Reducing Uncertainties in Large-Scale Solar Resource Data: The Impact of Aerosols

Christian A. Gueymard[1], Aron Habte[2], and Manajit Sengupta[2]

[1] Solar Consulting Services, Colebrook, NH 03576, USA

[2] National Renewable Energy Laboratory, Golden, CO 80401, USA

***Abstract* — This study examines the impact of various aerosol databases on the accuracy of irradiance predictions pertaining to the National Solar Radiation Database (NSRDB) over the Americas. Compared to the MERRA-2 reanalysis and MODIS spaceborne observations, the various improvements that have been made to develop the SOLSUN aerosol database are described, using a monthly temporal resolution and a 4-km spatial resolution. Relative to MERRA-2, these improvements result in lower uncertainty in the solar irradiance components. The most recent version of the NSRDB now uses hourly MERRA-2 aerosol data with bias and elevation correction. This significantly improves the frequency distribution of hourly direct irradiance, while having only a small impact on the annual solar resource, as suggested by the validation undertaken here at twelve control sites.**

I. Introduction

The issue of solar resource assessment accuracy is critical in the context of solar applications using—e.g., photovoltaic (PV) generators—because any bias in the resource data used to design a large system ultimately affects its bankability and long-term performance evaluation. The uncertainty in solar resource estimates is often cited as a main contributor to the overall uncertainty of the lifetime energy yield prediction for PV systems (e.g., [1]). Most generally, designers of PV systems must rely on model-derived resource data because of the paucity of high-quality solar radiation measurements at the appropriate locations. In general, a succession of modeling steps is required [2], each contributing to the overall uncertainty in the predicted PV power production [3], [4].

Ideally, the design of PV plants would rely on solar databases providing high-quality, multi-component solar irradiance data over the whole world, at high spatiotemporal resolution (hourly or sub-hourly time steps with a grid size of, e.g., 5 km or better), and for multi-decadal periods. This kind of product only exists commercially, however. A few public-domain databases do exist too, but are limited in their spatial extent or other characteristics. Noticeably, a recent update of the PVGIS database developed by the Joint Research Center (http://re.jrc.ec.europa.eu/pvg_tools/en/tools.html) offers solar radiation data at hourly resolution over at least a part of four continents. Depending on region, one or more data source is selectable. One of these data sources is the National Solar Resource Database (NSRDB), which is the focus of this study.

At the request of the industry, the NSRDB has been continuously been developed by the National Renewable Energy Laboratory (NREL) since the early 1990s. Large parts of the Americas (from 60°N to 21°S) are now covered by the latest version of the NSRDB at fine spatial resolution (4 km) [5]. This major source of freely available solar data benefits solar engineers for their routine analyses using either time series or Typical Meteorological Years. As NREL continues to improve its modeling capabilities, more scrutiny is necessary to also improve the accuracy and consistency of the atmospheric input data required by these models.

The incident irradiance is normally at its maximum under cloudless conditions. Clear-sky irradiance is conditioned in great part by the abundance of atmospheric aerosols [6], which are highly variable over time and space. In parallel, a larger aerosol burden tends to reduce direct normal irradiance (DNI) and increase diffuse irradiance. Because of this partial compensating effect, global horizontal irradiance (GHI) is much less impacted than DNI [7]. This makes fixed flat-plate solar technologies (such as PV) much less sensitive to aerosol optical depth (AOD) than, e.g., concentrating solar power, which uses DNI exclusively. An intermediate case, however, is represented by tracking PV technologies, because their solar resource contains a larger fraction of DNI than fixed-mount systems. Compared to the annual resource available for the latter, the mean energy gain achieved by a variable (tracking) geometry is a direct function of sky clearness and DNI availability [8]. This translates into a stronger dependence on aerosols than in the fixed-mount case.

