

# Geographic smoothing of solar photovoltaic electric power production in the western USA

Kelly Klima<sup>1</sup>, Jay Apt<sup>1,2</sup>, Mahesh Bandi<sup>3</sup>, Paul Happy<sup>4</sup>, Clyde Loutan<sup>5</sup> and Russell Young<sup>4</sup>

<sup>1</sup> Department of Engineering and Public Policy, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA

<sup>2</sup> Tepper School of Business, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA

<sup>3</sup> Collective Interactions Unit, OIST Graduate University, Onna, Okinawa, 9040495 Japan

<sup>4</sup> SoCore Energy, 225 W. Hubbard, Suite 200, Chicago, IL 60654

<sup>5</sup> California Independent Systems Operator (CAISO), 250 Outcropping Way, Folsom, CA 95630

**E-mail:** [apt@cmu.edu](mailto:apt@cmu.edu)

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**Abstract**

We examine the geographic smoothing of solar photovoltaic (PV) generation from 15 large utility-scale plants in California, Nevada, and Arizona and from 19 installations on the roofs of commercial buildings in California. Plant sizes for the utility-scale generators were 125-315 MW and the plants cover an area ~300 x 800 km. The commercial rooftop PV generators were 80-520 kW and cover ~175 x 900 km. Examining the power output of these generators in the frequency domain, we quantify the smoothing obtained by combining the output of geographically separated plants. Utility-scale and commercial rooftop plants exhibit similar geographic smoothing, with 10 combined plants reducing the amplitude of fluctuations at 1 hour to 18-28% of those seen for a single plant. The smoothing observed for these western USA PV generators is greater than that seen in the Indian state of Gujarat. PV does not exhibit as much geographic smoothing as is seen for combining wind plants.

## 1. Introduction

Solar photovoltaics (PV) provided 7.5% of Germany's 2015 net electricity consumption [1] and PV's market share is increasing in other countries. Solar power production has significant short-term variability caused by clouds, diurnal intermittency, and seasonal variability. Analysis of the effects of this variability and intermittency on power systems began well before the recent increase in PV's market penetration [2,3]. It has long been recognized that a portion of the short-term variability in PV plant generation might be mitigated by summing the outputs from geographically dispersed plants.

Several authors have examined observed geographic smoothing of the output of PV plants<sup>1</sup>. Wiemken et al [4] examined the standard deviation and generation duration curves of the average daily power generation from 100 rooftop PV systems in Germany using 5 minute time resolution data. Murata, Yamaguchi, and Otani [5] used a metric of the largest PV output fluctuation in a given time interval to examine geographic smoothing of PV generators in Japan, finding modest decreases in their output fluctuation coefficient as up to 20 small (0.1-5.6 kW) generators were summed. Mills and coauthors [6] used the  $3\sigma$  power output change rate (ramp rate) of utility-scale plants in Arizona, finding a reduction in the 1-min and 10-min extreme ramp rates when geographically separated plants are added. Marcos et al [7] used data from 7 PV plants with a total installed capacity of 20 MW and separated by 6-360 km to examine the reduction in the largest observed power fluctuation at discrete periods of 1, 4, 20, 60 and 600 seconds by adding plants together. They found that adding the first few plants together quickly reduced fluctuations, but that adding additional plants was of limited value. Lave, Stein and Ellis [8] examined the sum of residential rooftop PV in Ota City, Japan (2.1 MW total) and a 19 MW utility-scale plant in Colorado. The plants were similar in geographic extent (the utility-scale plant covered roughly twice the area as the rooftop installations). Using the maximum output change in 1 sec over a single day at each site, they find that (1) the ramp rates are reduced by roughly an order of magnitude for the entire plant as compared to those at a single point, and (2) the relative variability decays exponentially as additional houses, or (in the case of the utility-scale plant) inverters are added. They find that the smoothing decreases quickly as the first few houses or inverters are added, then much more slowly as additional units are added.

