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VALIDATION OF PV PERFORMANCE MODELS USING SATELLITE-BASED IRRADIANCE MEASUREMENTS: A CASE STUDY

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ABSTRACT

Photovoltaic (PV) system performance models are relied upon to provide accurate predictions of energy production for proposed and existing PV systems under a wide variety of environmental conditions. Ground based meteorological measurements are only available from a relatively small number of locations. In contrast, satellite-based radiation and weather data (e.g., SUNY database) are becoming increasingly available for most locations in North America, Europe, and Asia on a 10x10 km grid or better. This paper presents a study of how PV performance model results are affected when satellite-based weather data is used in place of ground-based measurements.

1. INTRODUCTION

Photovoltaic (PV) system performance models are relied upon to provide accurate predictions of energy production for proposed and existing PV systems under a wide variety of environmental conditions. Ground based measurements, including typical meteorological year (TMY) data, are only available from a relatively small number of locations. In contrast, satellite-based radiation and weather data (e.g., SUNY database) are becoming increasingly available for most locations in North America, Europe, and Asia on a 10 by 10 km grid or better. Several studies have compared satellite-based radiation data with ground-based measurements (e.g.,[1]) but far less work has been done to evaluate the results of using satellite data as input to PV performance models [2]. Because each performance model is unique and has specific sensitivities to model input parameters the use of satellite-based irradiance inputs will have different effects depending upon which model is used.

In this study, we consider the performance of a small (1 kW) c-Si grid-tied PV system deployed at Sandia National Laboratories (SNL) in Albuquerque, NM between April 2007 and March 2008. We measured irradiance (direct normal, diffuse horizontal, and global horizontal), air temperature, and wind speed, among other weather parameters during the deployment. We also monitored electrical performance on the DC (current and voltage) and AC (power) sides of the inverter. In addition we obtained hourly satellite estimates of direct normal and global horizontal irradiance as well as air temperature and wind speed. In the following sections of this paper we will first compare the ground-based measurements to those estimated from satellite imagery. Second, we will employ several PV performance models using both ground and satellite-based weather inputs and compare model results of electrical performance and measured performance.

2. DATA ACQUISITION METHODS

Ground-based measurements of weather parameters made at 2-minute intervals were collected at SNL's PV weather station adjacent to the PV test array. Direct normal irradiance (DNI) was measured with two pyrheliometers (a Kipp & Zonen CH1 and an Eppley NIP), diffuse horizontal irradiance (DHI) was measured with two Eppley PSP pyranometers (one fitted with a shade disk and the other with a shade band). Global horizontal irradiance (GHI) was measured with a Kipp & Zonen CM21 pyranometer. Air temperature was monitored with two Climatronics Aspirated Shield Temperature Sensors and wind speed was measured with a Climatronics Wind Mark III Wind Sensor at 10 m above ground level. Weather data were processed to obtain representative hourly values consistent with the Typical Meteorological Year (TMY) model. Specifically, irradiance data was combined in order that the total amount of energy reaching the sensor during the 60 minutes preceding the hour is reported. Hourly values of temperature and wind speed are reported as average values from the period spanning 30 minutes before and after the hour. Because satellite data represents instantaneous estimates of irradiance, the average of irradiance at the present hour and one hour prior was used to estimate the total amount of energy reaching the ground during the previous hour.

Satellite-based irradiance estimates (DNI and GHI) for the same period were obtained from Clean Power Research's SolarAnywhere database for a 10x10 km area that includes the location of the PV test array. Details on how irradiance data are generated are available elsewhere (e.g., [3]). SolarAnywhere also provides instantaneous estimates of air temperature and wind speed at hourly intervals at each satellite pixel. These data are interpolated from the METAR network of ground stations (several 1000s in the US) – this worldwide network feeds aviation forecasts and the National Weather Services' real time modeling process with ongoing ground-based data. The source of these data are referred to as "satellite-based" in this paper even though they are derived from ground stations.

For several brief periods during the one-year deployment, the PV system went offline for maintenance. Weather data obtained during these periods is excluded from the comparisons and analyses described in this report. Similarly, data during the night and occasional periods when either ground or satellite measurements were missing were also excluded.