The radiative impact of aerosols is mostly influenced by AOD, which is thus considered the most essential characteristic of aerosol attenuation from a radiative transfer perspective. AOD provides a dimensionless indicator of the amount of aerosols in an atmospheric column and their potential optical effects. To model the historical irradiance over large continental areas, the necessary AOD input data can be obtained from a number of possible sources with various spatiotemporal resolutions. Considering the ubiquitous usage of the superposition principle [9], the clear-sky irradiance constitutes the foundation for the all-sky irradiance. Hence, incorrect AOD estimates can introduce errors (such as systematic bias) at all stages of modeled solar resource databases. It is also stressed that high-AOD situations impact the performance of PV systems because of a diminished resource [10]–[12] and/or technology-dependent spectral effects [13]–[15]. In addition, in dust-impacted areas, a significant correlation between AOD

and the rate of soiling of PV panels and their performance degradation might exist [16].

In this contribution, the potential impacts of local biases in aerosol data and their temporal averaging on the statistical properties of the modeled irradiance (bias and frequency distribution) are investigated, and their impact on the accuracy of the NSRDB irradiance data is discussed from the standpoint of the PV power production uncertainty.

II. Aerosol Data

As part of its long-standing partnership with NREL, Solar Consulting Services (SCS) has provided the aerosol databases used to model irradiances for the successive versions of the NSRDB since the 2000s. The main components of the aerosol database consist of a multiyear time series of monthly values of the AOD at 550 nm (AOD550) and of the Ångström exponent (AEX). Whereas AOD directly affects the overall magnitude of DNI, AEX (a function of aerosol size) modulates that impact depending on waveband. Both quantities also greatly affect the diffuse irradiance. These two inputs are necessary to run NREL's radiation models [5], [17]–[19].

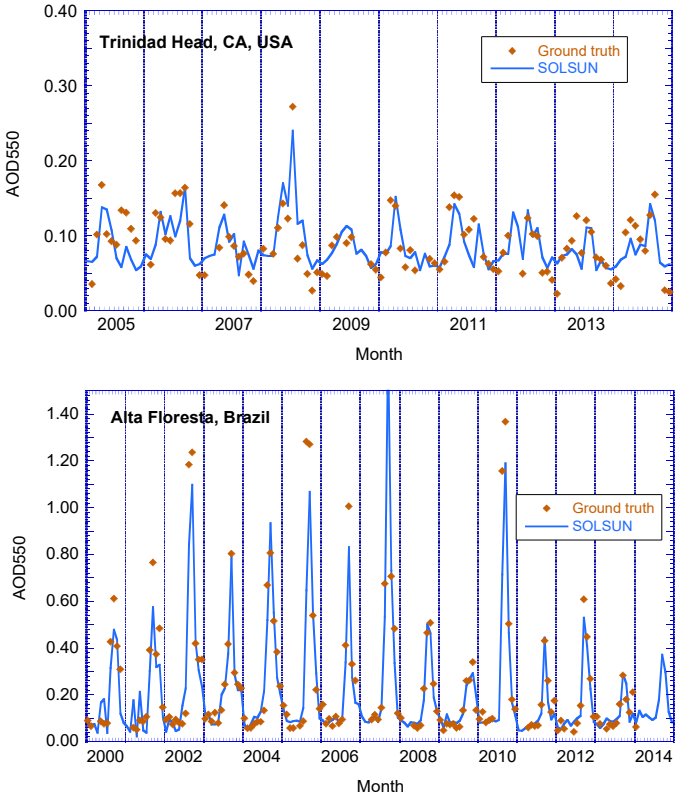

Fig. 1. Time series of monthly AOD550 data from SOLSUN and ground truth at Trinidad Head (top) and Alta Floresta (bottom).