A few groups have studied the decrease in variability as sub-arrays within a larger PV plant are added together. Van Haaren, Morjaria and Fthenakis [9] examined sub-arrays at one 48MW plant, plotting a cumulative distribution function of the 1-min ramp rate for increasing sub-array size. They make an estimate of the highest ramp rates for a plant that is covered by a cloud. If the cloud is larger than the areal extent of the plant and is moving at mean velocity  $\bar{v}$  parallel to the shortest side of a rectangular array with short dimension  $L$ , they argue that the maximum ramp rate in time interval  $\Delta t$  will be  $\bar{v} \Delta t / 2L$  for the case where  $L / \bar{v} > \Delta t$ ; they examine other cases numerically.

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<sup>1</sup> Observations of output data from plants is preferred to work using measured or simulated solar irradiance, in part because real solar plants have power electronics that respond to changes differently than do irradiance monitors. For example, the inverters have a maximum power output that limits responses to cloud focusing; they also have finite response rates.

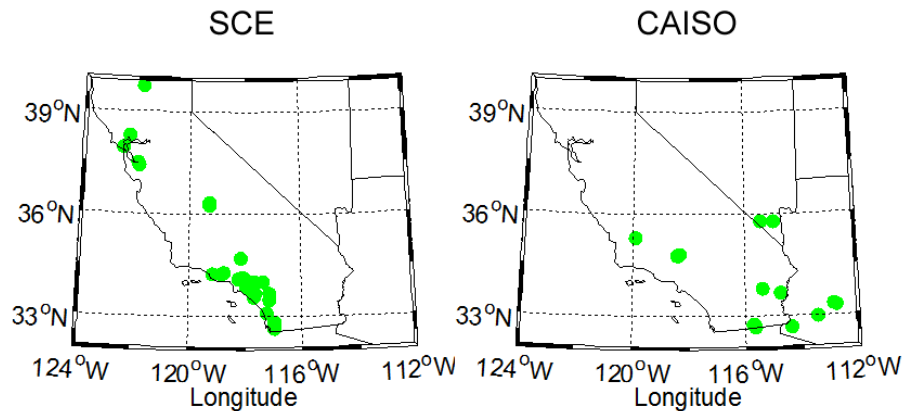
Methods that use the step change over a particular interval or the standard deviation of output fluctuations in a period of time give information on fluctuations at selected time scales. However, there is a method that can allow the determination of how much smoothing is obtained at any desired time scale. The power output of a PV plant contains fluctuations at many frequencies. Curtright and Apt [10] obtained 10 sec time resolution data over two years from a 4.6 MW utility-scale array in Arizona, Fourier transformed the time domain data into the frequency domain, and found that the power spectrum shows a falloff toward higher frequencies that goes roughly as frequency  $f^{-1.3}$  (in addition to the expected peak at a frequency corresponding to 24 hours and its harmonics).

Klima and Apt [11] used information from the frequency domain to examine geographic smoothing of 20 utility-scale (3-221 MW) plants in the Indian state of Gujarat at 1-2 min time resolution. They found that “Interconnecting approximately 20 plants yields a 25%-45% reduction in variability depending on [the] frequency examined.” This technique allows the decrease in variability by adding plants together to be examined at any desired time scale. Similar to wind [12], there is more smoothing at time scales of 10 minutes than at time scales of 6 hours. Also similar to wind, there is considerably more amplitude in the variations at long time scales. In agreement with Marcos et al and with Lave, Stein and Ellis, they found quickly diminishing returns as more plants are summed. However, the Gujarat data showed quite modest geographic smoothing for these plants even over 400 km. At time scales of one hour, for example, the Gujarat data showed that only half the amplitude of the variability at this time scale was eliminated; for wind plants with a similar geographic spread 95% of the variability is extinguished.

