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VARIABILITY IN DIRECT IRRADIANCE AROUND THE SAHARA: ARE THE MODELED DATASETS OF BANKABLE QUALITY?

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Abstract

The design, energy output, and cost effectiveness of CSP projects critically depend on the resource in direct normal irradiance (DNI). Many modeled DNI datasets now exist, and a recent preliminary study has shown some areas of serious disagreement in Europe. So far, no rigorous performance assessment has been undertaken for other parts of the world. The present contribution focuses on North Africa and bordering regions, which have great CSP potential. The mean monthly and annual performance of eight different modeled datasets providing DNI is analyzed here, with respect to measured radiation data at 14 sites. Relatively good results are generally obtained for sites in southern Europe. Serious problems, however, are found at various sites in North Africa or Middle East. Most of these problems appear linked to inadequate aerosol optical depth data used by the models, and to the dust storms from the Sahara that regularly, and strongly, modify the aerosol regime. A method that can potentially correct these problems, or allow for model benchmarking based on a reference aerosol database, is proposed. The bankability of current datasets is questioned.

Keywords: CSP, Direct normal irradiance (DNI), aerosol optical depth, radiative model validation, solar resource assessment, Sahara dust storms.

1. Introduction

Many concentrating solar power (CSP) projects are currently being proposed in the world, and particularly in Mediterranean and North African regions. Among all these projects, the ambitious Desertec initiative has gathered considerable attention. To perform correctly and be cost effective, CSP power plants must rely on a very intense resource in direct normal irradiance (DNI). Accurate knowledge of the DNI resource in sunny regions is essential to assess the technical and economic viability of any CSP project, since, as a first approximation, the energy output of a CSP plant is proportional to its input, i.e, DNI. For the region under scrutiny here (loosely defined as the area between latitudes 8 and 40°N, and longitudes 17°W to 51°E), existing solar maps of mean DNI do show an abundant resource. These maps are only based on modeled data, since weather stations measuring DNI are extremely scarce over that region. At its early stages, any CSP project must also rely (at least in great part) on modeled data. Therefore, an essential issue is the reliability of these modeled datasets and maps. This issue has not yet received the attention it deserves, considering the importance of its financial implications. The only known preliminary report that has been devoted to an intercomparison of a few direct solar radiation maps was limited to Europe [1], where many solar radiation monitoring stations exist—thus providing abundant data for the fine tuning and validation of modeled datasets before they are even released to the public. Still, that study revealed a number of problem areas where significant disagreement existed between the tested datasets. Unfortunately, some of these areas are also those with the best solar resource. It was found that differences of more than ≈30% between datasets were likely in many regions. From the perspective of financial institutions or policy makers, any single large CSP project that would not deliver its nominal energy output due to inaccurate resource evaluation would cast a doubt on the whole industry, akin to what happened in the early years of large wind energy projects.

The critical questions that all developers and investors of CSP projects in North Africa are confronted with could thus be summarized this way: (i) Are the existing DNI datasets of sufficient quality and accuracy to be considered “bankable”?, and (ii) Are modeled DNI data of sufficient accuracy to replace costly local measurements? This contribution’s goal is to help answer these fundamental questions, and propose a method that could potentially improve the accuracy of the existing DNI datasets over North Africa.

2. Aerosol effects on DNI

The radiative effects of aerosols are function of different variables. The most important one is called the aerosol optical depth (AOD), which varies widely with wavelength. This spectral variation can be described by Ångström's law, which defines the turbidity coefficient, β, and the wavelength exponent, α. The combined effects of α and β on DNI can be evaluated through radiative transfer calculations. These calculations must also take the sun geometry into account, as well as the extinction effect of other atmospheric constituents, most importantly water vapor (measured in terms of precipitable water, PW). For North Africa, some calculations of this type have been made with the SMARTS code [2]. For sea-level conditions and an air mass of 1.25, which is typical of the conditions of CSP operation at low latitudes, it is found that a change from relatively clean conditions ($\beta = 0.1$, $\alpha = 1.1$) to dust storm conditions ($\beta = 1$, $\alpha = 0$) results in a severe decrease in DNI, from $\approx$850 to $\approx$300 W/m^2. Additional calculations with SMARTS show that DNI is about 3–5 times more sensitive to β than global horizontal irradiance (GHI), depending on air mass and atmospheric conditions. This implies that, due to the usually large uncertainties in β, DNI predictions might be in error even if those of GHI appear correct.

