EVALUATION OF PROCEDURES TO IMPROVE SOLAR RESOURCE ASSESSMENTS: OPTIMUM USE OF SHORT-TERM DATA FROM A LOCAL WEATHER STATION TO CORRECT BIAS IN LONG-TERM SATELLITE DERIVED SOLAR RADIATION TIME SERIES

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ABSTRACT

In this paper, two methods are reviewed and tested for significantly reducing solar power production estimation errors, and thus improving bankability, by combining long-term, satellite derived irradiance time series with available short-term observations. The first method consists of correcting the modeled clear-sky irradiance data using local aerosol optical characteristics data. This method has been previously shown to be effective at removing the bias in time series of Direct Normal Irradiance (DNI) at hazy locations experiencing large aerosol optical depth (AOD). The second method consists of correcting bias out of independent satellite modeled data using on-site ground observations through a Model Output Statistics (MOS) correction. The essential question to answer is: How does one extend the record of short-term observations using satellite data? The significant findings obtained here can help resolve this question. The positive effects of these methods on bankability are also discussed.

1. AOD CORRECTION METHODOLOGY

Recent research results [1] have shown that many satellite-derived hourly time series of DNI could have significant monthly and/or annual bias when compared to high-quality irradiance measurements. This was found to be particularly the case in regions bordering the Sahara, where high dust aerosol loads are frequent. This load, measured here with the AOD, can be monitored with sunphotometers from the ground, or from spaceborne spectrometers, such as MODIS. More recently [2], it was shown that AOD is normally the driving factor behind the daily variability in DNI, and to a lesser extent, to that in Global Horizontal Irradiance (GHI). At high-AOD (or "hazy") locations, such as over or around deserts in Africa and Asia, DNI was found particularly sensitive to AOD [2]. Therefore, to obtain high accuracy and low bias in modeled estimates of DNI or GHI over these regions, the AOD data used as inputs by radiative models must have the lowest bias possible.

A correction method based on ground observations of AOD and predictions with the high-performance REST2 model [3] was introduced in [1], and showed generally good results over the Saharan region. Due to the scarcity of world sites conducting ground observations of AOD, particularly near sites of high interest for solar power production developments, a generalization of this correction method needs to be based on large-scale AOD datasets rather than site-specific data. For the present analysis, a new dataset, SOLSUN, is used for that purpose. It covers the world at 0.5x0.5° spatial resolution, and provides the necessary aerosol inputs to REST2 or other radiative models at monthly intervals, between 2000 and 2011 [4]. These inputs are Ångström's AOD at 1 µm, β, and the Ångström exponent, α, which relates the AOD at various wavelengths. For instance, the AOD at 550 nm, τ_{a550}, which is the primary output of most current spaceborne sensors, is related to β and α according to:

$$\tau_{a550} = \beta\, 0.55^{-\alpha}. \quad (1)$$

In this study, the potential of the AOD correction method developed in [1] is demonstrated at Sede Boker—a site where most modeled DNI data series were found highly biased. For instance, the 3TIER long-term average raw satellite data series were found to underestimate DNI by ≈5–20% depending on the month [1]. The AOD data used by 3TIER are derived (and corrected) from MODIS. Figure 1 shows a comparison of the monthly AOD between reference ground observations (AERONET), SOLSUN, and MODIS, during the period 1998–2010. Before 2000, the SOLSUN climatology is used, which explains the identical monthly values in 1998 and 1999. It is obvious that MODIS overestimates AOD most of the time at that site, particularly in summer. This is the likely cause of underestimation of DNI in the 3TIER and other data providers' data series, noted in [1].

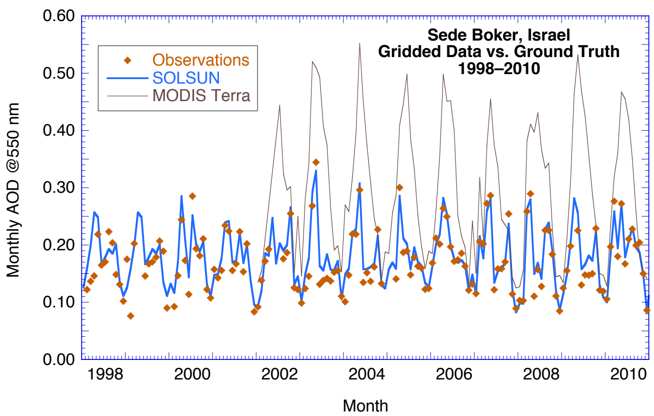


Fig. 1: SOLSUN and MODIS databases vs. ground observations: monthly AOD at Sede Boker, Israel.