Here we use both utility-scale and rooftop PV data from locations in the US states of California, Nevada and Arizona to study smoothing using the frequency domain method. We compare geographic smoothing of commercial building rooftop PV to that for utility scale PV, finding that geographic separation provides a similar degree of smoothing for rooftop PV and for larger PV plants. We conclude by proposing a theory that may provide some insight into the difference between geographic smoothing for wind and that for solar photovoltaic power.

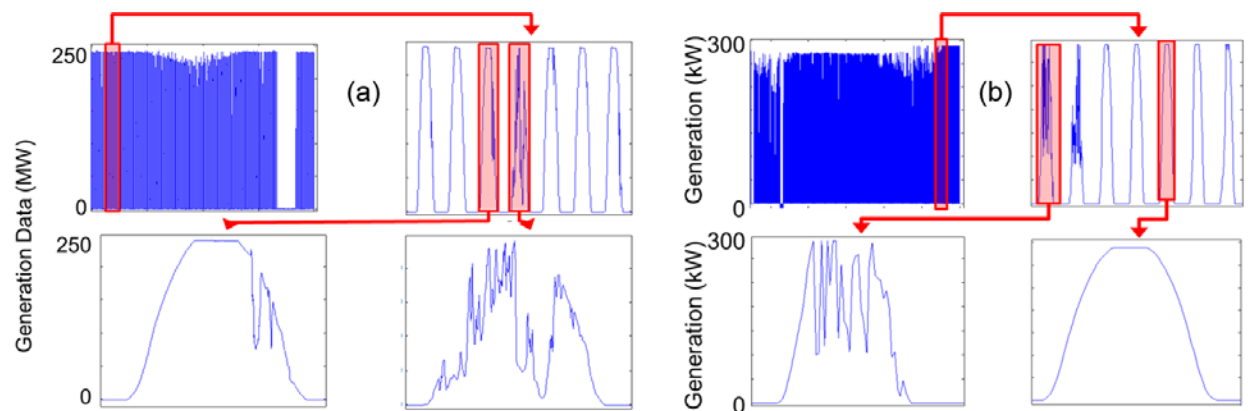
## 2. Data

For utility-scale PV plants in the USA, we used data provided by the California Independent Systems Operator (CAISO) for one year at 1-minute resolution for 15 plants in California, Nevada, and Arizona at one-minute time resolution. Plant sizes were 125-315 MW. Southern California Edison (SCE) and SoCore Energy provided one year of 15-minute resolution data on 19 rooftop PV arrays of 80-520 kW placed on commercial buildings such as drugstores. Plant locations for the CAISO and SCE data are shown in Figure 1. Additional characteristics of the data sets are provided in the online supplementary material.



**Figure 1.** Locations of solar PV systems. The green dots represent sites with excellent data that were used. The CAISO data cover  $\sim 300 \times 800$  km, and the Southern California Edison (SCE) data  $\sim 175 \times 900$  km. The CAISO data are utility-scale PV arrays, while the SCE data are rooftop arrays on commercial buildings.

Sample generation characteristics for the CAISO data and SCE rooftop data are shown in Figure 2. Many of the SCE commercial rooftop inverters were sized so that the output reached the rated capacity on sunny days and thus has a characteristic flat profile near local noon during clear days during spring, summer, and fall months. Comparing geographic smoothing between the CAISO and SCE data only for January 2016 avoided any distortions that may arise from the saturated output.