3. Sources of DNI and aerosol data

3.1. Measured DNI data

Within the present study area, datasets from 14 weather stations with high-quality radiation measurements are used (Table 1). Due to the paucity of DNI measurements, some stations measuring only GHI and diffuse irradiance (DIF) have been added to the pool. The direct horizontal irradiance (DHI) is obtained by simple difference between GHI and DIF. For one site only (TEI Crete), data at 1 to 5 minutes intervals were available, so that DNI could be derived from DHI, using the "instantaneous" zenith angle. In all other cases, however, only daily or monthly data of DHI were available, thus precluding the determination of DNI by the same method. DHI is lower than DNI, but proportional to it. On a monthly basis, the ratio DHI/DNI equals the cosine of the effective monthly-average zenith angle. Since this quantity can only be approximated using empirical means (which might introduce non-negligible uncertainties), no attempt at transforming DHI into DNI has been made in such cases. The two main data sources here are BSRN (http://bsrn.awi.de) and WRDC (http://wrdc.mgo.rssi.ru). The former source provides 1-min data, whereas only daily values are available from the latter. Therefore, DHI rather than DNI was used for all WRDC sites. Datasets of 5 years or more were also used to define "long-term" monthly averages, or "climatologies". Ideally, at least about 15 years of data should be used to define the climatology of DNI, considering its large interannual variability [3]. However, this stringent requirement had to be relaxed here due to the paucity of long datasets.

Station	Lat.	Long.	Elev. (m)	DNI or DHI	# Months	Source
Aswan	23.97	32.78	193	DNI	123	[4]
Bahrain	26.24	50.80	25	*DHI*	12	[5]
Caceres	39.47	-6.33	405	*DHI*	139	WRDC
Cairo	30.13	31.47	35	DNI	173	[4]
Granada	37.13	-3.63	687	*DHI*	76	WRDC
Huelva	37.28	-6.92	19	*DHI*	40	WRDC
Ilorin	8.32	4.34	350	*DHI*	95	BSRN
Izana	28.31	-16.50	2391	*DHI*	51	WRDC
Santa Cruz (Tenerife)	28.27	-16.20	25	*DHI*	26	WRDC
Sede Boker	30.86	34.78	480	DNI	83	BSRN
Solar Village	24.91	46.40	764	DNI	51	BSRN
Tamanrasset	22.79	5.53	1377	DNI	123	BSRN
TEI Crete	35.30	25.10	122	DNI	15	SolRad-Net
Valencia	39.48	-0.38	23	*DHI*	55	WRDC

Table 1. Radiation measurement stations used for this study.

3.2. Modeled DNI data

Various sources of modeled DNI data with large geographic coverage currently exist, which should help the rapid development of CSP projects in many countries. Eight datasets are used here, representing at least half of what is currently available (Table 2). Two of them are in the public domain and available online: NASA-SSE and NREL-SWERA. One of them can be obtained freely if for research purposes (DLR-ISIS). Another one is actually not a dataset, but commercial software to calculate radiation and other weather information by interpolation (Meteonorm; version 6.1.0.19 is used here). Finally, four datasets represent the burgeoning marketplace for commercial data vendors: 3Tier, EnMetSol from the University of Oldenburg, HelioClim3 from the Soda online service, and SolarGIS from GeoModel. These vendors graciously provided data for some of the ground-truth sites listed in Table 1 especially for this study, with the exception of HelioClim3, for which the only year (2005) freely available from the SoDa service could be used here. Note that the DNI dataset from the public-domain PVGIS website (http://re.jrc.ec.europa.eu/pvgis) could not be used because it is not accessible, unfortunately. Whereas Meteonorm makes irradiation predictions for any ground location, all the other datasets provide gridded data. The grid sizes vary widely, between coarse resolution (ISIS), medium resolution (SSE and SWERA), and what is currently labeled "high" resolution (3Tier, EnMetSol, HelioClim3 and SolarGIS). Furthermore, the latter four datasets offer hourly or sub-hourly (15-min) data series. For the present study, only monthly data and monthly climatologies are used. However, whenever a month is affected by a bias, the corresponding hourly time series must also be biased in some way. Conversely, bias-free annual results may mask large alternating monthly biases, which may affect bankability, etc. Thus, the results of the present study have potentially large implications. Note that, since diffuse irradiance results were not available from all datasets, the assessment of DHI has a reduced scope compared to that of DNI.

