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Final Technical Report

Advanced Solar Resource Modeling and Analysis

Sandia National Laboratories

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Final Technical Report (FTR)

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Executive Summary

The SunShot Initiative coordinates research, development, demonstration, and deployment activities aimed at dramatically reducing the total installed cost of solar power. The SunShot Initiative focuses on removing critical technical and non-technical barriers to installing and integrating solar energy into the electricity grid. Uncertainty in projected power and energy production from solar power systems contributes to these barriers by increasing financial risks to photovoltaic (PV) deployment and by exacerbating the technical challenges to integration of solar power on the electricity grid.

The dominant contribution to uncertainty in projected power and energy from solar power systems arises from uncertainty in the estimated solar resource. Most often, the solar resource is estimated from satellite measurements which may be supplemented by on-site ground measurements. To project system power and energy, irradiance must be estimated over the system's footprint, separated into direct and diffuse components, and translated into the array's plane. Uncertainty in the estimated irradiance thus arises from uncertainty in the models that: translate satellite measurements to estimated irradiance; portray the spatial and temporal variation in irradiance over a power plant's footprint, or over a fleet of solar power systems; and separate global horizontal irradiance into its beam and diffuse components.

Research and development leading to improved models can reduce these uncertainties and thus lead to reduced financial and technical risk to solar power deployment. Accordingly, Sandia National Laboratories pursued activities in the area of Solar Resource Assessment designed to:

1. Improve irradiance estimated from satellite data by advancing methods for comparing satellite-based irradiance with ground measurements, and through in-depth analysis of the GHI estimates in the National Solar Radiation Database (NSRDB) version 3.
2. Improve upon current methods to represent the geographic smoothing of irradiance over the spatial extent of utility-scale power plants as well as over fleets of solar power systems, and provide guidance for the number of sensors required for accurate spatial irradiance measurement.
3. Improve models that estimate direct normal irradiance (DNI) and plane-of-array (POA) irradiance from global horizontal irradiance (GHI).

At the project's conclusion we highlight several significant publications:

– Analysis of GHI in the NSRDB version 3. Our analysis not only provides benchmark statistics for the uncertainty in these widely-used solar resource data, but also identifies several avenues for improvement of the NSRDB GHI data.
– Techniques for aiding in analysis and validation of solar resource data, including (1) a method to identify periods with clear sky GHI using only GHI measurements, and (2) a method to automate identification and removal of periods of local shading in ground-measured GHI data.
– Research on the application of cutting-edge spatial-temporal statistical methods to modeling irradiance on the scale of a utility-sized PV plant, leading to a new method for creating semi-parametric, data-driven statistical models, with potential to reduce error in predicted irradiance by 15% generally.
– Analysis of commonly-used models for translating from GHI to POA irradiance, including guidance on the use of combinations of decomposition (i.e., GHI to direct and diffuse irradiance) and translation(direct and diffuse irradiance to POA irradiance) to achieve lowest errors in annual POA insolation.

Project Objectives

Research and development leading to improved models for translation of satellite measurements to estimated irradiance, spatial and temporal variation in irradiance over a power plant's footprint, and translation of irradiance to a system's plane of array can reduce uncertainties in solar energy predictions and thus lead to reduced financial and technical risk to solar power deployment. Accordingly, Sandia National Laboratories pursued research activities in the area of Solar Resource Assessment designed to:

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3. Improve models that estimate direct normal irradiance (DNI) and plane-of-array (POA) irradiance from global horizontal irradiance (GHI).

Project Results and Discussion

Over the course of the project from FY13 through FY15, the Statement of Project Objectives (SOPO) underwent significant modification. The project objectives listed above are those represented in the FY15 SOPO. Here we briefly summarize the project's activities and accomplishments in each fiscal year.

Project narrative

FY13

As originally planned at the beginning of FY13 the project's objectives were overly ambitious. In FY13 effort focused mainly on Task 2, executed through a contract for research at Baylor University. Work for Task 1 was limited due to completion of significant work carried over from FY12 involving assessments of GHI forecast capabilities ([1] through [4], summarized in [5]) and competing demands for the PI's time. Work for Task 3 was planned from the outset to be carried out in FY14. In FY13 the project spent $80k from a budget of $337k, carrying the balance forward to FY14.

FY14

At the beginning of FY14, Task 1 was re-scoped from addressing satellite irradiance in general to an analysis of the anticipated update to the NSRDB by NREL, using an adaptation of NOAA's Global Solar Insolation Project (GSIP) to produce improved GHI estimates from satellite data. Work in FY14 on Task 1 primarily involved analysis of various datasets of ground-measured irradiance in preparation for comparison with satellite irradiance derived using GSIP. NREL was not able to provide NSRDB output for comparison with ground data until early FY15.

Work on Task 2 continued at Baylor University although the technical challenges involved in development and validation of the resulting algorithm resulting in significant delay in accomplishing the validation objectives. Conference presentations were given and a dissertation was published [6]. FY14 plans for Task 2 included validation by modeling power production from a second large-scale PV plant which was not accomplished; efforts to obtain data from an appropriate plant did not succeed.

