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Environmental Research Letters

LETTER

# Geographic smoothing of solar PV: results from Gujarat

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## Abstract

We examine the potential for geographic smoothing of solar photovoltaic (PV) electricity generation using 13 months of observed power production from utility-scale plants in Gujarat, India. To our knowledge, this is the first published analysis of geographic smoothing of solar PV using actual generation data at high time resolution from utility-scale solar PV plants. We use geographic correlation and Fourier transform estimates of the power spectral density (PSD) to characterize the observed variability of operating solar PV plants as a function of time scale. Most plants show a spectrum that is linear in the log–log domain at high frequencies $f$, ranging from $f^{-1.23}$ to $f^{-1.56}$ (slopes of −1.23 and −1.56), thus exhibiting more relative variability at high frequencies than exhibited by wind plants. PSDs for large PV plants have a steeper slope than those for small plants, hence more smoothing at short time scales. Interconnecting 20 Gujarat plants yields a $f^{-1.66}$ spectrum, reducing fluctuations at frequencies corresponding to 6 h and 1 h by 23% and 45%, respectively. Half of this smoothing can be obtained through connecting 4–5 plants; reaching marginal improvement of 1% per added plant occurs at 12–14 plants. The largest plant (322 MW) showed an $f^{-1.76}$ spectrum. This suggests that in Gujarat the potential for smoothing is limited to that obtained by one large plant.

## 1. Introduction

Low-pollution electric power sources, such as solar power, have significant potential to reduce the emissions associated with generating electricity. However, solar photovoltaic (PV) generation is a variable energy source, with large and rapid changes in output [1, 2]. This variability of solar PV is sometimes cited as a barrier to its large scale integration into the grid [3–6].

Many authors have examined the potential for geographic smoothing of PV in the time domain. That literature is of two broad types. One uses modeled or (less commonly) measured solar illumination. The second uses observed data from power plants. There are few of the second type because data are often proprietary and unavailable to researchers. Here we use 13 months of approximately 1 or 2 minute time resolution data from 50 utility-scale PV plants separated by up to 470 km; we have made these data publically available.

Some irradiance studies suggest that geographic separation may smooth PV variability. The correlation of solar irradiance measured at two locations decreases as the distance between the sites increases [7–14]. In addition, cloud models have been used to estimate the smoothing effect of geographic diversity [15, 16], and changes in clear sky index for 23 locations show smoothing is likely for as few as five plants [2].

However, studies examining actual generation data provide conflicting results. Five-minute step changes in normalized PV power from one German plant can exceed ±50% but are never larger than ±5% for 100 summed German PV sites [17]. Modeled generation at hourly resolution shows smoothing, which is greater on partly-cloudy days [18]. Other studies have examined area effects, suggesting that larger capacity plants [19, 20] or plants spread out over a wider area [21] exhibit less variability than smaller or more densely packed solar farms,

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respectively. Similarly, geographic smoothing using a large number of smaller plants can reduce variability [22–25], where the maximum variability is theoretically proportional to the square root of the number of plants aggregated [26]. On the other hand, several studies suggest smoothing may not occur. For instance, correlation of real power output for three tracking PV sites in Arizona is high, suggesting smoothing might not be effective there [1]. Similarly, Murata *et al* find that sites in Japan separated by less than about 200 km are not independent [27], which suggests smoothing might also not be effective there.

Here we examine the potential for geographic smoothing of solar PV in the Indian state of Gujarat using actual generation data from multiple utility-scale solar power installations. We use geographic correlation and Fourier transform techniques to estimate the power spectral density (PSD) [28, 29] and characterize the observed variability of operating solar PV plants as a function of time scale.

## 2. Data

Real time generation data from the State Load Dispatch Centre of Gujarat Energy Transmission Corporation website are available [30] for 50 solar PV plants in Gujarat, India. These measured power output values are updated at uneven time intervals, generally between 1 and 2 min. We captured website data at 1 min intervals from 17 February 2014 to 16 March 2015. The data capture process, link to our archived data, and power plant characteristics are in the supplementary data.

We used four tests to clean the data. In the first two tests, the full datasets from 13 sites were discarded either because (1) peak generation exceeded the inverter's capacity (resulting in a flat generation during peak hours), or (2) the resolution of the instruments measuring generation was too coarse (resulting in reported generation at increments of 0.1 MW or larger). For the remaining data, we conducted two tests at each timestep. Reported generation values less than −0.1 MW occurred almost entirely during nighttime hours, but the individual points (as opposed to the full day) were discarded. Finally, we used visual inspection to confirm the 'goodness' of the data, resulting in discarding one additional day of a small MW plant that our data cleansing algorithm had not captured.