3. COMPARISON OF WEATHER DATA FROM GROUND AND SATELLITE SOURCES

Satellite-based estimates of radiation, temperature, and wind speed are not expected to be as accurate as ground-based measurements of these parameters for a number of reasons. First, the satellite-based estimates are indirect interpretations of data observed from space (irradiance) and widely-spaced ground stations (temperature and winds speed) and therefore are associated with all the uncertainties inherent in generalized modeling. Second, the spatial and temporal resolution of the satellite imagery is coarse when compared with our ground based measurements. The satellite-based values are calculated from snapshot images of the earth and do not distinguish differences between locations within a single pixel. These factors can cause significant deviations between satellite and ground measurements, especially during partly cloudy conditions. Figure 1 compares ground-based measurements and satellite estimates of irradiance for two days. The raw ground measurements are plotted in grey at a 1-min interval. The hourly data is averaged over a one hour window and plotted as red crosses. Satellite estimates of hourly averages are also shown as blue circles. These estimates are the average of the instantaneous satellite values on the hour and for the previous hour and plotted 9in between. It is evident from the figure that the satellite data is quite accurate during clear conditions (first half of day 1), but that the satellite estimates can deviate significantly from the hourly averages during periods of partly cloudy conditions.

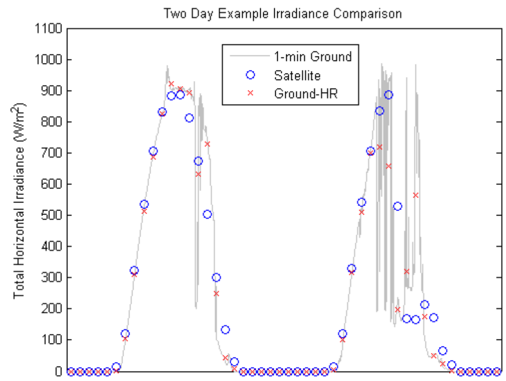


Fig. 1. Two day example of irradiance record comparing ground measurements and satellite-based estimates.

Table 1 lists the mean and standard deviation of the residuals (difference between satellite estimates and ground measurements). Residuals for GHI are significantly smaller than for DNI. Scatter plots comparing ground and satellite-based values of GHI, DNI, air temperature, and wind speed are shown in Figure 2. The correlations between ground and satellite estimates of global horizontal irradiance and air temperature are significantly stronger (R^2 values of 0.92 and 0.97, respectively) than the correlations for direct normal irradiance and wind speed (R^2 values of 0.78 and 0.5, respectively).

It is interesting to note that the temperature and wind speed residuals appear to be sensitive to the time derivative of the "satellite" estimates for these parameters. Figure 3 shows that there is a positive correlation between the "satellite" temperature and wind speed residuals and the time derivative of these quantities. In other words, when these "satellite" values change significantly from one hour to the next, the residual tends to be higher than normal, which indicates poor agreement with ground-based measurements at these times. This correlation suggests that one characteristic of the satellite estimates is occasional hours when temperature and/or wind speed appear to change rapidly while the ground measurements do not. A similar correlation is not evident for the satellite irradiance estimates. A plausible explanation of this pattern is that the METAR data are interpolated from instantaneous measurements made every hour from a network of stations while the ground data from the SNL weather station use mean values calculated from many measurements over the hour. The difference between time averaging frequent measurements and spatial interpolation of widely-spaced hourly measurements might explain the correlation observed, especially during periods when weather fronts are passing over the area.

