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Towards building solar in India - A combined mapping and monitoring approach for creating a new solar atlas

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ABSTRACT

Against the background of rising energy demand and climate change, solar energy applications are expected to become one of the fastest growing sources in India. To support India's solar policy and to respond to a growing demand for high-accuracy solar resource data a new solar resource atlas was created in the study presented. To derive temporal and spatial consistent datasets measured values from 51 ground measurement stations distributed over the whole country were used to derive site-specific correction factors. Another 61 stations were used to validate the resulting maps of long-term monthly-averaged datasets. Correlation factors were transferred to the needed spatial extent using geospatial interpolation and used to adjust satellite-derived data sets with a resolution of approx. 3 × 3 km. Solar datasets created based on the years 1999 to 2014 provide a comprehensive overview of solar resources in India. Long-term averages, annual averages for each month of the year, as well as standard deviations, are presented for all three components of irradiation. The results show that the adjustment using monthly correlation factors significantly improves the quality of long-term estimations from satellite-derived sources and reduces the associated uncertainty.

Introduction

Global energy demand is expected to rise worldwide over the next three decades. The largest increase in energy demand is projected for non-OECD countries with less mature economies and rapid population growth, particularly India and China (U.S.EIA, 2016). India is also one of the largest emitters of greenhouse gasses. Since 1950 fossil fuel sourced CO_2 emissions have increased in average 5.7% per year making India one of the five largest CO_2-emitting countries (Boden et al., 2011). As by today, the energy sector is responsible for 71% of country's total greenhouse gas emissions (Ministry of Environment, Forest and Climate Change, 2015).

It is expected that fossil fuels will remain the largest source for energy production for many years, however, renewable energy sources are likely to become the world's fastest growing source increasing by an average 2.6%/year between 2012 and 2040 (OECD/IEA, 2015). In 2016, India's installed capacity in solar reached 6.7 GW. Compared to an overall power generation capacity of 306 GW this shows how solar power offers great possibilities for further development replacing fossil sources in power generation (CEA, 2016; MNRE, 2016). India is already considered a pioneer in solar energy production being ranked under the ten leading countries in terms of solar electricity production per Watt installed. This is also due to the JNN Solar Mission launched in 2010 by the Government of India. The mission adopts a 3-phase approach with the target of deploying 100 GW of grid connected solar power by 2022. The objective of the mission is to create a policy and regulatory environment that enables large-scale investment in a timely manner lowering the cost for solar energy applications (Government of India, 2016). India's targets for solar energy deployment are ambitious and to succeed the right issues must be addressed. Therefore, it is important to establish an operating environment for solar energy development that encourages investors and challenges potential barriers such as financial viability, regulatory approval and grid infrastructure.

Any energy policy should aim to develop the right type of resource at the right location at the right time (Chattopadhyay and Chattopadhyay, 2012). A key factor to ensure a proper design and secure bankability of a solar project is to accurately assess solar resources at potential locations (Hoyer-Klick, 2009; Polo et al., 2011; Vignola et al., 2012). It is in no doubt that India, in general, has high potential due to its location in the sunbelt of the Earth. However, solar irradiation over India varies

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significantly and not knowing this variation can seriously harm the return of investment for solar energy projects (Lohmann et al., 2006). Financial stakeholders become progressively aware of risks associated with the accuracy of solar resource data, particularly because they are used to calculate the projects cash flow from early stages of the project development ongoing. The projects capital structure and accordingly the ability to obtain financing for projects are directly affected by the quality of the available solar resource data. Another important effect of the availability of standardized solar data is that the performance of solar projects can be assessed more accurately, resulting in increasing competition among solar companies and thus improvements in cost, performance, and pricing.

Two main sources of solar resource estimates are used in practice: satellite-derived models and measurements. Satellite derived model results are available from numerous public and private sources. They have the advantage to be available for most locations and over long time periods. On the downside, the information is limited to the grids resolution and although satellite data is improved by numerical models to reproduce the effect of the atmosphere and gap-filling techniques, they have a significantly lower accuracy than measurements. A well planned and maintained measurement campaign is best practice to obtain accurate information about solar resource at the selected location. Nonetheless, a measurement campaign commonly covers only one complete year and therefore cannot capture inter-annual variability and how well the period of record represents the long-term historical average.

Maps showing the distribution of solar radiation for India are available for more than 50 years. Few studies originate from the 60s of the last century and intended to better understand the general balance of energy on earth. They were created using ground measurement stations complemented by empirical relationships using the same physical principles as today. For example, Mani et al. (1966) created monthly averaged maps showing the distribution of the solar radiation over the Indian ocean by the adaption of 107 ground stations. Depending on the lack of data, early studies are characterized by low resolution and even lower accuracy due to the high uncertainty of the measurements with up to 15%. It is surprising that it took another 20 years until the next comprehensive study on solar potential for India became available. The Handbook of Solar Radiation Data for India (Mani, 2008) was the first comprehensive document that provided ground measured data and solar radiation maps and was considered a standard for meteorologists in India.