Figure 1 shows generation data for a 15 MW plant for a year, a week, a clear day, and a partly-cloudy data.

## 3. Methods

Given an improved understanding of type of variability exhibited by different power sources, a power system operator can understand what combination might be needed to match demand. We use Fourier decomposition to examine the generation data in the frequency domain, where the PSD at a particular frequency indicates the relative amount of variability at the corresponding timestep.

### 3.1. Calculating the PSD

To handle the observed uneven time steps, we used the Lomb periodogram [31] as coded in Press [29]. An attribute of the Fourier or Lomb methods of estimating the 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 with an oversampling frequency of 4 (such that most data points are in four time segments), resulting in time segments of approximately 1.5 months. Since most time steps were less than 2 min resolution, the highest frequency the data can represent without aliasing (the Nyquist frequency) corresponded to 4 min.

### 3.2. Scaling plants for comparison

To understand the potential for smoothing plants over thousands of plant combinations, we needed a simplifying process to compare plants. A linear line of best fit would not work due to the unusual shape of the PSDs. Therefore, we make the simplifying assumption that the PSD of a single plant has a flat spectrum (constant PSD) in the log–log domain at low frequencies and an $f^{-m}$ spectrum at high frequencies, such that the PSD can be approximated using coefficients $A$ (the PSD value at low frequencies), $m$ (the slope of the PSD at high frequencies), and $\beta$ (relates to $y$-intercept in log–log domain) via equation (1):

$$\mathrm{PSD}(f) = \frac{A}{1 + \beta f^{m}} \tag{1}$$

Since the day–night cycle causes solar PSDs to exhibit a peak at 24 h (and its harmonics), we fit this equation in Matlab in the log–log domain to frequencies corresponding to times slower than 48 h and faster than 12 h. Figure 2 shows the PSD of a 5 MW and a 25 MW plant with their respective fitted curves.

To compare the PSD of a single plant to the PSD of interconnected plants in a way that controls for plant capacity, we scale the PSDs using equation (1)'s $A$ values. First we fit equation (1) in the log–log domain to both the PSD of a single plant and the PSD of the interconnected plants to determine the respective $A$ coefficients, $A_{\mathrm{single}}$ and $A_{\mathrm{interconnected}}$. We then multiply the interconnected PSD by $A_{\mathrm{single}}/A_{\mathrm{interconnected}}$ so that $y$-intercept at low frequencies is identical to the single plant PSD. Finally, we refit the PSD of the interconnected plants with $A$, $\beta$, and $m$ such that the lines

