SOLAR 2014: REDUCING SOLAR PROJECT UNCERTAINTY WITH AN OPTIMIZED RESOURCE ASSESSMENT TUNING METHODOLOGY

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ABSTRACT

This paper describes procedures suitable for the optimal combination of ground-based and satellite-based irradiance data to reduce the overall uncertainty of the solar resource assessment. It presents a case study depicting the application of these approaches, and illustrates the benefits of proper solar resource tuning methods to ensure the production of a robust solar resource dataset.

1. INTRODUCTION

The long-term production risk of solar project developments is largely based on the uncertainty of the solar resource. This risk can be reduced through the collection of solar resource data. One method is the collection of ground-measured data by procurement, calibration, installation and operation of an on-site irradiance and ancillary meteorological station (Figure 1). Another approach is to evaluate the solar resource via long term satellite-based irradiance measurements, utilizing techniques developed by Perez et.al. [1].

By combining these two techniques, it is possible to reduce the overall uncertainty of the solar resource assessment, thus increasing a solar project's viability [2]. We present new techniques for optimally tuning long-term reference satellite data with accurate on-site ground measurements.

2. OBJECTIVE

Ground-based, pyranometer measurements are effective at determining site-specific irradiance conditions, while satellite-based techniques represent the average irradiance condition over the area that corresponds to the satellite data image resolution (~1 km^2). Even for a project site close to a ground station, research shows that beyond a 25-km radius from the station, satellite-based methods are more accurate [3]. Sixteen-plus years of satellite data such as SolarAnywhere® Data also provide understanding of the expected inter-annual solar resource variability associated with a particular solar energy project.

Various methods have been reported for comparing these two measurement sources for relative accuracy [4]. In this paper, we will describe new techniques for resolving the unique sources of error inherent to satellite-based irradiances. These techniques will incorporate accurate short-term ground measurements with long-term satellite-based data, resulting in a low-uncertainty dataset that is ideal for solar resource assessments.

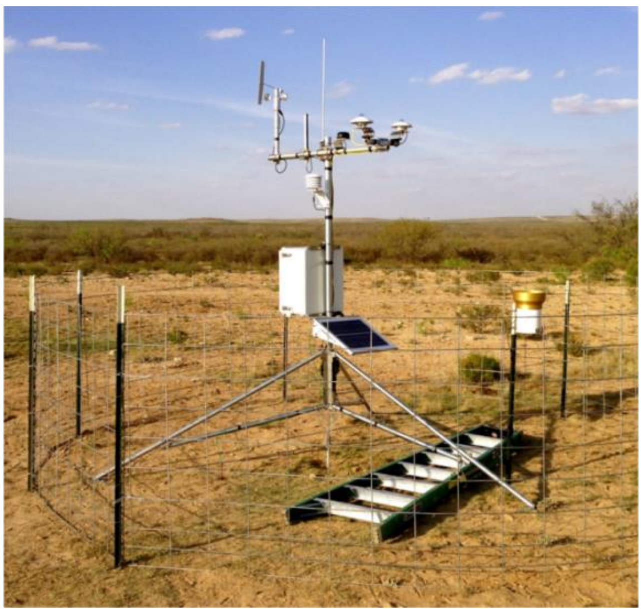

Figure 1: Example solar prospecting ground site
(*image courtesy of GroundWork Renewables, Inc.*)

3. ANALYSIS

We present results from a satellite tuning case study consisting of 12 months of high-quality ground meteorological data. The data were taken from a ground station with redundant secondary standard quality pyranometers that received routine, sub-weekly maintenance. This station is located in the San Joaquin Valley in California (Figure 2), where many utility-scale PV plants are being installed.

Ground data collected are used to tune overlapping SolarAnywhere satellite-derived irradiance data to help reduce the overall long-term solar resource uncertainty. SolarAnywhere Data offer 15-plus years of consistent, validated, time-series irradiance measurements available in resolutions as high as 1 km x 1 km spatial, 1-minute temporal. Measurements include Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DIF), along with other location-specific weather data. For this case study, 10 km, 1-hour SolarAnywhere Data was used

Understanding how satellite-based irradiances are derived will help determine how to optimally tune and correct systematic biases that can exist.