Nevertheless, the availability of spatial comprehensive and high-resolution maps remained rather limited until 10 years ago. Connected to the upcoming use of satellite derived data and their availability to the public, several global datasets became available, e.g. NASA SSE (NASA SSE, 2008). Although global datasets provide respectable information, they suffer from accuracy in spatial and temporal resolution.

In 2010, NREL published new solar resource maps and data for India. The dataset covers global horizontal, direct normal, and diffuse horizontal irradiance, as well as auxiliary meteorological data for the period from 2002 to 2014 on a 10 km × 10 km grid. Later versions of the maps were validated using five ground measurements from pyranometers and pyrheliometers and compared to previous versions of the map. It should be noted that according to Sengupta et al. (2014) the mean bias error of the Direct Normal Irradiance (DNI) predicted by the satellite was found to be approximately 60 W/m^2 for three stations but more than 110 W/m^2 for the other two stations, while results for GHI were much better. Of particular interest is the comparison of the newer map version to the previous version, that shows a relative difference of DNI up to 120%. This study is, as others, subject to the inherent limitations of any satellite data based estimation of DNI, a consequence of high temporal and spatial variability of DNI.

One year later, Polo et al. (2011) published a study to estimate solar radiation over India using satellite images with a significantly higher resolution of 5 km × 5 km. In the study, solar radiation estimations have been performed for six Indian locations using the generating time series of hourly values of two radiation components during the period of 2000–2007. The results were compared to the previously described NREL maps and few available ground measurements. Compared to the NREL maps, slightly lower values of GHI and DNI were retrieved. However, the authors note that to accurately validate the model results the number of ground measurements must be increased, especially for DNI.

Altogether, the quality of previous studies can be considered acceptable having in mind that the satellite data is characterized by higher uncertainties. One shortcoming all studies suffer from is the lack of ground measurements for calibration and validation of satellite-derived data sets. Against this background, 15 years of satellite-derived solar irradiance data was combined with ground-based data from 51 measurement stations distributed over India to construct high quality and spatially consistent solar resource data for India.

Materials and method

The methodology applied in this study aims to create consistent and high-resolution solar resource data spatially covering the whole country of India. Satellite-derived radiation covers large areas but is also associated with a lower accuracy, compared to measurements. Moreover, the most important advantage is the long continuous time series of satellite data reaching back to 1980 for some places on earth. Calculating inter-annual variability and long-term averages of solar radiation data at a specific site requires datasets covering at least 10 years (Lohmann et al., 2006). Data from ground-based measurement stations, on the other hand, is known to be very precise but at the same time limited in its spatial representation.

The applied methodology addresses the described issue by combining high-quality measurements from SRRA stations of one to three years with satellite-derived data covering 16 years. Fig. 1 gives an overview of the applied methodology and the datasets used in this study.

Solar radiation measurements from SRRA network

The measured solar radiation data used for this study was provided by the currently largest network of solar radiation resource assessment stations measuring simultaneously in India - the Solar Radiation Resource Assessment (SRRA) stations. The location of each station wasselected with care to gain the best knowledge of solar radiation distribution over the country. Moreover, regions with high potential for solar power plants were prioritized resulting in the majority of stations to be located in the north-west of India, a region with promising potential for solar resources (Mitra et al., 2014). The distribution of the measurement stations is shown in Fig. 2.

The installation of 117 SRRA stations was implemented in two phases. Under the first phase, finished until October 2011, a total of 51 stations were installed. Another 60 stations were installed in 28 states until June 2014 under phase 2. In addition, stations from a local weather service were taken into account. All stations are identical in design and are equipped with the same number of sensors that comply with the highest international accepted criteria for quality (e.g. ISO 9060 (International Organization for Standardization, 2016) and CIMO Guide(WMO, 2008)) to ensure comparability while reducing the uncertainty of the provided solar data. The solar measurements are made accessible to the public under the data sharing and accessibility policy of the Ministry of New and Renewable Energy, India.

Solar radiation reaching the earth surface can be divided into different components. All of them are important to know to get a comprehensive overview of solar resources at a certain location. Therefore, all SRRA stations are equipped with sensors to cover all three components of solar irradiation. Global Horizontal Irradiance (GHI) and Diffuse Horizontal Irradiance (DHI) are measured by two pyranometers, respectively. A first class pyrheliometer was installed to measure Direct Normal Irradiance (DNI). A two-axis solar tracker is used to track