A large monthly and interannual variability in AOD is obvious in Fig. 1. The daily variability is even larger, and seriously impacts daily or hourly DNI or GHI predictions [2]. Currently, SOLSUN is limited to monthly values. Daily values would be desirable, particularly at dust-impacted sites such as Sede Boker. Therefore, the AOD correction method described below will only reach its full potential when accurate daily AOD data become widely available.

In addition to monthly values of β and α, the method uses monthly values of precipitable water (PW), derived from MODIS observations. As with AOD, daily or sub-daily PW data, such as that now provided by some reanalysis datasets, would be desirable. Other inputs to REST2, such as atmospheric pressure, column ozone amount, column nitrogen dioxide amount, aerosol single-scattering albedo, and surface albedo have only a small effect on DNI and GHI, and interpolated monthly-mean values or default values are thus used. All the monthly values are subjected to a cubic spline interpolation, so that their smoothed hourly values can be obtained over the whole period of interest.

Hourly DNI and GHI outputs of the REST2 model are then compared to the clear-sky DNI and GHI estimates from the 3TIER model. A correction factor, R_c, is thus obtained:

$$R_c = I_{\mathrm{cREST2}} / I_{\mathrm{c3TIER}} \qquad (2)$$

where I_c is the clear-sky irradiance (DNI or GHI) obtained by either the REST2 or 3TIER model. (The latter is a production model, which would make any direct spatial or temporal correction to its AOD input data impractical.) A value of R_c highly different from 1 indicates a strong correction, and therefore the use of a highly biased AOD dataset during the original production of the modeled time series. These original all-sky irradiances (DNI or GHI), I, can then be corrected by multiplying each of their hourly occurrences with R_c. The hourly AOD-corrected irradiance is therefore:

$$I_{\mathrm{corr}} = I\, R_c. \qquad (3)$$

2. AOD CORRECTION RESULTS

Radiometric measurements are available at Sede Boker from BSRN since 2003. For the period 1998–2002, local observations of DNI and GHI were obtained from the Negev solar project [Pers. comm. with Dr. David Faiman). Both stations use thermopiles, and thus provide compatible data. The daily trace of I_c should coincide with the envelope of the daily all-sky irradiation measurements, since these peak values normally correspond to cloudless conditions. Figure 2 (for DNI) and Fig. 3 (for GHI), each obtained for a typical year, demonstrate that this is actually *not* the case. The trace of each model's I_c predictions is much smoother than the daily observations, suggesting that the use of monthly values for AOD and PW is far from optimal, even with cubic spline interpolation. These two figures also confirm the substantial underestimation of the 3TIER clear-sky model, compared to REST2 or the envelope of the daily measured data. Since the all-sky irradiance is proportional to its ideal clear-sky counterpart, any underestimation in the clear-sky model will be reflected in the ultimate results, i.e., all-sky I.

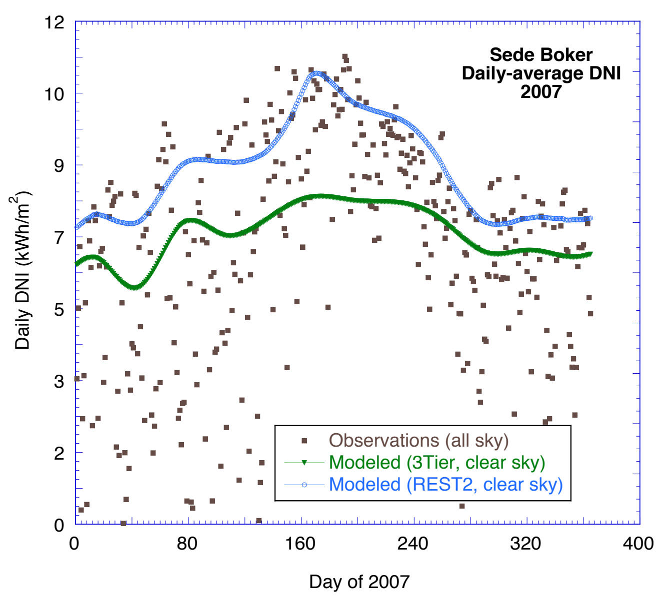


Fig. 2: Daily DNI all sky observations at Sede Boker vs. ideal clear-sky estimates of the 3TIER and REST2 models.

