chance during the climatological worst year, it can be too pessimistic by about 13% to 23%. (Variance in cloudiness affects good years and bad years in roughly equal amounts, but additional aerosol burdens from volcanic activity can only lower DNI—hence, the stronger variability effect during bad years.)

Although modeled solar data are commonly available, the source of data with the lowest uncertainty is generally obtained from radiometers located at a target location. Data sets spanning decades are not only accurate measures of the magnitude but also a definitive source of data to determine variability. A single year of data—no matter how accurate—cannot assume to represent all years by any statistical measure (especially for DNI) because climate factors influence radiation differently each year. However, if advance knowledge indicates an area of interest has low interannual variability, one could reason that a shorter period of time could yield a data set likely to hold means and variability similar to those seen over longer time spans. Likewise, knowledge of lower spatial variability could provide justification for using a solar resource data set from the measurement location for a location some distance away. Because of the high cost of solar measurements, these are attractive prospects. Knowledge of variability then becomes valuable when deciding how long to make measurements at a particular location and whether the character of the solar resource at that location can be extended to other nearby locations.

2. METHODOLOGY FOR IRRADIANCE VARIABLITY ANALYSIS

Eight years (1998–2005) of data from the National Solar Radiation Database (NSRDB) [9] have been analyzed in both realms of temporal and spatial variability. The analysis summarizes the values in each 10-x-10-km cell of the satellite-derived irradiance data in the NSRDB (derived from the State University of New York at Albany model, hereafter SUNY model) and calculated monthly mean daily totals, annual mean daily totals, and the mean daily total for the entire eight-year period.

2.1 Temporal Variability

For each cell, eight annual values are used to calculate a coefficient of variation (COV). The eight-year mean irradiance $<E_p>$ and each annual value E_i are used to derive the standard deviation of the data set, according to

$$\sigma_t = \left[\sum_{i=1}^{i=8} (< E_p > - E_i)^2 / 8 \right]^{1/2} .$$

The temporal COV is

$$C_t = \sigma_t / < E_p >.$$

The COV in this report are expressed as percentages. Although the actual scatter in the data is likely larger than what the COV indicates, the COV expresses the likelihood of data falling within the resulting value range around the mean. More specifically, outlier years could exceed the range defined by $<E_p> \pm\sigma_t$ because, by assuming a Gaussian distribution of the monthly or annual total irradiance, there is only a 66% likelihood that measurements for any given year will be within the distance from the mean just stated. Alternatively, one can assume a 95% likelihood that the individual data points are within a range twice as wide (i.e., $<E_p> \pm 2\sigma_t$). For applications in which so-called "bankable data" are required, and only a 5% margin of error is admissible, the use of the 95% confidence rule is highly recommended. This translates into *doubling* all the COV numbers provided here.

Using results from the NSRDB, the analysis just described was performed for DNI and for a global tilt irradiance (GTI) modeled for a surface tilted at the location's latitude [10]. GTI is a combination of DNI and diffuse irradiance, which normally varies in opposition to DNI. Therefore, GTI's variability must be lower than that of DNI.

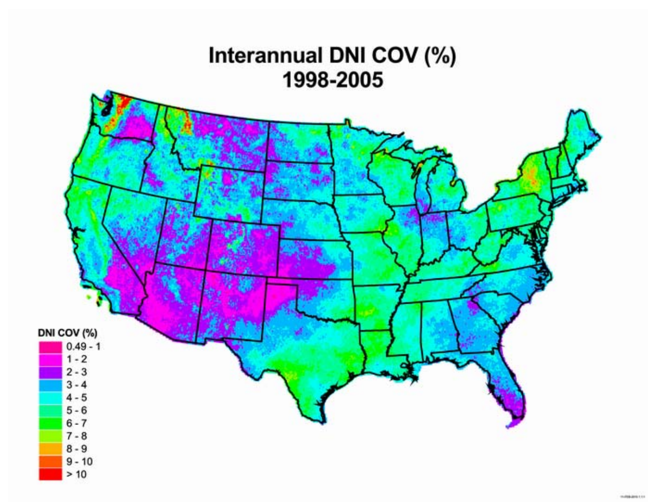

Fig. 1: Interannual COV for DNI. Note similar patterns with GTI in Fig. 2, but higher magnitude for DNI by about a factor of two.