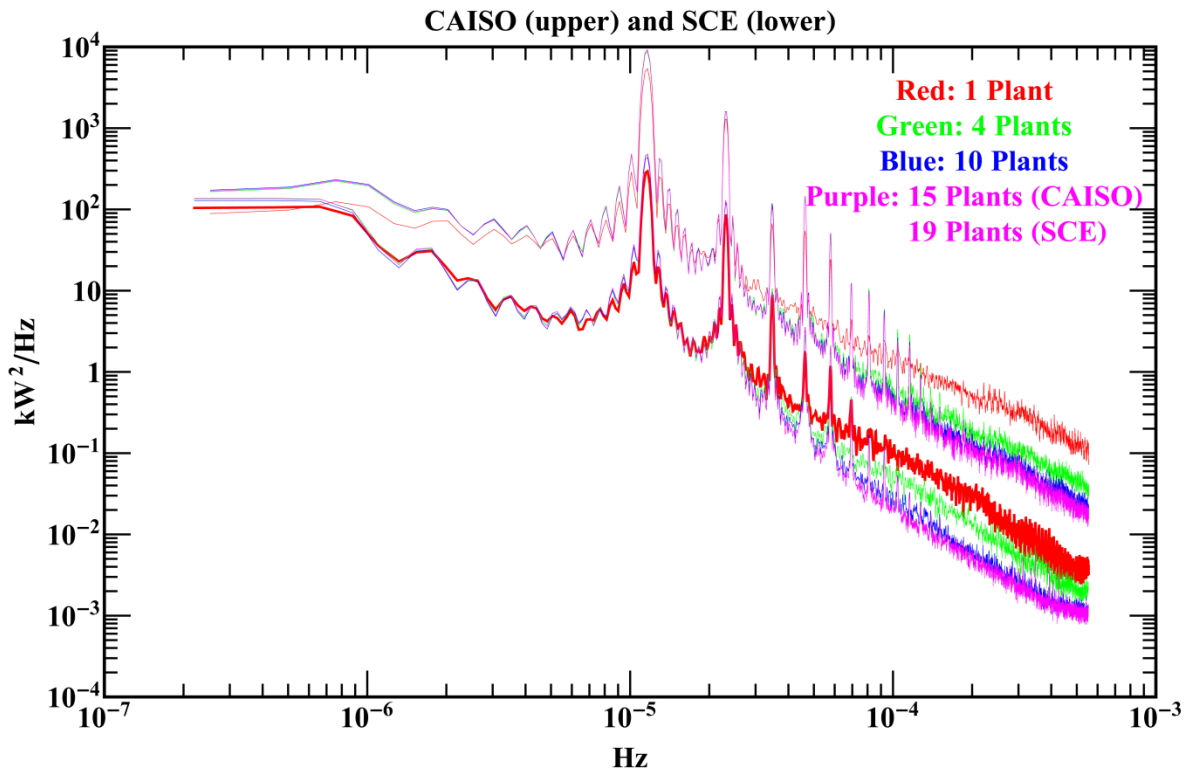
**Figure 2.** Generation data for one representative CAISO large plant (a) and for an SCE commercial building rooftop plant (b) for one year beginning July 1, 2015, one week, a partly cloudy day, and a clear day. The power electronics for both are sized so that the maximum output saturates on sunny summer days.

### 3. Methods

Following [11] and [12], we examined the generation data in the frequency domain. To handle the observed uneven time steps in the Gujarat data, we used the Lomb periodogram [13] as coded in Press et al [14]. Although we find no difference between the Lomb periodogram

procedure and a standard Fourier transform procedure, to ensure our procedure was similar between datasets, we also used the Lomb periodogram for all data sets.

An attribute of the Fourier or Lomb methods of estimating the power spectral density (PSD) is that increasing the temporal length of the dataset does not reduce the standard deviation of the PSD at any frequency. To increase the signal-to-noise ratio, we used the standard technique of partitioning the dataset into time segments. Figure 3 shows representative PSDs for CAISO and SCE.