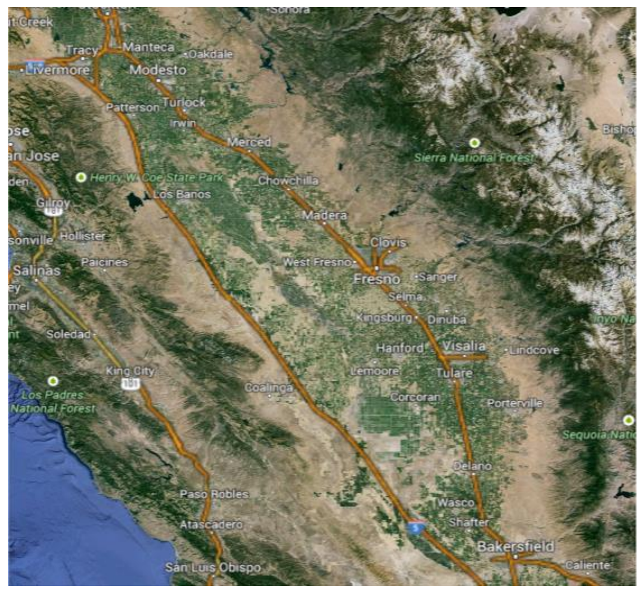

Figure 2: Google map image of the
San Joaquin Valley region in California

The Perez method of deriving satellite-based irradiance starts with a clear sky radiative transfer model that is then modulated by an empirically-derived cloud index. An example of this process is illustrated in Figure 3.

Errors in satellite model irradiances are introduced at both the clear sky modeling point (due to aerosol optical depth (AOD) and water vapor discrepancies), and during the cloud indexing process. Ground vs. satellite comparisons during cloudy conditions are often skewed by the pinpoint ground vs. area-averaged values from satellite cloud data, and are not reliable in correcting cloudy satellite-based irradiance errors.

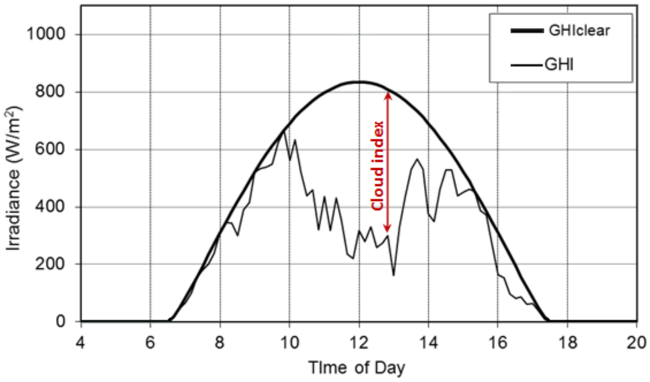

Figure 3: Example satellite-derived cloud index image

The errors that are subject to correction are clear sky model-based, and primarily stem from regional AOD variances. Separating out the clear sky bias from the overall satellite bias is critical to the proper satellite data tuning process.

3.1 <u>Clear Sky Bias Corrections</u>

In this case study, the overall Mean Bias Error (MBE) observed for 12-months of 10 km SolarAnywhere GHI data is -4.63%, and the clear sky MBE is -4.18%. The clear sky MBE is calculated by using only the hours that are within 20% of SolarAnywhere clear sky GHI data. It is essential to ensure clear sky threshholding does not result in significant data loss in regions where more day-to-day cloudiness occurs, such as over the Eastern U.S.

To further tune the SolarAnywhere GHI data, Kolmogorov-Smirnoff Integral (KSI) goodness-of-fit test [5] is used to minimize the cumulative distribution between the two. The initial KSI between ground-measured and satellite-derived GHI is 1.02%. The aim in the satellite data tuning process is to minimize both the clear sky MBE and KSI to provide the ideally tuned solar resource assessment.

3.2 <u>Seasonal and Dual-Sliding Window Corrections</u>

The satellite-based GHI dataset at this location exhibits a larger clear sky bias during the summer months than during the winter months (Figure 4) due to seasonal variations in regional AOD. To correct for these uneven biases, a sinusoidal-based seasonal correction (Figure 5) is applied to help align the overall satellite-derived GHI data bias corrections.

Figure 4 shows the monthly breakdown of clear sky MBE adjustments, with January experiencing a 5.1% correction and June experiencing a 2.4% correction. With the correction, the annual clear sky MBE decreases from -4.18% to nearly zero.