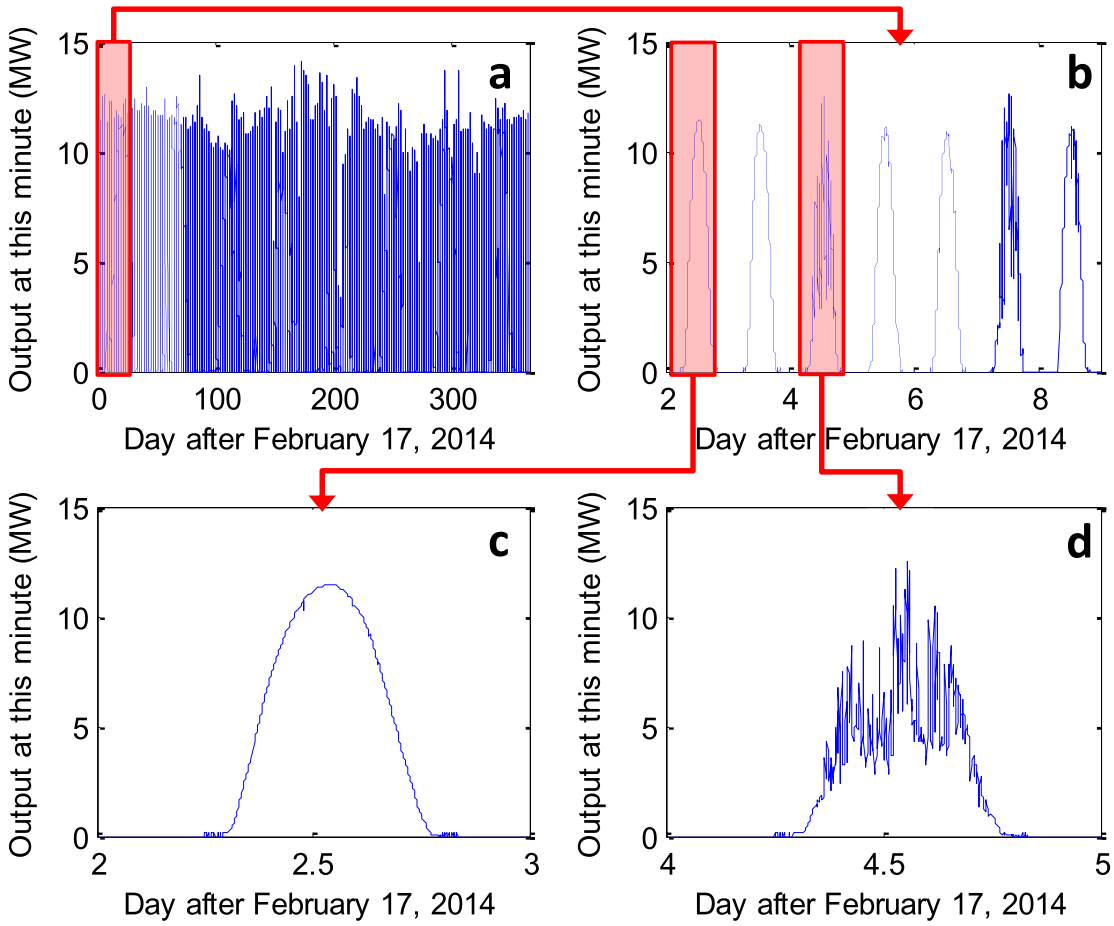


**Figure 1.** Generation data for the Precious Energy's 15 MW plant (Plant 5 in the listing in the supplementary data) for (a) a year, (b) a week, (c) a clear day, and (d) a partly-cloudy day.

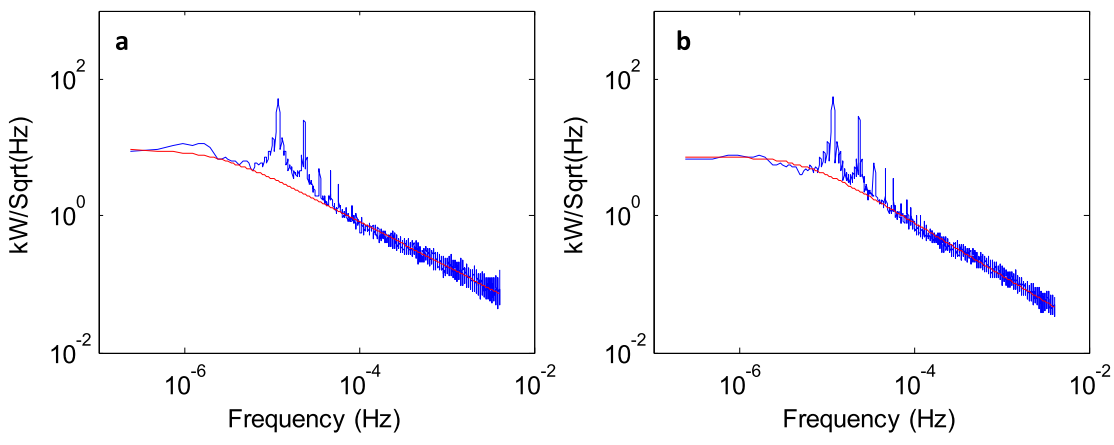


**Figure 2.** Sample PSDs (blue) and line of best fit via equation (1) (red) for two plants. (a) Plant 27, 5 MW, slope of $f^{-1.31}$. (b) Plant 35, 25 MW, slope of $f^{-1.53}$. Plant numbers correspond to the listing in the supplementary data.

of best fit for the single and the interconnected plants cross at $f = 1/24$ h. After scaling, a spectrum with a steeper negative slope (e.g. $f^{-1.76}$) has smaller high-frequency fluctuations than a spectrum with a less-steep slope (e.g. $f^{-1.23}$); in other words, a steeper negative slope represents more high-frequency smoothing. This is the procedure used by Katzenstein [39] for wind plants.

### 3.3. Understanding the potential for smoothing plants

To understand the potential for smoothing variability in plants, we summed plants, calculated the PSD, and compared the slopes $m$. Averaging over all possible combinations for 2 through 20 plants, we investigate how interconnecting plants can potentially provide smoothing.