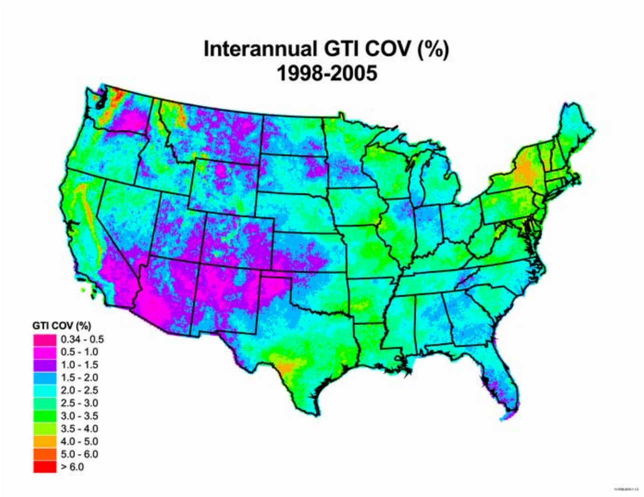

Fig. 2: Interannual COV for GTI. See comment under Fig. 1.

To understand the variability in a seasonal scope, the process was repeated on monthly bins of data (e.g. the eight Januaries, Februaries, etc.). The results, expressed as percentages, represent a measure of the variability in the solar resource over time at the cell's geographic location. The resulting COV for DNI and GTI for all cells plotted as contour maps of the United States are shown in Figs. 1 and 2, respectively, providing a quick visual measure of differences in interannual variability for a 66% confidence level. The DNI temporal COV for the 48 United States for this analysis ranges from a low of 0.49% in south-central Washington State to a high of 15.8% in northwest Washington State—an interesting contrast of climate within a single state. See discussion in Section 3.

Although the geographical patterns of temporal variability between DNI and GTI are very similar, the magnitude of the variability in DNI is about twice that in GTI, thus confirming an earlier report, which was based on a longer, 30-year dataset [8]. Similar plots for the monthly DNI and GTI temporal COV are shown in Figs. 3 and 4, respectively. Note the significant changes in the pattern of variability among months, with a strong seasonal modulation (summer versus winter).