The current SCS aerosol database (referred to as SOLSUN) is based on monthly-mean spaceborne observations from the MODIS sensor and gridded data from NASA's MERRA-2 reanalysis model. Each source of aerosol data has strengths and weaknesses. For instance, MODIS provides retrievals of AOD, but it tends to overestimate it (sometimes by a large amount) over arid areas [20], and it has many gaps because of, e.g., cloudy periods. In contrast, MERRA-2 provides a gapless time series of modeled AOD over the whole world, but it has variable bias depending on the region. After calibration and appropriate combination of these sources to reduce errors, the AOD and AEX values in SOLSUN are finally regridded to the appropriate spatial resolution using a digital elevation model. Because AOD normally tends to decrease rapidly with elevation, an appropriate correction is performed based on [21].

To validate the resulting aerosol database, reference ground observations from NASA's AERONET sunphotometric network are used here. This network has been established to provide the necessary "ground truth" for spaceborne aerosol observations [22]. Cloud-screened and quality-controlled ("Level 2") time series provide the necessary ground truth at a total of 396 AERONET sites (338 in North America and 58 in South America) during the period 1998–2015. The number of observations varies widely from site to site, since many AERONET sites are operated only on a temporal basis, or may experience long interruptions. The total number of monthly-mean observations used for development is 10388 over North America and 1991 over South America, for a grand total of 12379.

Fig. 1 compares time series of SOLSUN's monthly AOD to the corresponding ground truth at one "clean" site (Trinidad Head, California) and one Amazonian site experiencing large seasonal excursions in AOD because of intense smoke episodes (Alta Floresta, Brazil). Larger daily variability can be expected at the latter site because of its higher mean AOD [7]. Note also the significant interannual variability at both sites.

Scatterplots comparing the MERRA-2 and SOLSUN results to ground truth pertaining to the whole American continent are shown in Fig. 2. The number of monthly-mean observations used for validation is 8298 over North America and 1846 over South America, for a grand total of 10144.

It is clear that SOLSUN's correction method can significantly reduce the mean continental bias of the raw data overall, but the RMS errors (0.039 over North America, 0.066 over South America, and 0.045 overall) are still non-negligible. The propagation of errors between AOD and the irradiance components can be evaluated with the Aerosol Sensitivity Index (ASI), which is the multiplication factor to be applied to the *absolute* error in AOD to obtain the induced *relative* error in DNI [7]. Assuming a low average air mass of 1.0–1.5 and AEX≈1.3, ASI is ≈0.81–1.66, so that deviations in the range 3.2–11.0% can be expected in the modeled DNI on average. The impact on GHI would be ≈3–4 times less [7], hence in the range ≈1.0–3.5%. Somewhat larger deviations are likely at very hazy sites or during atypical months.

To prevent any systematic negative bias in the predicted DNI caused by the monthly temporal resolution, all AOD values are further statistically corrected downward per previous results [23]. A final step consists in smoothing the monthly

data into pseudo-daily values to limit temporal artifacts, such as discontinuities on the first and last day of a month. A mean-preserving algorithm [24] is used for that purpose (Fig. 3).

