Evaluating Satellite-Derived and Measured Irradiance Accuracy for PV Resource Management in the California Independent System Operator Control Area

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ABSTRACT

This article evaluates the ability of three operational satellite models (SolarAnywhere® Standard, Enhanced, and High Resolution) to reflect ground-based measured irradiance conditions and thus provide the information required to monitor the output of fleets of PV system and their impact on the power grids to which they are connected. SolarAnywhere Standard, Enhanced, and High Resolution produce hourly irradiances at 10 km geographical resolution, half-hourly irradiances at 1 km resolution, and 1-minute irradiances at 1 km resolution, respectively.

Results suggest that the performance of the satellite-based monitoring approaches that of well-maintained redundant sensors at the fraction of the operational cost. SolarAnywhere Enhanced and High Resolution have an *annual* error that is slightly higher than collocated ground sensors when the invalid measured data are excluded from the analysis. SolarAnywhere High Resolution has 1/3 less error at an hourly time interval compared SolarAnywhere Standard Resolution. Results also show that SolarAnywhere High Resolution has 10 percent Mean Absolute Error on a one minute time interval making it well suited to provide the basis for data required to perform high penetration PV studies

A consistent finding of previous studies is that PV output variability is reduced when PV systems are geographically dispersed. This paper documents that the principle of geographic dispersion that reduces PV fleet variability also applies to reducing prediction error. That is, not only is there less variability when there are more PV systems that are geographically dispersed, the prediction error decreases as well. This result is consistent with recent observations that regional solar resource prediction for past, current and forecast data is considerably more accurate than for a single site [e.g., 1].

1. INTRODUCTION

Solar photovoltaic (PV) plant power production variability is one of the critical challenges to greater penetration of PV into the state's electricity system. As illustrated by the list of References, a number of studies have examined the issue of PV output variability [2-12]. A consistent finding of these studies is that variability is reduced when PV systems are geographically dispersed. That is, variability is reduced as the number of systems increase across a sufficiently large geographic region.

A second critical challenge to greater penetration of PV is the ability to accurately forecast PV power production variability when it occurs. The California Energy Commission's (CEC) Public Interest Energy Research (PIER) program has embarked on a data validation effort titled, "Demonstration and Validation of PV Output Modeling Approach." A methodology has been developed that uses satellite-derived solar data to forecast PV fleet output and quantify variability given the design attributes and locations of PV systems [13]. The methodology uses advanced algorithms to track cloud patterns and calculated plant correlation coefficients. The California Independent System Operator (California ISO) sees potential of using this methodology to calibrate its studies of system operations under alternative renewable energy scenarios as well as potential for forecasting PV output. However, before the methodology will be practical and usable in studies and forecasting by the California ISO and others, additional work is needed in data analysis, validation, and system integration.

The California Solar Initiative (CSI) funded the development of an enhanced resolution satellite-based solar resource database for the state of California. It is referred to as SolarAnywhere Enhanced Resolution [14]. The data base has a 1 km spatial resolution and ½ hour temporal resolution, using the native spatial and temporal resolution of the US geostationary satellites. This data set has been further expanded to have a 1 km spatial, 1 minute temporal resolution by applying intra-interval short-term forecasting [15]. It is referred to as SolarAnyhwere High Resolution [14]. These data sets have the potential to provide the solar resource data required by the methodology described above. The first step, however, is to quantify the accuracy. This first step constitutes the main objective of this article.

There have been some initial efforts at data validation of the SolarAnywhere Enhanced Resolution. For example, Jamaly, Bosch, and Kleissl [16] compared measured output for a fleet of 86 PV systems in San Diego County to simulated PV fleet output using SolarAnywhere Enhanced Resolution data during high ramping conditions. The authors concluded that "the satellite data were able to closely follow the aggregate power output and detect the timing of the ramps while 5 irradiance measurement stations [dispersed within the region occupied by the PV systems] stations were not as accurate due to smaller number and non-representative geographical distribution with respect to the PV sites." This useful observation calls for a systematic and quantitative evaluation of prediction accuracy as presented in this paper.

2. METHODS

4.1 Definitions

Accuracy validation often means different things to different people. As such, it is useful to begin with a definition of how accuracy quantification can be performed.

There are three fundamental questions that need to be answered in order to provide a clear definition of how accuracy validation is performed.

1. What is the data source?
2. What are the time attributes?
3. What is the evaluation metric?

Data Source

The first step is to identify the data that is being evaluated. Options include irradiance data or PV power production simulated using irradiance data and other parameters. In addition, the analysis can be performed for individual locations or fleets of locations. This paper focuses on irradiance data. The analysis is performed for both individual locations and fleets of locations.