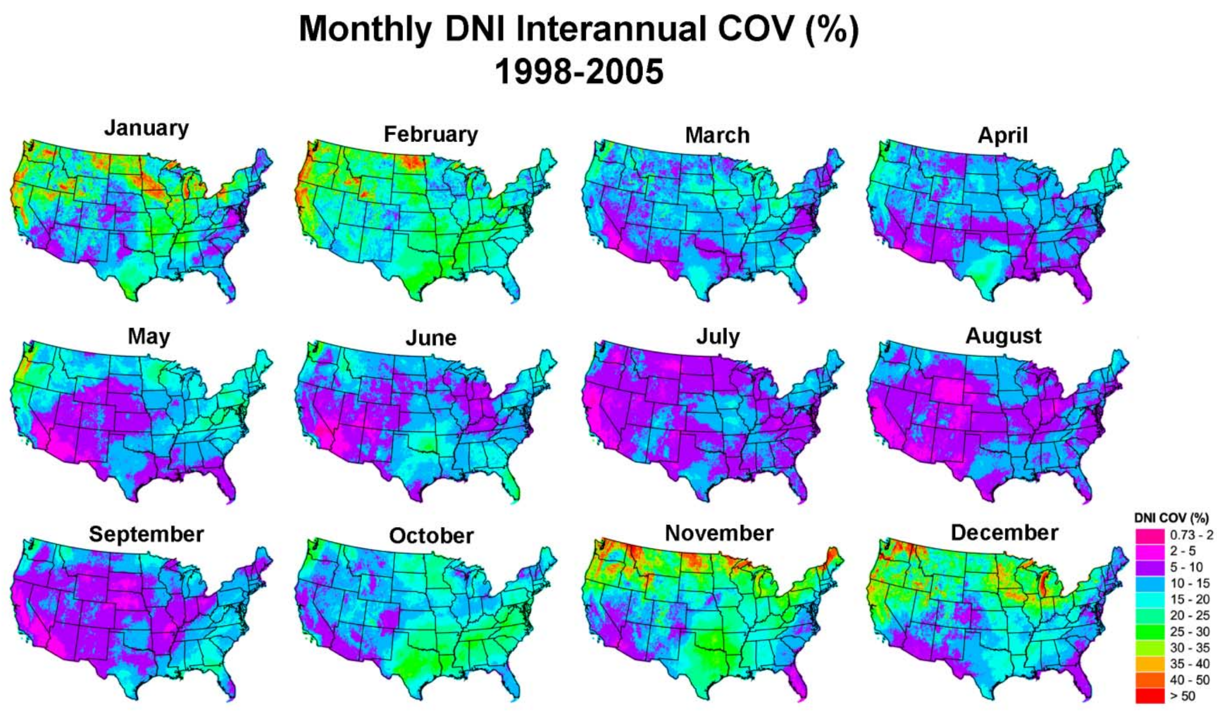

Fig. 3: DNI interannual COV by month.

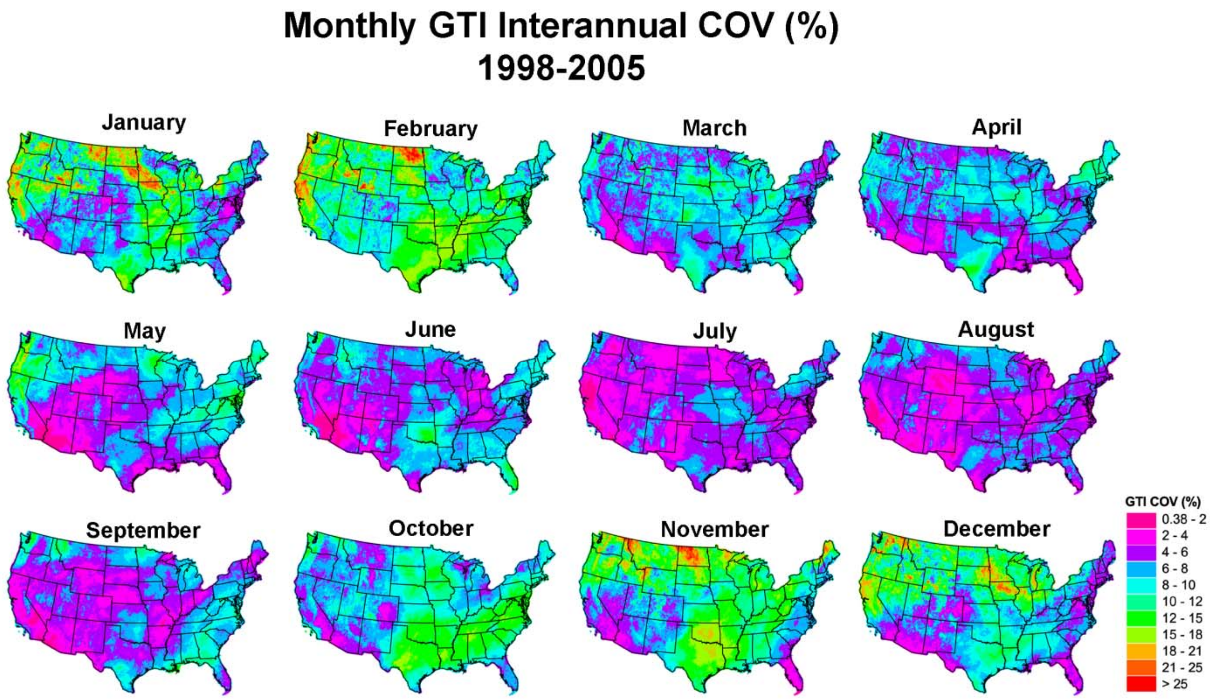

Fig. 4: GTI interannual COV by month.