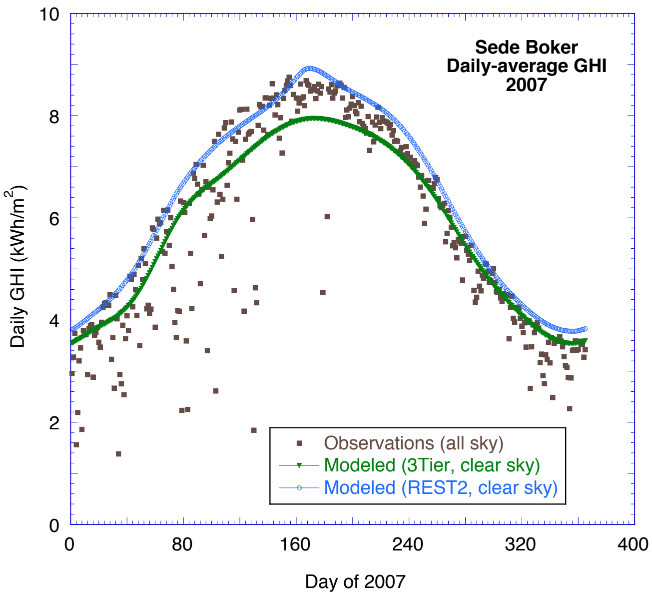


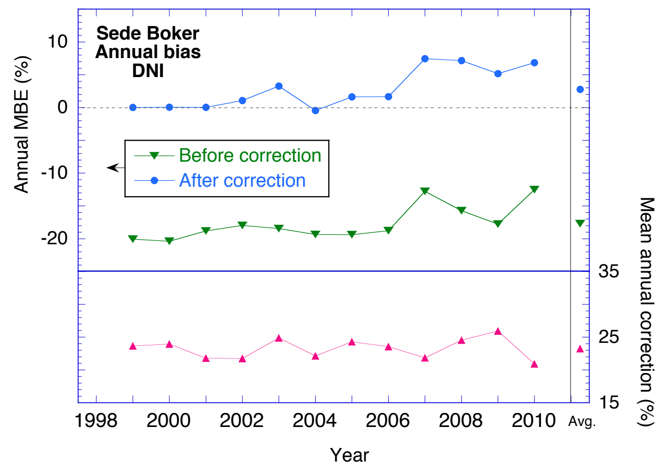
Fig. 3: Daily GHI all sky observations at Sede Boker vs. ideal clear sky estimates of the 3TIER and REST2 models.

The performance of the correction method is illustrated in Fig. 4. The reduction in annual bias is particularly important in the case of DNI. This could be expected since DNI is more sensitive to AOD than GHI. Before the DNI correction, the mean bias varied annually from -20.4% to -12.5%. It becomes -0.5% to 7.5% after correction. Similar results for GHI are -7.5% to -3.9% before correction, and 0.7% to 3.6% after correction. Annual mean values of R_c (expressed here in percent) are also displayed in Fig. 4. R_c is about 3 times larger in the case of DNI than GHI. Besides a systematic reduction of the bias, the random errors in hourly all-sky irradiances are also reduced, but not as dramatically.

Tests of the correction method undertaken at cleaner (low AOD) sites generally show a slight improvement in bias. Depending on the possible compensation or errors between AOD and cloud transmittance, the AOD correction method may occasionally overcorrect. Hence, most generally, the AOD correction method is intended for use only at sites where AOD is known to be high, and where local DNI measurements confirm a significant bias between such ground truth and long-term modeled time series. Since seasonal effects are likely [1], at least one year of local measurements should be used to assess the aerosol situation.

3. MOS-CORRECTION METHODOLOGY

For utility-scale solar projects 3TIER uses on-site observational data to validate and correct its raw satellite modeled data via a process called Model Output Statistics (MOS). 3TIER's proprietary MOS technique uses a multi-linear regression equation to remove bias and adjust the variance of the raw satellite modeled output to better match the observational data. This method has been successfully applied in the wind power industry for many years and that experience is now being applied to the solar power industry.



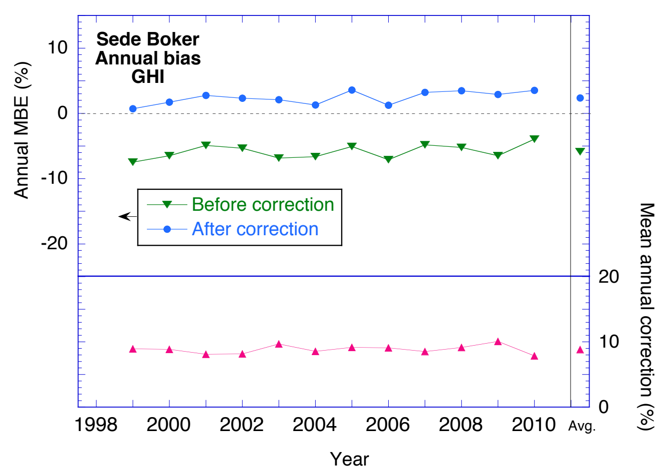


Fig. 4: Annual bias in the all-sky DNI and GHI irradiance data before and after AOD correction. The red line shows the mean annual amount of correction.