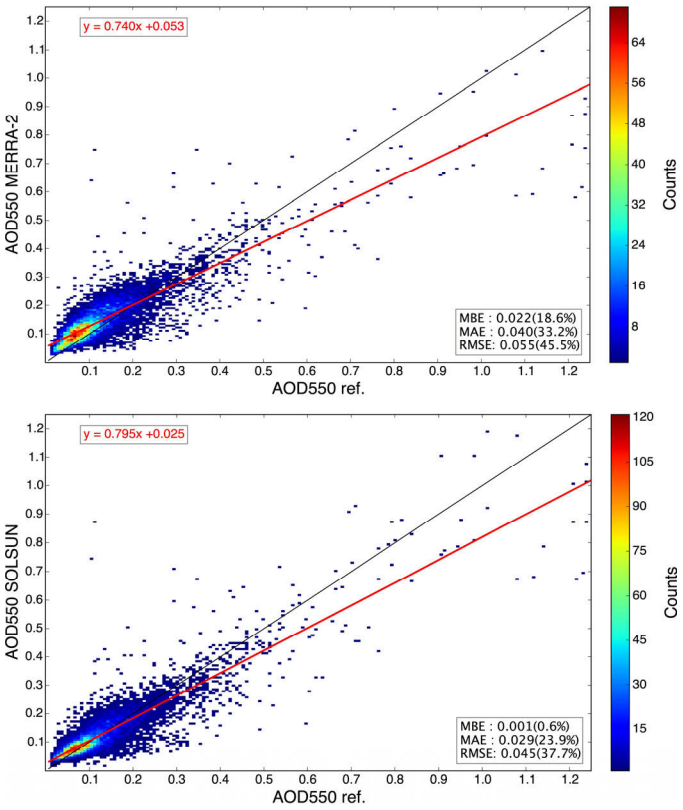

Fig. 2. Density plots of monthly MERRA-2 (top) and SOLSUN (bottom) AOD550 predictions vs. ground truth over the Americas.

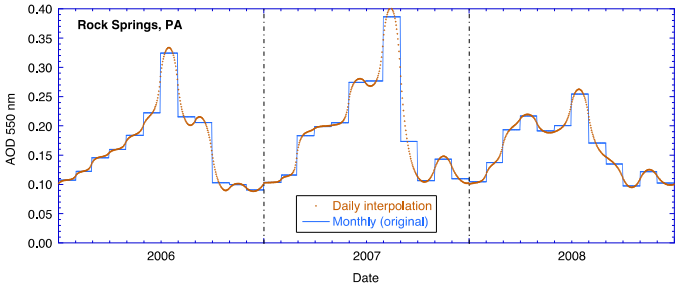

Fig. 3. Example of smoothing of monthly AOD into pseudo-daily values using a mean-preserving algorithm.

III. Validation

Because the accuracy of the NSRDB irradiance predictions directly depends on that of all data sources and corrections described above, a detailed validation study is necessary. This is done here under clear-sky conditions, as identified using a proven method [25]. A selection of results is presented here pertaining to four stations where high-quality GHI, DNI, and AOD observations are conducted. These stations are Bondville, Illinois (BON), Desert Rock, Nevada (DRA), Sioux Falls, South Dakota (SXF), and Tucson, Arizona (TUC). BON, DRA and SXF belong to NOAA's SURFRAD network, whereas TUC belongs to NREL's MIDC network. DRA and TUC are sunny sites in the dry southwest United States, whereas BON and SXF experience cloudier climates.

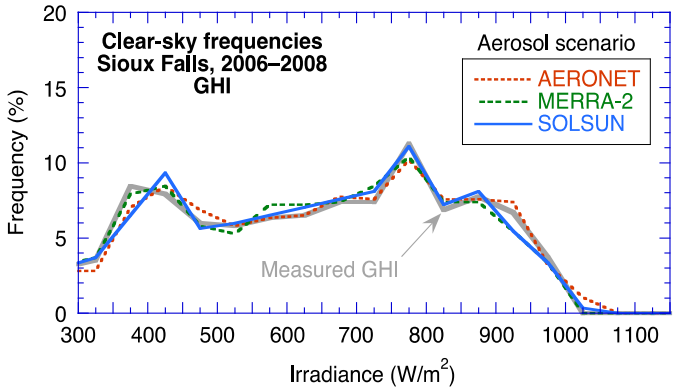

Fig. 4. Frequency distribution of clear-sky GHI at Sioux Falls, from either actual measurements or REST2-modeled estimates based on various sources of aerosol data.

