Quantifying Uncertainty in PV Energy Estimates Final Report

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Technical Report
NREL/TP-7A40-84993
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Executive Summary

Uncertainty in photovoltaic (PV) energy estimates is one of the most critical areas in which we lack understanding, according to independent engineers, financiers, PV model developers, and other industry stakeholders. The primary problem is a lack of rigorous, transparent, widely accepted methods for quantifying uncertainty in energy production estimates.

Uncertainty in energy production estimates arises from variability of the solar resource, inexact PV performance models and their parameters, and system reliability considerations. Uncertainty in annual energy production is frequently calculated for larger projects in order to quantify financial risk. Key statistics for energy, such as the P-values "P50" and "P90" (the annual energy values that are exceeded in future years with 50% and 90% probability, respectively) are used by financing institutions to calculate the repayment risk for the project. The current methods to estimate these statistics are typically proprietary, specialized, and involve significant post-processing of commercial performance model results. This black-box approach leads to inconsistent P-value estimates from different parties, which reduces investors' confidence in the results. Because the financial community bases its risk assessment on these estimates, reduced confidence increases perceived project risk, and consequently financing costs.

The goal of this project was to establish a set of best practices for quantifying uncertainty in energy production estimates, including identifying what sources of uncertainty must be considered with clear definitions and metrics, determining which sources are the largest drivers of uncertainty, and providing a computationally efficient framework for combining different sources of uncertainty that is flexible enough to accommodate substitutions of data or methods when better information is available. We engaged a wide set of stakeholders to ensure industry endorsement and adoption, and leveraged complementary projects investigating individual sources of uncertainty in great detail, as well as others' work that started down this path.

This project presents a method for combining inter-annual solar resource variability, modeled using historical weather files, with annual factors representing other sources of uncertainty in a computationally efficient framework. Using annual factors was a strong recommendation of our stakeholder group, and allows many previously published studies to inform the uncertainty values. By surveying the literature on this topic, we are able to provide a list of uncertainty categories that should be considered, and populate some of those values with reasonable estimates found by other work. We also quantify two factors, related to uncertainty in solar resource measurements and energy from bifacial PV systems, which have not been previously available. To demonstrate the uncertainty quantification method and encourage its adoption, we have implemented it in the widely deployed, freely available, and open-source National Renewable Energy Laboratory's (NREL's) System Advisor Model (SAM) platform.

Acknowledgment and Disclaimer

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1 Introduction

Photovoltaic (PV) systems have become a popular energy investment that can provide clean energy from a renewable energy source. As PV systems receive continued investment and make up a greater portion of the worldwide energy generation profile, performance modeling of the expected outcome of individual PV systems must be reasonably accurate so as to be bankable and provide a proper evaluation of the risk associated with these PV system investments [Feldman (2018)]. In the past several years, trends of underperformance in PV systems relative to initial model projections have motivated research into the different factors of PV performance modeling and the uncertainty that each of these factors brings into the performance estimates, particularly in probability of exceedance analysis aimed at determining the threshold energy yield that should be expected in future years at a given probability [kWhAnalytics (2022,2021,2020)]. Lack of accounting for the different factors of model uncertainty, whether the uncertainty is derived from solar resource variation over time, the measurements that provide the performance model input data or uncertainties in the models themselves, leads to increased risk from project financiers that could dissuade from future investment in PV projects. kWhAnalytics has published annual reports on the state of PV system underperformance, and has found that approximately 1/7 of the evaluated PV systems have underperformed their P99 value (i.e., the energy yield expected to be exceeded with 99% probability in future years [kWhAnalytics (2022, 2021, 2020)]). The vast majority of lost revenue from these underperforming projects has been traced to the underperformance of the PV projects, which indicates a need for improved uncertainty modeling practices used in PV performance modeling estimates.