The MOS technique is optimized to fit the satellite-derived data to short-term fluctuations. This approach uses multiple statistical parameters to better match modeled data to diurnal or hourly variability at the site. The technique provides excellent results, yet avoids over fitting modeled data to observations—a common result of standard non-linear algorithms.

The MOS equation for each observation station is trained over the observational period of record. The equation is then appropriately applied for all time steps of the satellite modeled dataset, so that corrections can be made for periods during which direct observational data are unavailable. Performing MOS-correction has a high value because it captures the unique characteristics of a site through on-site observations and places them into the long-term historical perspective provided by satellite modeled data.

Hourly observations from five sites were used in this study in order to compare the efficacy of the MOS-correction technique in different climates and satellite regimes. Stations from the SURFRAD and BSRN networks were selected as the test sites. As part of this study we also wanted to evaluate the length of on-site data necessary to positively impact the MOS-correction. To test this minimum observational length, the observations were broken into 3, 6, 9 and 12 month periods, based on calendar months. These observations were compared to the corresponding data from the satellite dataset and various weather inputs. Then an overall statistical correction was derived based on multiple inputs, and a correction based on mean variance for each hour and month was applied.

These corrections were then applied to the full satellite dataset, and compared to the observations for the full year periods that were independent of the observations. For example in the case of Desert Rock, presented in Figs. 5 and 6, observations from 1999-2009 were used, and compared to full years from 1999-2011. A total of 170 models were generated (44 3-month periods, 43 6-month periods, 42 9-month periods, and 41 12-month periods). Each year from 1999-2011 was compared, excluding the years where the ground observations were used for the model (for a total of 528 3-month comparisons, 506 6-month, 484 9-month, and 462 12-month).

Two versions of the model were compared, for the 3, 6 and 9-month periods: one "naive" version where the statistical correction was applied blindly across the entire year, and one "conservative" version where it was only applied for those months in which the original observations existed.

Figure 5 shows the annual bias error for Desert Rock with the satellite dataset represented by the “0 month” of observations. Also represented are the two model versions, the “naïve” represented by the purple quartiles on the left and the “conservative” represented by the blue quartiles on the right for the various periods of ground observations used (3, 6, 9, and 12 months). In Fig.5 the conservative correction method clearly produces results that have smaller annual bias differences than the naïve method. The tipping point for the number of months of ground observations necessary to positively reduce the bias in the correction appears to be ≈9 months. With 9 and 12 months of observations, little to no bias reduction in the resulting dataset can be produced. Note that the two correction methods are the same at 12 months.

Figure 6 shows similar information for the hourly RMS (Root Mean Squared error) values compared on an annual basis at Desert Rock. Unsurprisingly, the naive correction method overcorrects the bias error and has a lot of scatter in both bias and RMS for the 3 and 6-month periods. These RMS results reinforce the idea that using 9 months of observations is the minimum that can be applied throughout the year using the naïve method, since such a period improves both the bias and RMS compared to the conservative method, albeit with a slight increase in scatter in the RMS results. In all cases, having 12 months of observations is better than any shorter period, as could be expected.

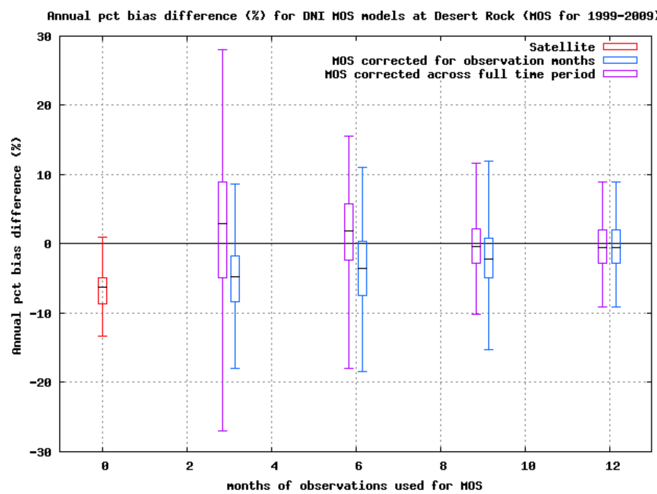


Fig. 5: Annual percent bias difference for MOS-correction of DNI trained on 0, 3, 6, 9 and 12 months of observations at Desert Rock from 1999-2011. The “naïve” correction method is represented by the purple quartiles on the left and the “conservative” method is represented by the blue quartiles on the right.