TABLE 1. RESIDUAL SUMMARY STATISTICS (WEATHER INPUTS)

Variable	Mean	Stdev
GHI Residual (W/m^2)	0.019	83.061
DNI Residual (W/m^2)	17.257	166.452
Temp Residual (deg C)	0.157	1.811
Wind Speed Residual (m/s)	0.114	2.183

4. SIMULATION OF PLANE OF ARRAY IRRADIANCE

Most PV performance models require as input DNI and GHI. Both weather datasets examined here included both of these components. The first step performed by the models is to calculate the plane of array (POA) irradiance. There are a number of different radiation models that have been developed for this purpose. The model by Hay and Davies [4] accounts for increased diffuse radiation near the sun (circumsolar diffuse). The model by Reindl et al. [5] added the effect of horizon brightening; in addition to the circumsolar diffuse. The model by Perez et al. [6,7] accounts for both of these components using an empirically-based method. In order to identify any effect due to the choice of radiation model, we compared POA irradiance predicted by these three radiation models to irradiance measured with a pyranometer mounted at POA. The results of this comparison indicated that at this site and during this test period there is little difference between POA radiation predicted by the models and measured by the pyranometer. The Perez model fit the measured data slightly better than either of the other two models but all performed very well (R^2 values > 0.99 in all cases. We will use the Perez radiation model for all subsequent calculations presented.

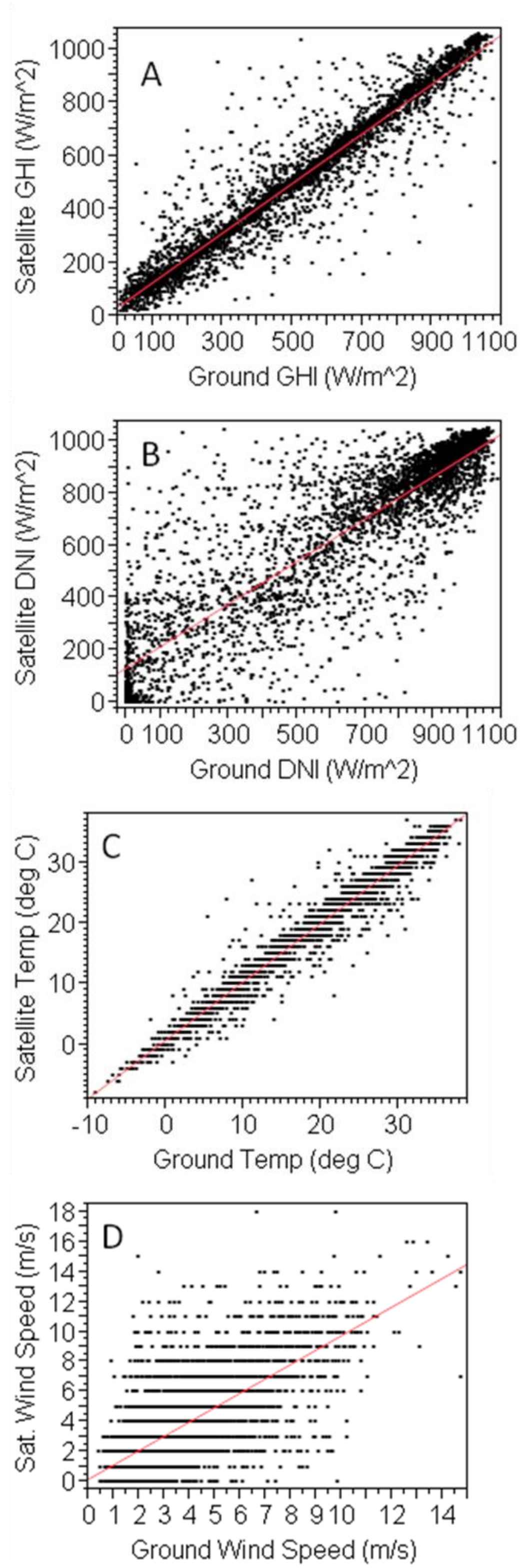
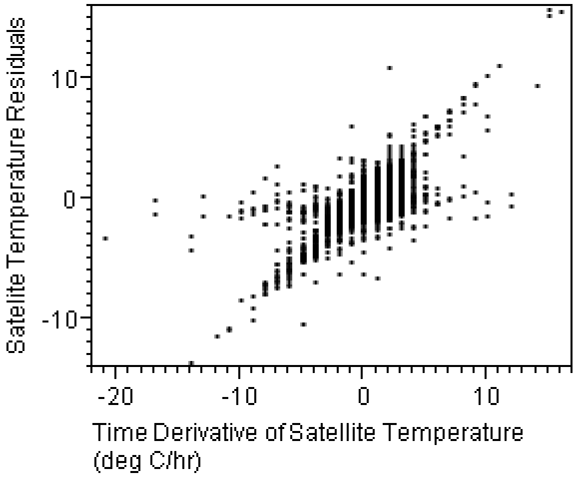