2.2 Spatial Variability

The eight-year daily total means for each 10-x-10-km cell can also be compared with a matrix of surrounding cells to determine the variability of the solar resource within the matrix, as depicted in Fig. 5.

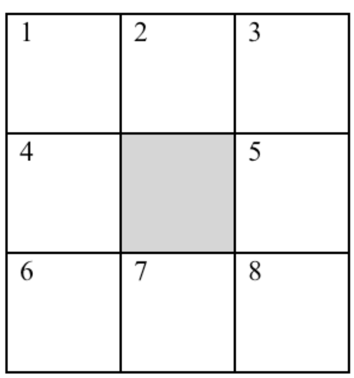

Fig. 5: 3x3 grid layout with anchor cell in the center and eight surrounding neighbor cells.

Here, the standard deviations of the surrounding cells are calculated as

$$\sigma_s = \left[\sum_{i=1}^{i=n} (E_p - E_i)^2 / n \right]^{1/2}$$

and the spatial COV is

$$C_s = \sigma_s / E_p.$$

The process is applied to both DNI and GTI for each pixel. The same process is also applied to the eight-year means on a monthly level (e.g., the means of all Januaries, Februaries, etc.).

Two matrix sizes are analyzed: 3x3, as shown above in Fig. 5, and a larger matrix of 5x5. These represent areas of approximately 30x30 and 50x50 km, respectively, and likewise roughly represent an area within 15 and 25 km of a measurement site. The results for annual DNI spatial variability and both spatial matrixes, expressed as percentages, are mapped in Fig. 6, which provides a quick visual representation of how the solar resource varies with distance, still with a 66% confidence level. Similarly, the results for annual GTI are shown in Fig. 7.

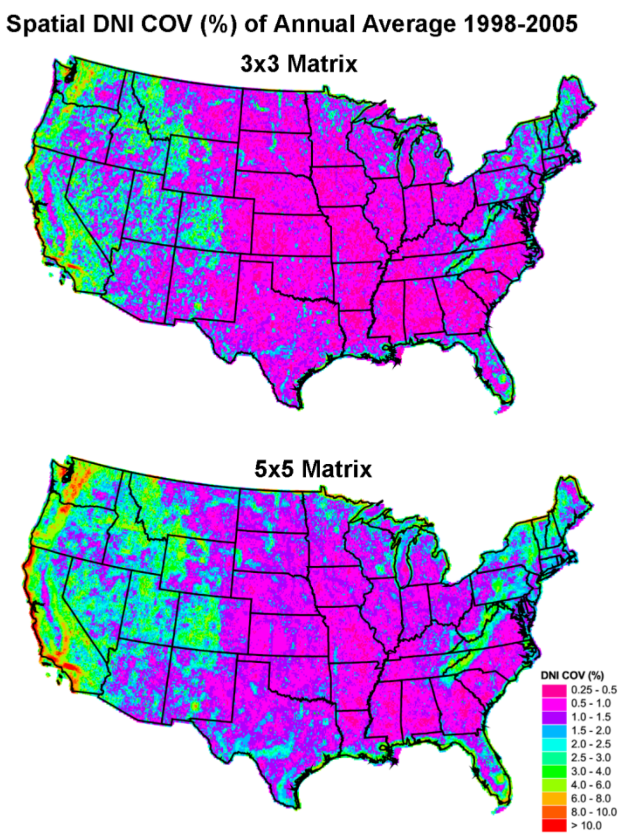

Fig. 6: DNI annual spatial COV for 3x3 cell matrix (upper) and 5x5 cell matrix (lower). Note similar patterns but different magnitudes (binning scales are identical).