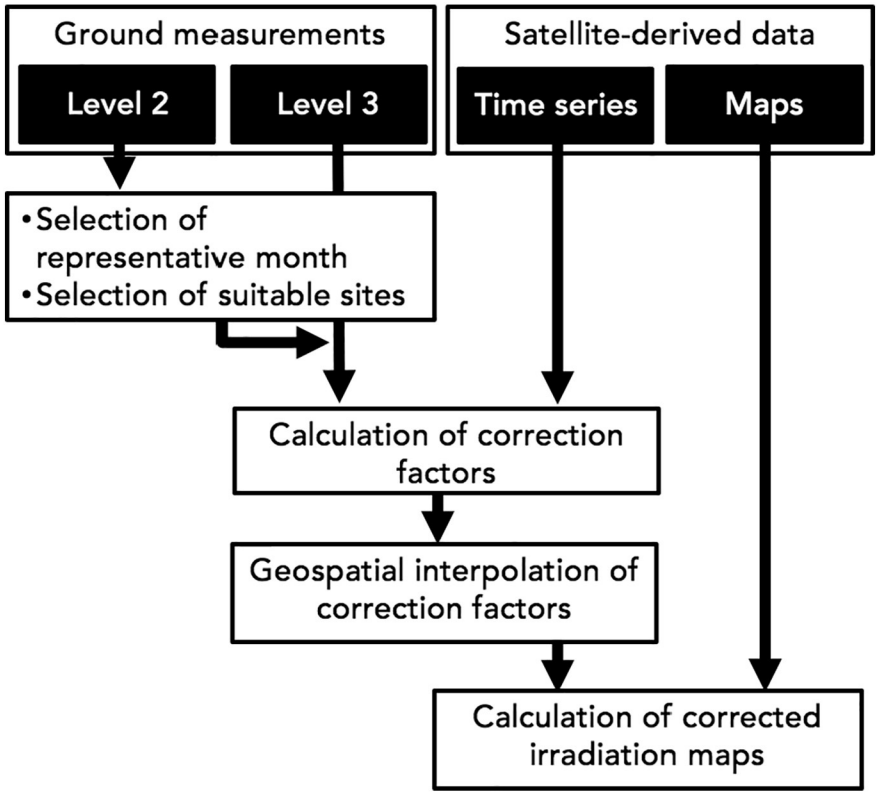

Fig. 1. Methodology applied and input data used to create consistent and high-resolution solar resource data for India.

the sun with the installed pyrheliometer. In addition, the tracker moves the shading assembly for the DHI pyranometer. Apart from solar radiation parameters, these stations also measure auxiliary meteorological parameters like ambient temperature, wind speed and direction, relative humidity, barometric pressure and rain rate. All data were previously averaged to 10-min time resolution. Since August 2012, they are measured in 1 s and integrated to 1 min.

Before the SRRA data were used for this study a quality assessment was conducted to ensure reasonable data values. Basically, the test applied searches for physical limits and differentiates potentially correct values from potentially erroneous data. If data values exceed or underrun physical possible values, they are identified and flagged. This proceeding enables the user to maintain consistent data without destroying information that might be useful in later stages of the project. The quality-check tests applied in this study follow international best practices like those established by NREL's SERI-QC (NREL, 1993), WMO's BSRN (Long and Dutton, 2002) and those used in the EU-project MESOR (Hoyer-Klick et al., 2008). Fig. 3 shows the different levels according to their state of processing. Level 1 data refers to the raw instrument data stored by the server. Level 2 data refers to quality checked raw data and consecutive data after the application of a gap filling algorithm is referred to as Level 3 data.

For establishing a higher comparability between measured values and satellite data it was decided to use data in hourly resolution, rather than the available 15-min resolution data. Temporal coverage from the data changes from station to station. However, in this study data until end of 2014 was considered, meaning that for most stations a whole year of measurements are available and for 51 stations from Phase 1 three years of data could be used. It is important to note that only monthly averages representative for the correspondent month were used for adaption of satellite data, meaning that months with more than 20% missing radiation values were excluded. Only quality checked data is used for the comparison purpose for creation of solar radiation atlas of India. Further details on data processing and data levels of the SRRA project can be found in Schwandt et al. (2014).

Satellite-derived dataset

Spatially explicit datasets were required to create the solar radiation atlas. Spatial datasets used in this study were derived from the Meteosat-5 and Meteosat-7 platforms. Meteosat-5 covered India from July 1998 through February 2007, while Meteosat-7 took over and covers India from February 2007 through February 2014 and is in continuing service. Both satellites are from the first generation of Meteosat satellite and their visible band (0.45–1.0 μm) is used for deriving the radiation data. Satellite-derived datasets were pre-processed, validated and afterwards provided for the project by 3TIER (Vaisalla, 2015). In this study two different data products were used. Time-series data for all SRRA measurement sites and irradiation maps to be used in Geographic Information Systems (GIS). The temporal coverage of the time-series is from January 1999 to December 2014, encompassing 16 years of data. All three major solar radiation components GHI, DNI and DHI, as well as auxiliary meteorological parameters like ambient air temperature, relative humidity, wind speed, wind direction and barometric pressure are available in hourly time resolution. The GIS maps were available in the same temporal coverage, but consist of monthly averaged radiation values. Spatially, the maps cover entire India with an approximate resolution of 3-arc minutes (approx. 3 × 3 km).