TABLE I
PERFORMANCE OF MODELED CLEAR-SKY IRRADIANCE

Statistic	DNI				GHI			
Station	BON	DRA	SXF	TUC	BON	DRA	SXF	TUC
N	739	1464	568	6106	739	1464	568	6106
Measured (W/m²)	871.6	946.6	881.5	841.3	625.4	768.5	637.6	529.4
AERONET								
MBD (%)	0.0	0.3	-0.6	0.1	0.7	1.0	1.5	-0.4
RMSD (%)	2.1	2.9	2.2	1.6	2.4	2.4	2.2	1.5
MERRA-2								
MBD (%)	-12.9	-3.2	-10.4	-5.2	-2.6	0.1	-0.9	-1.7
RMSD (%)	14.1	5.4	11.5	7.6	3.9	2.3	2.1	2.5
SOLSUN								
MBD (%)	-6.1	0.0	-5.0	-0.7	-0.8	0.9	0.4	-0.5
RMSD (%)	8.6	3.9	7.0	3.9	3.1	2.4	2.0	1.8

At each station, the performance of the DNI and GHI predictions using the high-performance REST2 model [26]—the clear-sky component of NREL's Physical Solar Model (PSM) [5]—is assessed in Table I, alternatively using three sources of AOD and AEX data: instantaneous values from AERONET (ground truth), raw monthly MERRA-2 data, and optimized monthly SOLSUN data. The usual statistics are used: mean bias deviation (MBD) and root mean square deviation (RMSD), all expressed in percentage of the mean measured irradiance, for a number *N* of instances. The results using AERONET are excellent, thus confirming previous studies (e.g., [27]). Substantial degradation in performance is observed when using the monthly MERRA-2 aerosol data, particularly for DNI. The SOLSUN-based results are intermediate, which means that the various steps described above to improve the AOD database have had a significant impact.

In terms of frequency distribution, no significant difference is observed for GHI when using either of the three AOD datasets, as shown here for SXF (Fig. 4). In the case of DNI, however, a degradation is observed when using monthly data, as could be expected [23]. The magnitude of this degradation depends on the radiative climate of each site (with more distortion when the mean AOD increases), but it is always less marked with SOLSUN than with MERRA-2. An example is shown in Fig. 5 for TUC (low AOD) and SXF (higher AOD).

IV. Impact of Temporal Resolution

The monthly resolution of aerosol data is convenient, and, until recently it was the only resolution available with reasonable accuracy, geographical coverage, and an absence of gaps. This explains why monthly aerosol data were used in the development of the NSRDB until the 1998–2015 update, based on the PSM v2 and released in 2016.

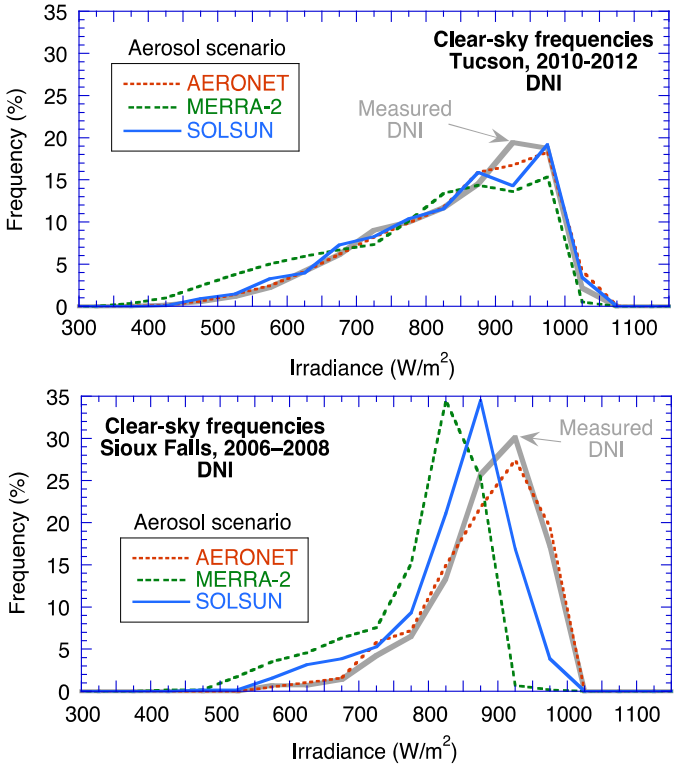

Fig. 5. Frequency distribution of clear-sky DNI at Tucson (top) and Sioux Falls (bottom) from either actual measurements or REST2 model estimates based on various sources of aerosol data.