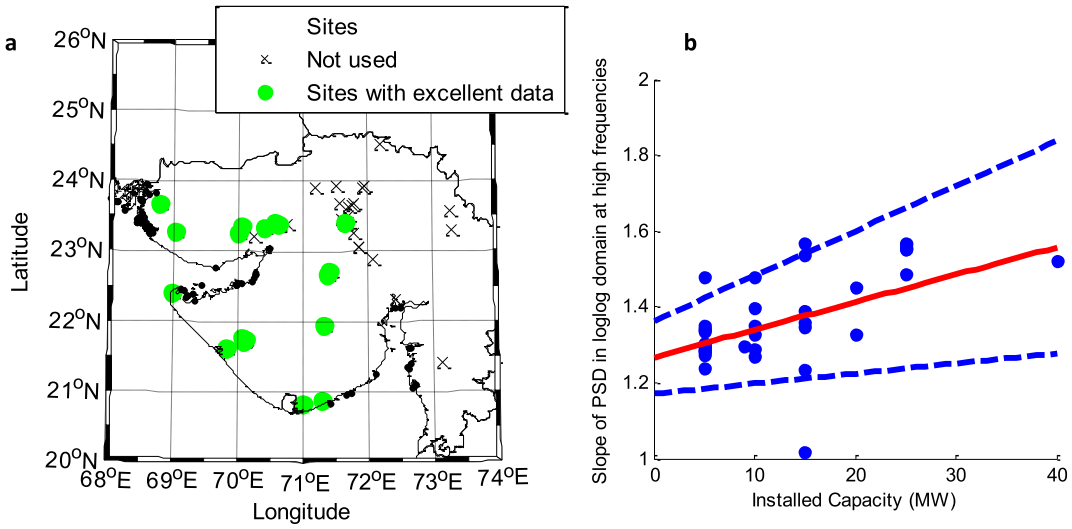


**Figure 3.** (a) Location of Solar PV Power Plants in Gujarat, India. (b) Installed capacity versus absolute value of the slope of PSD at high frequencies. Blue dots are the observations, while the solid red and dotted blue lines are the line of best fit and the 95% confidence interval, respectively.

The PSD of some plants was noisy due to frequent data dropouts. For some others, the PSD exhibited low-pass filtering at frequencies above $10^{-3}$ Hz (corresponding to approximately 15 min). In what follows, we used 20 plants with spectra that had neither of these features (figure 3). For each period when good generation data existed for all 20 plants, we calculated the PSDs for all possible initial plants and combinations of 2 through 20 of the plants. For each combination, we normalized the interconnected PSD to the single plant PSD using the process described above. We then compared the line of best fit for the two PSDs at particular frequencies by taking the ratio of the single plant value to the interconnected plants value in the $x$–$y$ domain. If no smoothing occurs when solar plants are interconnected, the result should be close to 1 for all frequencies. If there is a reduction in variability then there will be frequencies for which the fraction is less than 1.

## 4. Results

### 4.1. Calculating individual PSDs

The supplementary data contains a PSD for each of the plants. Most plants exhibit a spectrum at high frequencies ranging from $f^{-1.23}$ to $f^{-1.56}$, with the very large 322 MW plant displaying a $f^{-1.76}$ slope. We find that larger plant size is correlated with a steeper slope with a correlation coefficient of 0.57 at $p < 0.001$ (figure 3). These results agree with the approximately $f^{-1.3}$ spectrum identified by previous research using generation data [1, 32, 33], (as well as the $f^{-0.7}$ spectrum identified when the $y$-axis is the square of the power [34]). This implies that there is still a large need for fast ramping power or demand response to compensate for PV fluctuations at high frequencies. Our results also validate for a real plant the conjecture based on irradiance data that as the capacity of the plant increases, it is likely that the plant will cover a larger horizontal area and thus be able to naturally filter out some of the variability [19, 20].

### 4.2. Understanding the potential for smoothing plants

To understand the potential for smoothing plants, we summed generation of 20 plants as described above. The time domain generation data are given in the supplementary data, and figure 4 shows the PSDs and resulting lines of best fit for 1, 5, 10, and 20 plants. The amplitude of variability of 20 interconnected PV plants at a frequency corresponding to 1 h has ∼45% of variability than that of a single PV plant (figure 5). Just as for wind's geographic smoothing, the reduction is very dependent on the time scale examined; at 6 h the variability of 20 plants is 80% of that of a single plant. We find a steepening of the $f^{-1.3}$ spectrum toward $f^{-1.66}$ as the number of plants increases.