Independent engineers and PV system developers currently incorporate uncertainty into their models when projecting energy yield to report to investors, but these practices can vary wildly due to different assumptions on the types and degrees of uncertainty that should be included in these analyses. Several uncertainty quantification efforts have been published detailing uncertainty quantification methods and results [Müller (2015), Hansen (2015)], but no single uncertainty quantification methodology has become widely accepted and broadly applied in industry. Each developer has different ideas about the methods used to calculate uncertainty, how many simulations are sufficient, and the factors that represent uncertainty in quantities such as solar resource, PV module temperature, and DC wiring losses. Based on feedback from independent engineers on their uncertainty quantification, there is a need for standardized uncertainty modeling practices for PV system performance estimates.

This work describes the development of a methodology for quantifying the uncertainty in an annual energy production estimate that standardizes and better defines probability of exceedance estimates for PV projects. This work also covers quantification of two poorly-understood sources of uncertainty: (1) solar resource measurement uncertainty and (2) uncertainties stemming from bifacial gains in bifacial systems. We describe the implementation of this methodology into the National Renewable Energy Laboratory's (NREL's) System Advisor Model (SAM), a free and open-source software tool that contains robust PV performance calculations and financial modeling, in order to better disseminate the methodology described in this paper [SAM (2022)].

A key element of the uncertainty quantification methodology presented in this report is the separation of the variability in solar resource from the other factors that contribute to solar performance uncertainty. Current practices often treat these two uncertainty sources in the same manner, but a key difference between the two is the ability to know or improve in knowledge of the uncertainty stemming from said categories. For resource variability, while the trends in year-to-year solar resource variation can be predicted, future resource cannot be known exactly. For other uncertainty categories that involve measurement of system specifications or modeling of system component performance, theoretically more information or better understanding can be achieved to reduce the impact of these factor on the overall uncertainty of the energy estimates.

The remaining sections of this report define and describe the types of uncertainty that should be considered in the PV performance calculations, the different sources of uncertainty that should be considered in the calculations, methods for quantifying and combining the individual sources of uncertainty, and examples of results generated from the newly developed SAM uncertainty tool.

2 Methodology

Uncertainty in PV annual energy yield estimates is typically quantified through probability of exceedance analysis. The probability of exceedance refers to the percentage likelihood that the annual energy yield in a future year will exceed the specified energy value; for example, the P90 value is the annual energy that one would expect to be exceeded with 90% probability. Recent trends in deployed PV system behavior have shown consistent overestimation of the expected annual energy yield estimates, with the systems often even failing to outperform P99 estimates due to losses in actual system behavior that are not accurately characterized in modeled annual energy yield estimates [kWhAnalytics (2022, 2021, 2020)].

Uncertainty in annual energy yield estimates arises from two main categories of uncertainty: aleatory, or random uncertainty; and epistemic, or lack of knowledge uncertainty. Aleatory uncertainty is inherent in annual energy estimates and cannot be reduced with improved data collection, data quality, or model accuracy. The primary component of aleatory uncertainty in PV energy yield estimates is the inter-annual variability (IAV) of the solar resource for the site being considered. Future solar resource cannot be known exactly. Multiple years of historical weather are often used to represent this uncertainty and to quantify its effect on modeled annual energy yield. Solar resource uncertainty represents one of the largest sources of uncertainty in annual energy modeling, and therefore the methods developed here includes explicit and separate treatment of this uncertainty [IEA (2018)].

The second category of uncertainty affecting PV annual energy yield estimates is epistemic uncertainty. Epistemic uncertainty includes all modeling parameters, data and model formulations that are inexact representations of the physical system, and which (in theory) could be improved upon with improvements in performance models, or more accuracy in data measurement. The epistemic uncertainty category includes all PV performance model and submodel uncertainties, as well as uncertainties in the measured data used as inputs to the models.

In probability of exceedance calculations, epistemic uncertainty factors can be represented by distributions of uncertain input parameters or alternative models. However, due to the large number of parameters and models involved in annual energy simulations, this approach is generally impractical, as it requires quantifying the uncertainty of each input. An alternative is to compute a base annual energy value and estimate uncertainty in this base annual energy value using multiplicative factors. We adopted this alternative approach, as explained next.