Fig. 2. Scatter plots of satellite vs. ground measurements of (A) global horizontal irradiance, (B) direct normal irradiance, (C) air temperature, and (D) wind speed. Lines are linear fits to the data.



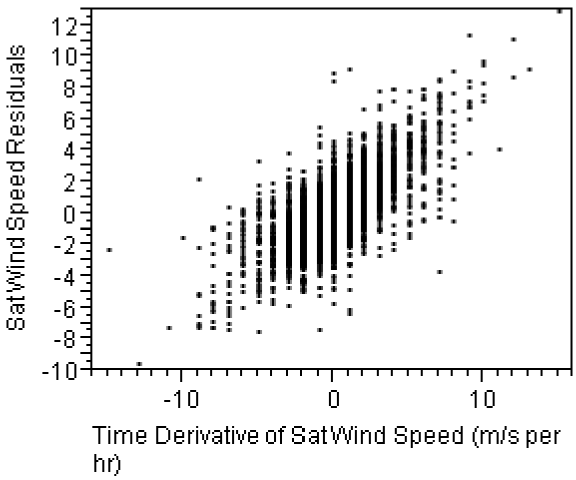


Fig. 3. Correlations between residuals and time derivatives for satellite air temperature and wind speed estimates.

5. SIMULATION OF PV DC POWER OUTPUT

Two commonly used performance models were examined in this validation study. The names of the models are kept anonymous, but they were selected to represent two fundamental conceptual approaches for PV modeling. Model 1 uses an empirical fitting approach while Model 2 represents the array as an equivalent circuit with a single diode. Both models were run twice, once with ground-based weather data and once with satellite-based inputs. Other than weather inputs, all model parameters were identical between runs. Derate factors on the DC side were excluded from the analysis (no derate was assumed). This was done to compare each model's ability to translate weather to power output without including each model's unique way of handling derate factors such as soiling and resistive losses, which might have affected the comparison.

To compare measured and simulated performance, hourly values of DC power output are compared. Figure 4 presents scatter plots of modeled DC power against measured power for both models using both weather datasets. Although the scatter is greater for the simulations based on satellite data, the annual bias error is very similar between ground and satellite-based simulations for a given model. At this stage of the comparison, we can conclude that the use of satellite data as model input for this array only appears to increase the variance in the hourly values power predictions, but has little effect on the annual bias. In other words, annual energy estimates vary more from the choice of model than from the source of the weather data.

We also made comparisons of energy produced over longer periods (days and months). The results indicate that the R^2 values of daily output from the satellite runs are nearly identical to those shown for hourly output, but that the R^2 values are significantly higher for the monthly output comparisons (0.9536 for Model 1 and 0.9817 for Model 2). One reason that daily values exhibit a similar amount of scatter might be related to the position of the SNL site, which is located directly to the west of the Sandia mountain front, which rises about 5,000 ft above the eastern plain. The mountains directly affect local cloud patterns, which can vary over short spatial scales at this site, which might explain why the daily residuals vary as much as the hourly ones.

6. RESIDUAL ANALYSIS AND VALIDATION OF PV PERFORMANCE MODELS

Analysis of model residuals (difference between modeled and measured values) provides a useful approach for investigating differences between models. Residual analysis is based on examining the distribution and sensitivity of residuals with respect to other time-varying variables in the analysis. Table 2 lists summary statistics for the model residuals of DC power for the four model runs considered.