Figure 4 also shows the outcome of a straight clear sky bias correction, which would result in a sub-optimal monthly tuning. Seasonal tuning should only be applied to ground data sets consisting of a minimum of 12 months of data so all seasons can be properly gauged.

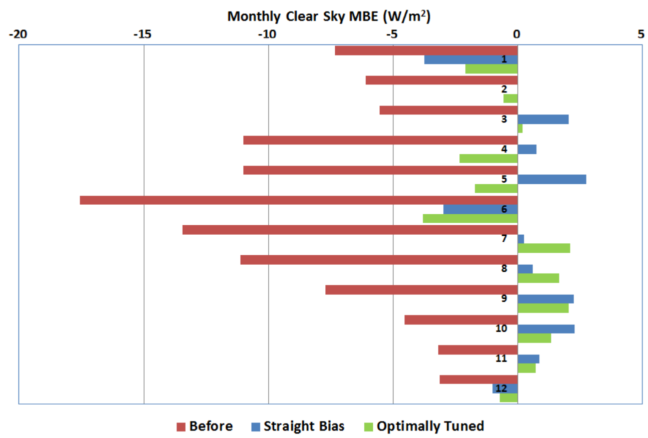

Figure 4: Monthly (Jan – Dec in descending order) clear sky MBE and corresponding bias corrections.

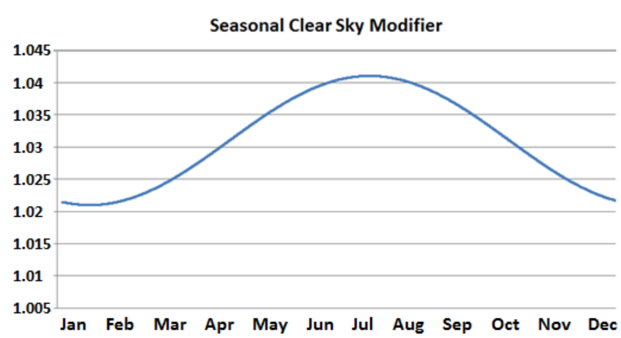

Figure 5: The sinusoidal-based seasonal bias modifier used for this case study

In addition to correcting for observed clear sky biases, a dual-sliding window technique is applied to correct for any remaining systematic errors that could affect the cumulative distributions between ground-measured GHI and SolarAnywhere GHI. By applying proper dual-sliding window parameters, the KSI obtained by integrating the absolute difference between the two decreases from 1.02% to 0.28%.

Figure 6 shows the cumulative distributions for the ground-measured GHI, the initial SolarAnywhere GHI, and the tuned SolarAnywhere GHI. The tuned SolarAnywhere GHI data has a much closer cumulative distribution to ground-measured GHI data, and a lower uncertainty than the initial SolarAnywhere GHI data.

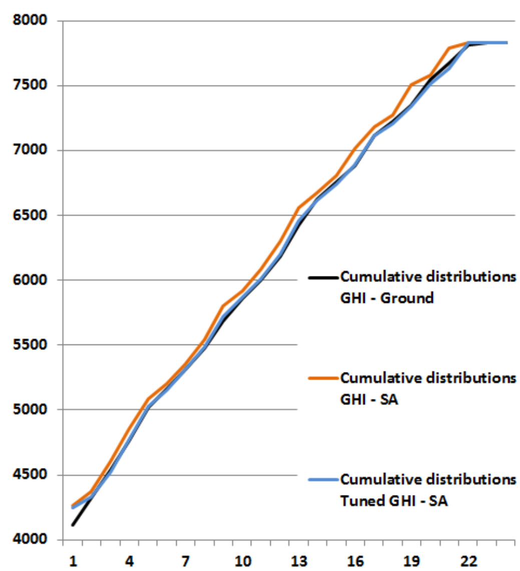

Figure 6: Cumulative distributions of ground-based, initial and tuned SolarAnywhere GHI data

Figures 7 (pre-tuned) and 8 (post-tuned) show scatter plots of 12-months of ground-measured GHI versus satellite-derived GHI. After eliminating clear sky MBE and minimizing KSI, we observed a tighter distribution of data centered along the one-to-one line.