To outline the methods, we introduce some notation. Denote by Y the annual energy from a PV system. Formally, Y is a random variable with uncertainty stemming from both epistemic uncertainty in models and parameters, and aleatory uncertainty in weather. Denote by $\overline{Y}$ the annual energy of the PV system for a selected base year of weather (which could be a typical meteorological year) and a "best estimate" performance model with selected models and parameters. $\overline{Y}$ is a single value, whereas Y has a distribution of values, which we estimate as described next.

Epistemic Uncertainty in Annual Energy

Epistemic uncertainty in Y is estimated by means of a set of factors $F_k, k = 1, \ldots, K$ where each factor represents uncertainty in the base annual energy $\overline{Y}$ that arises from uncertainty in parameters or components of the performance model. For example, one factor could represent uncertainty in annual energy that arises from uncertainty in irradiance measurements. Each factor F_k has units of fraction of $\overline{Y}$. The sign of F_k reflect the convention that each factor represents a "loss" or reduction in energy (e.g., $F_k = 0.03$ indicates a 3% reduction in energy). Each factor F_k is itself a random variable having an uncertainty distribution. Assuming that the factors F_k are independent, the random variable Y is computed as:

$$Y = \overline{Y} \prod_{k=1}^{K} (1 - F_k) \tag{2.1}$$

The distribution of Y represents uncertainty in $\overline{Y}$ that results from the combined effects of the uncertainties represented by the factors F_k. Y has the same units as $\overline{Y}$. If each F_k is described by a normal distribution with parameters (μ_k, σ_k), statistics for the distribution of Y can be computed directly:

$$E(Y) = \overline{Y} \prod_{k=1}^{K} (1 - \mu_k) \tag{2.2}$$

$$Var(Y) = \overline{Y} \prod_{(k=1)}^{K} (\sigma_k^2 + \mu_k^2) \tag{2.3}$$

For any other statistic of the distribution of Y, such as a percentile, or for the case where at least one factor F_k is not described by a normal distribution, a sampling scheme can be used to compute the distribution of Y:

1. For each F_k generate a random sample of size M, $f_{(i,k)}, i = 1, \ldots, M$, from the distribution of F_k.
2. Compute a sample of the uncertainty distribution for Y: $y_i = \overline{Y} \prod_{(k=1)}^{K} (1 - f_{i,k}), i = 1, ..., M$
3. Compute the statistic of interest from the set $y_i, i = 1, \ldots, M$

To obtain a percentile P, M should be chosen so that $M > 10/P$. For example, for the 5th percentile, $P = 0.05$, so $M > 10/0.05 = 200$.

Aleatory Uncertainty in Annual Energy

Interannual variation in weather, primarily irradiance, causes variation in annual energy that is separate from any other uncertainty affecting a single year's annual energy. Interannual variation in weather is commonly represented by using multiple different years of historical weather data. A common source of sufficient years of data is the NREL National Solar Radiation Database [NSRDB], which contains more than 20 years of historical weather data for many locations. Using historical data assumes that future weather is well-represented by past weather, which in many cases, is the best available assumption. Long-term predictions of future weather could be used in this same methodology in addition to, or instead of, historical data.

For uncertainty in annual energy arising only from interannual weather variability, we assume that any historical weather year is equally likely to occur in the future. We simulate the annual energy for the specified PV system for each year of weather data supplied, keeping all other inputs fixed at their nominal values, to obtain a set of annual energy estimates $\overline{Y}_j, j = 1, ..., N$ where N is the number of years of weather data. To understand the effect of the uncertainty in weather, and to compare with the uncertainty arising from all other factors, we may calculate an empirical probability distribution from this set of annual energy estimates.

