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Preliminary survey on site-adaptation techniques for satellite-derived and reanalysis solar radiation datasets

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Abstract

At any site, the bankability of a projected solar power plant largely depends on the accuracy and general quality of the solar radiation data generated during the solar resource assessment phase. The term "site adaptation" has recently started to be used in the framework of solar energy projects to refer to the improvement that can be achieved in satellite-derived solar irradiance and model data when short-term local ground measurements are used to correct systematic errors and bias in the original dataset. This contribution presents a preliminary survey of different possible techniques that can improve long-term satellite-derived and model-derived solar radiation data through the use of short-term on-site ground measurements. The possible approaches that are reported here may be applied in different

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ways, depending on the origin and characteristics of the uncertainties in the modeled data. This work, which is the first step of a forthcoming in-depth assessment of methodologies for site adaptation, has been done within the framework of the International Energy Agency Solar Heating and Cooling Programme Task 46 “Solar Resource Assessment and Forecasting”.

Keywords: Satellite-derived solar radiation; Site adaptation; Bankability of data for solar projects; Solar radiation model-derived data

1. Introduction

Accurate and precise knowledge of the local solar resource is a prerequisite for the successful deployment of any solar energy system. For instance, reliable and accurate data of different components of solar radiation are needed for concentrating solar power (CSP) projects, which are primarily interested in direct normal irradiance (DNI), and flat-plate collectors (PV or thermal) which require good predictions of the incident global horizontal (GHI) or global tilted irradiance (GTI), also referred to as “plane of array” (POA). From the initial site selection stage to the plant’s design and financing the solar resource assessment plays a major role in the success of the project whenever monthly or annual plant predictions are needed (Stoffel et al., 2010; Sengupta et al., 2015).

High-quality solar resource measurements at the target site are usually not available to ensure proper solar resource assessment and thus to secure the final acceptance of the project. Additionally, the inter-annual variability of solar radiation components plays an important role in the uncertainty associated with the energy yield prediction of solar plants. As a consequence, long-term, typically multi-decadal, time series of the key solar radiation components are required at various stages of any solar plant project (Meyer et al., 2006; Stoffel et al., 2010). Since multi-decadal measurements are hardly available at any potential solar power plant site, long-term time series of solar irradiance must generally be supplied from modeled data, typically using satellite imagery to derive the influence of clouds on solar radiation at the Earth’s surface.

Solar radiation components at the Earth’s surface can be determined from several methods and different approaches. The most widely known ones are those based upon the use of meteorological satellites (Hammer et al., 2003; Mueller et al., 2003; Rigollier et al., 2004; Janjai et al., 2005; Polo et al., 2008; Perez et al., 2013). The underlying methodologies have been evolving during the last 30 years, following advances in remote sensing and computational techniques. The literature documents this trend that started with simple methods based on a crude atmospheric energy balance (Gautier et al., 1980; Moser and Raschke, 1983; Cano et al., 1986) and has progressed to the more intricate methods currently in use (Perez et al., 2002; Rigollier et al., 2004; Mueller et al., 2004; Schillings et al., 2004; Viana et al., 2011). For solar applications, most developments follow an empirical or semi-empirical approach, also referred to as the cloud-index method. The common approach to determine DNI with the cloud-index method is the use of a GHI-to-DNI separation method (Gueymard and Ruiz-Arias, 2014). In recent years, a convergence between the physical and the semi-empirical approach has started to manifest, with semi-empirical models tending to include more physical descriptions. Physical methods (using retrievals of cloud optical properties from satellite observations) can now provide appropriate datasets for solar applications (Sengupta et al., 2015).

Satellite based methods are able to provide long-term hourly or even sub-hourly time series of solar radiation components. A thorough validation exercise of most of the current satellite-based databases has been performed within the International Energy Agency (IEA) Solar Heating and Cooling (SHC) Programme Task 46 “Solar Resource Assessment and Forecasting” activities (Ineichen, 2014). Different comparative and evaluation studies have shown that despite the high accuracy and reliability of satellite-derived data, significant differences from ground data may result (e.g., Gueymard, 2011; Ineichen, 2014). This is a consequence of several sources of error, whose complex causes typically affect GHI, GTI and DNI differently (Cebecauer et al., 2011). For instance, satellite-derived methods usually require external atmospheric information on the most important attenuating components under cloudless conditions, namely aerosols and precipitable water vapor, with an important impact on the final uncertainty (Gueymard and Thevenard, 2009; Gueymard, 2012, 2014). In addition, site-specific information (albedo or topography) is also needed and can affect the final uncertainty. A complete list of known issues and potential uncertainty sources in satellite-based solar models is outlined in previous works (Suri and Cebecauer, 2014).

For sound solar resource assessments, all model-derived estimates must be validated and qualified as much as possible using locally available ground measurements. Moreover, all large solar power projects must respond to stringent bankability criteria, following the regular practice of financial institutions. In this context, detailed and accurate knowledge of the seasonal and inter-annual variability in the solar resource is of crucial importance. Therefore, bankable energy production scenarios must be based on a statistical analysis of long-term time series. Since a large inter-annual variability of the solar resource means a larger risk, this variability must be thoroughly assessed. Current studies demonstrate that the inter-annual variability in

DNI is significantly larger than that in GTI, and larger than that in GHI (Lohmann et al., 2006; Gueymard and Wilcox, 2011; Gueymard, 2012).

Therefore, the proper evaluation and characterization of the uncertainty sources embedded in satellite-derived data constitutes a crucial step toward the bankability of solar resource assessments for solar power plants. For instance, the proper identification and correction of systematic errors or bias in satellite-derived data by comparison with high-quality ground data can lead to a large reduction of uncertainty. More precisely, if the satellite-derived estimates for a specific site can be calibrated against a short-term local measurement campaign, the long-term solar resource accuracy can be substantially improved. Such an on-site campaign is normally required by financial institutions, and typically starts a few months after the beginning of the project.