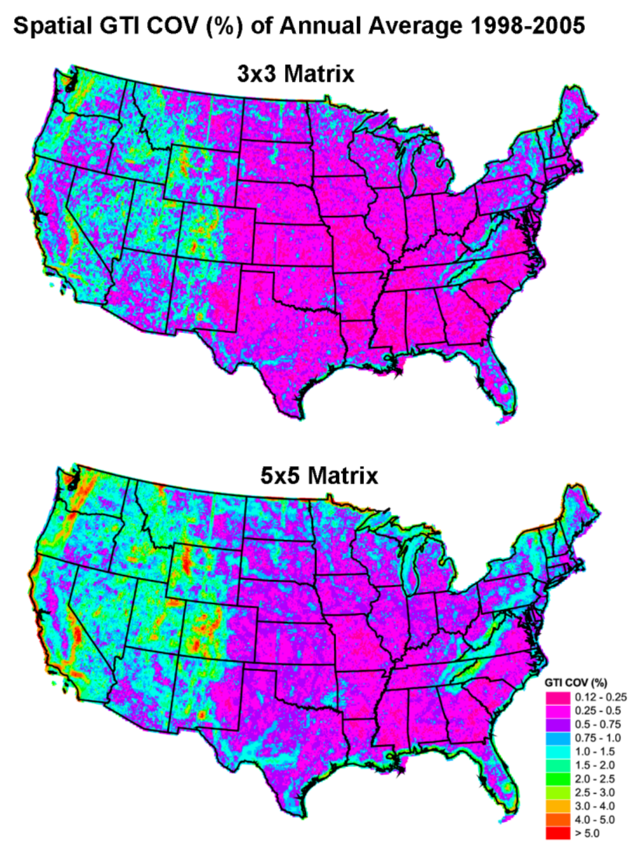

Fig. 7: GTI annual spatial COV for 3x3 cell matrix (upper) and 5x5 cell matrix (lower). Note similar patterns but different magnitudes (binning scales are identical).

For DNI and the 3x3 matrix, the values range from 0.12% in central Missouri to about 11.5% along a corridor between Los Angeles and San Bernardino, California. Greater variability tends to occur in coastal areas (particularly the California coast) and mountainous areas. Greater variability is seen in the 5x5 matrix, which is to be expected because of the microclimate effects of topography. Further, the general pattern of high and low variability (though of different magnitudes) is quite similar between the 3x3 and 5x5 maps, indicating that, in locations of significant variability, the magnitude of C_s is much a function of distance, which could be expected. The monthly spatial DNI and GTI maps for the 5x5 matrix are shown in Figs. 8 and 9. The monthly 3x3 matrixes are not presented here because of the similarity of variability patterns with the 5x5 matrixes.

3. DISCUSSION

These maps indicate that a wide range of variability exists in the solar resource in the United States, and the values range from insignificant (in the context of measurements and economic analyses) to highly significant. Climatological records are normally defined for periods of 30 years to encompass as many potential climatic effects as possible. Users are cautioned that the much shorter eight-year period used here may not be long enough to produce definitive variability values for all climate regions. Consequently, the uncertainty of this analysis has not been defined.

Some sources of potential error have been identified, however. In particular:

- There was no major volcanic eruption during 1998–2005. The temporal variability over a 30-year period, such as 1976–2005, would be larger.
- The SUNY model was run with *long-term average* aerosol data, thus eliminating the interannual variability in this variable, which has a strong effect on DNI. This is another reason why all the calculated DNI temporal COVs (and in a lesser way, the GTI temporal COVs) are most likely underestimated.
- The data used in this analysis are affected by the "Eugene syndrome" that has been found in the then-current version of the SUNY model [6]. This problem creates prohibitively overestimated monthly-average DNI in areas with extended cloudy periods combined with possible snow on ground, such as Eugene, Oregon, in winter. This problem most likely leads to overestimated COVs for the temporal variability and (to a lesser extent) the spatial variability. This may explain, at least in part, the large gradient in temporal variability within Washington State that was mentioned in Section 2.1. It is anticipated that future releases of the NSRDB will be cured of this problem.
- Other artifacts in the SUNY model or its input data may also create false levels of variability. For instance, in the area of White Sands National Monument in southern New Mexico, difficulties in evaluating the magnitude and time variations of the ground albedo might affect the spatial COV results presented here.