Dataset	Developer	Website	Spatial resolution	Temporal resolution	Period	Spatial coverage
3Tier	3Tier	http://www.3tier.com	≈3x3 km	Hourly	1998–present	World
EnMetSol	Univ. Oldenburg	http://www.energy-meteorology.de	≈5x5 km	15-min	2004–present	Some continents
HelioClim3	SoDa	http://www.soda-is.com	≈5x5 km	15-min	2004–present	Some continents
ISIS	DLR	http://www.pa.op.dlr.de/ISIS	280x280 km	Monthly	1984–2004	World
Meteonorm	Meteotest	http://www.meteonorm.com	≈1x1 km	MC†	variable	World
SolarGIS	GeoModel	http://geomodel.eu	≈5x5 km	15-min	2004–present	Some continents
SSE	NASA	http://eosweb.larc.nasa.gov/sse	1x1°	MC†	1983–2005	World
SWERA	NREL	http://swera.unep.net	40x40 km	MC†	1985–1991	Some continents

Table 2. Modeled dataset sources used in this study. (†MC: Monthly climatology only).

3.3. Aerosol data

All radiation sites (except Aswan) of Table 1 are collocated or near another station where sunphotometric measurements are performed. Such measurements (here from NASA's Aeronet network) provide AOD at up to seven wavelengths, as well as PW. For this study, the spectral AOD data has been reduced to monthly-average α and β values, using a conventional technique [6]. Figures 1 and 2 show examples of seasonal and interannual variations in β at four of the sites under scrutiny, from the cleanest (Izana) to the most turbid (Ilorin). The large interannual variance (such as in June at Izana and Tamanrasset) is a direct function of dust storm activity in the Sahara. Since all current modeled datasets in Table 2 (with the exception of 3Tier, to our knowledge) only consider a long-term *climatology* of AOD—rather than actual daily or monthly data—a significant interannual variation in DNI performance of these datasets can be expected.

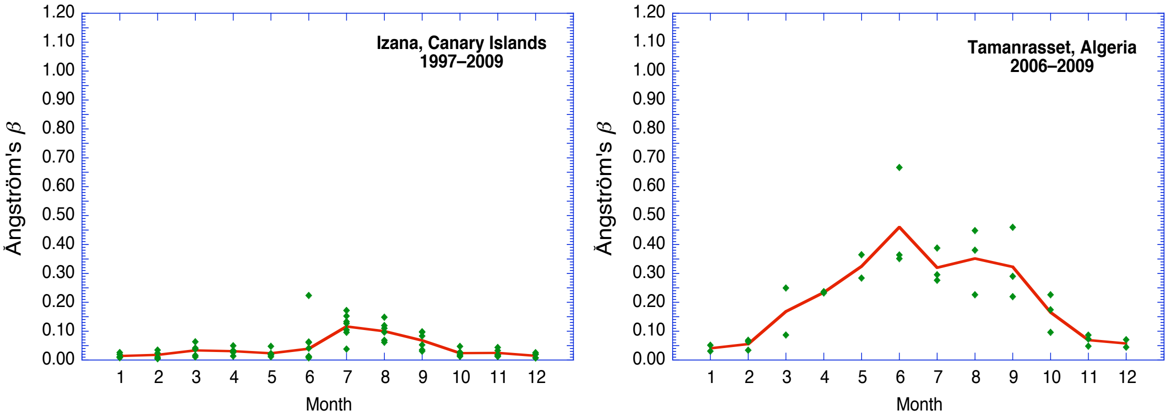

Fig. 1. Interannual variation of the mean monthly turbidity coefficient at Izana (left) and Tamanrasset (right). The climatology is indicated by the continuous red line.

