On the Ability of Ground Based Global Horizontal Irradiance Measurements to Reduce Error in Satellite Derived Plane of Array Irradiance data for Fixed Tilt Photovoltaic Power Plants

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***Abstract* — Solar resource uncertainty has the potential to significantly contribute to the financial risk of a PV project. This uncertainty has been studied in depth for satellite-derived global horizontal irradiance (GHI), which are often used as long-term average dataset for project valuations. Resource uncertainty, however, is not as well quantified in the plane of the array of the solar modules. This paper presents results that quantify the residual errors in plane of array irradiance (POAI) at locations where ground-measured GHI and POAI instruments are installed. Reductions in error to the modeled PAOI are observed when using satellite derived GHI that has been tuned with ground measured GHI for reduction in respective model errors.**

***Index Terms* — Plane of Array irradiance, SUNY satellite irradiance model, transposition models, PV power, SolarAnywhere**

I. INTRODUCTION

Long term solar resource datasets are used in conjunction with simulation of PV power models to forecast solar photovoltaic (PV) power plant revenue generation in multi-year time periods (often 20-year or 30-year projections). These resource datasets are typically provided hourly in three key components: GHI, Direct Normal Irradiance (DNI), and Diffuse Horizontal Irradiance (DHI). DNI is defined as collimated solar irradiance that reaches the ground directly from the sun without being scattered and which is measured on a surface perpendicular to the sunbeam. DHI is the irradiance which has been scattered before reaching a horizontal surface. GHI is the sum of all incident irradiance on a horizontal surface. Using these three components it is possible to utilize a transposition model [1]–[2] to derive Plane of Array Irradiance (POAI) which is the sum of all incident resource on tilted surface. Plane of Array Irradiance is then used in conjunction with ambient temperature and wind speed as inputs to the aforementioned PV simulation models that forecast expected long-term solar PV power plant generation.

Clean Power Research (CPR) is a provider of long term satellite derived solar resource data based on the SUNY satellite-to-solar irradiance model and in the commercial software platform, SolarAnywhere (SA). CPR also provides a service which reduces uncertainty in that long term dataset by tuning satellite derived GHI with concurrent and co-located ground measured GHI. In this tuning method, the error between the ground measured GHI and the satellite derived GHI are compared, and corrections are made to the long term satellite derived solar resource GHI dataset. CPR has published literature on their satellite models [3] and on the method by which they correct their satellite models using ground measured GHI data [4]. The purpose of this paper is to quantify the magnitude of the reduction of error in POAI by applying the correction to the satellite model using ground based measured GHI data. Reduction in error is quantified hourly, daily, monthly, and annually.

II. METHODOLOGY

At five locations GHI and POA was measured using ground based thermopile sensors for time periods exceeding one year. For each of these locations the measured Gain is defined as the relative increase in irradiance received at the plane of the array with respect to the horizontal surface, and can be calculated as:

$$Gain_{measured} = \frac{\sum_i POA_{i,\,measured}}{\sum_i GHI_{i,\,measured}} - 1 \qquad (1)$$

GHI was also modeled using satellite derived resource data from the SolarAnywhere Version 2.4 satellite model.

The diffuse component (DHI) was derived using various methods for the purpose of comparison, including ground measurement (where available), Erbs model [5] based on ground GHI measurements, and modeled [6] using satellite GHI. A special case of the satellite modeled DHI, called "rebalanced DHI", used the tuned satellite GHI data and the satellite modeled DNI to calculate DHI:

$$DHI = GHI - DNI \times \cos(Z) \qquad (2)$$

where Z is the angle between the solar disc and the zenith.

GHI and DHI were used in conjunction with a transposition model to calculate modeled POA irradiance. We utilized both the Hay-Davies [1] transposition model as well as the Perez [2] transposition model. Finally, modeled POA and Gain were compared to measured POA and Gain and residual analysis was conducted. Table 1 provides a summary of the locations, durations, and equipment utilized to obtain the GHI and POA measurements.