TABLE 2. RESIDUAL SUMMARY STATISTICS

Model	**Mean (W)**	**Stdev (W)**
Model 1 (Ground)	29.6	26.7
Model 1(Satellite)	31.7	98.7
Model 2 (Ground)	15.1	27.6
Model 2 (Satellite)	16.5	98.9

The relationship between predictions of a "perfectly valid" model and measured performance should be "statistical" rather than deterministic. This is because models are based on mathematical functions and model parameters are derived to match mean behavior, not point-by-point behavior of the system [8]. Furthermore, all measurements (weather and performance) are characterized by uncertainties, meaning that any particular measured value is a sample from some underlying uncertainty distribution, which is often poorly defined. For these reasons, a completely valid model is one which results in residuals that are randomly distributed with respect to all variables in the analysis. Therefore, model validation can be summarized as a process of testing whether model residuals are random with respect to other simulation variables. There are a number of different approaches to testing the randomness of residuals. These are discussed in the sections below.

6.1 Stepwise Regression

Stepwise regression can be applied to residuals to identify and rank simulation variables in order of their contribution to the variance in residuals. Stepwise regression is based on performing a series of linear regressions of the form:

$$Y = b_o + \sum_{j=1}^{P} b_j X_j \, , \qquad (1)$$

where Y is a vector of dependent variables and X is a set of P vectors of independent variables included in the stepwise model. The b coefficients in (1) can be used to develop a prediction model, if desired. In the first step, the method tests the linear regression between Y (in our case, model residuals) and a set of independent variables (time-varying variables in the analysis) to see which variable results in the best linear fit (highest R^2). For the second and subsequent steps, additional independent variables are added to the regression in order of which variable provides the highest R^2 value for each step. This process continues until the probability (p) that an effect is due to chance is exceeded. For our application we are interested in the order of the X variables that are selected for the model and the resulting R^2 values. This method is limited in that it can only identify linear trends, but if applied judiciously, it can shed light on which variables are most correlated with model residuals and help to quantify the validity of a PV performance model.

To illustrate the utility of stepwise regression for this application, we ran a stepwise analysis on the DC power residuals for the four sets of model results displayed in Fig 4 and summarized in Table 2. The independent variables included in the analysis were global horizontal irradiance (GHI), direct normal irradiance (DNI), air temperature (Temp), wind speed (WS), wind direction (WDir), angle of incidence (AOI), and air mass (AM). For the models using satellite data, the irradiance, temperature, and wind speed data (SA_GHIa, SA_DNIa, SA_Temp, and SA_WS) were obtained from that dataset and wind direction was not included. Table 3 lists the first four parameters identified in the stepwise analysis (p = 0.05).

TABLE 3. STEPWISE REGRESSION RESULTS

Model 1 (Ground)			
Order	**Variable**	**R^2**	**Incremental R^2**
1	Temp	0.2302	0.2302
2	DNI	0.3143	0.0841
3	WS	0.3301	0.0158
4	AOI	0.3350	0.0049
Model 1 (Satellite)			
Order	**Variable**	**R^2**	**Incremental R^2**
1	SA_Temp	0.0281	0.0281
2	SA_DNIa	0.0573	0.0292
3	AMa	0.0736	0.0163
4	SA_WS	0.0776	0.0040
Model 2(Ground)			
Order	**Variable**	**R^2**	**Incremental R^2**
1	AOI	0.0886	0.0886
2	AMa	0.2115	0.1229
3	GHI	0.2575	0.0459
4	DHI	0.2646	0.0071
Model 2 (Satellite)			
Order	**Variable**	**R^2**	**Incremental R^2**
1	SA_DNIa	0.0288	0.0288
2	AMa	0.0655	0.0368
3	SA_GHIa	0.0753	0.0098
4	SA_Temp	0.0794	0.0041

The interpretation of these results is made by examining the variables that are identified and the R^2 and incremental R^2 values for each step. For example, the model residuals for Model 1 (Ground) exhibit a correlation with air temperature that accounts for approximately 23% of the variance in the residuals. This correlation is illustrated graphically in Fig 5. After correcting for this effect, an additional 8% of the variance is accounted for by including a correction for DNI. It must be noted that the standard deviation of model