Task 3 was expanded to include an evaluation of state-of-practice models for translating from GHI to POA irradiance, in collaboration with FirstSolar Inc. and Southern Company. The comparison resulted in several publications containing guidance on how to minimize error in annual POA insolation when using current models ([7], [8]). In addition, research was carried out at Sandia to investigate whether dynamic, data-driven time-series methods could be adapted to produce GHI-to-POA translation methods with significant improvements in accuracy. The work identified an algorithm with significantly reduced prediction error but with impractical computational requirements. In FY14 the project spent $215k, leaving an unspent balance of $438k (from a combination of FY13 carryover and FY14 funds). A summary of work to date was provided to DOE/EERE/SETP [9].

FY15

In FY15 Task 1 was completed which dominated the project effort. We completed two iterations of analysis of the GHI data in the new NSRDB version 3 (which is produced using an adaptation of NOAA's GSIP algorithm) and published the results ([10], [11]). We established baseline statistics for the agreement of NSRDB v3 GHI with ground measurements. More importantly we identified several opportunities for future work to further improve the NSRDB GHI. In the course of the analysis we developed and have submitted for publication two analytical tools which apply to measured ground data, and which proved useful in the comparison of satellite data with ground measurements: identification of clear sky periods; and removal of short-duration shading due to near-field objects.

For Task 2, validation of the algorithm was completed and the results published after protracted reviews ([12], [13]). The project planned to convert the algorithm's code from R to Matlab for general distribution; this was not accomplished due to departure of a graduate student from the research program at Baylor. The project also planned to carry out validation by modeling power production from a second large-scale PV plant. Data for the validation were obtained for the Long Island Solar Farm (LISF) through Brookhaven National Laboratories (BNL) and an initial version of a calibrated irradiance-to-power model for the plant was created; this model would be necessary to the validation, which was designed to compare predicted with measured power, using the plant itself as the integrator over the actual and unobserved spatial irradiance. Delays in funds transfers to BNL and other work commitments resulted in the validation being incomplete when FY15 ended.

Task 3 was deemed as less of a priority than either of the other two tasks, and no efforts were made in FY15 toward its objectives.

In FY15 the project received $48k in FY15 funds. A total of $461k was spent in FY15, leaving approximately $25k unspent for FY16 close-out activities. Since the end of FY15 the majority of these funds have been used to prepare and submit two papers [14], [15] and the remainder to prepare this report. Over the course of the project a total of $781k was received as compared with an originally planned three-year amount of $1180k.

Significant Accomplishments and Conclusions

Results from Task 1

Evaluation of GHI in NSRDB v3

We reported an analysis [11] that compares global horizontal irradiance (GHI) estimates from version 3 of the National Solar Radiation Database (NSRDB v3) with surface measurements of GHI at a wide variety of locations over the period spanning from 2005 to 2012. The NSRDB v3 estimate of GHI are derived from the Physical Solar Model (PSM) which employs physics-based models to estimate GHI from measurements of reflected visible and infrared irradiance collected by Geostationary Operational Environment Satellites (GOES) and several other data sources. Because the ground measurements themselves are uncertain our analysis does not establish the absolute accuracy for PSM GHI. However by examining the comparison for trends and for consistency across a large number of sites, we may establish a level of confidence in PSM GHI and identify conditions which indicate opportunities to improve PSM.

We focused our evaluation on annual and monthly insolation because these quantities directly relate to prediction of energy production from solar power systems. We found that generally, PSM GHI exhibits a bias towards overestimating insolation, on the order of 5% when all sky conditions are considered (Figure 1), and somewhat less (~3%) when only clear sky conditions are considered (Figure 2). The biases persist across multiple years and are evident at many locations. In our opinion the bias originates with PSM and we view as less credible that the bias stems from calibration drift or soiling of ground instruments.

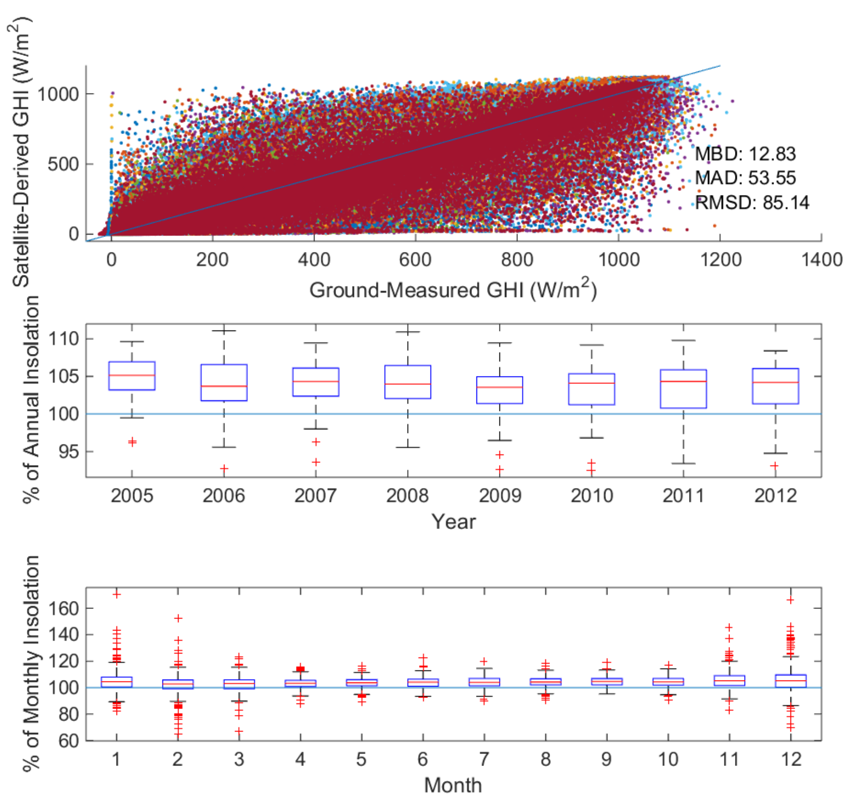


Figure 1. Ratios of NSRDB to ground GHI across 43 locations.