Combined Uncertainty

After estimating the uncertainty distribution of the base annual energy, $\overline{Y}$, and calculating the annual energy $\overline{Y}_j$ for each weather year $W_j, j = 1, ..., N$, we can combine both sources of uncertainty in an efficient, straightforward manner. We assume that the uncertainty distribution of $Y/\overline{Y}$ is independent of the weather year W, that is, the uncertainty factors applied to $\overline{Y}$ to obtain the distribution of Y are independent of weather. As a consequence of this simplifying assumption, we may estimate uncertainty in each $\overline{Y}_j, j = 1, ..., N$ using the sample $y_i, i = 1, \ldots, M$ from the uncertainty distribution for Y:

$$y_{i,j} = \frac{\overline{Y_j}}{\overline{Y}} \times y_i, i = 1, ..., M \tag{2.4}$$

The samples $y_{i,j}$ are pooled over all weather years to form a sample from the distribution of overall uncertainty in Y:

$$X = y_{i,j}, i = 1, ..., M, j = 1, ..., N \tag{2.5}$$

The sample X can be sorted from least to greatest and its exceedance probabilities correspond to the usual interpretation of P50, P90, etc., as representing the likelihood of future annual energy given all sources of uncertainty.

We think it useful to implement the computation in two stages in order to provide insight into the source of variation in annual energy: does the variation arise primarily from interannual variability in weather, or from uncertainty in models and parameters? If the effect of uncertainty in models and parameters exceeds that of weather variability, then in concept uncertainty can be reduced by investment in more accurate models.

3 Uncertainty Factors

3.1 Factors From Literature Review

Epistemic uncertainty factors to be included in the SAM uncertainty modeling tool were identified through sensitivity analysis of factors previously identified in Table 15 of the IEA Task 13 report *Uncertainties in PV System Yield Predictions and Assessments* [IEA (2018)]. Factors were divided into first-order and second-order factor categories based on the sensitivity of annual energy to each factor. Our categorization is also informed by previous work to identify sensitivity of PV model outputs to uncertainty in their inputs [Hansen (2015)].

By design of Eq. 2.5, epistemic uncertainty in annual energy is proportional to the uncertainty in each factor. However, some factors are known with greater certainty than others. Generally, first-order factors are those with greater uncertainty, as indicated by wider uncertainty distributions, where second-order factors are those whose distributions are narrower.

The first-order and second-order factors listed below span the PV performance model chain from solar resource to the electricity output of the system. These factors account for the majority but not all of the uncertainty in annual energy yield estimates, aside from the solar resource interannual variability, which is handled through separate calculations.

First-Order Factors:

First-order uncertainty factors include:

Irradiance transposition: this factor covers the transposition modeling used to go from global horizontal irradiance (GHI) to the amount of irradiance that is incident on the module surface at any given timestep. The SAM PV models allow for the use of the Perez, Isotropic, and HDKR transposition models [Gilman (2018)]. These models, along with any other potential modeling methods used to derive incident irradiance, introduce uncertainty to the annual energy outputs, as the irradiance is the driving factor in the PV module power output.

Shading (horizon and local): the inclusion of shading effects that reduce incident irradiance on portions or entire surface areas of modules and thereby reduce the overall power output of the PV system. The shading can come from obstructions such as buildings or mountains, or the rows of modules in the PV system can shade adjacent rows throughout the day.

Standard test conditions (STC) power: the standard temperature and conditions power rating of the module. This STC rating defines the power output at a standard set of irradiance, wind speed, and module temperature condition. The STC rating is then used in module performance modeling to determine the power output for conditions that deviate from these standard conditions. Uncertainty in the methods used to generate the STC module rating can lead to uncertainty in the module annual energy yield.

Inverter availability: whether the inverter is available to convert the DC power generated from the PV system into AC power that can be delivered to the grid or electrical load. Lack of knowledge into when the inverter will be down from device failure or routine maintenance can introduce uncertainty into the annual energy yield.

Second-Order Factors:

Second-order factors include:

Spectral response: adjustments made to the module power output based on the wavelength of light incident on the module surfaces and the module's ability to convert light at said wavelengths into electricity.