This process of calibration or correction of modeled data is similar to what has been developed for the wind industry in the past (Potter et al., 2008). Similar to the case of wind energy resource assessment, different methods may be used, which are discussed in the following sections. Whereas the purpose of these methods is generally agreed, the terminology varies depending on the method's proponent. For instance, these methods may be referred to as "site adaptation" (Suri and Cebecauer, 2011), "dataset merging" (Thuman et al., 2012), or "measured record extension" (Bender et al., 2011; Gueymard et al., 2012). For clarity and conciseness, all these methods will be collectively referred to as "site adaptation" in what follows. In summary, all the various statistical methods that have been developed to decrease the uncertainty in the local solar resource try to improve satellite-derived irradiance data (by lowering their random errors, and most importantly their bias) using characteristics of corresponding ground observations during overlapping time periods.

Within IEA-SHC's Task 46, a considerable effort has begun to improve the bankability of solar radiation datasets by developing procedures and methods designed to increase the quality of both ground measurements and modeled data, and to combine them as efficiently as possible. In this sense, a thorough benchmarking exercise on site adaptation techniques is being designed and will provide results in the near future. This paper is a first step in exploring the issue of site adaptation for bankability and offers a preliminary, but needed, survey of the different techniques for site adaptation reported elsewhere. The information here gives a general overview on the current state and points out the further work to be done.

2. Importance of quality ground measurements

For an effective use of ground irradiance measurements in improving and evaluating solar radiation datasets, the quality of the measurements must be assured to be as high as possible. All types of instruments should be properly calibrated, operated and well maintained, which in particular implies regular and frequent cleaning. The measurement protocol should be rigorous and follow the best practices and available standards (Stoffel et al., 2010; Sengupta et al., 2015). In addition, the derived time series should be thoroughly quality controlled, and the number of data gaps minimized. Quality check methods such as BSRN recommendations (McArthur, 1998), SERI-QC (NREL, 1993) or those delivered in the MESoR project (Hoyer-Klick et al., 2009) should be used to detect either values beyond physical limits or inconsistent values as a consequence of errors in solar tracking systems. The use of such methods requires the availability of the three essential solar irradiance components: GHI, DNI and Diffuse horizontal irradiance (DHI).

Long-term datasets of solar irradiance components to be used for bankability should be accompanied by their corresponding uncertainty. Site adaptation methods require high-quality ground solar radiation data, i.e. low data uncertainty, whose magnitude must also be assessed.

The highest accuracy in solar radiation measurement is normally achieved by using thermopile radiometers for the simultaneous measurement of GHI, DNI and DHI (Vignola et al., 2012). Among the thermopile-based instruments currently available, those denoted as "secondary standards" have the highest precision (ISO, 1990). Secondary standards, under typical operating conditions and proper maintenance, have a measurement uncertainty (at 95% confidence) of 5% for GHI, 3% for DNI, and 7% for DHI (Vignola et al., 2012). The three main solar radiation components can be alternatively measured by a single rotating shadowband radiometer (RSR), also referred to as rotating shadowband irradiometer (RSI). This device uses a photodiode sensor that is periodically shaded by a shadowband that rotates across the horizontal detector. Therefore the RSI measures GHI when unshaded and DHI when shaded, out of which DNI is appropriately derived by calculation from the other two components (Sengupta et al., 2015; Wilbert et al., 2015a). They usually require less maintenance than thermopile-based instruments, which is an important advantage in remote areas where soiling conditions could prevail. The proper calibration of RSIs involves various steps and empirical corrections, the effectiveness of which are still being investigated (Jessen et al., 2015). The analysis of long-term behavior of the accuracy of RSI typically requires a recalibration of the device after two years of operation (Geuder et al., 2014). A thorough analysis of accuracy and uncertainties in broadband shortwave radiometers is found in the literature (Vuilleumier et al., 2014). In addition, RSI uncertainty has been investigated recently with significant updates and improvements (Wilbert et al., 2015b).

As a summary of the existing literature, the steps described below need to be followed with care to ensure an optimum quality of ground measurements that are intended to be used in site adaptation techniques:

1. Proper design of the ground station technical characteristics according to the intended aim of the data (data logger, instrument selection for additional relevant parameters such as wind speed, temperature, grounding and shielding; also general aspects like stable instrument mounts, security/fence, position of station without shading, etc.).
2. Selection of radiometers having low uncertainty for the solar component(s) under scrutiny, e.g., DNI and/or GTI taking also into account the available maintenance.
3. State-of-the-art calibration of the radiometers and an adequate schedule for future calibrations.
4. Regular maintenance of the station – mainly cleaning of sensor heads and verification of alignment and level.
5. Commissioning and regular check of the station by qualified experts including proper documentation of all quality-related aspects.
6. Extensive quality control of the recorded data to assess their effective accuracy, flagging data, and applying corrections (only where advisable).

Only measurements fulfilling all these requirements can be regarded as valid and can be used for fusion with, or correction of, model-derived datasets. Otherwise, the quality of model-derived datasets could be lowered by measured data of insufficient quality, due to, for example, significant bias. In addition, measurements of temperature and wind speed observations at heights critical to the planned solar system can be useful for the de-biasing of ancillary long term temperature and wind speed measurements that are also needed in many simulation tools.