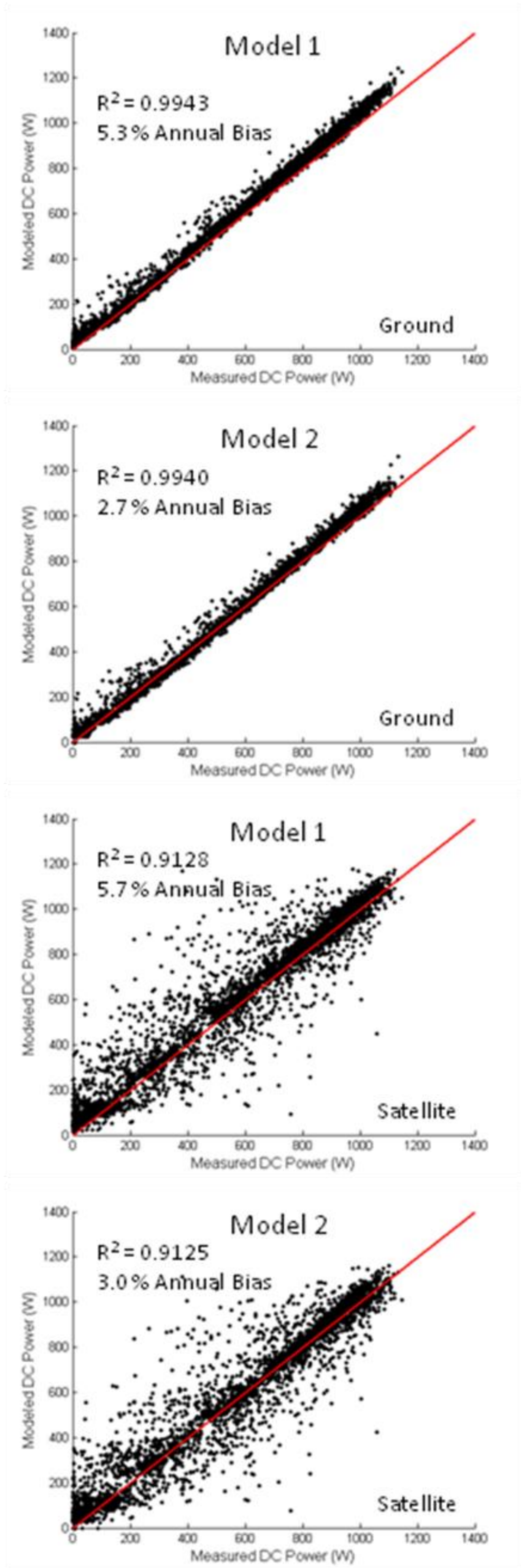


Fig. 4. Scatter plots comparing measured and modeled DC power for two models each run with ground and satellite weather data. 1:1 lines shown in red.

residuals for this model are already quite small (Table 2), so that the total 31% reduction in the variance (square of standard deviation) obtained by including corrections for these two variables would result in a change in the standard deviation for this model from 26.7 W to 22.2 W per hour. The variables listed in the next two steps account for such small reductions in variance they are not discussed here.

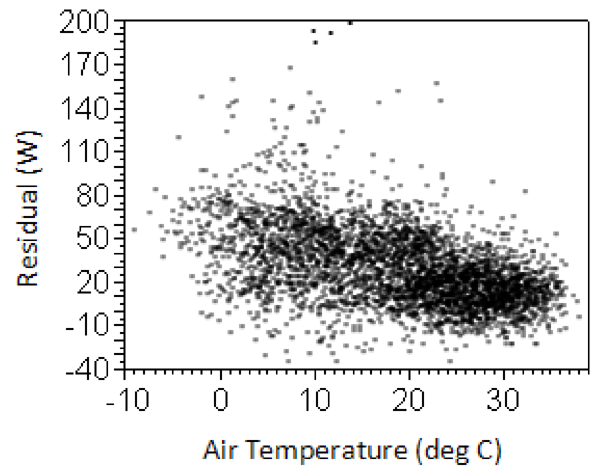


Fig. 5. Scatter plot of model residuals vs. ground-based air temperature for Model 1 illustrating the correlation present.