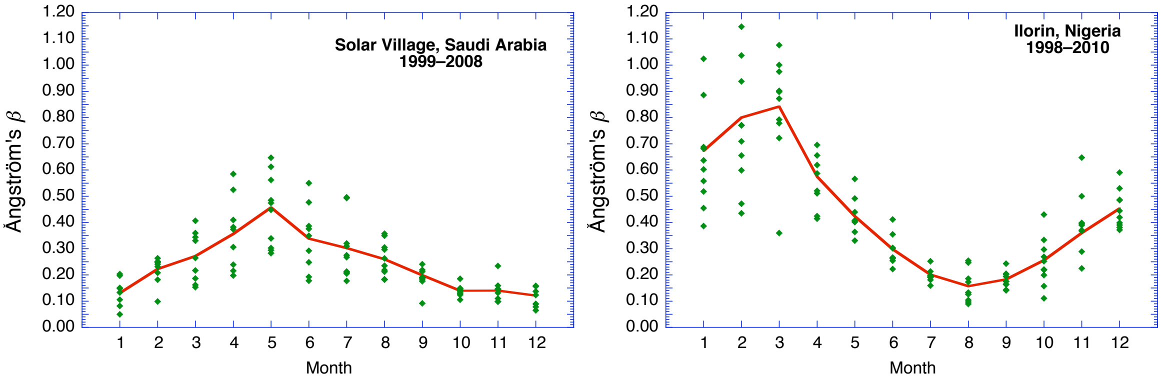

Fig. 2. Same as Fig. 1, but for Solar Village and Ilorin.

4. Monthly performance

The performance of the modeled monthly *climatologies* of DNI and DHI is assessed first. Percent differences between the modeled and measured long-term mean monthly DHI for two stations (Caceres and Granada) in southern Spain appear in Fig. 3. The seasonal variations in measured DHI (shown in the top plots) are similar, whereas the modeled DHI's performance varies somewhat from one month to the other. Due to error cancellations throughout the year, the overall annual differences are all within ±10% of the measured mean.

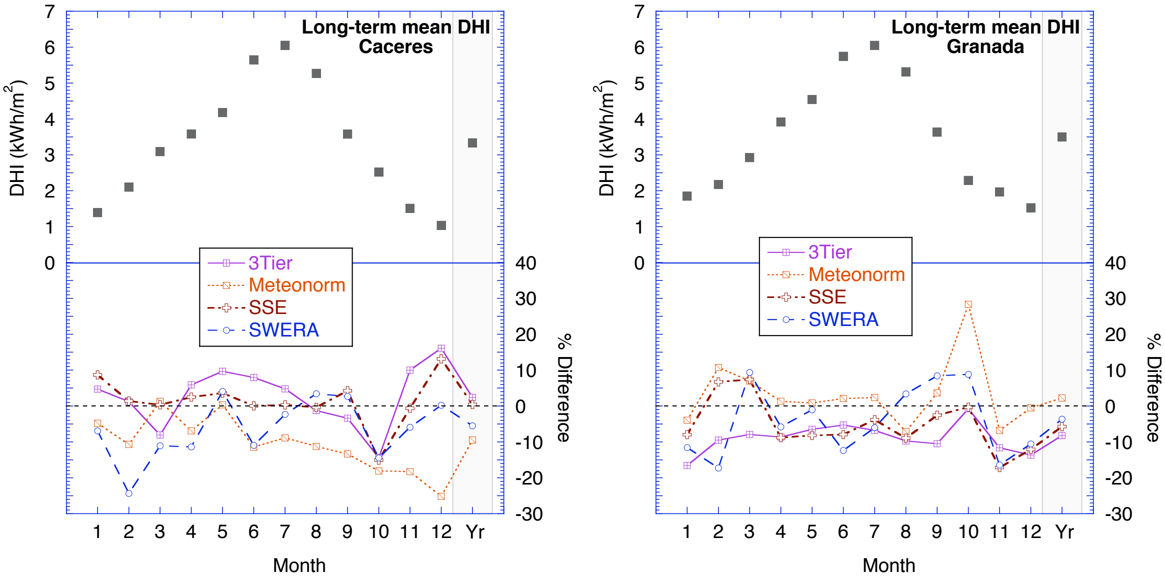

Fig. 3. Monthly performance results at Caceres and Granada, based on climatologies.

For North Africa, however, the situation is different. At Aswan, the results of Meteonorm and SWERA are similar to those in Fig. 3, with mean annual differences of only +3% and -3%, respectively. The two datasets with lower spatial resolution (ISIS and SSE) do not perform as well, but still manage to predict the annual average within -10% and +10%, respectively. For Aswan, like for Caceres or Granada, using an average of all the available datasets can improve the results, and bring the annual bias down to ≈0. Results for Cairo, Ilorin, Sede Boker and Tamanrasset show much larger monthly and annual differences (Fig. 4), and do not support the same recommendation. Interestingly, for Ilorin and Tamanrasset, the monthly differences exhibited by most datasets are in phase with the seasonal AOD variation (Figs. 1 and 2). It is thus likely that the noted discrepancies can be explained by the use of incorrect gridded AOD climatologies in the models. In the case of Cairo, all models (particularly SSE) tend to overestimate all the time. It is highly likely that these models do not take into account all the radiative extinction processes that occur in a polluted urban environment. Moreover, the accelerated urbanization of Cairo has resulted in increased AOD (from local aerosol production) and decrease in global and direct irradiance [4], [7], usually referred to as the "dimming" effect.