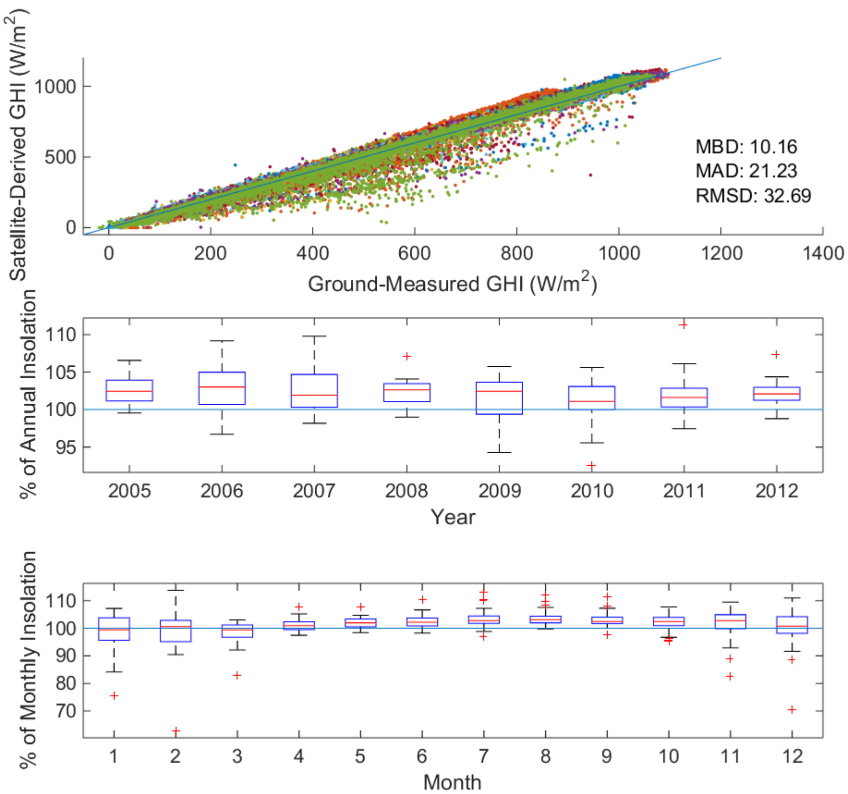


Figure 2. Annual insolation ratios (NSRDB GHI to ground GHI) for clear sky periods.

We observed that PSM GHI may significantly underestimate monthly insolation in locations subject to broad snow cover. We found examples of days where PSM GHI apparently misidentified snow cover as clouds, resulting in significant underestimates of GHI during these days and hence leading to substantial understatement of monthly insolation. Analysis of PSM GHI in adjacent pixels shows that the level of agreement between PSM GHI and ground data can vary substantially over distances on the order of 2 km. We conclude that the variance most likely originates from dramatic contrasts in the ground's appearance over these distances.

We developed a simple algorithm for identifying periods of time with broadband GHI similar to that occurring during clear sky conditions from a time series of global horizontal irradiance (GHI) measurements. Other available methods to identify these periods do so by identifying periods with clear sky conditions using additional measurements, such as direct or diffuse irradiance. Out algorithm compares characteristics of the time series of measured GHI with the output of a clear sky model without requiring additional measurements. Using data from several locations we validated our algorithm by comparing our results with those obtained from a clear sky detection algorithm, and with satellite and ground-based sky imagery. Our algorithm agrees well with the method of Long and Ackerman [reference] which is widely regarded as the best available method (Table 1). The algorithm is published within a Sandia report [16] and is in review for publication in Renewable Energy [14].

Table 1. Percent of 1-minute daytime measurements identified by each algorithm as cloudy or clear.

		Long and Ackerman	
		Clear	**Cloudy**
Reno and Hansen	**Clear**	51.1345 %	3.1914 %
	Cloudy	2.0868 %	43.5874 %

Identification of clear sky periods

Identifying local shading

We developed an algorithm [15] to identify short-duration shading from near-field structures in measured global horizontal irradiance (GHI) data. Shading from wires, poles and trees can contaminate measured irradiance data being used for analyses on short time scales, such as quantifying the frequency and magnitude of changes in irradiance, which are fundamental to analysis and control of electrical power networks which host photovoltaic generation. Particularly in urban areas it may not be possible to site the GHI instrument so as to avoid such shading. On any single day, shading may be brief in duration and appear similar to the shadow from a passing cloud. However, the shading repeats over many consecutive days thus exhibiting structure and pattern that is identifiable using image processing methods. Our algorithm uses image processing techniques to identify and remove from measured irradiance data values that are compromised by near-field shading.