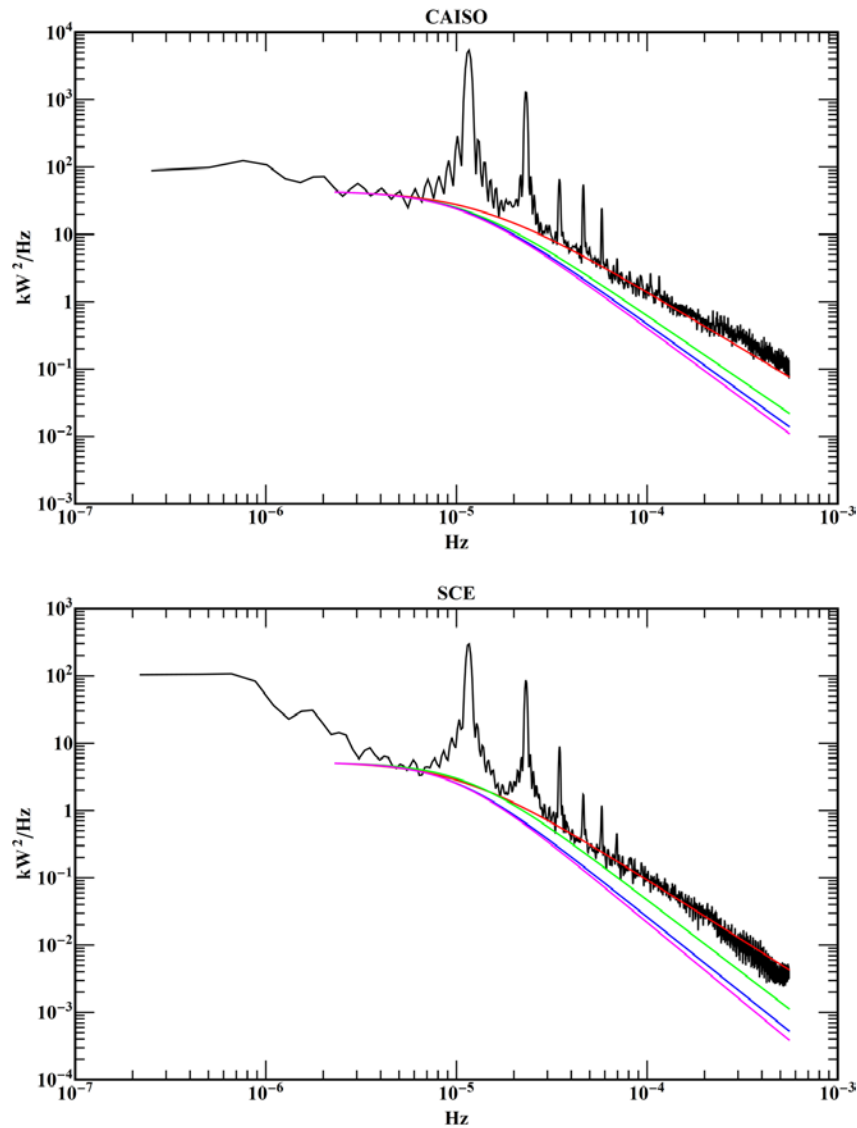


**Figure 3.** Power spectral densities for a representative plant in CAISO and SCE (red), the sum of 4 plants (green), 10 plants (blue), and all plants (purple). The SCE data are snapshots taken at 15-minute intervals, so the Nyquist frequency corresponds to 30 minutes. The PSDs for the 1-minute CAISO data have been truncated at the same frequency. 32-segment averaging has been used.

Next, to understand the potential for smoothing variability in plants, we summed plants, calculated the PSD, and compared the slopes.

We investigated how interconnecting combinations of plants in each data set can potentially provide smoothing (Figure 4). The procedure (as in [11] and [12]) was to compare the line of best fit for the two PSDs at particular frequencies by taking the ratio of the single plant value to that of the interconnected plants value. If no smoothing occurs when solar plants are interconnected, the result should be close to one at all frequencies. If there is a reduction in variability then there will be frequencies for which the fraction is less than one. This procedure

allows the determination of the fraction of the amplitude fluctuations that are smoothed by adding a given number of plants at any given frequency (for example, the frequency corresponding to 6 hours or to 1 hour, Figure 5).