Cell temperature: the temperature of the cells within the PV modules at any given timestep. Increases in cell temperature linearly decrease the efficiency of the PV modules. The cell temperature is directly impacted by the incident irradiance and the ambient conditions at a given timestep. SAM contains several models for the calculation of cell temperatures for both steady-state and transient thermal conditions, and any cell temperature model introduces uncertainty into the results based on potential bias errors or differences in modeled and actual system thermal behavior.

Mismatch loss: mismatch in the performance of modules within a string or array. Differences in module performance can lower the performance to that of the worst-performing module in a string. Failure to account for the amount of mismatch loss in the PV array can introduce uncertainty into the yield estimates.

Electrical loss: voltage losses from the wiring of the PV system or losses that occur when AC power output passes through the transformer.

Other factors not listed above may also have a significant influence on the uncertainty in the annual yield estimates. Such factors are omitted because we lack a technical basis to quantify a distribution of values; omitted factors include uncertainty in transformer performance and the effects of soiling and snow on energy production, among others. As a contribution toward quantifying uncertainty factors not listed above, we summarize original work done in this project to quantify two additional factors: uncertainty in measurements of the solar resource, and uncertainty in energy from bifacial PV systems.

3.2 Quantifying Uncertainty for Measured Solar Resource

In this section, we consider quantifying a factor F that represents uncertainty in annual energy resulting from uncertainty in irradiance measured with a pyranometer. Pyranometer accuracy relative to broadband irradiance is often reported to be in the range of 3% to 20% (at 95% confidence) for hourly totals, with lower uncertainty for daily totals (2% to 10%) ([WMO (2020)], Volume I, Table 7.4). The per-time-interval uncertainty of a pyranometer results from a variety of physical and operational factors; lower uncertainty is achievable but requires "constant attention to uncertainty sources...Failure in controlling (these factors) quickly results in a strongly degraded accuracy..." [Vuill (2014)]. Pyranometers are typically calibrated by comparison to a previously-calibrated standard instrument, at conditions specified in [ISO9947 (1992)].

In contrast, an uncertainty factor F to be applied to a base estimate of annual energy should represent the effect on energy production of pyranometer uncertainty averaged over all conditions, with greater weight given to values at high in-plane irradiance when most energy is produced. Because high in-plane irradiance generally corresponds to the calibration conditions, we may expect that F would be less than the "all-condition" uncertainty of a randomly-selected measurement, and less than the hourly or daily values published in [WMO (2020)].

Hansen and Scheiner report an analysis quantifying the factor F for a set of pyranometers of differing quality, using data at a single location (Golden, CO). The subject instruments are maintained on a daily basis, and the resulting measurements are regarded as among the best achievable. A secondary standard pyranometer (Kipp and Zonen CMP-22) is regarded as providing ground truth of GHI; uncertainty in GHI measurements for other instruments is estimated by the deviation from the selected ground-truth GHI. Using a year of data, a statistical model of deviation from ground-truth GHI is constructed for each instrument, accounting for dependence on irradiance level, air temperature, solar zenith, and for autocorrelation in deviation with time. The model is used to simulate many years of irradiance values that (by virtue of the model) are statistically similar to the observed year. For a notional PV system, annual energy is simulated for each synthetic GHI time-series, keeping all other models and factors constant, to generate a distribution of deviation from the annual energy that results from simulating energy with the base year of GHI. The resulting uncertainty distributions appear similar for many pyranometers. Hansen and Scheiner recommend that the factor F be characterized by a normal distribution with uncertain mean and standard deviation sampled from uniform distributions with ranges [-0.4%, 0.4%] and [0.35%, 0.6%], respectively. The resulting distribution for F is substantially narrower than suggested by the hourly or daily uncertainty given in [WMO (2020)] (Figure 5 of [Hansen (2022)]).