Time Attributes

The second step is to specify the required time attributes. These include:

- **Time period**: total amount of data included in the analysis. This can range from a few hours to many years. This paper focuses on one year worth of data.
- **Time interval**: how the data in the time period is binned. This can range from annually to high frequency (a few seconds). For example, if the time period is one year and the time interval is one hour, the time period would be binned into 8,760 time increments. This paper examines one-minute to one-year time intervals.
- **Time perspective**: when the predicted observation is reported. This can range from historical (backward looking) to forecasted a few hours ahead to forecasted multiple days ahead (forward looking). This paper focuses on historical data.

Evaluation Metric

The third step is to select the evaluation metric. Error quantification metrics used in assessing absolute irradiance model accuracy such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) have been precisely defined [17, 18]. Their relative counterpart (results expressed in percent), however, can be subject to interpretation and may cover a wide range of values for a given set of data depending on reporting practice.

Hoff et al. [19] suggest that the MAE relative to available energy is a good method to measure relative dispersion error. This is the method used in the present analysis. The MAE relative to the average energy available is calculated by summing the absolute error for each time interval over the time period and then dividing by the available energy.

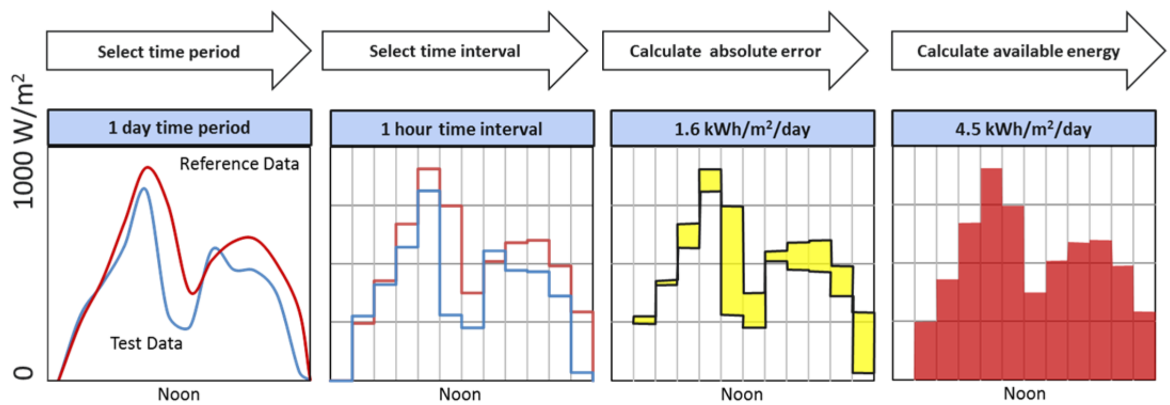
$$Relative\ Mean\ Abosolute\ Error = \frac{\sum_{t=1}^{N}\left|I_t^{test} - I_t^{ref}\right|}{\sum_{t=1}^{N} I_t^{ref}} \qquad (1)$$

where I_t^{test} is the test irradiance at time t, I_t^{ref} is the reference irradiance at time t, and N is the number of observations.

It is useful to provide a hypothetical example of how to calculate the Mean Absolute Error relative to available energy. A short time period (1 day) is selected so as to be able to graphically illustrate the calculations; the actual calculations in this paper use a 1 year time period. As presented in Figure 1, the process is follows:

- Select time period: 1 day.
- Select time interval: 1 hour.
- Calculate absolute error for each hour and sum the result as described in the top part of Equation (1): 1.6 kWh/m^2/day.
- Calculate available energy for each hour from reference data and sum the result as described in the bottom part of Equation (1): 4.5 kWh/m^2/day.
- Calculate Relative Mean Absolute Error: 36% (i.e., 1.6/4.5).

Figure 1. Mean Absolute Error relative to available energy calculation example.



It is important to note that a more often reported measurement of error is MAE relative to generating capacity. In the above example, however, it is unclear over what time period the generating capacity should be selected. Should it be capacity during daylight hours or capacity over the entire day, including night time hours? MAE relative to daytime capacity is about 13.3% (i.e., 1.6/12) while Mean Absolute Error relative to full day capacity is about 6.6% (i.e., 1.6/24).

It is due to this sort of ambiguity, as well as the fact that MAE relative to energy is a much more stringent metric (e.g., in this example, MAE relative to energy is 6 times higher than MAE relative to daily generation capacity), that the MAE relative to energy is selected as the evaluation metric.