Figure 3 shows one example of data our algorithm can clean. GHI measurements at the instrument (red circle in Figure 3a) are affected by nearby poles, wires and trees (Figure 3b). By arranging the data as a two-dimensional image (axes correspond to time of day and day of year, color corresponds to magnitude GHI) the human eye can easily recognize the shapes of nearby structures which shade the sensor. Our algorithm searches for and identifies connected, non-horizontal features in the image distinguished by large changes in pixel value (i.e., large differences in color) which indicate shading that occurs at roughly the same time over many successive days. These data are identified and flagged for easy removal from the data set (Figure 4).

a

b

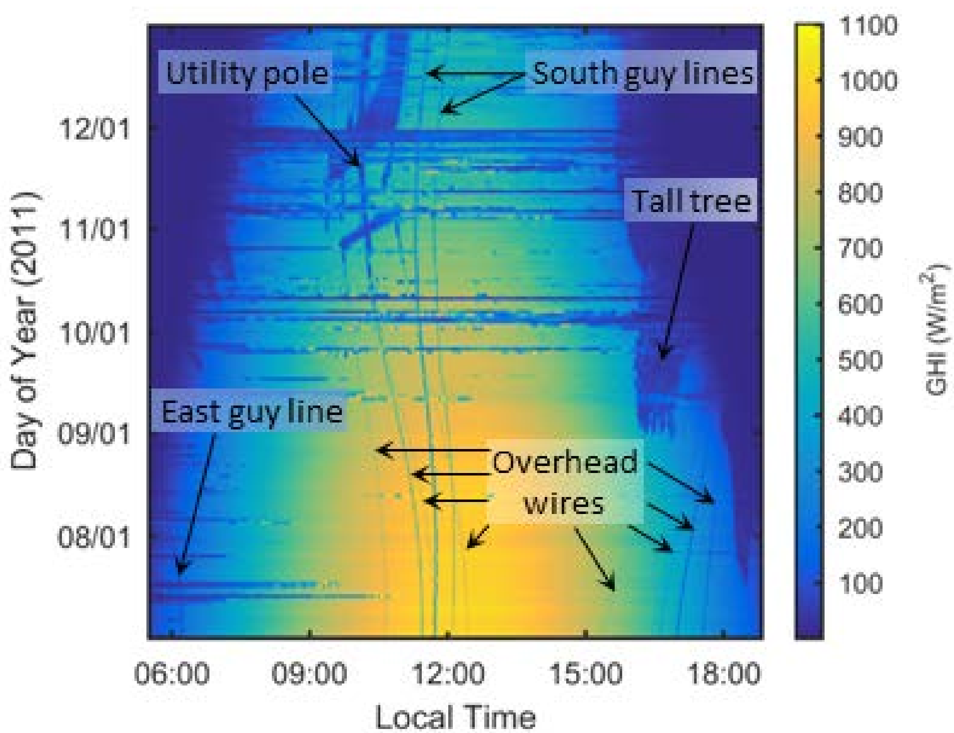


Figure 3. Google Street View image of SMUD station 22 with instrument circled (a); shadows evident in GHI data in image format (b).

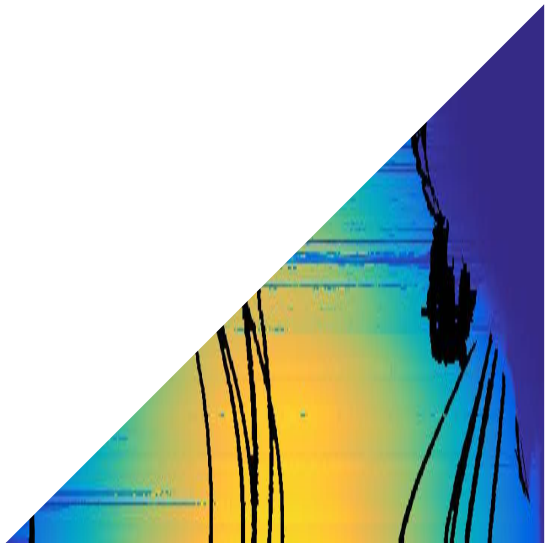
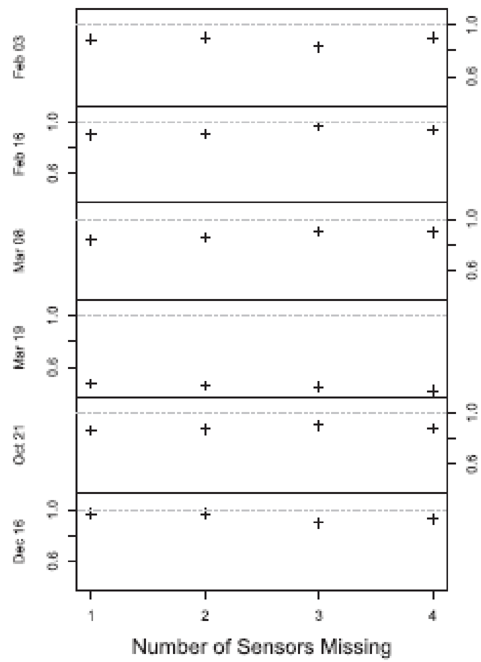