Looking at the results for Model 1 (Satellite), we see the same two variables (temperature and DNI) appear in the first two steps, each accounting for about 3% of the residual variance. The standard deviation in model residuals for the models based on satellite data is more than three times greater than it is for the ground-based models. Thus, a total 6% change in this variance results in a reduction in the standard deviation of the residuals that is of similar magnitude to that obtained for the ground-based simulation. This result suggests that results from Model 1 might be improved by adjustment to the temperature parameters used as input to the model or perhaps the use of an alternate form of the temperature correction. Additional comparisons from different arrays and sites are needed before the nature of the improvement is evident.

The results for Model 2 exhibit a pattern different from that observed for Model 1. For the ground-based model run, AOI, AM, and GHI together account for approximately 26% of the variance in model residuals. For the satellite-based runs, DNI and AM account for a total of about 7% of the variance. The appearance of AOI and AM as sensitive variables for Model 2 (Ground) runs suggests a possible complication of interpreting the stepwise regression results. These two parameters are functionally related and exhibit a complex but predictable relationship, which is shown in Figure 6. Although this relationship is not linear, these two variables are correlated and therefore corrections involving one of these parameters affect the sensitivity of the model to the other variable. For this reason, it is difficult to entirely separate the effects of these parameters with stepwise regression.

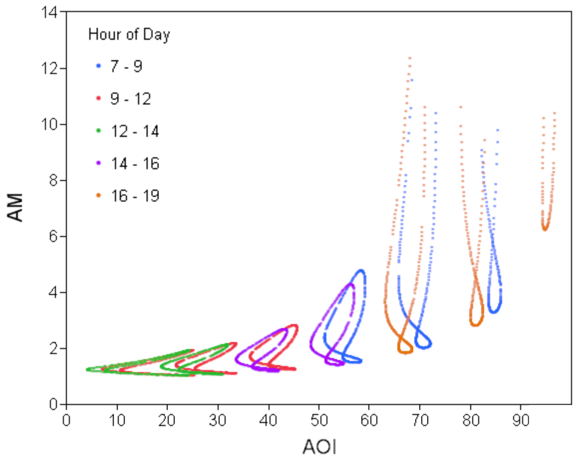


Fig. 6. Scatter plot of Air Mass (AM) vs. Angle of Incidence (AOI) showing complex functional relationship.

The fact that model residuals for Model 2 are sensitive to a different set of variables than Model 1 indicates differences between these models and point to areas where each of these models could be improved.

6.2 <u>Graphical Residual Analysis</u>

One of the limitations of stepwise linear regression is that it only tests for linear relationships between the dependant and independent variables. A more general approach based on graphical methods may also be useful, especially if there are significant non-linear relationships between model residuals and input variables. One such approach is to bin residuals by the selected time-varying variable and plot mean residuals in each bin against the binned midpoint value. Figures 7 to 10 show these graphical results for four selected variables. The points show the mean residuals at each bin midpoint, while the lines in the figures represent smoothed fits to data intended to show general patterns.

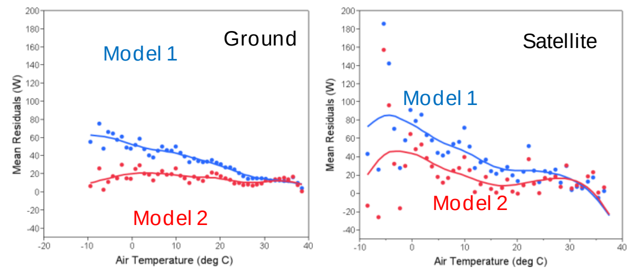


Fig. 7. Plot of mean residuals as a function of air temperature.

The relationship between residuals and temperature (Figure 7) appears to be quite linear, especially for the model runs with ground-based weather. It appears that there may be a systematic error at low temperatures in the model runs made with satellite data (residual peak at temperatures near and below zero degrees C). This may reflect the complication that snow on the ground or ice in the atmosphere brings to estimating radiation.