TABLE **I**

LIST OF GROUND AND SATELLITE DATA

Id	Location	Ground Data	Time Period	Ground Sensor	Satellite Data Model	Tilt (˚)	Az (˚)
BV2	Ontario, Canada	GHI, POAI	April 2011 - May 2014	Secondary Standard Pyranometer	SA V 2.4	30	0
BV3	New Jersey, United States	GHI, POAI	January 2012 - June 2014	EKO MS-402	SA V 2.4	25	0
BV4	Arizona, United States	GHI, POAI	January 2012 - December 2014	Secondary Standard Pyranometer	SA V 2.4	25	10
Sandia	Albuquerque, New Mexico	GHI, POAI, DHI	January 2011 – December 2011	Kipp & Zonen CMP 21 (GHI) / Eppley PSP (POA)	SA V 2.4	35	0
NREL	Golden, Colorado	GHI, POAI, DHI	January 2013 – December 2013	Kipp & Zonen CMP 22 (GHI) / Eppley PSP (POA)	SA V 2.4	40	0

The 5 different sets of inputs used to model POA were

a) ground measured GHI and DHI
b) ground measured GHI and Erbs modeled DHI
c) satellite derived GHI and DHI
d) satellite corrected GHI and unbalanced DHI
e) satellite corrected GHI and balanced DHI

Once each input set was calculated, Hay-Davies transposition model was used to obtain POA values..

III. RESULTS AND DISCUSSION

A. Satellite Tuning

The method to tune satellite and ground data, as developed by Kankiewicz et al. [4], derives a correlation for the concurrent period of data collection and projects these correlation parameters across the entire history of satellite data. The goal of this approach looks to leverage the site-specificity of the ground data with the long-term measurement of the satellite data. Specific correlation parameters, unique to each site location, are targeted at reducing the clear sky bias conditions separately from cloudy sky conditions, when the physically-based radiative transfer model and pseudo-empirical Perez cloud model dominate, respectively. The intended impact of the tuning method is a reduction of the mean bias difference (MBD) on GHI and reduction of Kolmogorov-Smirnov Interval (KSI) on GHI cumulative distribution functions for the concurrent time series data sets.

For the five test sites, the impact of the satellite tuning on MBD and root mean squared difference (RMSD) between the satellite and the ground data is shown in Figure 1. In all cases, the tuning reduced the MBD but had less to no effect on the RMSD. This is largely due to the efficacy of the tuning on MBD reduction from relative model biases, with the majority of RMSD resulting from the cloudy sky model and the tuning model's lessened impact on those sky conditions.

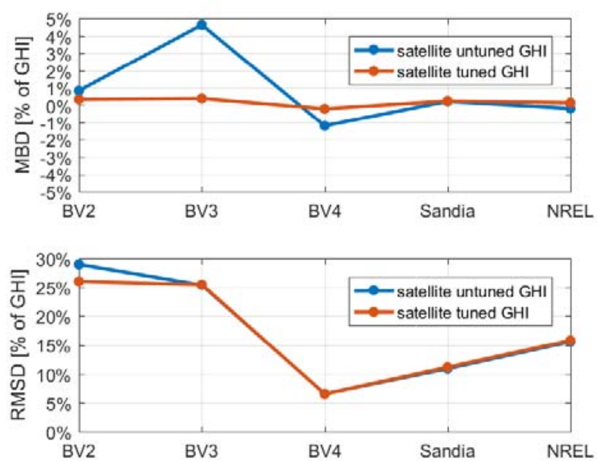

Figure 1: Mean bias difference (MBD) and root mean squared difference (RMSD) between satellite data and ground data.

B. Annual POA modeling results

Annual differences, modeled minus measured, for each of the five POA model methods are shown in Figure 2. As expected, models based on ground inputs generally perform the best. A notable exception is the MBD at site BV3, where it is suspected that the GHI measurement is biased high compared to the POA measurement. For the models which use satellite-based inputs, often the tuned GHI and rebalanced DHI was among the best performers, though performance is comparable among all methods at the Sandia and NREL locations.