The analysis procedure described in [Hansen (2022)] may provide a template for quantifying other annual uncertainty factors from data available as time-series, such measurements of module temperature, or for factors expected to exhibit strong auto-correlation, such as uncertainty in irradiance transposition. Quantifying annual uncertainty using a statistic such as standard deviation over a year would not account for auto-correlation in uncertain values and thus would tend to understate the magnitude of the annual uncertainty factor. Moreover, quantifying annual uncertainty using a per-value uncertainty neglects any reduction in magnitude that implicitly results from summation (averaging) over a year of data and thus tends to overstate the magnitude of the annual factor.

3.3 Quantifying Bifacial Modeling Uncertainty

This section describes efforts to investigate modeled bifacial module rear-surface energy gain uncertainties. This work was based on Monte Carlo PySAM simulations covering model sensitivities for the variable inputs for system albedo, ground clearance height, bifaciality, and module transmission factor [Prilliman (2022)]. These variables were chosen due to the difficulty associated with accurately measuring or quantifying the values of these variables for newly installed systems. The PySAM simulations were constructed based on a wide variety of bifacial system archetypes that were specified through variation of system input parameters covering the expected range of values to be seen in installed system for each system variable. For each system archetype, the albedo, ground clearance height, bifaciality, and transmission factor are each varied $\pm 10\%$ from the archetype parameter value over a total of 100 random samples. Each simulation was evaluated for the bifacial energy gain to be used in comparison against the output bifacial energy from the baseline archetype simulation results. Results from fixed-tilt bifacial simulations showed mean and standard deviation ranges in bifacial energy gain of [-0.04%, 0.04%] and [0.08%, 0.22%], respectively. For single-axis tracking systems, these mean and standard deviation ranges were found to be [-0.04%, 0.04%] and [0.09%, 0.16%], respectively. The analyses revealed increased deviation in bifacial energy gain results for higher GCR values due to the decreased row spacing and row-to-row shading impacting the bifacial energy gain of system archetypes. Full results can be found in [Prilliman (2022)].

4 Implementation in SAM

The methodology described above has been implemented in the free, open-source software tool SAM. This allows industry to experiment with the methodology, and to see the underlying implementation and calculations in order to facilitate adoption of the methodology.

The SAM implementation allows for users to provide distributions of annual energy factors attributed to uncertainty sources in the categories defined in this report. Default uncertainty distributions are provided in the SAM uncertainty tool interface and are summarized in Table 1. The distribution parameters in Table 1 are presented as a percentage of the annual energy, which would be converted to a fraction of annual energy to be used in the equations outlined previously in this report. Many of these default uncertainty distributions are defined as normal or triangular distributions based on previous uncertainty quantification work done through the IEA Photovoltaic Power Systems Programme Task 13 [IEA (2018)]. While the uncertainty distributions for each factor will vary at each site and the default values may not be appropriate for every situation, these default values serve as a helpful starting point for projects in early development or in situations where not enough data is available to properly identify the uncertainty distributions.

Table 1. SAM Default Distributions for Uncertainty Factors

Factor	Distribution type	Parameters
Irradiance transposition	Normal	$\mu = 11.5$, $\sigma = 2.5$
Horizon shading	Triangular	min.=-1, mode=0, max.=0
Row shading	Triangular	min.=-5, mode=-1, max.=0
Single module rating at STC	Normal	$\mu = 0$, $\sigma = 2.0$
Inverter availability	Triangular	min.=-5.7, mode-2.70, max.=0
Spectral response	Normal	$\mu = -1$, $\sigma = 0.5$
Cell temperature	Normal	$\mu = -2.4$, $\sigma = 1.0$
Mismatch loss	Triangular	min.=-1.8, mode=-0.8, max.=0
DC wiring	Triangular	min.=-2.5, mode=-1.5, max.=-1
Transformer	Triangular	min.=-2, mode=-1, max.=-0.5
Soiling	Triangular	min.=-1.5, mode=-0.5, max.=0

The probability of exceedance results generated by the SAM uncertainty tool are separated into three graphs: the combined effects of both weather and model uncertainty, and the individual effects of the two different uncertainty categories. The user can specify the desired probability of exceedance (e.g. P75, P90, etc.). The first graph, in Figure 1, shows the annual energy distribution from the combined effects of both aleatory and epistemic uncertainty (Eq. 2.5).