3. Solar radiation estimation from satellite imagery

The use of meteorological satellites for deriving solar radiation components at specific sites or over vast regions is nowadays the most usual approach for solar resource assessment studies. These methodologies have been evolving during the last 30 years, following advances in remote sensing and other techniques. The literature documents this trend from the first simple methods (Gautier et al., 1980; Moser and Raschke, 1983; Cano et al., 1986) through to the more intricate methods in current use (Perez et al., 2002; Rigollier et al., 2004; Mueller et al., 2004; Schillings et al., 2004; Janjai et al., 2005; Martins et al., 2007; Zarzalejo et al., 2009; Polo et al., 2012, 2014; Escobar et al., 2014, 2015).

Traditionally, there have been two main approaches for satellite-derived data. Physical models use the satellite information to solve the radiative transfer in the atmosphere and they usually retrieve vertically averaged properties of clouds and cloud optical depth (Miller et al., 2013). On the other hand, empirical models are based on the statistical relationship between spaceborne and ground observations. In recent years, some convergence between these two different approaches has started to manifest, so that most of the models in current use can be referred to as semi-empirical models. In effect, they include analytical methods to describe the interaction of radiation with gases and aerosols in the atmosphere, while using satellite-derived information to empirically retrieve the cloud index (Perez et al., 2013).

The high degree of maturity in models and methods for estimating solar radiation components from satellite imagery has resulted in the availability of many different databases and web services that provide time series of satellite-derived solar radiation data. Table 1 lists the most frequently used databases and summarizes some of their general characteristics. Note that some of these databases are in some way dependent on each other. Satellite-based databases and methods have been extensively assessed with ground measurements elsewhere. Thorough reviews and compilations of these validation results can be found in the literature (Ineichen, 2011, 2014; Sengupta et al., 2015).

Time series derived from satellite observations offer the great advantage of providing global (worldwide) coverage (at least between latitudes of 60°S and 60°N), and long periods of data (up to ≈20 years currently, for geographic areas covered by the oldest satellites with appropriate sensors). The current fleet of geostationary satellites is judiciously positioned to continuously monitor reflected spectral radiances from the atmosphere over the whole globe (except high latitudes) at hourly or sub-hourly time steps. The nominal spatial resolution of the satellite-derived irradiance data is in the range of 1–10 km. The large geographical coverage of these methods means they are able to supply solar irradiance information for almost every site on Earth. However, shortcomings do exist because satellite-based methods cannot always model all possible local effects or specific features of a target site. Indeed, complex terrain with very variable elevation, coastal areas, areas or periods with unusual or rapidly changing cloud conditions, highly reflective surfaces (typical of sand or salt deserts and snow-covered areas), and inaccuracies in information on local atmospheric constituents (mostly aerosol optical depth, AOD, and water vapor), are examples of the possible features that might substantially affect the final uncertainty, and hence the bankability of solar energy projects (Cebecauer and Suri, 2010, 2012; Cebecauer et al., 2011). Thus in case of ground snow cover under clear sky conditions the satellite models based on the visible channel might result in erroneous cloudy estimations; the multichannel (visible and IR) satellite model techniques can offer better results (Perez et al., 2010). Similar situations can occur in bright desert regions where specific models for ground albedo could prevent that errors (Polo et al., 2012). This leads to temporary overestimations of cloud optical thicknesses or, cloud indices. Satellite model performance is also affected by the solar and viewing geometry. At high solar zenith angles high clouds cast shadows upon lower clouds that can be misinterpreted as cloud free areas. At high view zenith angles a parallax effect occurs, where the apparent cloud position is different from the actual position.

Table 1
Databases and services providing solar radiation time series derived from satellite information.

Name	Time basis	Coverage	Web site
NSRDB update	30-min	USA	http://rredc.nrel.gov/solar/old_data/nsrdb/
NASA SRB	3-hourly	World	http://gewex-srb.larc.nasa.gov/
DLR-ISIS	3-hourly	World	http://www.pa.op.dlr.de/ISIS/
HelioClim	hourly	Europe–Africa	http://www.soda-is.com/eng/helioclim/
SOLEMI	hourly	Europe–Africa–Asia	http://wdc.dlr.de/data_products/SERVICES/SOLARENERGY/
SolarGIS	30-min	World	http://solargis.info/
EnMetSol	hourly	Europe–Africa	https://www.uni-oldenburg.de/en/physics/research/ehf/energiemeteorology/enmetsol/
IrSOLaV	hourly	Europe–Africa–Asia–America	http://irsolav.com/
CM-SAF (SARAH)	hourly	Europe–Africa	http://www.cmsaf.eu/
SUNY – SolarAnywhere	30-min	North America	http://www.solaranywhere.com/
MACC RAD	3-hourly	World	http://www.soda-pro.com/es/help/macc-rad/automatic-access
PVGIS	hourly	Europe–Africa–Asia	http://re.jrc.ec.europa.eu/pvgis/
Meteonorm	TMY	World	http://www.meteonorm.com/
CPTEC/INPE	daily	South–America	http://satelite.cptec.inpe.br/radiacao/
Vaisala	hourly	World	http://www.vaisala.com
Australian Bureau of Meteorology	hourly	Australia	http://www.bom.gov.au/climate/data-services/solar-information.shtml

Advancement of satellite-derived methods for solar radiation computation typically results from improvements in the design of satellite sensors and from improved atmospheric retrieval methods as well. Thus, new and better versions of the satellite-derived databases and their underlying models have appeared recently (Mueller et al., 2012; Amillo et al., 2014; Qu et al., 2014; Hammer et al., 2015; Perez et al., 2015). In addition, several methods are being optimized for working with different geostationary satellites without the need to modify their fundamental methodology (Amillo et al., 2014; Albarelo et al., 2015).

4. Methodologies for site adaptation of satellite-derived data

The rapidly increasing deployment of solar power plants over many different climatic zones in the world has encouraged studies and attempts focused on improving the accuracy of satellite estimations of solar radiation components. Most attention has been devoted to DNI because it is generally determined with higher uncertainty than GHI. This results from the much higher sensitivity of DNI to cloudiness and aerosols. Various possible site adaptation techniques exist and are reviewed below. They are all based on the use of short-term ground measurements of solar irradiance and/or accurate atmospheric data at the site under scrutiny to “anchor” the large-scale modeled resource data.