At site BV2, the ground measurement may be slightly biased high, and may lead to the tuned GHI, unbalanced DHI model over-predicting the POA irradiance compared to the unturned GHI. In this case, rebalancing the DHI appears to rectify this bias.

The high RMSD values when using satellite inputs compared to ground inputs is notable. As seen in Figure **1**, the satellite tuning does not have much impact on RMSDs. Thus, the large RMSDs from satellite data propagate through the POA models and are evident here in the POA predictions.

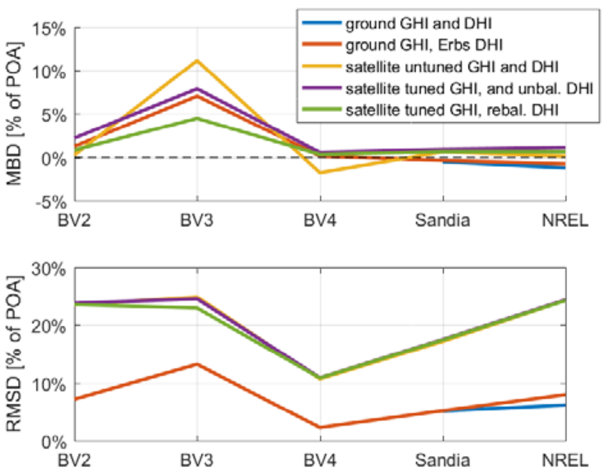

Figure 2: Mean bias difference (MBD) and root mean squared difference (RMSD) for one year of modeled versus measured POA data.

C. Monthly POA modeling results

Results from monthly rMBD values of the ten POAI datasets can be seen in Figure 3 and Figure 4 for the Sandia and BV4 sites.

The Sandia location (Figure 3) shows a strong seasonal dependence: all models tend to overestimate in the winter months and underestimate in the summer months. While the ground-based POA estimates are always within +/-5%, the satellite-based POA estimates reach +10% bias in December. These satellite-based models only reach -2% bias in the summer months. RMSDs are generally consistent month-to-month for ground-based models but vary more for satellite-based models.

The BV4 location (Figure 4), shows little season dependence for MBD, but does show some seasonal dependence of RMSD for the satellite-based models. For most months, there is a clear improvement in MBD when using tuned satellite GHI instead of untuned satellite GHI.

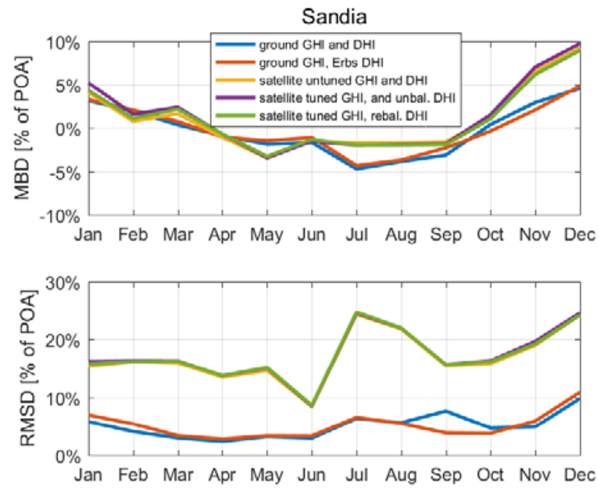

Figure 3: Monthly mean bias difference (MBD) and root mean squared difference (RMSD) for month segments of modeled versus measured POA data.

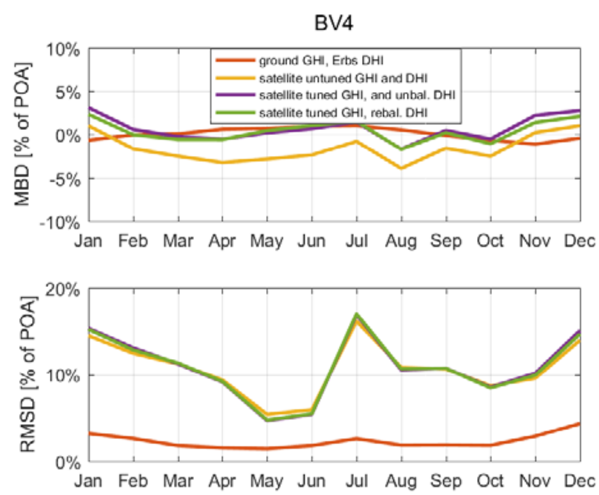

Figure 4: Monthly mean bias difference (MBD) and root mean squared difference (RMSD) for month segments of modeled versus measured POA data.