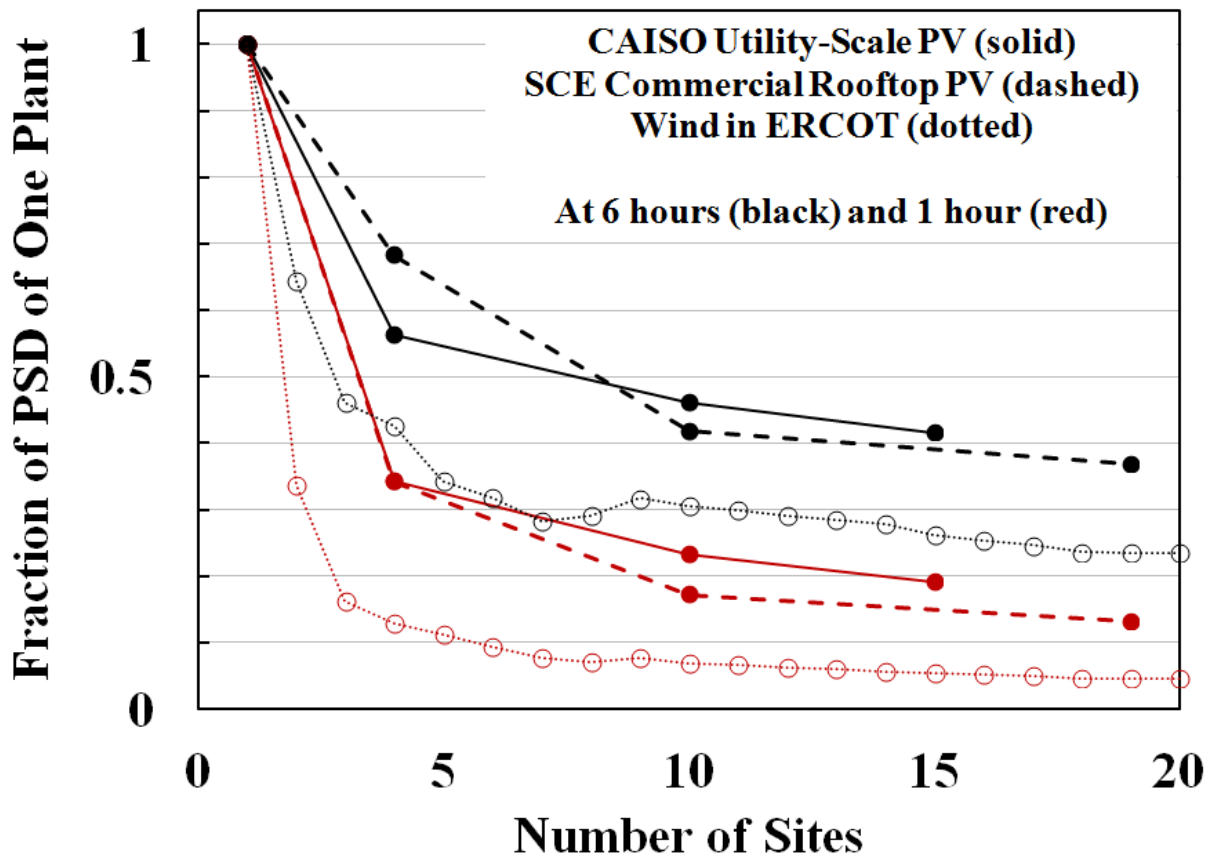


**Figure 4.** Power spectral density (PSD) plots for one CAISO utility-scale PV plant (top) and one SCE commercial rooftop plant (bottom). Colored lines are the fits of the form  $A/(1+Bf^\alpha)$  to the PSDs for one plant (red), 4 plants (green), 10 plants (blue), and 15 plants for CAISO or 19 plants for SCE (purple). PSDs for the combination of plants are not shown for clarity.