4.1. Physically based methods

One approach for correcting model-derived solar radiation data consists of adjusting the atmospheric input data so that the new results better match the ground-based observations. In principle, this approach might lead to a modification of any input, such as cloud properties, but in most cases the main focus is on aerosol turbidity because of its large impact on DNI (Gueymard, 2012).

Many satellite derived hourly DNI time series are affected by significant monthly and annual bias over regions where high aerosol loads are frequent (Cebecauer et al., 2011; Gueymard, 2011). Therefore, to obtain high accuracy and low bias in solar irradiance estimates (particularly DNI), AOD used as input in satellite-based methods must have the lowest bias possible (Ruiz-Arias et al., 2015a).

Clear sky transmittance models can be used with ground-based AOD observations for the purpose of correcting pre-existing model estimates. As an example, a method based on the REST2 model (Gueymard, 2008) is reported in the literature (Gueymard, 2012). However, due to the scarcity of ground AOD observations the correction method was generalized to the use of large-scale AOD datasets. The methodology consists of comparing hourly DNI and GHI outputs of the REST2 model with DNI and GHI derived from the satellite model for clear-sky conditions, I_{sat}. A correction factor (R_C) can be obtained and used to correct the satellite-based irradiance.

$$R_c = \frac{I_{\mathrm{REST2}}}{I_{sat}} \qquad (1)$$

Similar methods have been proposed that use other clear-sky models to adapt the atmospheric aerosol dataset according to the irradiance measured during clear days (Cebecauer and Suri, 2012).

The generation of new and more accurate global aerosol datasets is also an ongoing issue, to which important efforts are being devoted. For instance, Gueymard proposed a global aerosol dataset with 0.5° × 0.5° spatial resolution using monthly averages from MODIS retrievals, MATCH reanalysis and AERONET measurements, also introducing an altitude correction for AOD based on a Digital

Elevation Model (DEM) to reduce systematic errors (Gueymard and Thevenard, 2009). This dataset was later improved by the addition of other sources of data, such as MISR satellite retrievals and gridded climatology (Gueymard and Sengupta, 2013).

Similarly, Ruiz-Arias et al. (2013a, 2013b) proposed a data fusion approach of daily gridded AOD estimates from MODIS retrievals and daily point-wise observations of AOD from AERONET stations. The method is based on a combination of *kriging* and optimal interpolation methods and was tested in the continental United States. First, the missing satellite AOD estimates over cloudy areas were filled using kriging techniques. Second, the bias at regional scale was removed using a correlation model of this bias and the observed AOD MODIS values (Ruiz-Arias et al., 2013a). Third, the debiased AOD estimates were locally adjusted to match the AERONET aerosol observations using optimal interpolation. Therefore, the method proposes an approach that corrects the satellite AOD errors successively at regional and local scales. In contrast with other methods introduced above, the local adjustment does not correct the satellite estimates only where a collocated AERONET sunphotometer exists. In addition, it uses the covariance of the AOD error between neighboring sites in such a way that the AOD satellite error at the AERONET locations is cast over surrounding areas. In this way, the area of influence of the ground AOD observations is widened.

A DNI sensitivity analysis of this method conducted under clear-sky conditions showed that, using the original AOD satellite retrievals, filled by interpolation, the resulting DNIs for AOD below 0.2 are overall positively biased by more than 5%, with a significant spread over the observed value. If, in contrast, corrected AOD values are used, the overall DNI bias vanishes and 90% of the DNI estimates have an error lower than 5% (Ruiz-Arias et al., 2013b). These results were applied to North America, where AOD is generally low to moderate. Much larger aerosol loads are frequent over many regions of the world, where similar studies would thus be necessary.

Calibration of MODIS L3 daily values of both AOD and precipitable water have been recently proposed by using linear regression with AERONET measurements showing an improved performance of REST2 clear sky model (Zhong and Kleissl, 2015).

4.2. Statistical methods

Statistical adaptation of model-derived results is frequently used in various fields of applied meteorology. For instance, rain rates can be corrected to better reflect local conditions. Moreover, it is also quite common to adapt wind speeds to local measurements for wind resource analysis. Similarly, statistical methods can be applied to adjust model/satellite-derived solar radiation values to local measurements. Several such approaches are currently used in practice, and are described in the next subsections.

4.2.1. Bias removal by linear adaptation

Satellite-based methods for deriving solar radiation components may exhibit systematic errors that could yield an overall overestimation or underestimation trend, referred to as bias, and characterized by the mean bias deviation (MBD) statistic. Bias between the predicted and measured irradiance may result from systematic features of the radiative model or from regional inconsistencies in the external input data (particularly aerosols or water vapor).

When short-term high quality ground DNI and GHI measurements are available bias in satellite irradiance estimates can be reduced by calculating correction factors from the overlapping data (Carow, 2008; Cebecauer and Suri, 2010; Vindel et al., 2013; Harmsen et al., 2014).

The simplest method is to estimate the MBD and remove it from the whole dataset. A bias removal can also be developed by fitting a line to the cloud of points in a scatter plot and subtracting the $y = x$ line. Fig. 1 illustrates an example of this simple method (Polo et al., 2015). Correction by the difference between the fitted line ($y_{sat} = ax_{ground} + b$) and the $y = x$ line produces new estimates with negligible bias. The new estimates are computed by the following resulting equation:

$$y_{new} = y_{sat} - [(a-1)x_{ground} + b] \quad (2)$$

In many situations the linear fit corrections should be applied to a subset of derived data rather than to the whole dataset, for instance clear sky bias corrections (Kankiewicz et al., 2014). Likewise a seasonal method was proposed to adapt satellite estimates of DNI over India, where initial deviations were typically large and seasonal (Polo et al., 2015).