Generally similar results are found at the other four sites, although the degree of improvement from the MOS-correction varies. For locations where most years of the satellite dataset are biased in the same way, more improvement is obtained than at locations where the bias is scattered year-to-year. Almost all sites show improvement in RMS, with the exception of Carpentras where the satellite RMS is relatively low to begin with. Even at Carpentras there is improvement in the mean bias difference.

4. REGIONAL MOS-CORRECTION RESULTS

REGIONAL CASE STUDY SITE 1: Desert Rock, USA
The results for Desert Rock suggest the MOS-correction may be over fitting for the training period, but also, that the correction has skill outside of the period of overlap between the observations used and the satellite record. Figure 7 shows the DNI MOS-correction results using 12 months of observations from 2009. The figure shows the raw satellite

modeled data, in blue, the ground observations from the SURFRAD station, in black, and the corrected results, in orange. This figure is repeated for each of the five study sites for comparison.

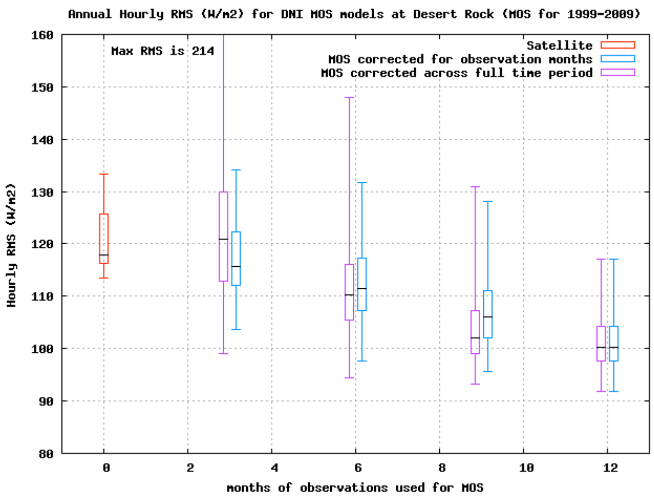


Fig. 6: Hourly RMS for MOS-correction of DNI trained on 0, 3, 6, 9 and 12 months of observations at Desert Rock from 1999-2011. See Fig. 5 for color symbols.

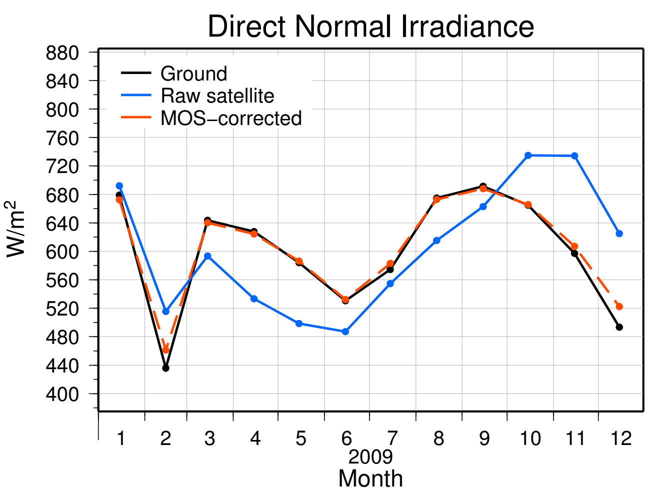


Figure 7: DNI values in W/m^2 for MOS-correction results for the training year (2009) at Desert Rock.

Table 1 shows the modeled data error as a percent of the mean for the MOS-correction training year and one additional year outside of the training period (the "Blind Comparison"). This is calculated using the RMS error, averaged over daylight hours only, of monthly-mean MOS-corrected DNI. For months where we do not have measured data the standard model error is used. The standard model error value used as the base uncertainty for all five sites, represented by the 0 month, was calculated based on a validation of the 3TIER satellite dataset compared to over 40 ground stations globally [1]. This table is repeated for each of the five study sites for comparison.

TABLE 1: Modeled data error for DNI at Desert Rock as percent of the mean for the MOS-correction training year (2009) and one other year outside of the training period (2011).

Length of Observations	Training Year Uncertainty	Blind Comparison Uncertainty
0 month	9.0	9.0
3 months	7.01	7.86
6 months	4.83	6.29
9 months	2.61	4.23
12 months	0.58	2.43

REGIONAL CASE STUDY SITE 2: Sede Boker, Israel
At Sede Boker the satellite data matches the seasonal cycle but has a clear low bias, as noted in Section 2 above. The MOS-correction removes this bias as shown in Fig. 8 and improves the RMS error as seen in Table 2.