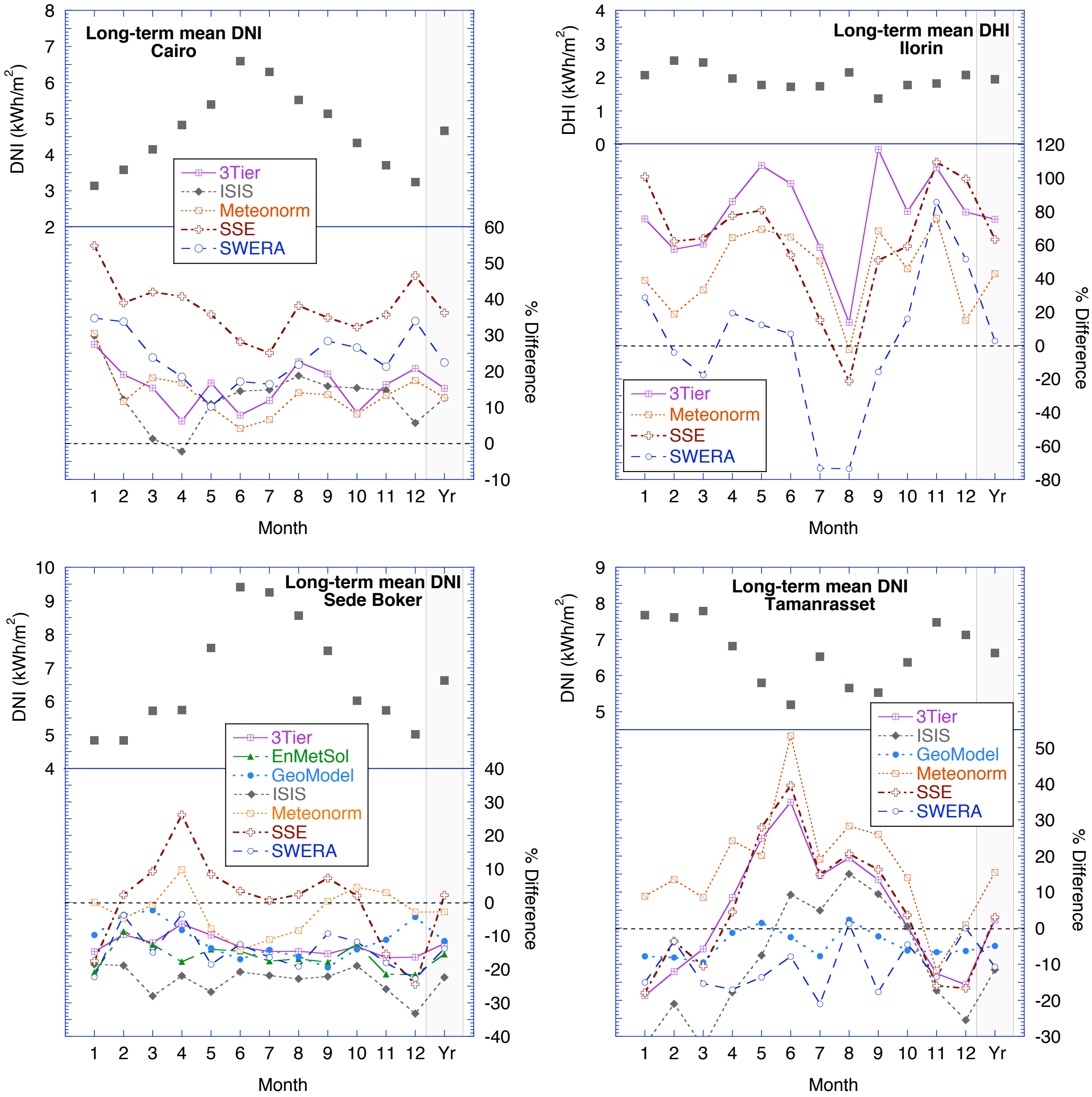

Fig. 4. Same as Fig. 3, but for Cairo, Ilorin, Sede Boker and Tamanrasset.