During the last few years, new aerosol products have appeared, including those provided on an *hourly* basis as part of the MERRA-2 reanalysis, which offers a consistent time series since 1980. Modeled aerosol optical properties are usually not as accurate as observations (including space retrievals). In the case of MERRA-2, however, regular aerosol observations from either ground-based instruments (such as AERONET) or spaceborne platforms (such as MODIS) are assimilated on a daily basis, hence anchoring the boundary conditions and substantially improving the modeled predictions overall. Because the NSRDB's irradiance data are obtained with the PSM, which obtains some of its hourly inputs from MERRA-2, it appears desirable to evaluate the advantages and disadvantages of using aerosol data from MERRA-2 at higher temporal resolution than the current pseudo-daily time step.

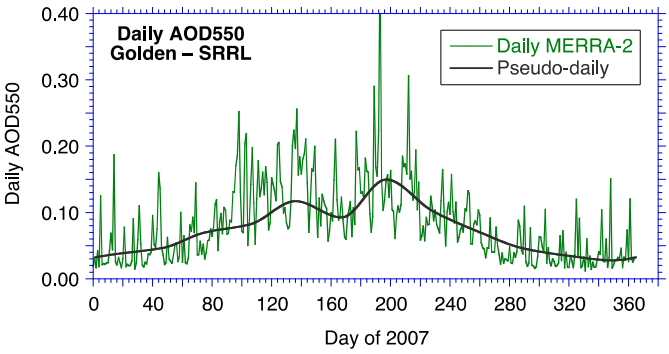

Fig. 6. Daily AOD variability at the NREL/SRRL station in Golden based on either monthly SOLSUN data or hourly MERRA-2 data.

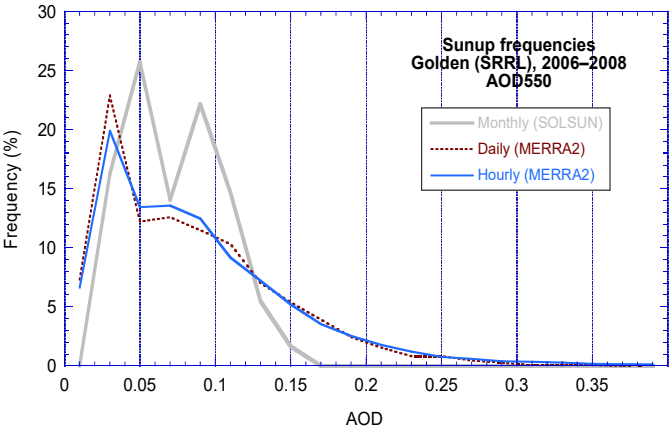

Fig. 7. Frequency distributions of monthly, daily, and hourly AOD at the NREL/SRRL station in Golden, Colorado.

One obvious advantage of a high data frequency is that it better describes the temporal variability in aerosol properties. This is apparent in Fig. 6, which compares the daily variations of AOD at the NREL/Solar Radiation Research Laboratory (SRRL) station in Golden, Colorado, when predicted from pseudo-daily data (SOLSUN) or from hourly data (MERRA-2). The difference between the two sources can be as high as 0.3 AOD at that site. Still, this range of daily variability—which is typical of most of North America, for instance—is only the lowest of the ranges observed on a worldwide basis, as revealed by a comparative analysis of Aerosol Variability Index [7].

Differences in temporal variability translate into differing frequency distributions. This is exemplified in Fig. 7, which

compares the frequency distributions of three years of AOD data of different temporal resolution at SRRL. Whereas the hourly and daily-derived MERRA-2 AOD data have very similar distributions, the monthly SOLSUN distribution is significantly different, because of the obvious compression of the AOD range. These results confirm those from a recent study that used a worldwide database of station-specific data [28].