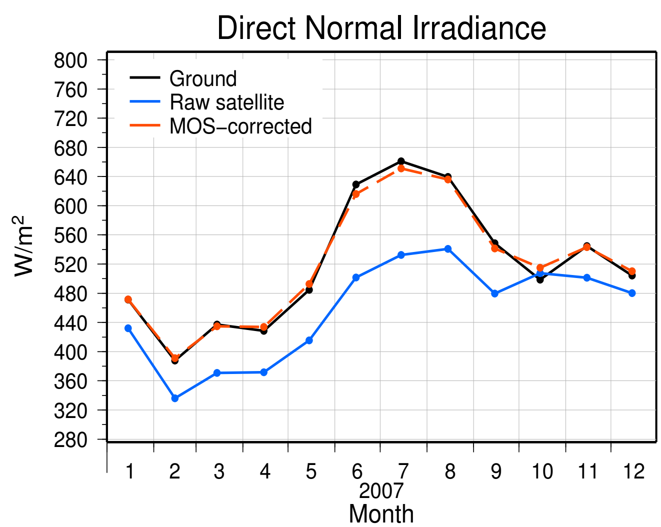


Fig. 8: DNI values in W/m^2 for MOS-correction results for the training year (2007) at Sede Boker.

TABLE 2: Modeled data error for DNI at Sede Boker as percent of the mean for the MOS-correction training year (2008) and one additional year outside of the training period (2009).

Length of Observations	Training Year Uncertainty	Blind Comparison Uncertainty
0 month	9.0	9.0
3 months	6.91	7.39
6 months	4.76	5.68
9 months	2.43	3.59
12 months	0.44	1.08

REGIONAL CASE STUDY SITE 3: Carpentras, France

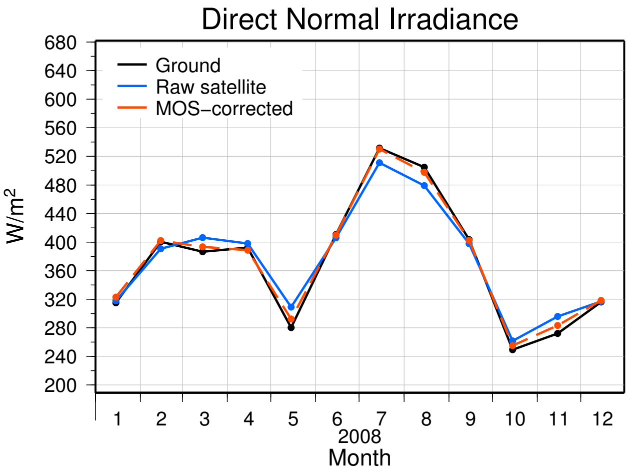


Fig. 9: DNI values in W/m^2 for MOS-correction results for the training year (2008) at Carpentras.

As mentioned previously the MOS-correction improves the mean bias at Carpentras, demonstrated in Fig. 9 above, but not the RMS because the satellite RMS is relatively low to begin with, as demonstrated in Table 3.

TABLE 3: Modeled data error for DNI at Carpentras as percent of the mean for the MOS-correction training year (2008) and one additional year outside of the training period (2009).

Length of Observations	Training Year Uncertainty	Blind Comparison Uncertainty
0 month	9.0	9.0
3 months	6.86	7.12
6 months	4.75	5.28
9 months	2.50	3.34
12 months	0.48	1.52

The Carpentras site shows that in locations where the raw satellite data are already very good there is still improvement in uncertainty to be gained through MOS-correction, but it is not as crucial as at some other locations.

REGIONAL CASE STUDY SITE 4: Solar Village, Saudi Arabia
A site like Solar Village shows how crucial a correction can be. In this case the satellite modeled data needs improvement both in its seasonal signal and in bias. The MOS-correction improves both cases.

The relatively high uncertainty in the year outside of the training period is likely due to the fact that the MOS-correction is improving the seasonal signal of the satellite dataset but is still missing the dip in DNI values during the month of May of the training period. This may result in overestimating DNI for that time period throughout the long-term record. However, as Fig. 10 clearly shows, the MOS-correction is having a positive effect overall.

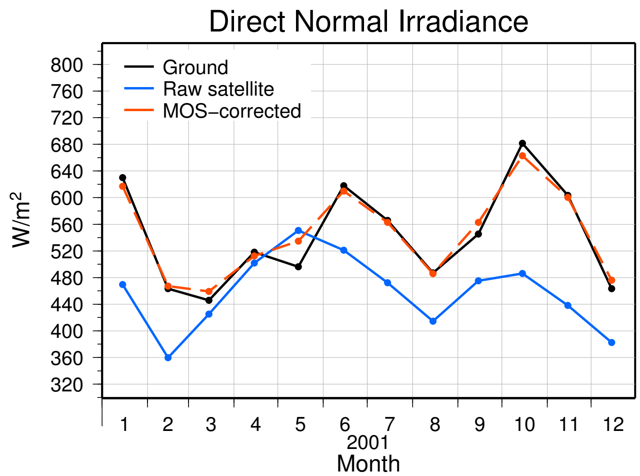


Fig. 10: DNI values in W/m^2 for MOS-correction results for a training year (2001) at Solar Village.