For reference, we calculated the Bird and Hulstrom Clear Sky Index for direct normal irradiance upon a horizontal surface and global horizontal irradiance upon a horizontal surface [35] at the location of Plant 50 (Charanka) using 1 min resolution for 1 yr. The slope of both of these models is −1.84 at high frequencies, and the full PSDs are given in the supplementary data.

Figure 5 shows the fraction of the spectrum of a single plant retained versus the number of interconnected solar plants ($N$) at different timescales. For reference, we show the reduction that would occur if cloud activity in all locations was independent per Hoff and Perez's $N^{-0.5}$ calculation [26] (which is very similar to empirical results showing a $N^{-0.46}$ relationship [24]). Interconnecting approximately 20 plants

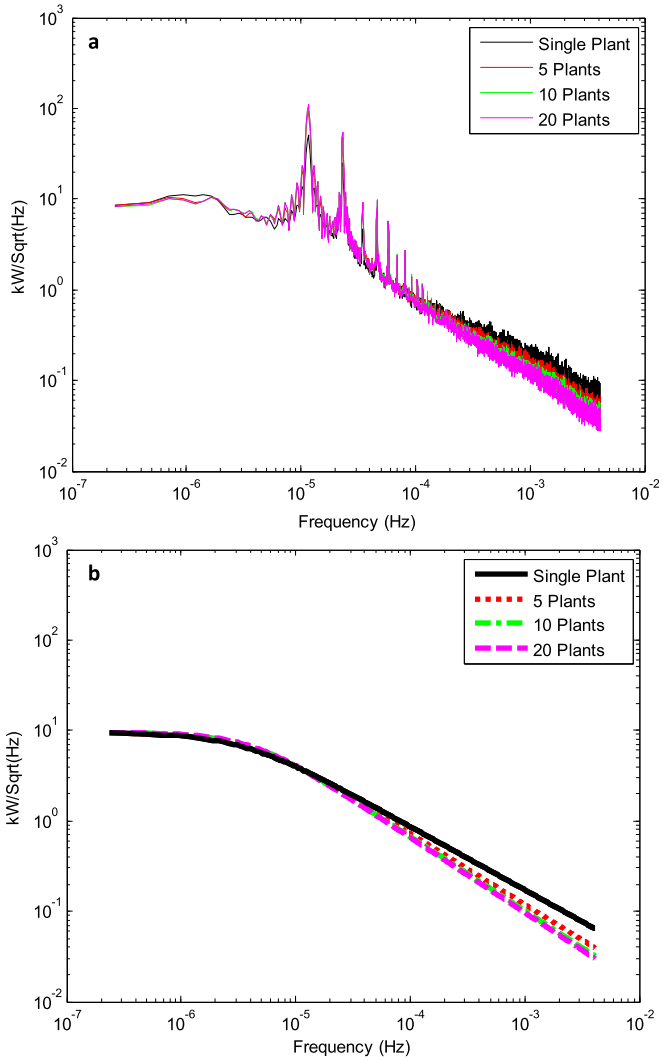


**Figure 4.** Sample summed power output for ten power plants. (a) The normalized PSD of 1, 5, 10, and 20 plants (in black, red, green, and magenta, respectively) using only the data for the days all 20 plants are available. (b) The corresponding line of best fit for these PSDs.

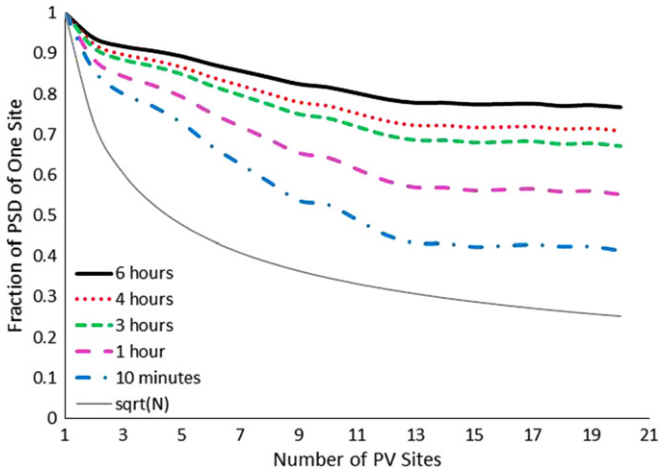


**Figure 5.** Fraction of the spectrum of a single plant retained versus the number of interconnected solar plants normalized at $f = 1/24$ h at different timescales. Interconnecting as few as 12 PV plants achieves the majority of the reduction of variability where additional plants reduce less than 1% of variability.

yields a 25%–45% reduction in variability depending on frequency examined. Approximately half the geographic smoothing occurs by interconnecting 4–5 plants, with marginal returns of less than a 1% change per plant after 12–14 plants have been connected. This observed smoothing is not only much less than that suggested by the theoretical $N^{-0.5}$ [26], it also appears to asymptote to a nonzero value at high $N$.