The correction method using ground measured data is applied to the monthly satellite-derived maps. Those were corrected by comparing SRRA measurements to the satellite-derived time series. From the overlapping time period correction factors for the maps were derived. For the adjustment, 51 SRRA stations distributed throughout the country and from all climate zones were selected. Suitable for the adjustment process are stations with at least one whole year of measurements

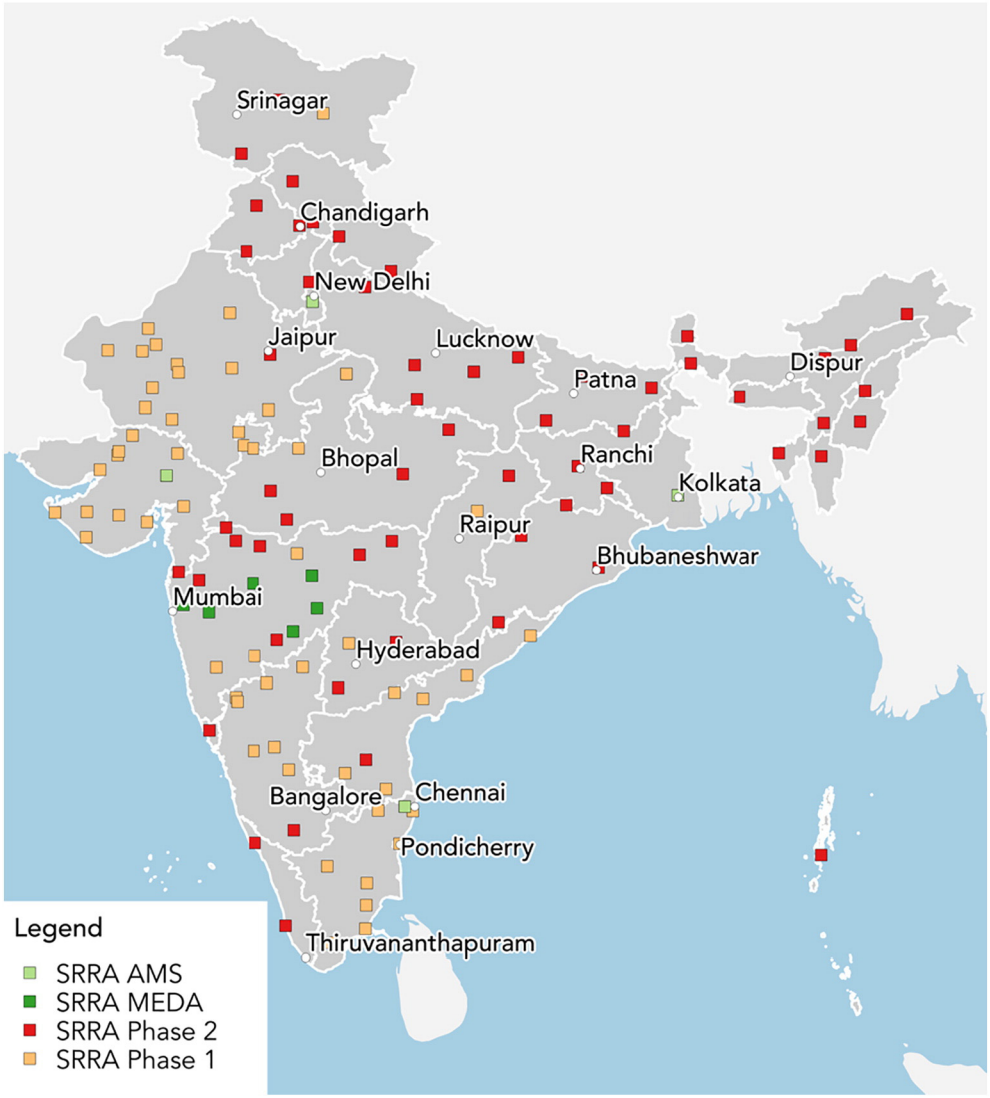

Fig. 2. Distribution of the SRRA station network in India.

available. Only short data gaps were allowed and sites with known heavy contamination in metropolitan regions or close to industrial regions were excluded as well as stations with known cleaning shortcomings. Data from the remaining stations were later used for map validation.

A very basic approach concerning monthly adjustment is a simple subtraction of the *average mean bias* of a satellite data set from each value. Consequently, the *overall mean bias* is forced to zero. The same accounts for a multiplicative modification, i.e. using the *relative mean bias* (rMB). Both approaches were tested for 51 SRRA sites by comparing the satellite-derived time series for distinct overlapping time periods dependent on the site with SRRA L3 values. It is important to emphasize that SRRA L3 data is used assuming better representation of a monthly value including gap-filled values. In Fig. 4, scatter plots show monthly satellite based radiation values in comparison to SRRA data before and after applying the two different adjustment techniques for the site Chennai. In general, the overestimation of satellite based radiation values is decreased for all radiation components. Diffuse radiation is not explicitly shown.