The next figure seen on the SAM uncertainty page (example shown in Figure 2) presents the distribution of annual energy considering only the uncertainty in weather, as represented by the different weather files supplied in the analysis. This distribution isolates the effect on annual energy of uncertainty in future weather. The final figure in the SAM uncertainty tool (example shown in Figure 3) displays the distribution of annual energy resulting from applying the uncertainty factors to the energy modeled for the base weather year (Eq. 2.1). This third distribution isolates the effect of uncertainty in models and parameters. Comparison of these two figures informs the modeler as to the relative importance of each type of uncertainty, and may indicate when investment in improved models could be of value.

The output data and graphical results from the uncertainty tool can be saved for future reference or modification. The results can also be exported to other data tools for further analysis. The code for the uncertainty calculations is available in the open-source repositories of SAM's code infrastructure. More information is available at the SAM Github. [1]

[1] https://github.com/nrel/sam

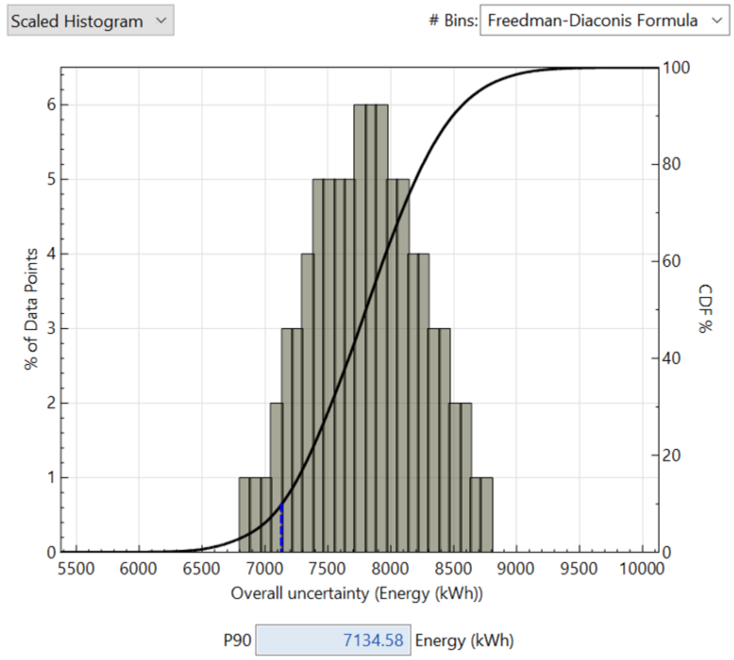

Figure 1. Combined uncertainty graph from SAM uncertainty tool

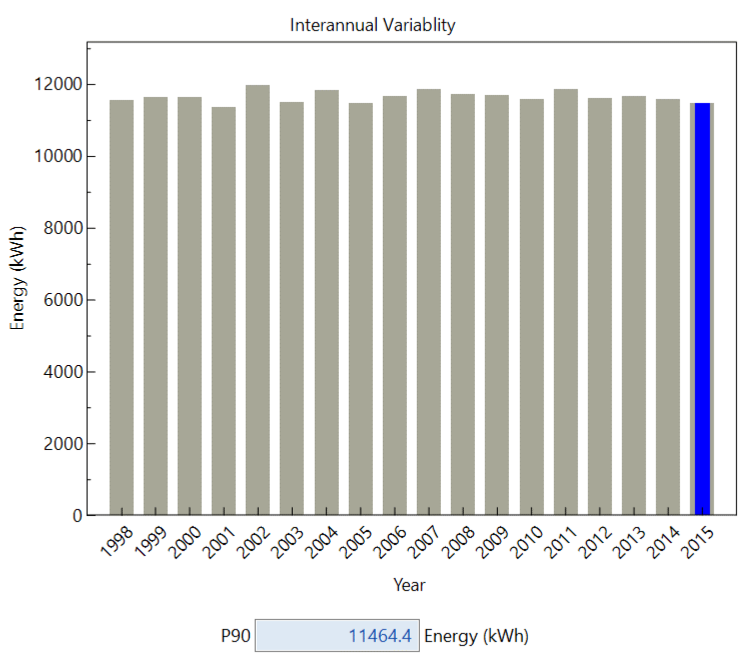

Figure 2. Weather uncertainty graph from SAM uncertainty tool

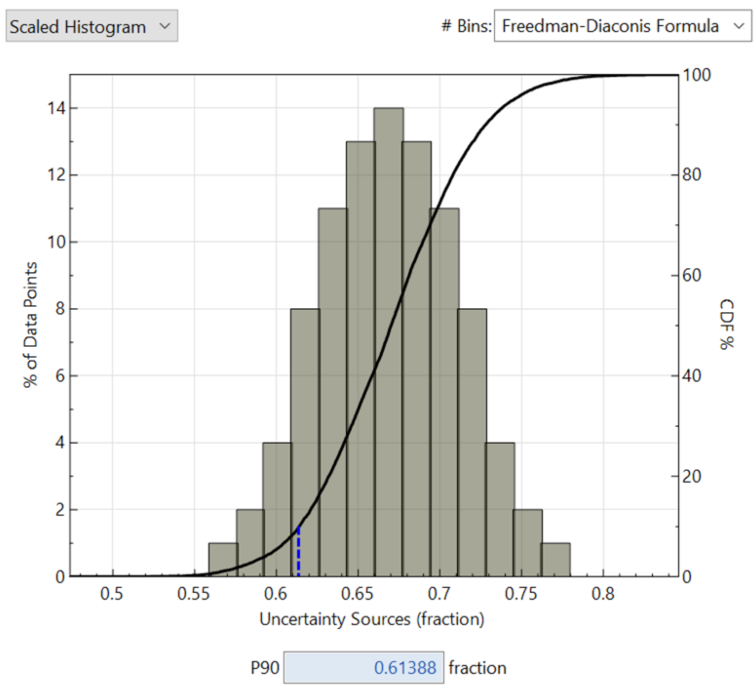

Figure 3. Uncertainty factor graph from SAM uncertainty tool

5 Conclusions

This report presents a methodology for PV energy yield calculations, identifies the key sources of uncertainty to be considered in PV system energy yield calculations, and describes a new uncertainty modeling tool contained within NREL's SAM. This work aims to improve uncertainty modeling practices and to facilitate a rigorous, transparent, and widely accepted method for uncertainty calculations within the energy yield modeling workflow of SAM or other modeling tools.

We think it valuable to separate the effects of variability in the solar resource from the effects of other sources of uncertainty. Separating these effects aids in communicating why energy estimates are uncertain and informs decisions to invest in more accurate modeling.

Our methods rely on multiple years of historical weather data to quantify uncertainty in future weather, and on annual uncertainty factors to represent all other sources of uncertainty. These methods provide for efficient computation of P-values, but demand that uncertainty factors be quantified as the effect on annual energy of the various sources of uncertainty. We provide default values for several factors we deemed of primary importance, including: transposition modeling of incoming irradiance, modeling of shading effects, STC power rating of PV modules, and inverter availability considerations. We also provide default values for other factors of substantial but secondary importance. The implementation of this uncertainty methodology in SAM allows for easy user interface definition of the uncertainty categories and weather files to use in the analysis, and generates useful graphical outputs to help investigators better understand uncertainty in the model results.

Future work to improve this methodology could include quantification of additional uncertainty factors, such as uncertainty in energy loss due to snow, and to refine the default quantifications for factors presented in this report.

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