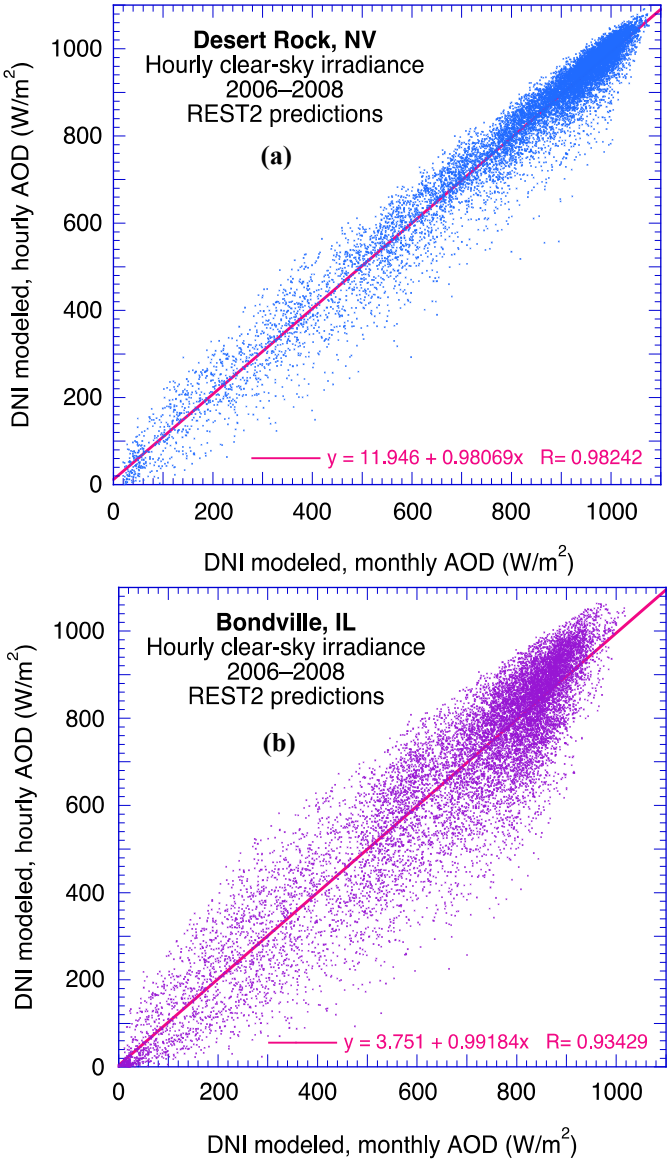

Fig. 8. Scatterplot of clear-sky modeled hourly DNI predictions based on hourly AOD data compared to those based on monthly data at (a) Desert Rock, Nevada, and (b) Bondville, Illinois.

Although the analysis above underlines the advantage of using AOD data at hourly or daily temporal resolution for a better representation of temporal variability, the bias and random errors of MERRA-2 that were noted in Section II might have a counterbalancing effect that could offset the anticipated benefit on irradiance predictions. To resolve this issue simply, it is assumed that any bias in the hourly MERRA-2 aerosol data (AOD550 and AEX) is conserved over time, at least up to the monthly timescale. The monthly bias in a given pixel is represented by the ratio of the MERRA-2 and SOLSUN values. Each hourly MERRA-2 value can thus be modified using this ratio as a correction function. This simple method must be considered a temporary correction until an improved version of the MERRA-2 aerosol model is released, with hopefully lower bias. The same kind of elevation correction as discussed above is also appended, which improves irradiance predictions over complex terrain.

Considering that the most recent update of the NSRDB (1998–2016) is now based on PSM v3, which uses the hourly, bias-corrected MERRA-2 aerosol data just described, it is useful to evaluate the impact of the change in aerosol data on the predicted irradiance. For instance, Fig. 8a compares the REST2-predicted hourly DNI under the low-AOD conditions of DRA when using either the original pseudo-daily SOLSUN AOD data or the hourly bias-corrected MERRA-2 data. The scatter denotes the effect of the naturally increased temporal variability in the hourly AOD data. More scatter is observed under the fairly hazier conditions of BON (Fig. 8b). It is expected that these short-term "random" features compensate each other to a large extent as a result of aggregating hourly values into annual results. How well this actually verifies is important because the annual mean values of DNI and GHI characterize the main features of the solar resource at any location, and they are thus essential to the proper design of any solar power system.