4.2 Validation Approach

The present model validation is part of a project whose overall goal is to demonstrate and validate PV power prediction models in collaboration with the California ISO. Two key objectives of this project are (1) to measure the accuracy of the models for PV sources within the California ISO control area and (2) to ensure that the data is delivered in a manner compatible with the existing energy and reserve market mechanisms.

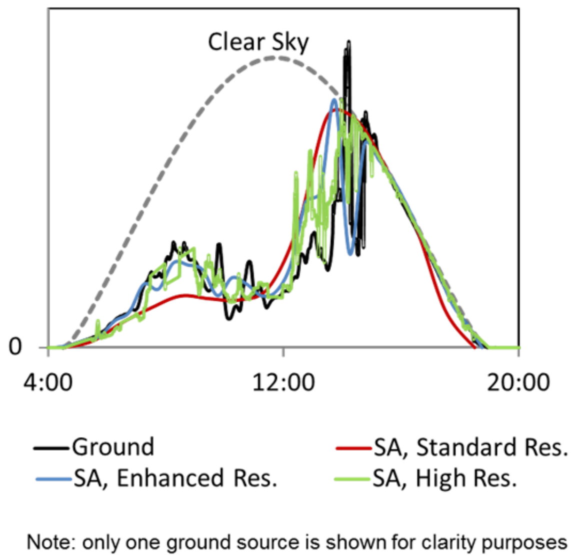
This paper focuses on the first objective and quantifies the accuracy of the irradiance data for a one-year time period (2011) and time intervals ranging from one minute to annually using a historical time perspective. The analysis is performed for both individual locations (i.e., single solar systems) and the ensemble of those locations (i.e., a fleet of solar systems).

A total of six test locations are analyzed where PV systems are located within California ISO's control area. The locations are identified as locations A through F for purposes of confidentiality. Each location is equipped with two redundant global horizontal insolation (GHI) sensors. One of the sensor is used as a reference and compared to three test configurations: the other sensor, and the two satellite-derived sources (SolarAnywhere Standard Resolution and Enhanced Resolution)

The validation approach involved the following steps:

- Obtain time-series GHI data for 2011 for 6 locations (see Figure 2 for an example of 1 day of data):
    - 4 second data averaged into 1 minute time intervals from two separate sensors at each location (sources: California ISO [20])
    - Satellite based data at the following resolutions (source: SolarAnywhere [14])
        - 1 minute, 1 km grid (High Resolution)
        - ½ hour, 1 km grid (Enhanced Resolution)
        - 1 hour, 10 km grid (Standard Resolution)
- Time-synchronize data sets by converting ground sensor data from Pacific Daylight Time to Pacific Standard Time.
- Evaluate all observations for data quality; exclude data where any one of the data sources has data quality issues.
- Calculate MAE relative to the actual energy available using the ground sensor that minimizes SolarAnywhere error as a reference.
- Calculate MAE relative to the actual energy available using the other ground sensor as a reference.
- Repeat the analysis for fleets of locations.

Figure 2. GHI data from 4 sources (July 4, 2011, Site B).



4.3 Evaluate all observations for data quality

As mentioned above, one of the steps in the analysis was to evaluate all observations for data quality. When evaluating accuracy, it is often simply assumed that reference data are correct. This is typically done due to the difficulty in determining whether or not the reference data is correct: to what can the data be compared?

A unique aspect of the data provided by the California ISO is that all the locations have two ground sensors. As a result, since either sensor could be the reference, the data quality of the ground sensors can be assessed by comparing the two ground data sets.

This is the process used to assess data quality:

(1) Compare the two sets of ground sensor data to each other to determine when one value is substantially different than the other value.
(2) Compare the enhanced resolution satellite and ground sensor data to search for 0 values occurring at incorrect times (e.g., mid-day on otherwise clear day) to determine when the satellite data is invalid.
(3) Compare ground sensor data to the SolarAnywhere Enhanced Res. data to determine if both ground observations are the same but are obviously incorrect (e.g., the irradiance value remains at a constant level for many hours).

For each of these steps, the complete data set was evaluated and then potential outliers were manually evaluated and screened.

Figure 3 illustrates the screening result when comparing the two ground sensors at one location. All of the data points would lie on the 45 degree red line if they were identical. The blue symbols correspond to valid data and the black symbols correspond to invalid data. Figure 4 illustrates the issue for one of the invalid observations when one of the sensor's recorded value remained constant after solar noon. Figure 5 illustrate the case when both ground sensors produce a similar value but are obviously incorrect, reading a constant low value on an otherwise clear day as assessed from the satellite data. Figure 6 illustrates the case when there was a night-time calibration error across the year. Site E was missing more than a month of data during the first part of the year as well as a 5 percent difference between the two ground sensors. Sites E and F were eliminated from the analysis as a result of the data filtering process. The remaining sites had about 1 percent of the ground data marked as invalid.