In order to enable comparison with earlier work [2, 9, 18], we also investigated the potential for smoothing by examining the distance dependence of the correlation of generation ramps. We first calculated ramp data (difference in generation between timesteps) between 10:00 and 17:59 local time. We then interpolated these data to even 1 min timesteps, then decimated the values to 5, 15, 30, and 60 min timesteps (thus accounting for selection bias). As shown in the supplementary data, we found a decrease in correlation as distance between plants increases toward 50 km. Near 100 km, the correlation becomes almost constant as a function of distance, as one might expect with the correlation in the solar cycle (e.g., $p = 0.55, 0.25, 0.1$a, and 0.01 for 1 h, 30 min, 15 min, and 5 min timesteps, respectively). These findings agree with the previous results examining distance versus correlation of irradiance data. In addition, to enable comparison with work on wind power [36, 37], we calculated the coherence. As shown in the supplementary data, we found that coherence is high at the 24 h and aliased frequencies. As the distance between plants increases, coherence at higher frequency decreases. However, even up to 242 km distance, there is some coherence at low frequencies.

## 5. Discussion

Prior to wide-spread solar PV adoption, the power sector will need to address solar generators' intermittency and variability. Here we study the potential for geographic smoothing of PV using 13 months of observed power production from utility-scale plants in Gujarat, India.

All of the plants examined displayed similar power spectra to those in previously published literature [1, 32, 33], albeit with slightly different slopes. The expected diurnal peaks at 24 h and harmonics are present. At high frequencies, the plants exhibit a spectrum similar to cloud processes [38, 39]. These processes may be a function of the $f^{-5/3}$ spectrum displayed by wind [32] and the $f^{-1}$ spectrum displayed by hydrologic processes [40], or the PV plant may act as a low pass filter [34].

When interconnecting Gujarat PV plants, approximately half of the smoothing can be obtained through connecting 4–5 plants. Reduction in variability exhibits diminishing marginal returns, with interconnecting 12–14 plants yielding a $f^{-1.66}$ spectrum. However, the largest plant, the 322 MW Charanka Solar Park (at 23°54′N, 71°12′E), has an $f^{-1.76}$ spectrum. This suggests that in Gujarat, the potential for smoothing may be limited to that obtained by one large plant.

We further note that the PSD of the clear sky index at the Charanka Solar Park showed a $f^{-1.84}$ slope, a steeper slope than all of our observed individual and combined plants. While this suggests more smoothing to reduce the noise from clouds may be possible, we do not observe this smoothing, suggesting that other limiting factors may be in play. Examining the distance dependence of the correlation of generation ramps, we find in agreement with prior studies (7–14) limits that may be associated with the clear sky index results. This is a physical characteristic that would be common to many locations throughout the world. However, at the higher frequencies where we are measuring the slope, we suggest that different physics dominate, such as those associated with cloud processes (which are in turn a function of local geography, weather, and climate) and mechanical processes associated with power plant machinery. Of course, this work was limited to one region, Gujarat, and if high time resolution data become available from other regions it would be of great interest to determine if these results are general.

The power sector may also wish to compare the potential for geographic smoothing of solar PV to that from other renewable energy types. In comparison to the geographic smoothing of distributed wind plants in Texas [41], the PV plants we examined show substantially less geographic smoothing. The two areas are of comparable size (roughly 400 km × 400 km). Interconnecting 20 wind plants in Texas was found to reduce fluctuations at frequencies corresponding to 6 h and 1 h by 65% and 95% respectively, substantially more than the 23% and 45% observed for PV plants in Gujarat. We also find that when interconnecting observed PV plants, reaching marginal returns of less than a 1% change per plant requires two or three times the number of interconnected plants than for wind (12–14 for PV, 3–6 for wind). Since the area examined is comparable in size to many balancing areas, the relatively small amount of smoothing is likely to be relevant to practical application of solar PV generation at grid scale.

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