D. Hay/Davies vs. Perez Transposition Models

The POA modeled using Hay/Davies and Perez transposition models were compared for all five sites, and are shown for site BV4 in Figure 5. Differences between the Hay/Davies and Perez transposition models was often larger than the difference between using ground GHI versus tuned, balanced satellite GHI and DHI, showing that transposition model selection is also very important to POA modeling.

The POA modeled using the Perez transposition model was consistently higher than POA modeled with the Hay/Davies model transposition model, consistent with [7]. Our results are also consistent with the finding in [7] that, when using modeled DHI as an input, the Hay/Davies transposition model appears to be less biased than the Perez transposition model. This is of particular importance when assessing the performance of operational projects, where ground measurements of DHI are often not available.

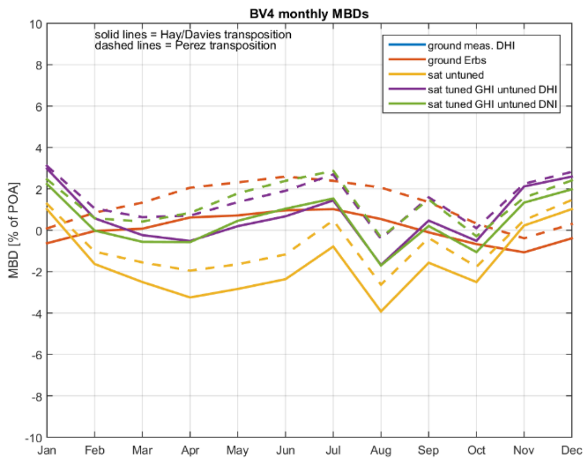

Figure 5: Monthly mean bias difference (MBD) and root or month segments of modeled versus measured POA data, showing both the Hay/Davies (solid lines) and Perez (dashed lines) transposition models.

E. Albedo Impact to POA modeling

Ground albedo is another input that can affect POA estimates. Albedo is seldom measured and a default value of 0.2 is usually assumed. It has been shown [7] that the effect on the model errors of changing the albedo value is larger for high tilts and high GHI scenarios like stations 5 and 6 in this study.

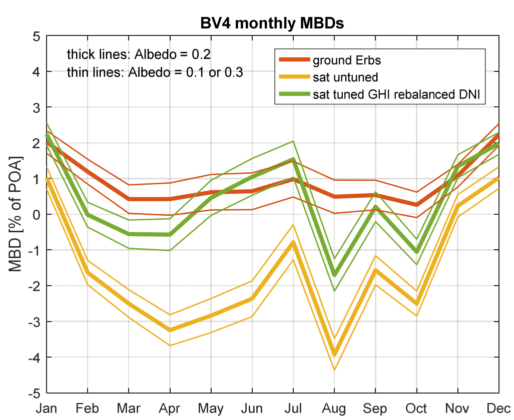

Figure 6: As seen above, using values of 0.1 or 0.3 could tip the balance in favor of the Perez or Hay-Davies models respectively for a given station.

IV. CONCLUSION

Seasonal biases may exist in POAI resource data and using ground based corrections does not always remove these biases. This is not true for all locations or all seasons. While GHI ground measurement tools have typically been preferred in project development due to their cost and reliability, the uncertainty on the modeled POAI dataset will more directly impact the PV project uncertainty.

Tuning the long term satellite dataset has been shown to reduce uncertainty in GHI, and results herein now indicate that this approach provides a lower uncertainty POAI dataset as well. RMSD errors indicate an opportunity to improve satellite model uncertainty through better cloudy sky models, while the impact of albedo has been highlighted as a potential transposition model selection criterion.

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