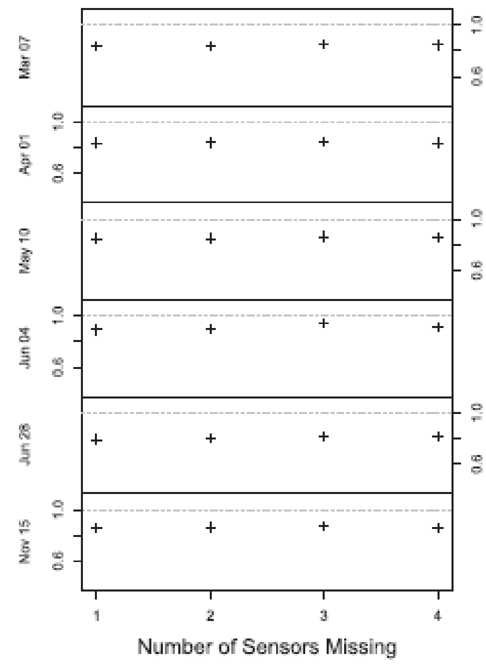
Figure 4. GHI data with shadows (black) identified as resulting from short-duration, near-field shading.

Results from Task 2

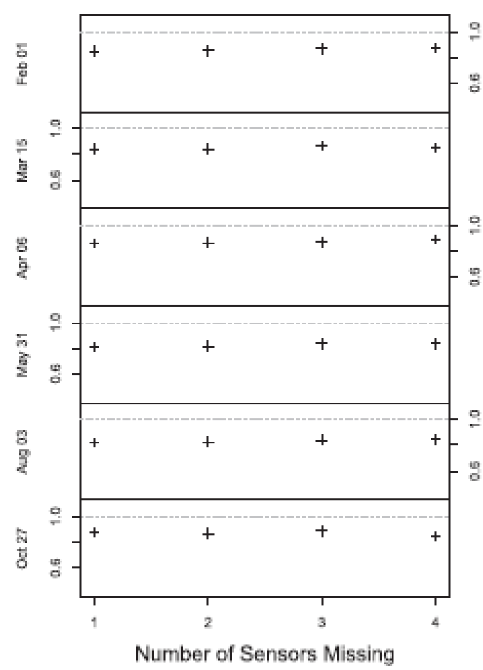
We evaluated semiparametric spatio-temporal models for global horizontal irradiance at high spatial and temporal resolution ([12], [13], [6]). These models represent the spatial domain as a lattice and are capable of predicting irradiance at lattice points, given data measured at other lattice points. Using data from a 1.2 MW PV plant located in Lanai, Hawaii, we show that a semiparametric model, termed the functional coefficient simultaneous autoregression (FCSAR) model, can be more accurate than simple interpolation between sensor locations. Figure 5 illustrates the improvement in accuracy as a ratio of root mean square error (over one day periods) for out-of-sample GHI predicted using FSCAR and by nearest-neighbor linear interpolation. The FSCAR model reduces RMSE by about 20% for most days including clear, partly cloudy and mostly cloudy conditions. In developing the FSCAR approach, in which the spatial and temporal variations are nonseparable, we investigated spatio-temporal models with separable covariance structures and find no evidence to support assuming a separable covariance structure, which would confer substantial simplification on the statistical methods.



(a) Clear days.



(b) Partly cloudy days.



(c) Mostly cloudy days.

Figure 5. Ratios of daily averages of RMSE (FSCAR model to linear interpolation) for predicted GHI by sky condition.

Results from Task 3

Other analyses at Sandia [17] have identified plane-of-array (POA) models (i.e., models that decompose and translate measured irradiance (usually GHI) to POA) as one of two primary sources of uncertainty in energy prediction. Frequently, POA models are used in the project proposal stages, to project earnings, select module and tracking technologies and design the ground configuration. The path to improve these models is not yet clear. We undertook two efforts in response to this challenge: a benchmarking analysis of available decomposition and transposition models, in which we quantified and analyzed the performance of industry standard models ([7], [8]) and a research effort to explore the potential for data-driven time-series methods to produce more accurate POA models.

Analysis of POA modeling error

The evaluation considered many combinations of GHI to direct/diffuse irradiance (i.e., decomposition) models with models that translate direct and diffuse irradiance to a specified tilted surface (translation models) (Figure 6). We examined annual averages of prediction error at several locations with varied climates. Several of these combinations (indicated by red text) are most frequently used in industry because they are the defaults or options within the PVsyst software. We found little to distinguish among the decomposition models, although the Erbs and DIRINT models performed best among those we considered. The two frequently transposition models (Hay/Davies and Perez) perform better than the other two we examined.