Visually, the two approaches show no significant difference in their results. Statistical measures confirm this ad hoc assumption so that both techniques could be used. However, for the additive adjustment a problem evolves for small radiation values. If the *average mean bias* of a dataset is high, the correction applied to small radiation values is disproportionally strong. In extreme cases, even negative radiation values could result due to the fixed correction value. Using a factor instead leads to the same result on average, but without the possibility of over-corrections at low radiation values. Hence, only a relative adjustment is further pursued.

In the next step a correction factor *f* is calculated for each month according to the following equation:

$$G_{adjusted} = \frac{1}{f} G_{original}$$

Afterwards, the data was filtered for representative values. It is defined that a monthly average is only used if a minimum of 80% of the hourly values were classified as suitable in the SRRA L2 data set, i.e. before gap-filling takes place. A high number of missing values in one month can lead to a distorted monthly average and therefore should not be considered in deriving a correction factor for the satellite data. Afterwards, factors from all available months at a site and for each month of the year were averaged respectively, so that in the end one factor is derived for each month of the year. Hereupon, a Gaussian filter encapsulating 5 values is applied to the 12 calculated factors to smooth high deviations that might occur, in case only one month is available for deriving the correction factor.

A positive side effect of applying a Gaussian filter is the possibility of filling gaps in the factor array where no months were available. Fig. 5

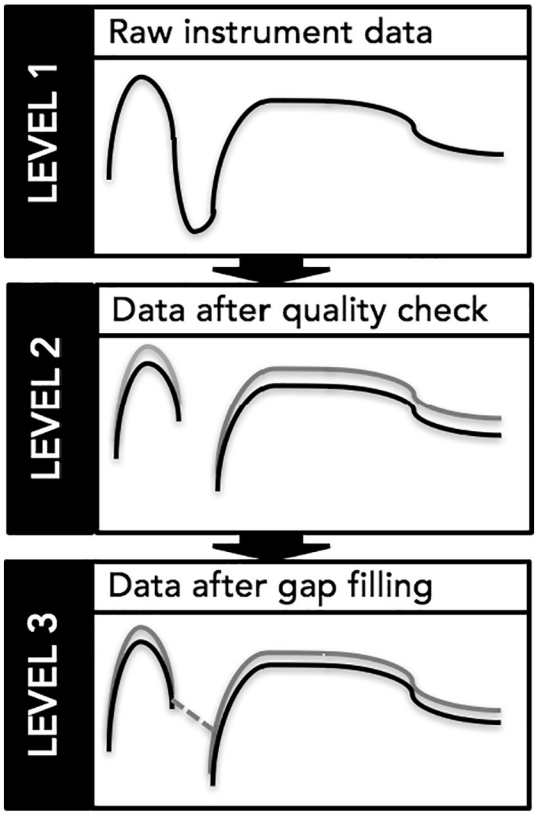

Fig. 3. Different levels of data processing for ground measurements from SRRA stations.

shows the correction factor with corresponding time series of ground and satellite-derived data at site Chennai. For data that do not fulfill the defined quality a gap is placed in the monthly time series and no correction factor is calculated. Again, a general overestimation of radiation values in the satellite derived dataset is obvious as the calculated monthly factors are mostly positive. Only for the diffuse component the average monthly correction factors are negative during the summer and autumn months at this specific site. However, for all radiation components the averaged factors show typical yearly cycles giving evidence to a systematic, seasonal dependent deviation of satellite data from ground-based measurements. Thus, a monthly varying correction seems to be a reasonable approach.

By applying the derived correction factors to the long satellite time series from 1999 to 2014 the long-term average for GHI is shifted remarkably from 225 W/m^2 to 205 W/m^2. For DNI the long-term average is corrected from 167 W/m2 to 142 W/m2, whereas DHI does not change through the adjustment at this specific site.

Geospatial interpolation of the correction factors

The correction characteristics, shown in detail for the site Chennai in the previous section, change from site to site. In general, a typical monthly over- or underestimation of radiation can be found in the time series at sites where correction of ground data was applied. The challenging part is to move from such single point correctors to a "correction surface" and to find the function best representing this surface. In the last decades' various spatial interpolation methods have been introduced for application in environmental science. The appropriate method for a specific dataset depends on factors like sample density and distribution, characteristics of the variable to be interpolated and possible relations to secondary variables (Li and Heap, 2011). Interpolation techniques can be either deterministic or geostatistical. While deterministic approaches, such as Inverse Distance Weighting (IDW), are based on the extent of similarity of the raster cells other techniques such as kriging are based on mathematical functions. For this study, kriging was tested expecting spatial correlations for certain environmental parameters. Consequently, for the ground measurement time series used in the adjustment site process, possible relations between the bias of radiation values and other parameters were investigated for each month. In the case of significant dependencies a so-called kriging mechanism could be applied. Next relations to latitude, longitude, elevation above sea level and the climate class classification of the region according to Köppen and Geiger (Kottek et al., 2006) were analyzed. Concerning elevation, no significant tendency in mean bias could be found. One problem is the low data density at high altitude sites. The latitude and longitude graphs show as expected a slight spatial dependence of the correction factors in all radiation components more pronounced during winter months. Concerning climate classes finding a dependency is rather difficult. The low data density in most defined classes does not provide enough information to deduce a clear relation. Because latitudinal and longitudinal dependencies are implicitly covered by any spatial interpolation and a relation to altitude and climate classes is rather difficult to derive, no additional parameters shall be included in the geospatial interpolation of the correction factors. Instead, two non-geostatistical interpolation methods, Inverse Distance Weighting (IDW) and interpolation with splines were tested for their suitability.