Figure 3. Half-hour energy production in 2011 from meter 2 vs. meter 1 (Site A).

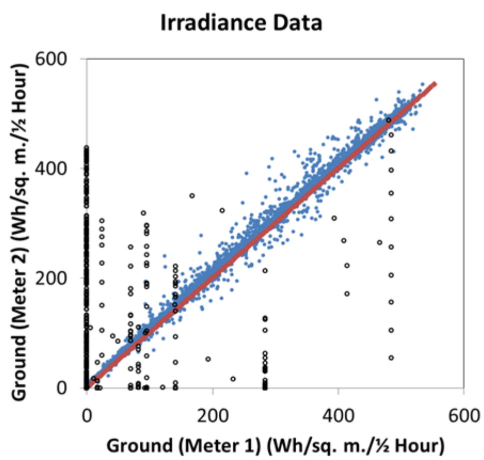


Figure 4. Example of when only one of the ground sensors has invalid data (Site A, June 22, 2011).

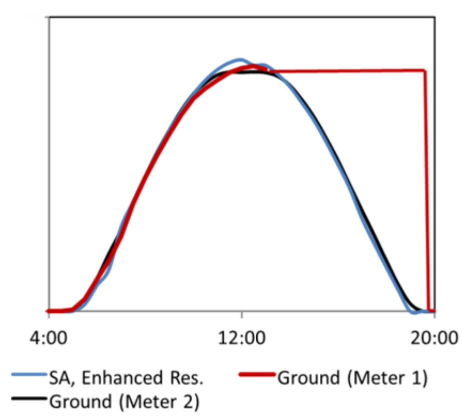


Figure 5. Example of when both ground sensors have invalid data (Site C, May 1-2, 2011).

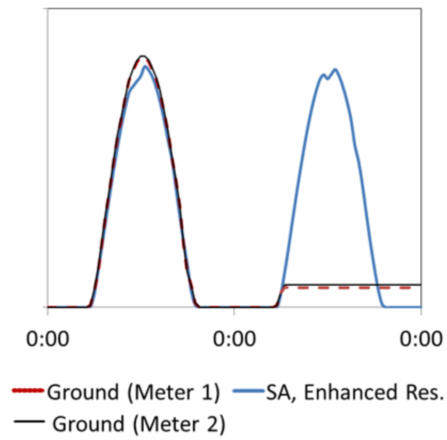
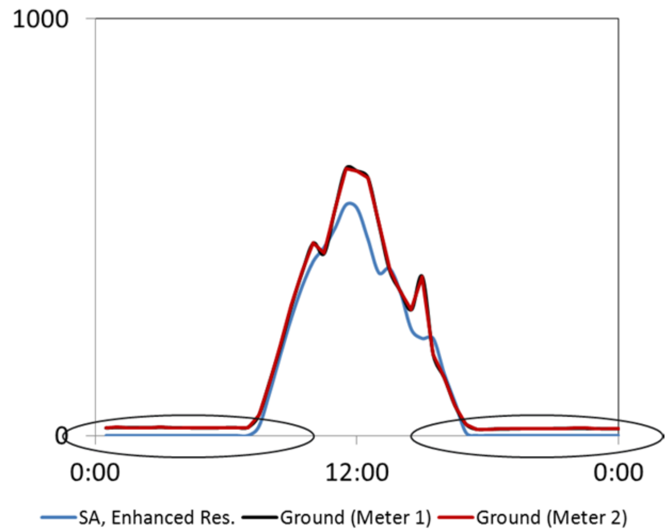


Figure 6. Site F has a night-time calibration error across the year.