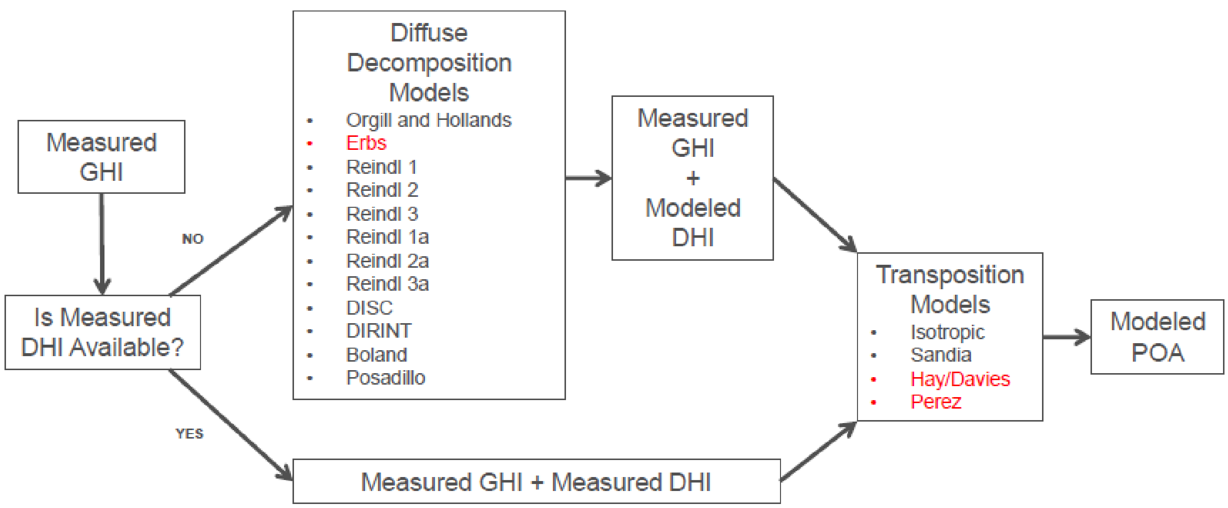


Figure 6. Models considered in our evaluation of GHI to POA irradiance modeling.

For combinations of models, little difference was observed in the combined models whether DIRINT or Erbs was used for the decomposition model, but a large difference was seen between the model combinations involving the Hay/Davies versus the Perez transposition models. Model combinations involving the Hay/Davies transposition model appeared to have less bias than combinations involving the Perez transposition model, even though both Hay/Davies and Perez had similar bias magnitudes when using measured diffuse irradiance. Further analysis testing the impact of varying albedo, minimizing the effect of sensor measurement bias, and examining the impact of decomposition and transposition model bias on combined model bias continued to suggest that combined models involving the Hay/Davies model led to smaller bias.

Currently, it is common for large, utility-scale PV plants to install one of more GHI sensors at the plant location before plant construction to obtain energy production estimates for financing. The combined model biases in transitioning from GHI to POA irradiance found here (often on the order of 1-3% even for the best model combinations) motivate additionally installing POA irradiance sensors to reduce errors in PV energy estimates. Conversely, in locations where no ground measurements are available and modeled GHI (e.g., satellite-derived or TMY) is used, bias and random errors in the modeled GHI will contribute to errors in the final POA estimate (in addition to errors in the GHI to POA conversion). Further analysis is needed to understand how these modeled GHI errors interact with errors in the decomposition and transposition models.

We note that, under the uncertainty analysis task in Sandia's Improving Prediction Accuracy project, we conducted a detailed analysis of the effect of ground albedo on POA modeling accuracy [22]. In that work, measured albedo was combined with detailed irradiance measurements to judge whether the common assumption of a constant, default value for ground albedo contributes significantly to uncertainty in POA irradiance estimates. We found that measuring albedo is not likely to be of value except in certain circumstances where very high or very low ground albedo persists.

Exploration of time series techniques applied to POA modeling

We explored the application of non-parametric time series methods to see if a more accurate method could be identified to translate GHI to POA irradiance. We assumed that a training data set would be available comprising concurrently measured GHI and POA irradiance during all-sky conditions for a sufficient length of time. Training a site-specific model is not unreasonable because many POA evaluations indicate that model accuracy can vary with climate and ephemerides (e.g. [18]).

Examining plots of GHI vs. POA irradiance (Figure 1, left) one readily observes that measurement pairs separate into several different groupings, which reflect sky conditions. One grouping which appears nearly linear indicates clear sky conditions, whereas other groups scattered below this line indicate varying types and degrees of cloudiness. However, the line corresponding to clear sky condition is not static; its slope and extent change in a systematic manner as the sun position and the plane of array change.

We hypothesized that translating GHI to POA irradiance would require different functions to be developed for each data grouping. Because the data groupings appear to correspond with sky conditions (Figure 1, right) and the only information we wish to assume to be available is the time series of GHI, we explored methods for automatically partitioning the GHI time series by sky condition in a manner that will reliably identify data groupings within the plot of GHI vs. POA irradiance.

We found a successful method by applying the Automatic Piecewise Autoregressive Modeling approach AUTOPARM [19]. This procedure identifies an optimal way to select breakpoints which partition a time series into components with different behavior where behavior is determined by the properties of the best-fitting autoregressive model within each partition. Figure 7 illustrates the application of AUTOPARM to the GHI time series. The middle panel shows the time series separated by the breakpoints into five subsets. The top panel shows how these subsets appear within the plot of GHI vs. POA irradiance and shows that the identified breakpoints are largely successful at distinguishing different groups. The bottom panel shows the differenced clearness index kt which, as partitioned by AUTOPARM, will be modeled by a regression technique.