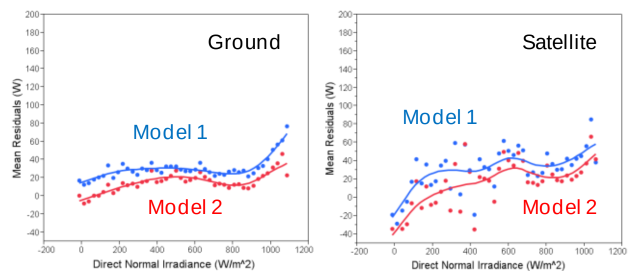


Fig. 8. Plot of mean residuals as a function of direct normal irradiance.

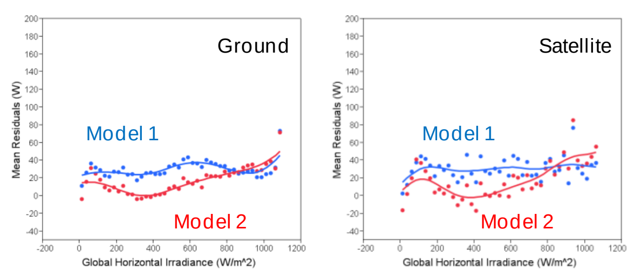


Fig. 9. Plot of mean residuals as a function of global horizontal irradiance.

Figures 8 and 9 show plots of mean residuals as a function of radiation components, GHI and DNI, respectively. Both models exhibit a slight positive correlation with DNI, as was identified in stepwise results. Both models exhibit little to no correlation with GHI.

Figure 10 shows plots of mean residuals as a function of air mass. There is a large increase in the mean residuals at high air mass values, which is seen for both models, but is especially large for the runs with satellite-based weather. This pattern may reflect a limitation of the models to represent the effects of high air mass, which is used as a proxy for spectral effects in the models. Or, perhaps, the high residuals reflect complications with predicting when inverters have enough light to operate. Regardless of the cause, periods of high air mass do not correspond with large amounts of energy production from PV systems and therefore this nonlinearity is likely to be academic.

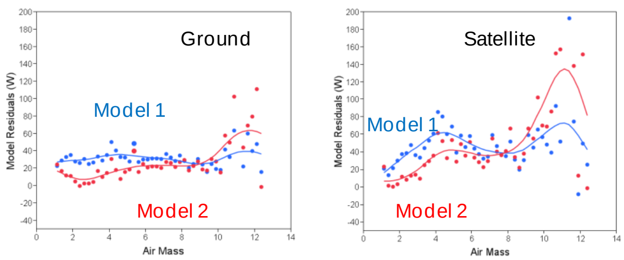


Fig. 10. Plot of mean residuals as a function of air mass.

7. SUMMARY AND CONCLUSIONS

Based on results from our test array in Albuquerque, NM, it appears that, PV performance models run with site-specific ground data provide the most accurate energy prediction from the system. However, models run with satellite derived weather inputs can provide very good estimates of the total energy produced by the array over longer time periods because errors associated with satellite-based weather are greatest over short time periods (hours or days). Over hourly intervals, the standard deviation of model residuals for DC power was more than three times larger for satellite-based simulations compared with ground-based runs. But the bias errors (mean of the residuals) were not very sensitive to whether ground-based or satellite data were used. If this result holds for locations in general, it suggests that satellite data are suitable for predicting energy output for proposed projects. In fact, if multiple years of archival satellite data are available for modeling, insights about annual variability in energy production for a given site can be gleaned, information which is lacking when only TMY data are used for such predictions.

8. FUTURE WORK

The scope of the present study was quite limited (single PV technology (cSi), single location, fixed tilt array, etc.). Future work will continue to develop and apply the model validation methods discussed here to a greater variety of PV systems. In addition, future studies are needed to determine whether satellite-based irradiance can be used for system monitoring applications. Because of the larger errors in satellite weather over short time periods, it remains to be seen whether these data are suitable for such an application.

9. ACKNOWLEDGMENTS

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