Although Ilorin is in a dusty and cloudy area, and therefore would probably not attract any CSP development, its results are instructive by the magnitude of the monthly differences obtained here, which oscillate between -75 and +120% (Fig. 4). Some part of this disagreement may be explained by the large seasonal and interannual variance in AOD (Fig. 2), the dust and biomass burning aerosols' absorption and scattering characteristics, and associated uncertainties. Moreover, it is most likely that the algorithms in current use cannot adequately reproduce the intricacies of radiative transfer though intense tropical cloudiness.

Results for *individual* months are equally instructive. For instance, Fig. 5 shows two typical cases for which limited scatter exists between models, while they all underpredict at high DNI. This type of summer bias also occurs at Bahrain, as well as (to some extent) Caceres, Granada and Huelva. In such cases, the datasets can be corrected with the method explained in Section 5. At Tamanrasset, most datasets exhibit substantial scatter (Fig. 6), with the exception of SolarGIS, which rather reflect the same summer bias as in Fig. 5. Results for Solar Village show important scatter too, but data from only two datasets were available there. At Solar Village, like at Tamanrasset, there is large variance in the interannual AOD, which might explain the disagreement in modeled DNI. Finally, the case of Izana is interesting because of its very high solar resource. Both 3Tier and SolarGIS have difficulty keeping the monthly bias under ±20%. In contrast, the 3Tier results at Santa Cruz are nearly perfect. The latter site is only 30 km away from Izana, but near sea level. Izana being above the boundary layer where both aerosols and water vapor are concentrated, the AOD and PW are much less there than at Santa Cruz. On average, Izana's PW is 14–26% of that at Santa Cruz (depending on season), whereas comparative numbers for AOD are 20–79%. The larger range in AOD difference may be explained by the occurrence of dust storms: AOD is then high anywhere since dust clouds travel at altitudes above 3 km. Irregular occurrences of dust storms, and related seasonal variations in AOD as a function of elevation, are usually not considered in radiative models, which can explain the scatter in the Izana results.

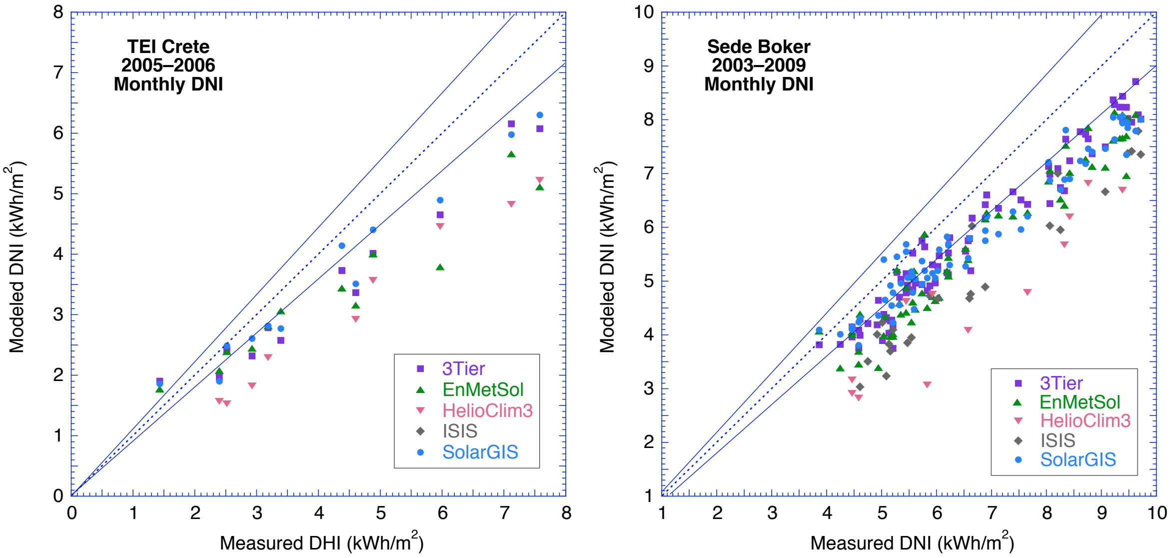

Fig. 5. Monthly performance results for various modeled datasets at TEI Crete and Sede Boker.