TABLE 4: Modeled data error for DNI at Solar Village as percent of the mean for the training year (2001) and one additional year outside of the training period (2002).

Length of Observations	Training Year Uncertainty	Blind Comparison Uncertainty
0 month	9.0	9.0
3 months	6.90	7.48
6 months	5.00	5.53
9 months	2.85	3.71
12 months	0.80	3.40

REGIONAL CASE STUDY SITE 5: Tamanrasset, Algeria
Tamanrasset is another site where the MOS-correction clearly improves the bias in the satellite dataset, as shown in Fig. 11, even though the uncertainty values are higher relative to a site like Desert Rock, as shown in Table 5.

For each of the five sites we decided to investigate if applying the MOS-correction using months from different seasons had any impact on improving the uncertainty. Figure 12 shows how the annual bias percentage improves during specific seasons using the conservative method for applying the correction. For each site, the 3-month MOS models are sorted by the starting month of the observations (Jan-Mar are plotted in column 1, Apr-Jun in column 4 and so on). These are the same comparison statistics used in Fig. 5, where each year of MOS-corrected model output is compared to observations for that year. Dependent periods, where the MOS is drawn from the same year, are excluded from the comparisons.

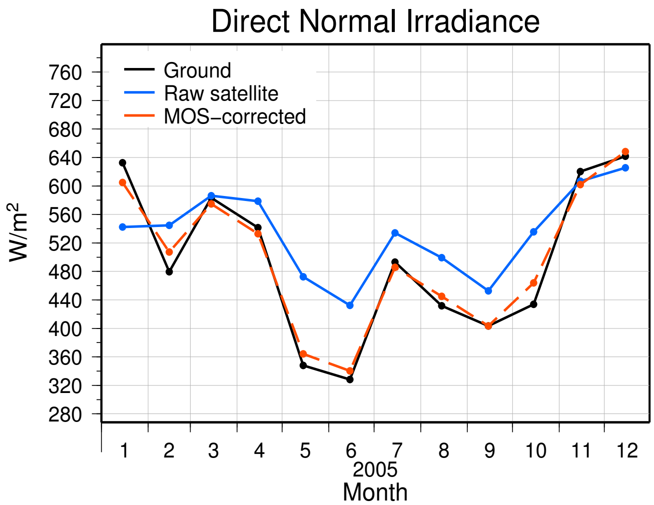


Fig. 11: DNI values in W/m^2 for MOS-correction results for the training year (2005) at Tamanrasset.

TABLE 5: Modeled data error for DNI at Tamanrasset as percent of the mean for the training year (2005) and one additional year outside of the training period (2007).

Length of Observations	Training Year Uncertainty	Blind Comparison Uncertainty
0 month	9.0	9.0
3 months	7.04	7.23
6 months	5.05	5.90
9 months	2.98	4.19
12 months	1.02	2.63

Desert Rock and Sede Boker show significantly better results for Apr-Jun, Carpentras slightly better, Tamanrasset shows improvement in Jul-Sep, and Solar Village in Oct-Dec. Our current explanation is that the signal is higher in the Northern hemisphere summer due to latitude effects (Carpentras is at 44°N, Desert Rock at 36°N, Sede Boker at 30°N, Solar Village at 24°N, and Tamanrasset at 22°N). Operating on the time period when the signal is higher improves the overall statistics. Comparisons between GHI MOS models (where seasonal effects are much stronger) show similar patterns.

To further investigate seasonality, the experiment should be run with the MOS-correction starting on cross-quarter days (i.e. centered on the solstices and equinoxes). Moreover, using more sites including some south of the equator, and sites with strong seasonal effects, such as in India during the monsoon, should be considered. This may be the subject of future work.