3. RESULTS

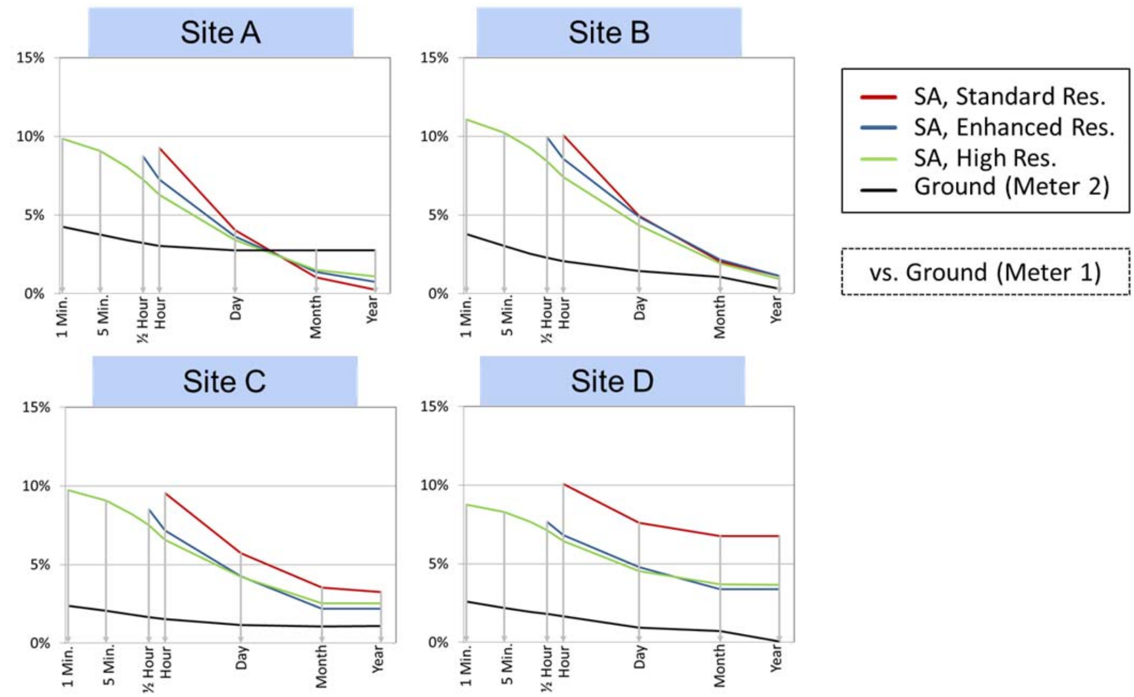
The relative MAE was then calculated for three scenarios:

- Each location individually.
- Average of individual locations.
- Fleet of locations.

4.4 Each Individual Location

Figure 7 presents the MAE for each of the four locations using time intervals ranging from 1 minute to 1 year.

Figure 7. Relative MAE for each location individually.

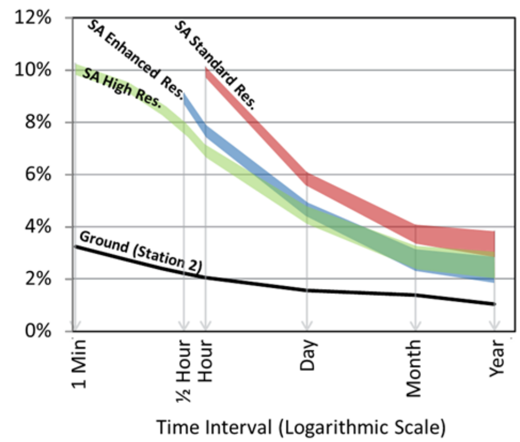


4.5 Average of Individual Locations

Figure 8 presents the average MAE of 4 individual locations. The black line summarizes the error when two ground stations are used (one is the reference and the other is the test). The green, blue, and red regions summarize the error when SolarAnywhere High, Standard, and Enhanced Resolution are compared to the ground sensor. The green, blue, and red areas are regions rather than lines because they compare satellite data to ground data using the two different ground sensors; the top of the region is the comparison using the ground sensor that maximizes error; the bottom of the region is the comparison using the ground sensor that minimizes error.

There are several important things to notice in the figure. First, as expected, error decreases for all data sources as the time interval increase. Second, accuracy improves for each of the three satellite models as the spatial and temporal resolutions are increased. Third, error exists even between two ground sensors that are in almost the same location (i.e., ground sensors have 1 percent annual error). Fourth, SolarAnywhere High Resolution has only 10 percent error over a one minute time interval, 7 percent error over a one hour time interval, and 2 to 3 percent error on a one year time interval.

Figure 8. Average MAE of 4 individual locations.



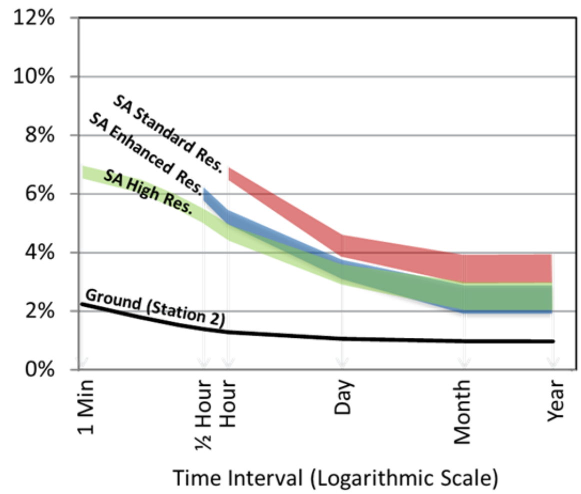
4.6 Fleet of Locations

As illustrated by the list of References, a number of studies have examined the issue of PV output variability. A consistent finding of these studies is that variability is reduced when PV systems are geographically dispersed. That is, variability is reduced as the number of systems increases across a sufficiently large geographic region.