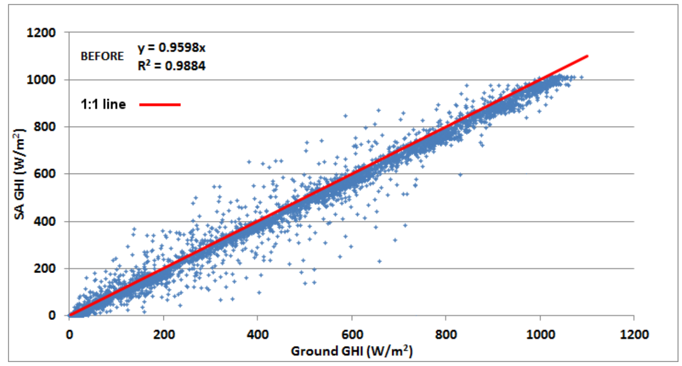

Figure 7: Scatter plot of ground GHI and pre-tuned SA GHI

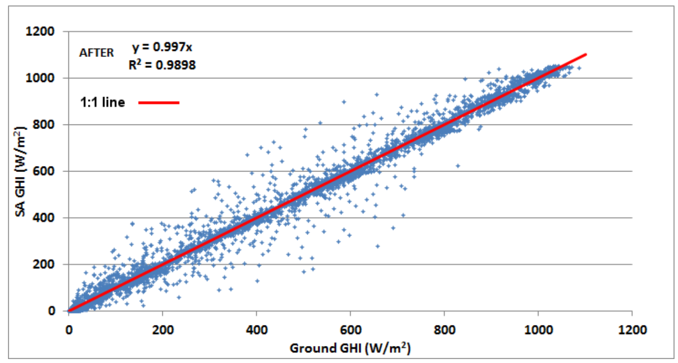

Figure 8: Scatter plot of ground GHI and post-tuned SA GHI

3.3 <u>Satellite Irradiance Rebalancing</u>

Once the satellite-based GHI data has been tuned, it is essential to relate any changes in GHI to the DNI (beam) and DHI (diffuse) components of the satellite-based irradiance dataset. This will ensure accurate translation to plane-of-array irradiance (POAI) within the PV energy simulation process.

The following equation governs the GHI to other component relationship that should be preserved during the overall ground/satellite data tuning process:

*GHI = DNI*cos (Z) + DHI (Z is the solar zenith angle)*

Tuned satellite-based GHI data should then be translated into rebalanced DNI and DHI components using the same processing from which the original DNI and DHI components were derived.

Figures 9 and 10 illustrate two possible results of the satellite irradiance rebalancing at this location on a clear summer day. Figure 9 shows results when one attempts to preserve the original GHI/DHI ratio.

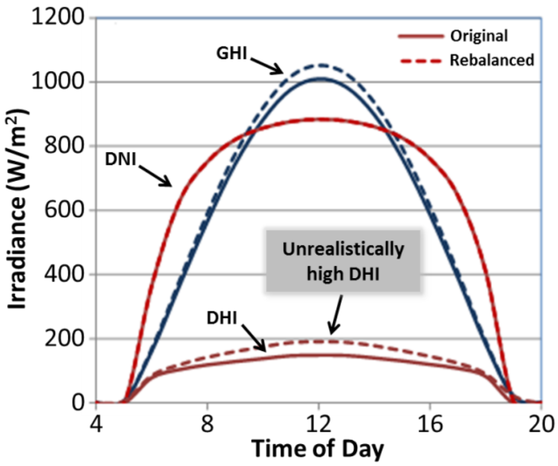

Figure 9: Clear sky summer day irradiances showing before (solid) and tuned GHI (blue dashed) and rebalanced (dashed) DHI. Note that there is no change in DNI.

This results in an unrealistically high increase in DHI with no corresponding change in DNI. Figure 10 shows the results when DNI is properly recalculated from the tuned GHI data. This rebalancing results in an increase in DNI with a subtle decrease in DHI. This correct rebalancing methodology ensures that any changes imparted to GHI are properly translated to the DNI and DHI components of the satellite-based resource data to prevent unrealistic translation to plane-of-array irradiance within PV simulation software (e.g. PVsyst).