## 4. Results

We compare the smoothing observed for the utility-scale CAISO plants in California, Nevada, and Arizona (~300 x 800 km) to that for SCE rooftop PV in California (~175 x 900 km) and to the observed smoothing for wind plants over a similar geographic extent in Texas. Utility-scale

and commercial rooftop PV plants exhibit similar geographic smoothing, considerably less than is observed for wind.



**Figure 5.** Comparison of smoothing at 6 hours in black and 1 hour in red among the 120-315 MW utility-scale plants in CAISO (solid lines) with the 5-400 kW SCE commercial rooftop plants in California (dashed lines) and with the smoothing found by adding geographically separated ERCOT wind plants over 500 km [12] (dotted lines with open circles). The CAISO data cover  $\sim 300 \times 800$  km, and the Southern California Edison (SCE) data  $\sim 175 \times 900$  km. The ERCOT wind data cover  $\sim 200 \times 500$  km. A full year of data is used for all PV plants shown here, beginning July 1, 2015; the wind data of [12] shown here was for the full year 2008.

## 5. Discussion

When geographically separated PV plants are added together, the slope of the summed power spectrum steepens; we observe nearly identical steepening when rooftop plants are summed as when utility-scale plants are summed (Figure 4).

We observe no significant difference in geographic smoothing between physically large utility-scale PV arrays and small commercial rooftop arrays. Geographic smoothing of PV variability is modest compared to geographic smoothing of wind power variability over comparable geographic areas (Figure 5).



Power spectral density plots are given in the supplementary data for the 19 rooftop and 15 utility-scale plants examined here. As for utility-scale PV generation examined in earlier research [10, 11], the spectra are relatively flat at frequencies lower than  $\sim 10^{-5}$  Hz, and fall off at higher frequencies.

We find that PV plants experience less geographic smoothing than do wind plants. Wind and solar photovoltaic power fluctuations arise from quite different physical considerations. Wind speed varies around a usually non-zero mean value, causing wind power to fluctuate, albeit with large magnitude, above and below a normally steady power. The largest length scales of atmospheric flows spanning hundreds of km and representing the lowest frequencies (inverse daylight time  $\sim 1.2 \times 10^{-5}$  Hz) influence all smaller length scales, hence higher wind speed fluctuation frequencies. Consequently, the largest atmospheric flow scales of hundreds of km represent the correlation length for wind power fluctuations [15], and control the geographic smoothing of wind plants situated distant from each other.

In solar PV however, since half the earth faces the sun at any point in time, all solar photovoltaic plants are globally correlated through time lags controlled by earth's rotation about its axis. As a result, solar PV has much longer (global) correlation length than the relatively local correlation length for wind power ( $\sim 100$ s of km). Cloud passage over solar PV plants locally disrupts this global correlation by causing a negative ramp in power output. In sharp contrast with wind, solar PV fluctuations are strongly asymmetric about the (mean) clear sky index. Negative power output ramps due to cloud passage contribute large magnitude fluctuations below the clear sky index (leading order effect), while cloud focusing contributes very small magnitude fluctuations above the clear sky index (higher order effect).

The geographic smoothing observed for PV in both CAISO and SCE is more substantial than that seen in Gujarat [11]. One hypothesis to explain the difference is that if the weather in the Gujarat desert region is consistently clear that there may be fewer fluctuations to smooth than in the southwest USA. We explored this hypothesis by noting that the 10-year average monthly cloud fraction in Gujarat is indeed considerably lower than for the regions in the USA we examined, but only in 8 months of the year. In June and September, the two areas have similar cloud fractions, and in July and August Gujarat is cloudier (supplementary data, section 5). When we performed our analysis dividing the data into one set comprising June through September and another comprising the remaining months, we saw no significant difference in the geographic smoothing. Thus we are forced to reject this hypothesis and simply note that there is considerably less geographic smoothing for utility-scale plants in Gujarat than for the plants in the USA.

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