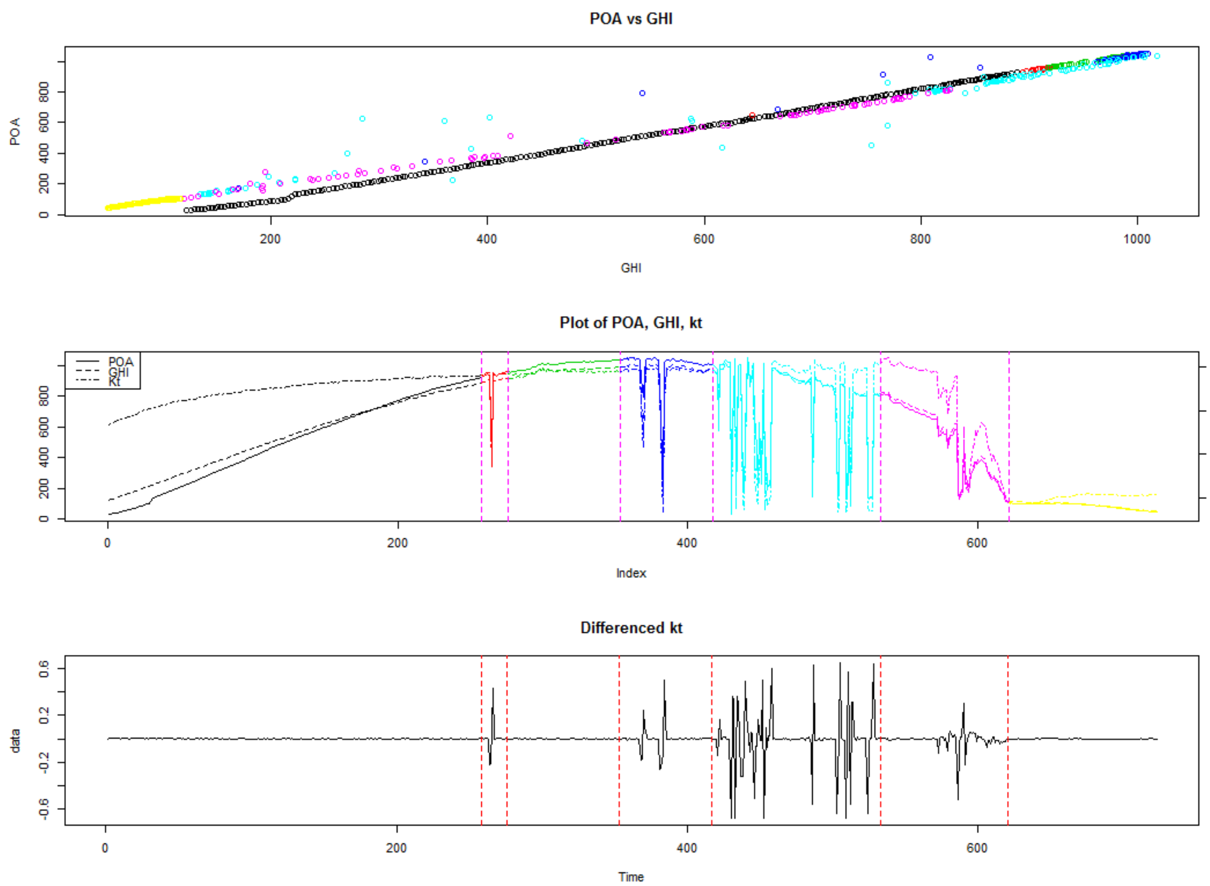


Figure 7. Example data used in exploration of GHI to POA modeling technique, showing GHI to POA comparison (top), partitioning of GHI (middle), and characteristics of differenced kt within each partition element (bottom).

We formulated the following algorithm:

1. Concurrent with a measured time series of GHI and POA irradiance, compute clearness index kt (i.e., the ratio between GHI and extraterrestrial irradiance), solar angles (zenith, azimuth and angle of incidence on the POA), and a moving average of kt.
2. Use AUTOPARM to segregate the GHI time series into subsets.
3. Group subsets by common features (using automated criteria currently being investigated)
4. Model each subset independently using a Multivariate Adaptive Regression Splines (MARS) model form [20].

We applied this algorithm to GHI and POA irradiance measurements at Sandia's PSEL in 2007 and 2008 to calibrate a local model, then used this model to predict POA irradiance for the 2009 and 2010. To avoid contaminating either the model calibration or validation we filtered the measured data to remove values where the measured GHI irradiance exceeded the extraterrestrial irradiance (translated to the same plane) because these values indicate erroneous measurements. Figure 8 displays root mean square error (RMSE), mean absolute error (MAE), mean bias error (MBE) and fraction of data within 2% of its true value for our candidate model (MARS) and several other commonly used models: the isotropic sky model, the Klucher model, Hay/Davies and Perez models [21]. The Klucher model has been identified in some analyses [18] as being competitive in terms of prediction accuracy with the widely-used Perez model [21]. We observe that the MARS model reduces both RMSE and MAE as compared to all these models, which indicates promise that the MARS approach may yield improved POA irradiance models generally. Testing of this algorithm across multiple sites (i.e., those used in [8]) showed that the approach yields an unbiased model with RMSE reduced by about 20% as compared to Hay/Davies or Perez. However, the computational demands of this algorithm are significant, and without substantial improvements would prevent this approach's use for most PV modeling applications.

Work on Task 3 was suspended during FY15 due to competing demands on the PI's time and prioritization of Task 1 by DOE. At the end of FY15, a paper documenting our findings from this exploration is incomplete.