4.2.2. Non-linear methods

Some proposed methods introduce a parameter-dependent correction, others a so-called “feature transformation” correction (Carow, 2008). The first method uses a specific combination of parameters (for example clear-sky index or sun elevation angle), and additively or multiplicatively modifies the original satellite-based time series. Typically, the additive correction efficiently reduces MBD and the Root Mean Squared deviation (RMSD) on average. The second approach, feature transformation, uses properties of the cumulative distribution function of the on-site ground measurements and transfers them via look-up tables to the satellite-derived time series. This process brings the distribution functions closer together. It has been shown that improvements made by feature transformation strongly depend on the length of the overlap period when both satellite-derived irradiance data and ground-based measurements are available (Schumann et al., 2011). It is recommended to take at least a whole year of measurements to develop this adaptation algorithm.

The literature reports another method based on the assumption that low irradiance values are often overestimated, whereas high irradiance values tend to be underestimated, thus

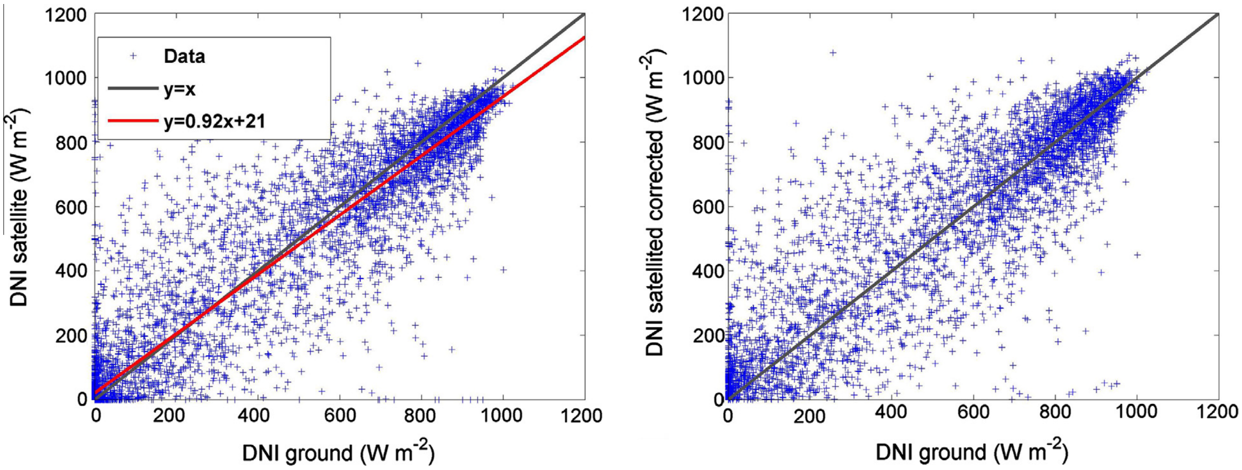

Fig. 1. Example of linear bias removal for DNI data for 2001 in Tabernas (Spain) according to Eq. (2). Uncorrected data on the left and corrected data on the right. Ground data from DLR-PSA station (Kipp and Zonen CH1 (until 30/8/2011) and CHP1 (afterward)). Satellite data estimated by CIEMAT procedure from Meteosat Second Generation imagery.

leading to an artificial compensation in terms of the yearly irradiation sum. A third-degree polynomial is then assumed to correct the data (Mieslinger et al., 2013).

Other reported methods of combining short-term ground measurements with longer-term satellite data are based on model output statistics (MOS) (Bender et al., 2011). MOS is a multi-variate linear regression analysis between a prescribed set of predictors (satellite derived data or estimates from numerical weather prediction models, for instance) and the surface observational dataset. The objective is to develop a multi-linear regression equation to correct the estimated values, thus effectively removing the bias and adjusting the variance. An example of MOS correction applied to DNI data from Tamanrasset, Algeria, evaluated the impact of varying overlapping periods of measured and modeled data, from 0 to 12 months in 3-month increments and showed how the bias was being lowered as a function of the overlap length (Gueymard et al., 2012). As expected, the longer the overlapping period the lower the uncertainty. However, an interesting result is that, for some of the five sites tested (which encompassed very low and stable to very high and variable AOD conditions), the improvement in modeled irradiance bias becomes modest for overlapping DNI observation periods longer than about nine months, particularly if an uncertainty of 5% is considered sufficient. This seems to indicate that the method is very efficient and converges rapidly. A short overlapping period is obviously desirable since it accelerates the final steps of the solar project preparation.

As with all other adaptation methods, the availability of high-quality ground data is crucial to the success of MOS, since the observations have a direct impact on how well the statistical model behaves for local conditions. A method similar to MOS, known as Measure–Correlate–Predict (MCP), is also reported (Thuman et al., 2012).

A novel method based on Fourier decomposition has been proposed to calibrate the daily global irradiation estimated by the HelioClim-3 database (Vernay et al., 2013). The method consist of performing a Fourier transform on the clearness index errors and developing a regression to correct the daily clearness index, KT, such as

$$\mathrm{KT}^*_{\mathrm{HC3}} = \alpha_{\mathrm{ST}} + \delta_{\mathrm{ST}}\mathrm{KT}_{\mathrm{HC3}} + \beta_{\mathrm{ST}}\cos(2\pi F d_j) + \gamma_{\mathrm{ST}}\sin(2\pi F d_j) \tag{3}$$

where KT is the daily clear index, F is the frequency ($1/365\ \mathrm{day}^{-1}$) and d_j is the day number of the year. This methodology effectively calibrates the satellite-derived daily global irradiation through the use of one year of on-site measurement campaign. Moreover, the authors have extended the method to allow the use of shorter on-site campaigns. For instance, for the Provence–Alpes–Côte d'Azur (PACA) region in southeast France, they conclude that a 9-month campaign starting between January and May can give good accuracy. The authors have also shown that good results could be obtained when extending this calibration method to other European and African sites using mainly BSRN stations (Vernay et al., 2012).