The spline method applied in this context creates a smooth surface passing exactly through the sample data. Mathematical functions are used to minimize the total surface curvature. Descriptively, the output

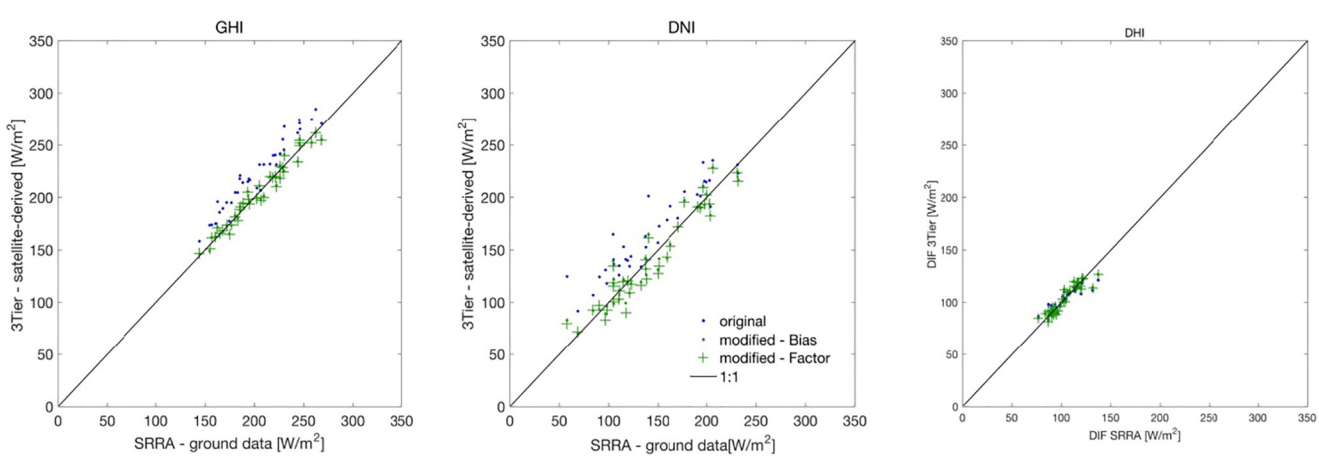

Fig. 4. Scatter plot of monthly SRRA L3 data with original 3Tier data (blue) and modified time series (green) from SRRA station at site Chennai. The modification is done using an additive (dots).

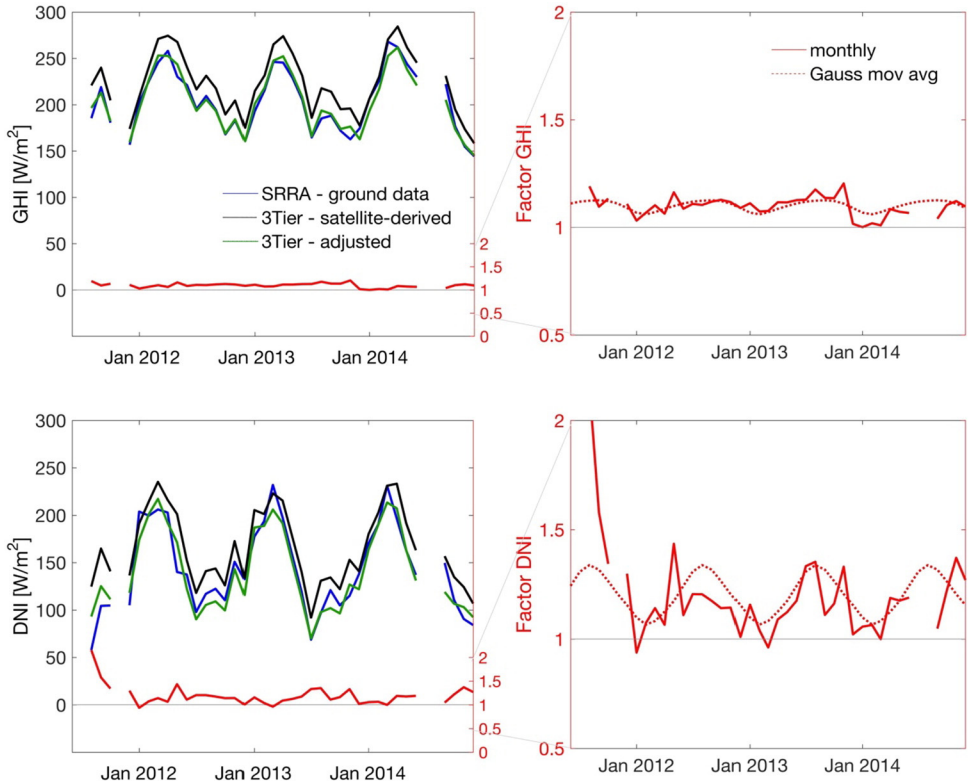

Fig. 5. SRRA L3, 3Tier and adjusted 3Tier data sets for the overlapping time period at site Chennai for the radiation components GHI (upper) and DNI (lower).