ABQ
RMSE

	Models				
Level	Proposed Algorithm	Isotropic Sky Model	Klucher Model	Hay/Davies Model	Perez Model
High	21.3109	38.5806	28.4446	30.5398	27.4167
Med	36.1981	41.6046	40.2500	43.3865	42.5565
Low	52.9446	55.0310	54.5593	57.2567	56.7201
Overall	29.6283	41.6021	34.6755	36.9636	34.8463

MAE

	Models				
Level	Proposed Algorithm	Isotropic Sky Model	Klucher Model	Hay/Davies Model	Perez Model
High	13.9122	29.4190	16.9477	19.5090	15.1696
Med	26.5914	30.3848	27.7699	30.3399	28.8021
Low	35.1614	35.9181	33.7274	36.3541	35.0252
Overall	18.2941	30.4351	20.4981	23.0695	19.4628

MBE

	Models				
Level	Proposed Algorithm	Isotropic Sky Model	Klucher Model	Hay/Davies Model	Perez Model
High	-0.0097	-22.8660	-3.2953	-7.3802	2.6568
Med	0.0099	-14.8196	5.9927	-2.2177	8.1822
Low	-0.0188	-17.5407	3.2672	-4.0393	6.2036
Overall	-0.0088	-21.2259	-1.3440	-6.3385	3.7677

Proportion of data within 2% of its true value

	Models				
Level	Proposed Algorithm	Isotropic Sky Model	Klucher Model	Hay/Davies Model	Perez Model
High	0.5227	0.1335	0.4508	0.3599	0.5091
Med	0.2519	0.1957	0.2581	0.2234	0.2620
Low	0.2460	0.2122	0.2784	0.2455	0.2807
Overall	0.4539	0.1514	0.4052	0.3287	0.4497

Figure 8. Accuracy of proposed POA irradiance model evaluated for out-of-sample data in Albuquerque.

Inventions, Patents, Publications, and Other Results

Publications

Task 1

Analysis of Global Horizontal Irradiance in Version 3 of the National Solar Radiation Database, Clifford W. Hansen, Curtis E. Martin, Nathan Guay, SAND 2015-8023, Sandia National Laboratories.

GSIP Verification and Validation: Preliminary Analysis, Clifford W. Hansen, presentation at 2015 PV Solar Resource Workshop, Golden, CO, February 27, 2015.

Identification of Detection of Clear Sky Periods Equivalent Irradiance in Time Series of GHI Measurements, Matthew J. Reno and Clifford W. Hansen, Renewable Energy (in review)

An Image Processing Algorithm to Identify Near-Field Shading in Irradiance Measurements, Curtis E. Martin and Clifford W. Hansen, Solar Energy (in review)

Task 2

Semiparametric Estimation and Forecasting for Functional-Coefficient Autoregressive Models, Joshua D. Patrick, Dissertation submitted to the Graduate Faculty of Baylor University, 2013.

A semiparametric spatio-temporal model for solar irradiance data, Joshua D. Patrick, Jane L. Harvill, Clifford W. Hansen, Renewable Energy (to appear).

Spline-backfitted kernel forecasting for functional-coefficient autoregressive models, Joshua Patrick, Jane Harvill, Justin Sims, submitted to Computational Statistics & Data Analysis. http://arxiv.org/abs/1502.03486

Task 3

Evaluation of Global Horizontal Irradiance to Plane of Array Irradiance Models at Locations across the United States, Clifford W. Hansen, Andrew Pohl, Matthew Lave, William Hayes, Will Hobbs, Proc. of the 40th IEEE Photovoltaic Specialist's Conference, Denver, CO, June 2014

Evaluation of Global Horizontal Irradiance to Plane-of-Array Irradiance Models at Locations Across the United States, Matthew Lave, William Hayes, Andrew Pohl, and Clifford W. Hansen, Journal of Photovoltaics **5**(2), 597-606, March 2015

Path Forward

At present Sandia National Laboratories has ended its research effort in solar resource assessment in support of DOE/EERE/SETP objectives, i.e., SunShot. The FY16-18 SunLamp request for laboratory proposals did not invite proposals for research targeted towards reducing uncertainty for predictions of energy from PV systems. Although the SunLamp call invited work related to solar resource characterization, respondents were limited to the National Renewable Energy Laboratory (NREL). Consequently Sandia did not propose continuation of this research.

We regard Task 1 as complete at this time and for the initial release of the NSRDB version 3. However, we recommend that DOE support equivalent analysis of the NSRDB as it evolves so that 1) the public remains well-informed of the accuracy of the data, and 2) the developers continue to identify opportunities for improvement.

In our best judgment, code resulting from Task 2 is valuable and should be made available for public use. Validation of the FCSAR algorithm by application to predicting power from a large solar plant should be completed in order to determine the improvement in accuracy offered by using this algorithm. The validation would comprise: 1) fitting the FCSAR model to measured irradiance data at the plant; 2) separately, constructing an appropriate irradiance to power translation model using, e.g., techniques packaged in PV_LIB [22]; 3) using the fitted FCSAR model to predict spatial irradiance across the plant's footprint over time and then using the irradiance to power translation model to convert the predicted irradiance to power; 4) predicting spatially-averaged irradiance and corresponding power using other irradiance modeling techniques in common use, e.g., linear interpolation and the wavelet model [Lave]; and 5) comparing predicted with measured power for each irradiance modeling technique. We expect that FCSAR would show an improved accuracy commensurate with the reduction in RMSE indicated by Figure 5, i.e., 20% lower RMSE generally.

We believe the work in Task 3 merits continuation but hesitate to recommend the particular algorithm to be carried forward. We remain convinced that efforts to improve the accuracy of POA irradiance modeling merit support, as this step in the modeling process will remain one of the primary sources of uncertainty in predicted energy.

References

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