So far, this paper has focused on the error associated with individual locations. While individual locations are of interest in some cases, there are certainly many other cases in the utility industry when users are most interested in the error associated with a set of locations.

The MAE analysis was repeated with the input data being the combined irradiance across four locations. The results are presented in Figure 9. A clear reduction in error due to combining locations can be seen by comparing Figure 9 to Figure 8. That is, the effect of geographic dispersion on reducing output variability reduction that has been observed by others is now also observed with regard to prediction accuracy: accuracy improves as a geographically diverse set of independent locations are combined.

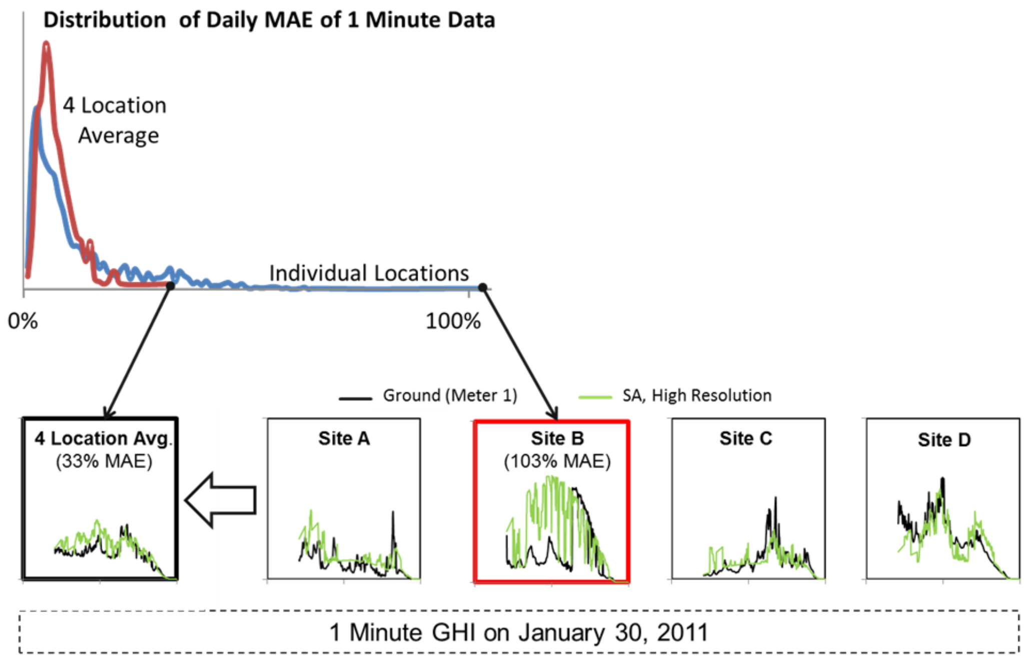
Figure 9. MAE of 4 locations combined.



In order to demonstrate why this is occurring, a "worst day" analysis was performed. In particular, the day was selected that has the highest MAE calculated using a one day time period and one minute time interval for each of the four locations. The results are illustrated in Figure 10. The top graph in the figure is a probability distribution of the daily MAE for all 4 sites and 365 days per year. As can be seen in the figure, the worst day of the year had 103 percent daily MAE on a one minute basis.

The black line in the figure points to the graph of the one minute GHI for January 30, 2011 at Site B, the worst day, and worst site of the year. While SA High Resolution clearly over predicted irradiance on this day, the prediction was good at the other three sites. As a result, the combined error for the day is 33 percent. As shown by the red line in the top distribution figure, this was still the day that had the highest daily error, but it is much lower than the one site by itself.

Figure 10. Site B had highest daily error on Jan. 30, 2011 – 4 location average reduces effect.



Furthermore, fleet error appears to be able to be approximated from average individual location error as follows.

$$Predicted\ Mean\ Abosolute\ Error = \frac{\mathrm{E}[MAE\ for\ selected\ time\ interval]}{\sqrt{N}} + |\mathrm{E}[MBE]|\left(1 - \frac{1}{\sqrt{N}}\right) \qquad (2)$$

where E[] is the expected value, MBE is the mean bias error, and N is the number of independent locations. This proposed relationship will have to be ascertained with a larger sample of data points, but it can be stated that the $\sqrt{N}$ dependence is an inference of the reasonable assumptions that errors at individual locations are not correlated. This follows along the Strong Law of Large Numbers that states that the average of a sequence of independent random variables having a common distribution will, with probability 1, converge to the mean of that distribution as the number of observations goes infinity [21].