4.2.3. Regional site adaptation

The methods presented so far make use of an overlapping period of concurrent ground and model-derived data to develop a correction for the latter over its entire record, thus including non-overlapping periods. Hence, the application of this methodology is possible only if overlapping modeled data and ground-based observations exist, for at least 9–12 months, in order to include seasonal effects. In addition, the likely decrease in temporal auto-correlation as the time lag between model's training and correction periods increases is not generally considered, which can result in over- or under-corrections. This fact is particularly critical for DNI, in which inter-annual variability is usually much higher than for GHI (Lohmann et al., 2006; Pozo-Vázquez et al., 2011; Gueymard et al., 2012). In this sense, and in order to extend the availability of measurements, some authors have proposed methods that make use of irradiance observations recorded at one or more locations close to the target site. This approach is valid inasmuch as the spatial covariance structure between the model-derived data and ground measurements is considered (Ruiz-Arias et al., 2013b).

Recently, regional fusion methods for model-derived solar radiation data and ground measurements have been presented (Wald et al., 2003; Skamarock et al., 2008; Journée et al., 2012). Also recently, Ruiz-Arias et al. (2015b) have proposed an advanced regional fusion method, consisting of a numerical process by which the modeled solar radiation data (obtained typically from satellite-based techniques or numerical weather prediction (NWP) models, and provided as two-dimensional geo-referenced grids) are objectively adjusted at each model grid cell as a function of the reliability of the modeled solar radiation value at that grid cell with respect to the reliability of the nearby ground observations cast onto that grid cell. The feasibility of the method is demonstrated using monthly-averaged values of daily GHI and daily DNI obtained with the Weather Research and Forecasting (WRF) NWP model (Skamarock et al., 2008). Although the correction method is demonstrated only for NWP-based solar radiation estimates, its authors state that it would be equally applicable to satellite-derived solar radiation gridded datasets and other time scales.

4.2.4. Site adaptation using the cumulative distribution function

Another type of correction method focuses on fitting and improving the cumulative distribution function (CDF) of satellite-derived data by comparison with the CDF of ground data (Cebecauer and Suri, 2012). The European ENDORSE project also investigated the application of a feature transformation using the difference of data sets in cumulative distribution functions (Blanc et al., 2012). The feature transformation is based on the adaptation of the frequency distribution of the modeled data to that of the ground data by using information of the relative distortion of the distribution of the satellite data from parallel sets (Carow, 2008; Schumann et al., 2011). The correction for a given satellite irradiance value is then defined as the difference between the ground-measured irradiance with the same CDF as the satellite irradiance and the satellite-derived irradiance itself. The main objective of this kind of method is to find a way to transform the estimated data based on the approximation of the CDF of satellite-derived dataset into the ground data CDF, as illustrated in Fig. 2.

The impact of the overlap period on the improvement of satellite-derived data has also been studied with the feature transformation method (Schumann et al., 2011). In some cases these authors found that three continuous months of ground data could largely improve the modeled dataset. However, they stated that in order to take into account different seasonal characteristics at least one year of ground data would be needed.

4.2.5. Adaptation of input parameters of a satellite-based solar radiation model

An alternative approach for site adaptation consists of correcting the input parameters of the satellite model instead of working on the solar radiation derived values. Two methods can be found in the literature (Cebecauer

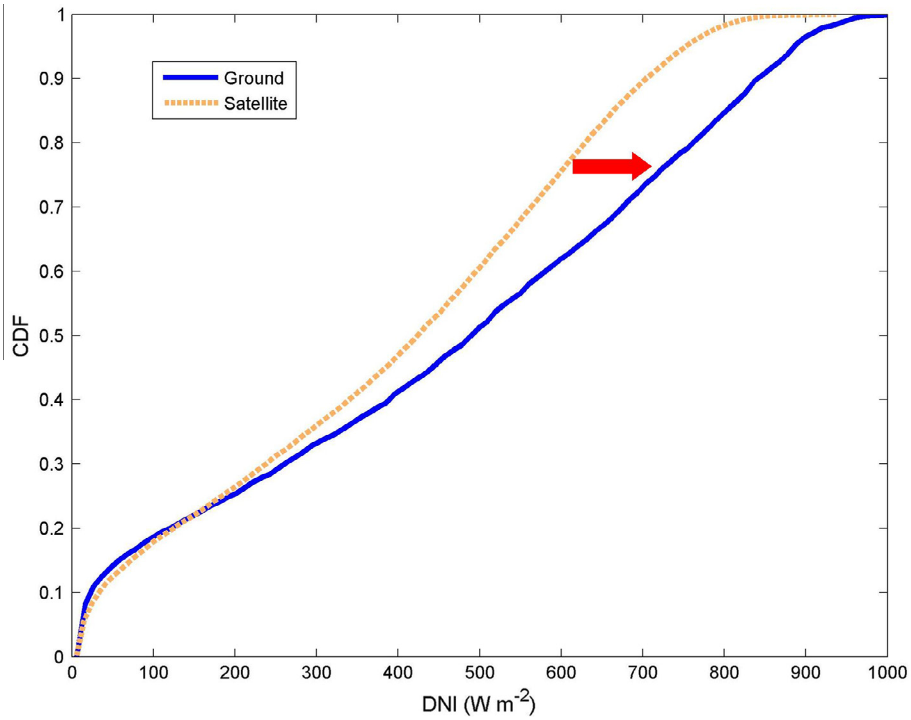

Fig. 2. Site adaptation based on fitting cumulative distribution functions.