The National Renewable Energy Laboratory plans to update this data set by drawing on data from a longer period of record when it becomes available; however, most of the results here are very likely accurate enough to give a fairly representative *relative* variability of the solar resource over most of the United States. These results also indicate that, for some areas, the variability is somewhat lower than the uncertainty of solar radiation measurements. For example, large geographic regions display a GTI interannual COV (temporal or spatial with a 66% confidence level) of less than 3%, which is a nominal uncertainty for high-quality measurements. In all cases, good climatological knowledge of the target area of interest is critical to understanding, interpreting, and applying these results.

High-resolution versions of these maps showing each pixel are available from the National Renewable Energy Laboratory along with the underlying data. In addition to the COV percent data covered in this paper, the variability for each pixel expressed in Wh/m^2 is also available. These data and documentation are available for internet download from http://rredc.nrel.gov/solar/new_data/variability .

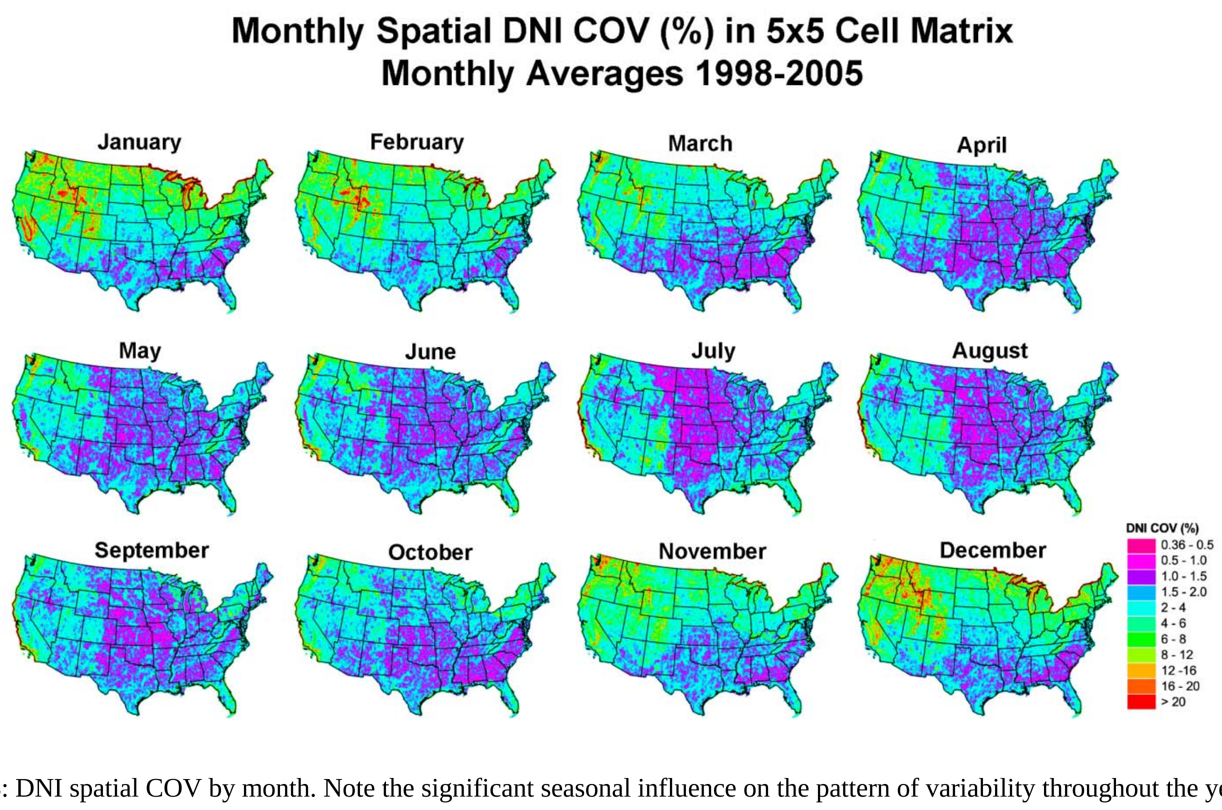

Fig. 8: DNI spatial COV by month. Note the significant seasonal influence on the pattern of variability throughout the year.