4. CONCLUSIONS

Two critical challenges to greater penetration of PV into a state's electricity system are: (1) PV output variability; and (2) ability to accurately predict PV output variability. A number of researchers focusing on the first challenge have demonstrated that PV output variability is reduced by geographic diversity. This paper begins to quantify the accuracy in predicting variability.

Results suggest that, first, satellite-based irradiance has annual error comparable to ground sensors. Thus, satellite data may perform as well as ground data for plant siting at a fraction of the cost plus the benefit of long-term data streams. It should be noted that ground sensors, even well maintained, produce considerably more invalid data points than the satellite (a ratio of one hundred to one in the present study) and that the satellite data were key in detecting these erroneous data points (particularly when both redundant sensors failed at the same time).

Second, Satellite-based irradiance has 10 percent one minute error, making it suited to provide the basis for data required to perform high penetration PV studies. Third, accuracy improves predictably due to the benefit of geographic dispersion. That is, the effect of geographic dispersion on reducing output variability reduction that has been observed by others is now also observed with regard to prediction accuracy.

5. Acknowledgements

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6. References

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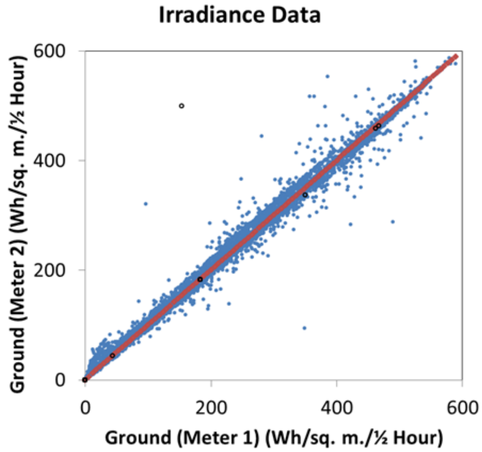
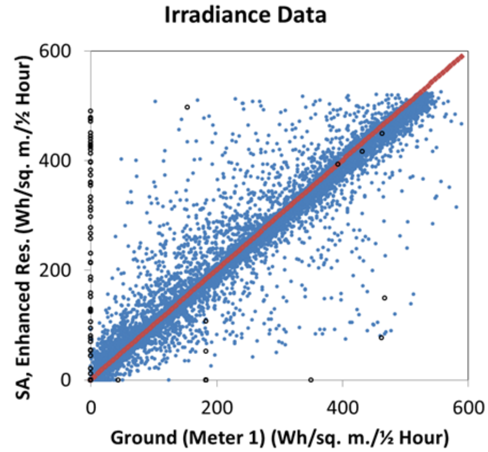
7. Appendix: Half-hour Irradiance Data

Site A





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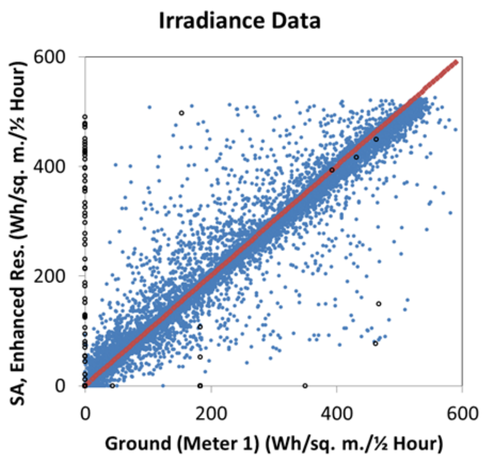