and Suri, 2015): (i) adaptation of clearness index; and (ii) adaptation of atmospheric input data. The clearness index integrates into a single number all properties of the atmosphere (effects of aerosols, water vapor and clouds) that eventually attenuate solar irradiance. This correction may be applied to high-frequency data (hourly or sub-hourly) or to daily data. It was found, however, that more accurate and consistent GHI and DNI results were obtained with methods based on the adaptation of the model's input data, combined with the control of parameters affecting the satellite model, and a subsequent recalculation of the satellite model over the whole long-term period. Hourly (or sub-hourly) data are typically used. Both approaches generally follow three main steps:

- Use of a solar radiation model and ground measurements to derive the primary model input parameters.
- Calibration/correlation of the input parameters by a least-square regression (or similar method) of hourly (or daily) difference between the input parameters derived from the ground measurements and the corresponding satellite-based parameters.
- Recalculation of GHI, DIF and DNI, with the solar radiation model now using site-adapted inputs.

Fig. 3 illustrates an example of the correction of AOD derived from MACC retrievals (Inness et al., 2012) using ground data from an AERONET sunphotometer station.

4.3. MCP applied to satellite and re-analysis data

Measure–Correlate–Predict (MCP) methods have been extensively used to estimate the wind resources that represent the long-term conditions at a target site where a short-term wind data measurement campaign has been held (Carta et al., 2013). The results of an exercise performed within the activities of the IEA SHC Task 46 for exploring the use of measure–correlate–predict (MCP) techniques applied to satellite and re-analysis data is presented in this section. The following MCP method is applied to yearly averages, assuming that the relationship between a shorter time period and a longer time period stays constant between the different datasets or nearby stations or grid points:

$$G_{y,l} = \frac{G_{x,l}}{G_{x,s}} \cdot G_{y,s} \tag{4}$$

where $G_{y,l}$ is the long term average at location y, $G_{x,s}$ is the short term (e.g., one year) average at location x, $G_{x,l}$ is the long term average at location x and $G_{y,s}$ is the short term (one year) average at location y.

The methodology has been tested with the following datasets:

- NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA), re-analysis, resolution: 0.5 × 0.67° (http://gmao.gsfc.nasa.gov/research/merra/).
- NOAA NCEP, re-analysis, resolution: 1.5 × 1.5° (http://www.ncep.noaa.gov/).
- ECMWF ERA-INTERIM, re-analysis, resolution: 0.75 × 0.75° (http://apps.ecmwf.int/datasets/data/interim_full_daily/).
- Helioclim3.0 (HC) dataset (Version 5), satellite data, resolution ≈5 × 5 km (http://www.soda-i-s.com/eng/helioclim/helioclim3_versions.html).

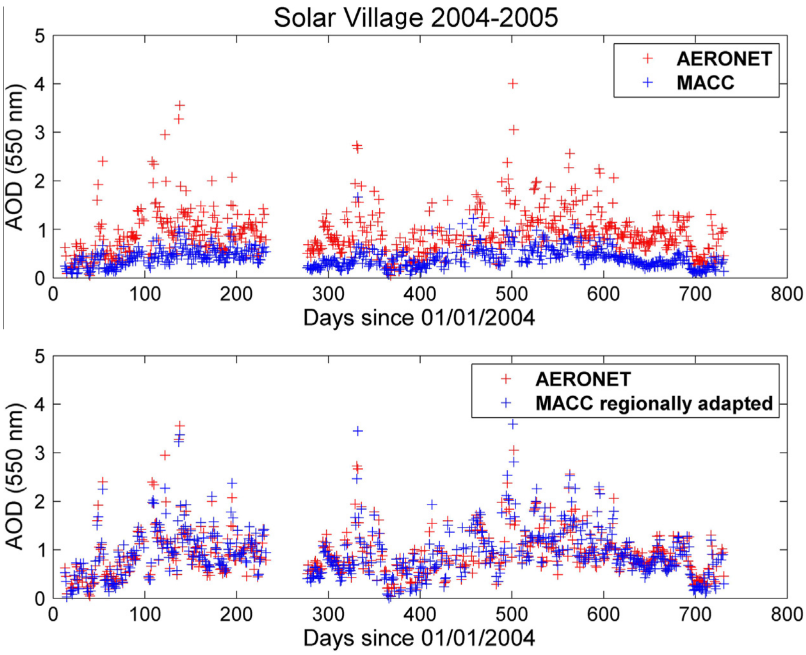

Fig. 3. Example of site adaptation on model input: correction of AOD.

An assessment of the results has been performed with irradiance observations from stations of the Baseline Surface Radiation Network (BSRN – http://bsrn.awi.de/); Tamanrasset and Carpentras), MeteoSwiss (Bern/Zollikofen, Locarno/Magadino and Zürich/Fluntern) and 22 sites of Global Energy Balance Archive (GEBA – http://www.geba.ethz.ch/). For BSRN and MeteoSwiss the 10-year averages for 2005–2014 are used, whereas for GEBA the 30-year period 1981–2010 is generally used.

Additionally, long-term trends of MERRA and ERA modeled estimates, and of GEBA ground measurements have been compared at 22 sites including the following tests:

- comparison of linear long-term trends,
- significance of trends (95% levels),
- relative standard deviation of yearly averages (12 monthly moving averages).