TABLE II
ANNUAL CLEAR-SKY IRRADIANCE AT 12 SITES: PERCENTAGE CHANGES IN DNI AND GHI FOR HOURLY VS. MONTHLY AOD

Site	Lat.	Long.	Elev. (m)	DNI	%	GHI	%
BIL	36.605	-97.516	317	708.1	-0.6	496.9	-0.1
BON	40.067	-88.367	213	677.1	-0.3	473.8	-0.2
BOU	40.050	-105.007	1577	802.9	-0.7	504.5	-0.2
DRA	36.626	-116.018	1007	820.2	-0.5	529.3	-0.1
FPE	48.317	-105.100	634	726.1	1.5	431.4	0.3
GCR	34.255	-89.873	98	679.8	-0.9	505.0	-0.3
GOL	39.742	-105.180	1829	811.9	-0.9	509.9	-0.2
PSU	40.720	-77.933	376	679.3	-0.1	471.0	-0.1
PTR	-9.068	-40.319	387	759.6	-0.8	603.7	-0.1
REG	50.205	-104.713	578	706.3	2.6	415.7	0.5
SXF	43.730	-96.620	473	705.3	2.5	458.2	0.5
TUC	32.230	-110.955	786	811.6	-2.2	547.1	-0.5

Summarizing three years of hourly simulations with REST2, Table II provides the percentage relative changes in the clear-sky DNI and GHI when based on the hourly bias-corrected MERRA-2 aerosol data relative to the monthly ("pseudo-daily") SOLSUN aerosol database. Twelve control stations are considered here, most of which belonging to

NOAA's SURFRAD network and/or the BSRN international network. Apart from the four stations (BON, DRA, SXF and TUC) already discussed earlier, eight more stations are considered here: Billings/ARM, Oklahoma (BIL); Boulder, Colorado (BOU); Fort Peck, Montana (FPE); Goodwin Creek, Mississippi (GCR); Golden/NREL, Colorado (GOL); Rock Springs, Pennsylvania (PSU); Petrolina, Brazil (PTR); and Regina, Saskatchewan, Canada (REG). Table II reveals that the annual changes to be expected from AOD data alone are minor: less than ≈3% (or ≈20 W/m^2) in DNI and less than 0.5% (or ≈2 W/m^2) in GHI. (The columns marked DNI and GHI provide the mean annual clear-sky irradiance when using monthly AOD data as input to REST2.)

V. Conclusion

The production of NREL's modeled NSRDB irradiance data over North America and South America has recently transitioned from using aerosol data on a monthly to hourly temporal resolution, as part of modifications in the PSM that predicts half-hourly irradiance time series since 1998. This contribution described the various steps that have been followed to ensure the lowest possible uncertainty in the aerosol data required by PSM at either timescale. The use of hourly aerosol data from the MERRA-2 reanalysis is expected to improve the frequency distribution of DNI, most importantly. In contrast, GHI (which is the key solar resource variable in PV applications) appears virtually insensitive to the aerosol input data's time step, both in magnitude and frequency distribution. Great care has also been taken to decrease the bias in the AOD data and, by way of consequence, in the predicted irradiance—particularly DNI.

Based on simulations of hourly clear-sky irradiance at 12 control sites in the Americas, the transition from using monthly to hourly AOD data in the NSRDB production is expected to result in annual differences of less than ≈3% in DNI and less than ≈0.5% in GHI, which is deemed reasonably small.

Acknowledgments

This work was authored in part by Alliance for Sustainable Energy, LLC, the manager and operator of the National Renewable Energy Laboratory for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

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