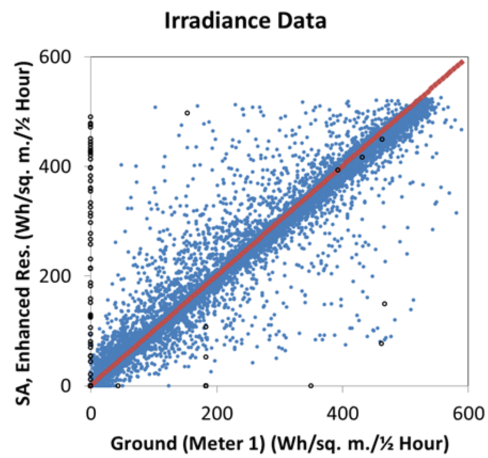

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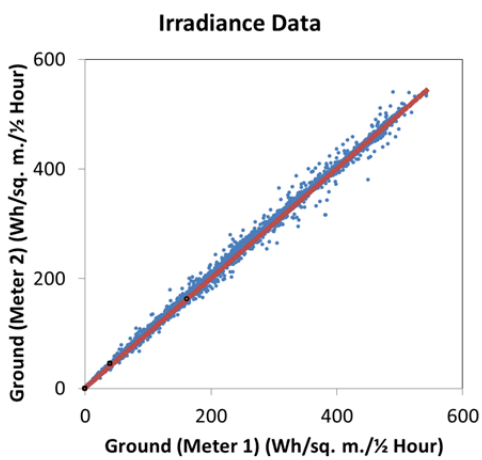

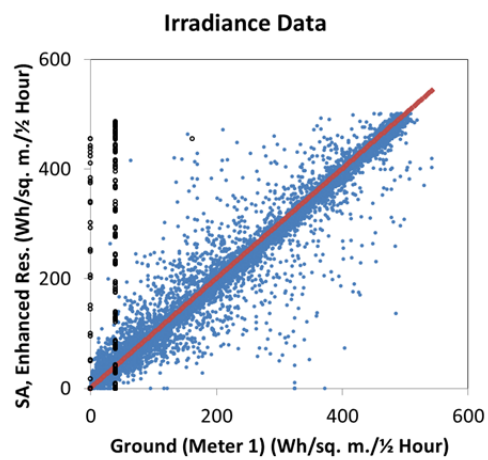

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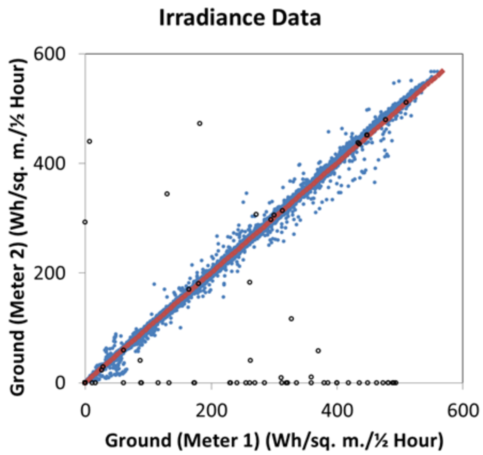
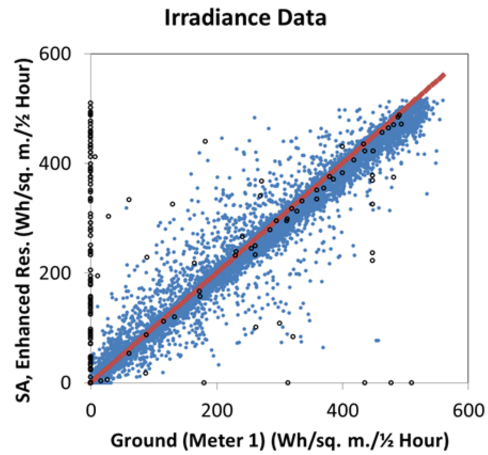
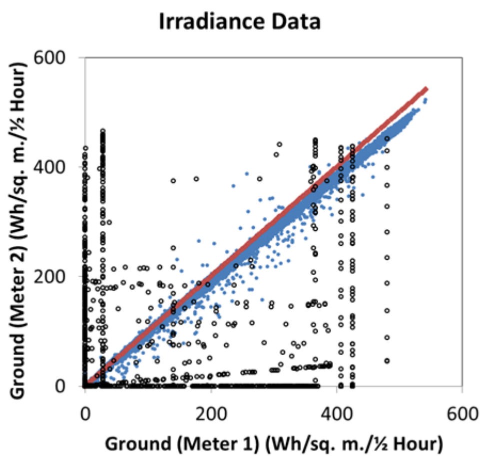
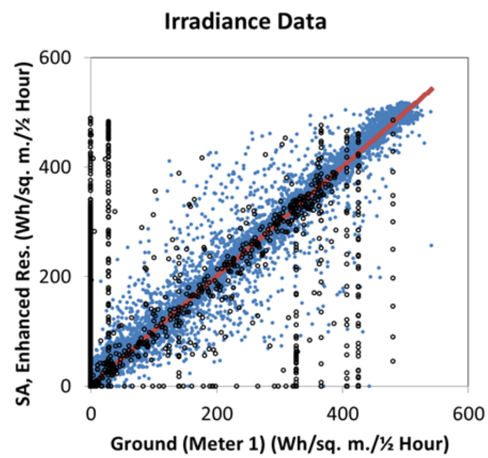




Site E





Site F