As shown in previous studies the bias of re-analysis data is high and is especially much higher than for satellite data (Boilley and Wald, 2015). For this reason re-analysis data should not be used without corrections. The results of the original RMSD values and the results based on MCP are listed in Table 2. The simple MCP method reduces the RMSD of re-analysis data by 60–70%, compared to 20% for the satellite data. MCP applied to satellite data leads to the best results (RMSD: 3.0%). MCP with re-analysis data results in only slightly higher uncertainties (3.3% for MERRA and 3.4% for ERA). Only the uncertainty in the MCP-corrected NCEP re-analysis is clearly higher (6.8%). Note that these RMSD values represent the year-to-year variability in the specific case of a 1-year measurement campaign. This shows that even though irradiance data derived from re-analysis tend to have higher uncertainties than those derived from satellite observations, they can still be useful for long-term approximations after proper MCP correction.

4.4. Combining satellite and weather model data

Improving the accuracy of satellite-derived solar irradiance can also be achieved by including the output of a NWP model. A study showed that using a nonparametric regression, satellite-derived global horizontal irradiance and direct normal irradiance can be improved by combining them with irradiance that has been dynamically downscaled using a NWP model. Irradiance, solar zenith angle and their interaction terms are taken as inputs to generalized additive models (GAM) using smoothing splines. GAMs are preferred over widely used fourth-order polynomial models after testing their relative performance. The addition of NWP-derived irradiance as a GAM predictor is shown to reduce the RMSE (with ground measurements serving as the point of truth) by a few percent, depending on location (Troccoli, 2015).

Table 2
Relative RMSD of the estimation of the long term averages for the 2 BSRN and 3 MeteoSwiss sites.

Dataset	Original RMSD (%)	MCP RMSD (%)
Re-analysis NCEP	20.3	6.8
Re-analysis MERRA	16.3	3.3
Re-analysis ERA	11.2	3.4
Satellite (Helioclim)	3.8	3.0

5. Discussion and conclusions

Different characteristics of a solar power project determine whether or not it can be funded by financial institutions at an acceptable and quantifiably small risk level. This bankability of a solar power project is strongly dependent on the solar resource assessment that is typically conducted at the onset of the project. Solar resource assessment studies have become a standard practice of the industry. A proper solar resource assessment is required for the identification of the best possible site. The assessment is normally dependent on a regionally validated satellite-derived solar radiation dataset, which in turn must be locally validated by on-site ground irradiance measurements of high quality.

Satellite-derived solar radiation datasets are necessary for site selection, solar resource assessment, power production projections, and system performance studies. However, satellite-derived datasets have uncertainties that originate from different sources and from the approximations adopted by the models. These uncertainties can be significantly reduced with the help of high-quality on-site irradiance observations spanning a minimum period of 9–12 months. The present literature review shows that various methods and approaches have been explored so far to properly combine ground radiation data with modeled radiation data, with the general goal to improve the accuracy of long-term satellite-derived datasets. In the solar energy world this process is often referred to as “site adaptation”.

The adjustment aims primarily at removing the annual and/or seasonal bias in the long-term modeled irradiance estimates. To that end, the necessary correction methodology can follow either one of two possible avenues. The first avenue consists in adapting the input data ingested by the model to better fit the local irradiance measurements. In the second avenue, empirical adjustments of the model output estimates are made by comparison with the measurements. Some of the empirical correction methods only modify the bias, whereas others also adjust the frequency distribution of the irradiance values. In some situations, correcting the bias and reducing the dispersion of satellite-derived data result in improvement of the cumulative distribution function. In most situations, however, it is likely that no unique empirical method can cover all the possibilities and thus can be successfully applied to the whole dataset. Consequently, each site would likely require a specific initial study to identify the sources of discrepancy and then help design a proper method for data adaptation. The site specific method is often a combination of the different approaches presented in this paper.

The optimum duration of the overlapping period between ground observations and model estimates has not been widely studied so far. In particular, the effects of multi-annual trends and inter-annual variability in the on-site measurements can potentially have large effects on the radiation values and cumulative distribution functions. So far, such dynamic effects have not been fully covered in any of the different site adaptation methodologies that have been reviewed here. Until additional knowledge is available on this topic, it is recommended that at least one year of high-quality on-site irradiance measurements be used for site adaptation, in order to cover the seasonal variability of solar radiation.

All site adaptation procedures reviewed here require high-quality on-site data, which in turn indicates that any short-term measurement campaign must follow existing standards and recommended best practice for the design, installation, operation and maintenance of all sensors, as well as for the a posteriori quality control and data processing phases. Since a successful site adaptation procedure critically depends on the quality of the on-site data, the utilization of low-quality data from substandard local ground measurement operations can lead to increased uncertainty of the modeled datasets, erroneous plant sizing and yield assessments. Such adverse results may in turn translate into questionable bankability and consequently increase the financial cost of the project, with the risk of making it unfeasible.

The uncertainty in long-term average solar irradiance is a dominating parameter in risk analysis of solar power projects. The calculation of this uncertainty needs to take into account the different uncertainties associated with the model used to generate the long-term dataset and those associated the on-site measurements used to validate and correct the modeled data. Therefore, a clear and systematic definition of the uncertainty associated with measurement-adjusted modeled data is strongly needed for bankable solar resource assessments.

Further studies are needed to evaluate how well the various algorithms presented here perform, depending on the overlap duration and on the atmospheric, topographic and environmental conditions of various regions. Since the performance of the site adaptation process also depends on the quality of the satellite- or model-derived dataset, other studies would have to investigate the impact of various satellite-derived datasets at many sites in widely different regions. In this sense, within the IEA community of solar resource experts it is planning to perform a deep benchmarking exercise of site adaptation methods that is intended to provide guidance on the choice of method depending on the local conditions. Finally, it is remarked that the standardization of both site adaptation procedures and data quality control methods for on-site measurements would also contribute to a desirable harmonization of solar resource datasets, leading to a smoother development of solar power projects and a stronger solar industry.

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