of a spatial interpolation with splines is similar to a sheet of rubber passing through a defined set of sample points. The stiffness and value range of the interpolated surface can be regulated (Childs, 2004). Splines work well in the domain considered in this study, but they have one major disadvantage. Close to the domain borders the polynomial functions have a higher degree of freedom in developing their shape and tend to take unrealistic values. Especially in regions with low data density, i.e. in the eastern states in India, strange behavior of splines interpolation can be observed.

Using IDW, trends are not considered and thus the surface is averaging out single high bias values rather than preserving them. IDW determines the point of interest using a linear combination of surrounding input data points each being weighted with the according distance d_i. The weight is given by the following equation where n is the number of input data points and p is the power parameter (Li and Heap, 2011).

$$\lambda_i = \frac{1/d_i^p}{\sum_{i=1}^{n} 1/d_i^p}$$

According to Tobler law of geography, "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). Consequently, cell values further away from station locations are less influenced than points closer. The significance of the distance to the station location relies mainly on the "power" assigned. The higher the power parameter the more local is the resulting interpolation because the influence of a sample point diminishes faster with increasing distance. We tested the power values 0.5, 1, 2 and 3. Application of $p = 1$ and $p = 2$ both result in the lowest mean bias on average at the validation sites. A power $p = 2$ leads to more localized adaptions, where the adaption is mostly dominated by the closest adaption station. It is assumed that measurements of single stations might be misleading and thus erroneous adaptions are possible. To avoid such $p = 1$ is chosen for adapting all three radiation components.

Results and discussion

The application of the above described methodology resulted in consistent and high-resolution solar resource data for India. With the objective to give a comprehensive overview of solar resources in India maps were created based on the years 1999 to 2014 that illustrate not only long-term averages of solar radiation for all three components of irradiation, but also annual averages for each year, monthly averages for all month over the year and standard deviations. The maps cover the whole country of India including Islands with a spatial resolution of approximately 3 km (2 arc minutes).

Long-term averages of GHI and DNI

Depending on local conditions GHI values in India varies by orders of magnitude. Long-term average values of GHI range from 153 W/m^2 to 288 W/m^2 showing perceptible regional differences with a given standard deviation of 16 W/m^2 and mean of 202 W/m^2. For GHI values grid cells for DNI range from 93 W/m^2 till 375 W/m^2 with a mean of 157 W/m^2 and a standard deviation of 38 W/m^2. For DHI values they range from 30 W/m^2 till 174 W/m^2 with a mean of 89 W/m^2 and a standard deviation of 9.5 W/m^2. Both GHI and DNI, generally increase with increasing altitude. Consequently, the highest values can be found in Jammu and Kashmir, a state in northern India located in the Himalayan mountains. The western state Rajasthan receives up to 210 W/m^2 of DNI showing potential for solar. Lowest values occur in eastern states of India, such as Bihar and West Bengal, and can be explained in part by high atmospheric suspended particulate matter in the area. The high level of air pollution in the Indo-Gangetic plains is widely known (Mani, 2008). Fig. 6 shows the long-term yearly average sum of solar