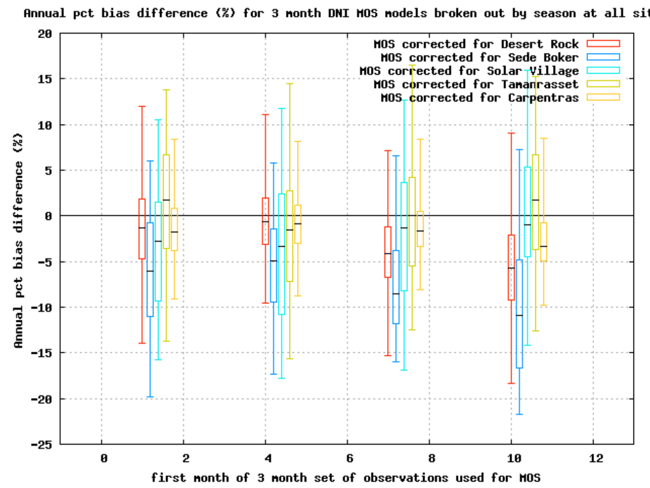


Fig. 12: Annual percent bias difference in DNI MOS corrected by season using the conservative methodology.

5. PRACTICAL APPLICATIONS FOR FINANCING

As part of this study we looked at the effects of performing a long-term dataset correction with short-term ground observations on reducing uncertainty in Probability of Exceedance Values. A 1-year P90 value indicates the production value that the annual solar resource will exceed 90% of the time. This is a common value financiers use to assign a level of risk associated with a particular project. It is directly tied to the finance rates available for project financing.

A 1-year P90 value (as opposed to a 10-year P90 value) is typically mandatory in project financing because if power production decreases significantly in a given year due to solar resource variability, debt on the project is at risk of being defaulted. The only way to determine 1-year P90, or higher, values acceptable to funding institutions is with long-term continuous data at the proposed site.

Using the uncertainty values presented in Section 4, we looked at the effect of reducing uncertainty on a set of standard P-values. We combine those standard model errors with an estimate of the variability for any single year based on the corrected long-term dataset to create a 1-year pooled uncertainty estimate. Assuming that annual average values are normally distributed, the pooled uncertainty results in 1-year P-values (P50, P75, P90, P95) using a formula like the one below for Desert Rock:

MOS-corrected DNI 1-yr P90 w/ 6 months of observations = P50 - 1.282 x (7.93 / 100) x P50 = 2436 kWh/m^2 per yr
Table 6 shows the resulting P-values for Desert Rock using the more conservative blind comparison uncertainty estimates. The table shows that as model uncertainties are re-

duced by using more months of ground observation in the MOS-correction, the annual estimates of irradiance for each of the P-values tends to increase. For most projects if they get below a certain annual average resource, the project becomes non-viable financially. That minimum value varies for different technologies. Having a P90 value above that threshold is critical.

TABLE 6: 1-year MOS-corrected DNI P-values in kWh/m^2 per year for Desert Rock from the blind comparison (2011) period.

Length of Observations	P50	P75	P90	P95
0 month	2613	2433	2270	2173
3 months	2603	2441	2295	2207
6 months	2712	2567	2436	2358
9 months	2790	2677	2576	2516
12 months	2728	2649	2577	2535

Table 7 below presents the same results for Tamanrasset. These results show that even for a location like Tamanrasset, where the uncertainty estimates were not as low as Desert Rock, performing the correction using multiple months of ground observations has a positive effect in raising the P-values in most cases.

TABLE 7: 1-year MOS-corrected DNI P-values in kWh/m^2 for Tamanrasset from the blind comparison (2007) period.

Length of Observations	P50	P75	P90	P95
0 month	2477	2320	2179	2095
3 months	2509	2378	2260	2189
6 months	2423	2316	2220	2162
9months	2366	2285	2212	2168
12 months	2351	2289	2233	2199

6. CONCLUSION

Satellite derived irradiance data are very useful for understanding the long-term context of the solar resource at project sites. However, this information is not always optimally correlated to local conditions, particularly in locations that see high aerosol loads. Taking on-site measurements for a year or more whenever possible is critical to mitigating resource related risk for solar projects. Since most on-site observations provide quality observations, but only for a short period of time, it becomes necessary to extend the resource data record in order to understand interannual variability. This paper showed two methods for correcting long-term satellite data with short-term high quality observations. The first method performs a clear-sky AOD correction based on the high resolution SOLSUN aerosol dataset. This correction can be correlated with ground observations of AOD if they are available. The advantage of this method is that on-site observations of AOD are not necessary. However, local DNI observations are necessary during about one year, since it must first be ascertained that satellite-derived data series are highly biased.

The second method performs a MOS correction based on on-site observations and investigated the optimal amount of ground observations necessary to improve the correction. With 6-9 months of on-site data or more there is a significant reduction in the bias and RMS errors in the long-term satellite data. Interestingly, no appreciable reduction in modeled irradiance bias can be obtained with DNI observations periods longer than about 9 months.

Both correction methods demonstrate skill and reduce the risk associated with variable generation power projects such as large solar installations. This provides project developers multiple robust methodologies for gaining high quality long-tem irradiance datasets, which can be used to improve the quality of production estimates.

7. REFERENCES

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