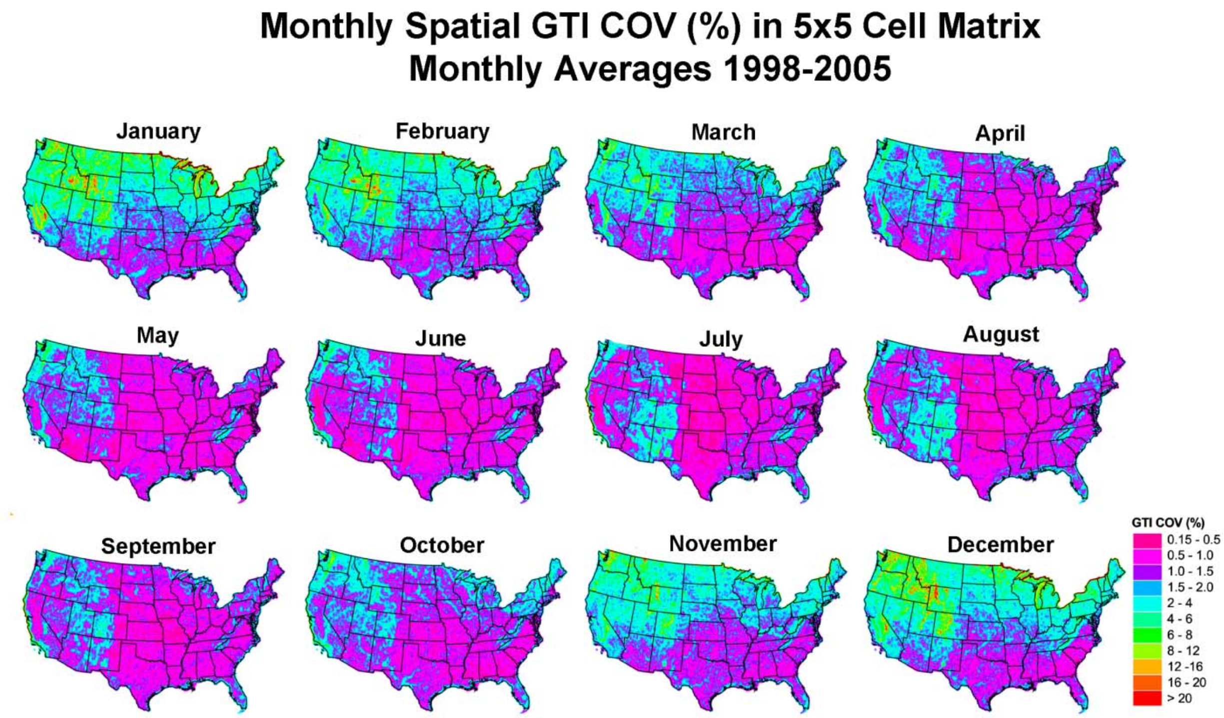

Fig. 9: GTI spatial COV by month.

4. CONCLUSION

Using the variability statistics presented here, users can better understand the extent of measurements required to best characterize the solar resource for a particular application. In areas with low *interannual* variability, a shorter local measurement period may suffice. In areas with low *spatial* variability, a measurement station could possibly represent the solar resource at nearby locations, which would negate the need for additional stations within about 50 km.

An analyst can also use this information to better build confidence in a data set as sufficient for a specific analysis. Additionally, an analyst or planner can use this data to help understand the consistency of future plant performance and how that relates to the economic viability of constructing a power plant at a particular location.

As could be expected, the DNI COV are noticeably larger than the GTI COV, therefore putting concentrator systems at a disadvantage compared with flat-plate systems, as far as solar resource *variability* is concerned. For applications that require “bankable data” and 95% confidence levels, it is recommended to *double* the COV values in the maps.

5. ACKNOWLEDGEMENTS

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