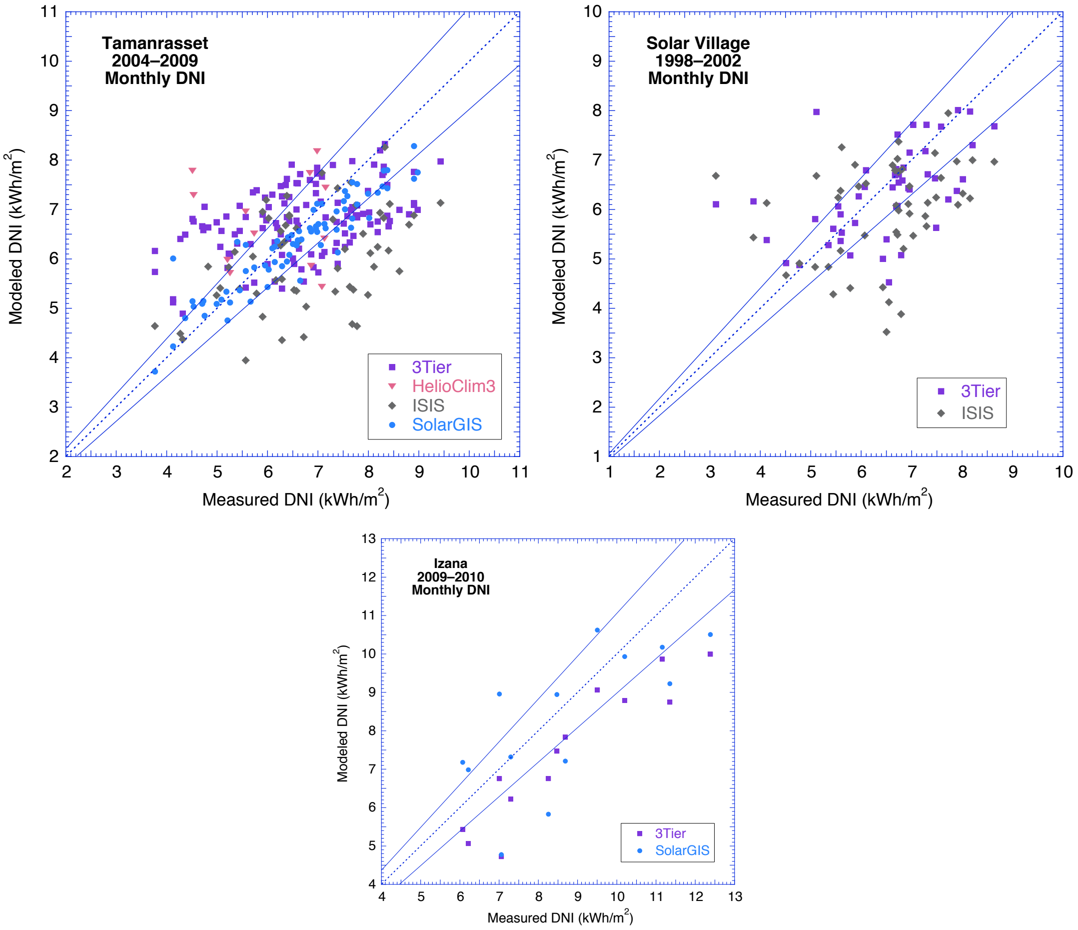

Fig. 6. Same as Fig. 5, but for Tamanrasset, Solar Village and Izana.

5. A posteriori irradiance data correction

The results discussed above clearly indicate that the disagreement between modeled and measured DNI is often linked to the models' AOD input data. Various projects exist to improve the quality of AOD databases. A method of regional combination and correction of multiple satellite datasets has recently been proposed [8], but is still in its infancy. Arguably, the desirable AOD databases of sufficient quality for worldwide accurate DNI prediction are still years away. In the mean time, it might be possible to remove some of the observed bias in monthly DNI data, provided local AOD measurements are available. Considering the current paucity in AOD ground-truth sites in the world, this might have only limited applicability. However, another application of this correction method would be to intercompare or "benchmark" DNI datasets after normalization to some common, "reference" AOD database, which remains to be defined. Most radiative models have separate, but linked, algorithms for the clear-sky and all-sky DNI. (A notable exception is SSE.) If the clear-sky DNI is available, in addition to the all-sky DNI that users have primary interest in, a correction of the clear-sky DNI can be done, using reference AOD data. In the present case, this method could only be applied to 3Tier, EnMetSol, Meteonorm and SolarGIS, due to lack of clear-sky data in the other cases.