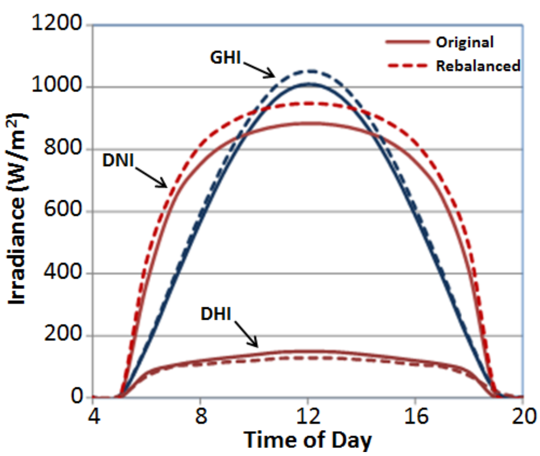

Figure 10: Clear sky summer day irradiances showing before (solid) and tuned GHI (blue dashed) and recalculated (dashed) DNI and DHI (dashed).

3.4 <u>Ancillary Meteorological Data Tuning</u>

Site-specific air temperature and wind speed data are also required for accurate PV energy simulations. Accurate 2 meter ground air temperature measurements can be used to remove biases present in modeled air temperature data. National Digital Forecast Data (NDFD) [6] and North American Regional Reanalysis (NARR) [7] 2 meter dry-bulb temperature data are used in this case study.

Figure 11 shows that NDFD model-derived air temperatures at this location tend to be lower than ground-measured air temperatures during the day and higher at night. These offsetting biases result in an overall MBE near zero. Since solar energy production is only influenced by daytime temperatures, it is important to correct for daytime MBE and not overall MBE. NARR temperature data exhibits a high bias at this location during all hours of the day. NARR is the underlying source temperature data in the NREL Solar Prospector site.

In this case study, daytime bias corrections of +0.8°C (NDFD) and -2.6°C (NARR) are derived, which will result in better-quality PV energy simulations. An overall-based MBE analysis would have resulted in no correction being applied to the NDFD data, which would have contributed to an over-prediction of energy during the PV simulation process. A +2°C swing in temperature results in roughly a 1% reduction in energy output within PVsyst for most PV modules. Similar methods can be used to correct wind speed biases, though none were noted in this study.

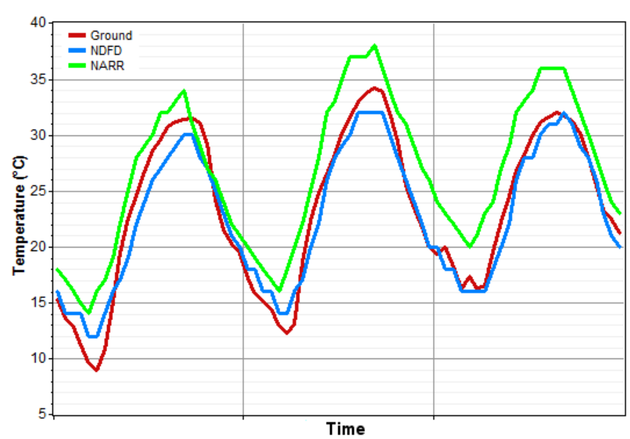

Figure 11: Example measured (red), NDFD (blue) and NARR (green) 2m dry-bulb temperature observations over several days during the month of May.

3.5 Final Wrap-up

All corresponding satellite-based and ancillary meteorological data tunings are then applied to the long term satellite and meteorological datasets from which needed typical GHI year (TGY) or typical meteorological year (TMY) files can be carved out. Additionally, financially-driven long term project risk analysis (e.g., P90, etc.) can be performed ensuring ideal project feasibility for all parties involved.

4. CONCLUDING REMARKS

The best investment decisions begin by understanding the characteristics of your solar resource. We have presented a new set of methods for the optimal tuning of satellite resource data with accurate ground solar resource data. Once satellite-based GHI data are tuned, accompanying DNI and DHI data must also be rebalanced to preserve the overall irradiance relationship. Finally, ancillary meteorological data tuning should focus on daytime bias corrections.

Proper application of these various tuning strategies will reduce the overall uncertainty of the solar resource assessment, and provide a robust, long-term, satellite-based solar resource dataset that will result in confident PV energy simulations and ensure the viability of a PV project.

5. REFERENCES

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