Since the all-sky DNI is proportional to the clear-sky DNI, DNI_c, it is then just a matter of correcting the existing all-sky DNI by the ratio $DNI_{c\ \mathrm{new}}/DNI_{c\ \mathrm{old}}$. The REST2 model [6], which is currently unsurpassed in terms of DNI prediction accuracy over a wide range of atmospheric conditions [9], is used here to obtain $DNI_{c\ \mathrm{new}}$. For the present tests, data of AOD and PW have been obtained as described in Section 3.3. The usual cumulative statistics (MBD and RMSD) are used here to characterize the accuracy of the predicted monthly DNI (or DHI) with respect to its measured counterpart, *before* and *after* applying the correction described above. Sample results appear in Table 3, and show that improvements (slight to substantial bias reduction in particular) are indeed possible in most cases (bold case indicates improved statistics). A notable exception is seen with Meteonorm, whose climatologies are not always improved, probably because it uses interpolation rather than a local radiative calculation as with the other datasets. The case of Ilorin stands out again, with only partial improvement, thus confirming that AOD uncertainties are not the only source of problem in such a cloudy climate.

Site/Model	Mean Daily Irradiation (kWh/m^2)	Monthly values				Climatology			
		Before		After		Before		After	
		MBD	RMSD	MBD	RMSD	MBD	RMSD	MBD	RMSD
Ilorin	3.231 (DHI)								
3Tier		76.3	83.8	**22.0**	**45.5**	79.5	84.3	**25.8**	**46.8**
Meteonorm		-	-	-	-	46.4	54.0	**-1.8**	**25.9**
Izana	5.184 (DHI)								
3Tier		-12.9	15.1	**6.1**	**9.4**	-13.0	14.0	**-4.1**	**12.4**
Meteonorm		-	-	-	-	-41.4	44.8	-45.7	48.9
Sede Boker	6.675 (DNI)								
3Tier		-12.3	13.7	**6.6**	**11.4**	-12.9	13.5	**-7.4**	**11.5**
EnMetSol		-16.3	18.0	**2.3**	**9.4**	-16.2	16.9	**-10.6**	**12.0**
Meteonorm		-	-	**-**	**-**	-3.7	8.6	-17.9	22.3
SolarGIS		-12.8	15.1	**4.9**	**9.8**	-12.0	14.1	**-7.8**	**12.4**
Tamanrasset	6.631 (DNI)								
3Tier		4.0	17.0	**-1.5**	**8.6**	2.2	15.4	-3.0	**6.2**
Meteonorm		-	-	-	-	15.5	19.8	**-12.3**	**15.7**
SolarGIS		-4.0	7.2	**-2.4**	11.3	-4.9	6.4	**-4.4**	8.1
TEI Crete	5.231 (DNI)								
3Tier		-16.8	20.1	**-2.3**	**8.3**	-	-	-	-
EnMetSol		-19.8	25.1	**-0.4**	**5.3**	-	-	-	-
SolarGIS		-13.0	16.2	**0.4**	**7.2**	-	-	-	-

Table 3. Performance statistics (%) before and after correcting DNI using measured aerosol data.

Although the present corrections are for monthly data, they can be applied directly to hourly or 15-min time series as well, since all current models used to derive time series consider only *monthly* AOD input data for their calculations. This correction method is therefore also of potential interest to users who need time series to simulate the thermal performance of CSP installations, or to obtain bankable assessments, for instance.

6. Conclusion

Using high-quality radiation data from 14 sites in North Africa and bordering regions, a preliminary assessment of the performance of eight DNI datasets (from both free and commercial sources) is proposed. It is found that, in general, these datasets are reasonably accurate over southern Europe. Over North Africa and the Middle East, however, the present results are generally not as good, and even reveal some important problem areas. Large monthly scatter is observed in many cases. Even the annual-mean DNI predictions may be affected by considerable biases (such as for Cairo and Ilorin).

An analysis of coincident radiation and aerosol data from collocated instruments shows that, in most cases, these biases are caused by inaccurate aerosol data being used to model DNI. An a posteriori correction technique is proposed to remove a substantial part of the observed bias in existing DNI datasets (monthly data or hourly time series). It is established that the current datasets would benefit from improved aerosol data, taking the variability of Saharan dust storms into account, in particular.

The large differences between modeled and measured DNI observed at various sites cast a doubt on the accuracy of solar resource maps and datasets for CSP applications in or around North Africa. Monthly data and hourly time series currently used for bankability assessments might embed large biases, depending on dataset, climate area, etc. Until such biases and uncertainties are better understood and ultimately corrected, it is safe to recommend local high-quality measurements to corroborate, supplement or validate modeled data.

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