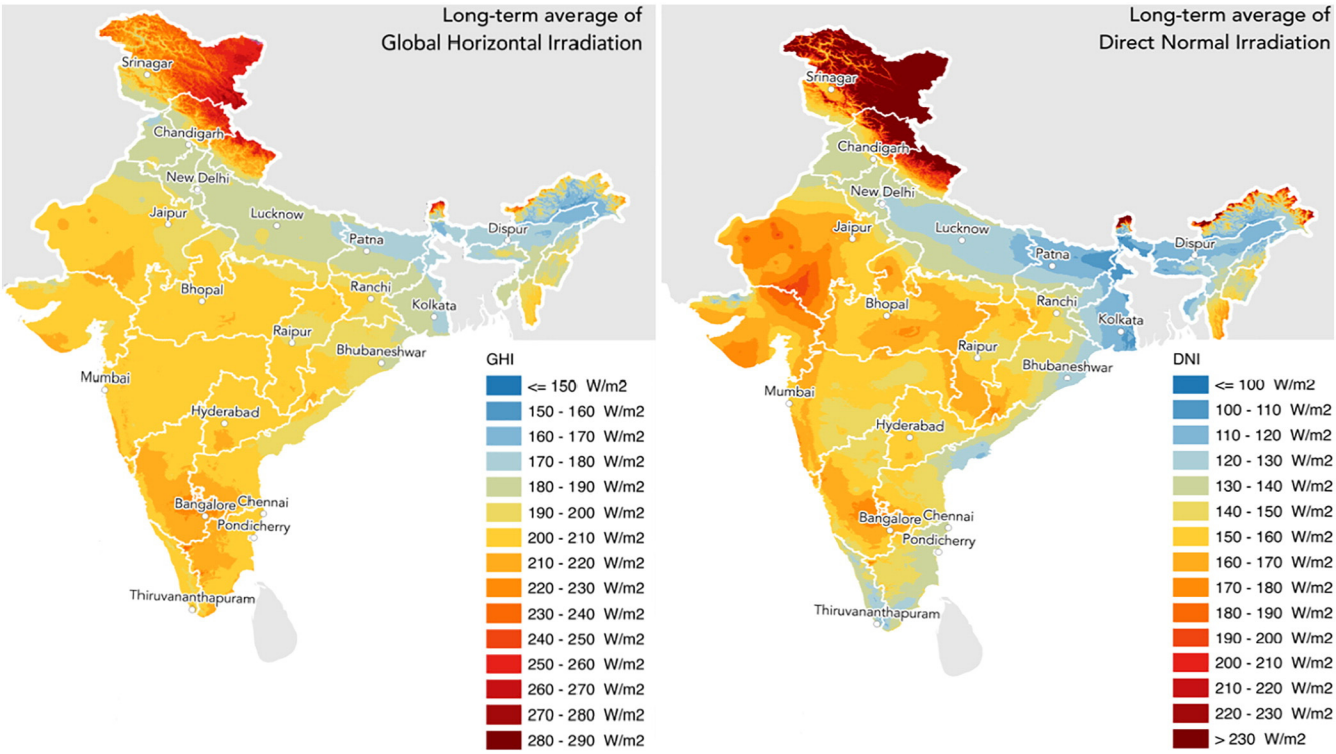

Fig. 6. Long-term averages for GHI and DNI for the years 1999 to 2014.

resource potential for GHI and DNI respectively for the years 1999 till 2014.

Seasonal and inter-annual variability

In India, the monsoon strongly influences the climate variations. Knowing the seasonal variability originating from the yearly solar cycle is important for grid integration analysis, maintenance and planning. In Fig. 7 climatological monthly means are shown for selected months throughout the year. From January to April the GHI is increasing due to higher sun elevation on the northern hemisphere. However, starting in May the Indian summer monsoon typically dominates the daily weather with clouds and heavy rainfalls leading to less irradiance during the summer months in central India.

The correspondent raster statistics over all cell values can be found in Table 1.

In July, the standard deviation over all cell values is the highest due to extremely high radiation values in mountainous regions in northern India compared to rather low irradiance reaching the ground in south-west India due to the monsoon. On the other hand, variation from one year to another typically is calculated as the standard deviation over annual averages. Inter-annual variability for maps of the years 1999 to 2014 is in the range between 2% and 3% for GHI, 2% to 6% for DHI and 4% to 8% for DNI. Similar to analysis of variability in other regions of the world DNI is about a factor of 2 to 3 more variable than GHI.

Validation of results

The quality of the newly created maps was evaluated by comparing single map pixels to the corresponding ground-based values at measurement sites. Data from measurement sites that was not used during the adaption process generally qualifies for the validation of the solar map products. Next to the regular quality checks, the time series at a site has to be at least 6 months in order to get more robust statistical results. For 61 validation sites the radiation values derived from corrected map pixels and ground-based measurements are compared on a monthly basis. The remaining deviation of the radiation maps after the adjustment was quantified by the relative mean bias (rMB) and fluctuations of it, i.e. the uncertainty. Statistical results at the site Rourkela in the middle east of India are exemplarily reported in Table 2.

The numbers in the table show that the uncertainty can be reduced in a small rate for GHI and DHI at this specific site and for the 11 months considered. In general, satellite retrievals can estimate diffuse irradiance quite well. In case of Rourkela initial deviations of DHI increase after being adjusted by correction factors. Improving a good data set is very difficult and modifications do not always lead to further improvement. The monthly individual correction of DNI at site Rourkela shows that the applied methodology can significantly reduce the average rMB and the uncertainty for DNI. However, an uncertainty of about 14% still remains.

Fig. 8 demonstrates that the original heavy overestimation of monthly satellite-derived data could be reduced significantly for each month in the period considered. However, the interpolated correction factors change from pixel to pixel and differently effect each location and month of the year. Therefore, the performance of the applied map adjustment is evaluated by statistical means calculated for all defined validation sites.

While calculating the overall-uncertainty for the whole Indian domain, two averaging processes take place, an averaging in space and a second in time. Because sites used for the adjustment, as well as the ones used for validation, are approximately equally distributed in space, we considered a simple spatial averaging of statistical parameters from all validation sites appropriate to represent the overall map uncertainty. A temporal averaging is done at the individual sites along the overlapping time periods of available ground-based measurements.

Overall, we found that applying the correction efficiently reduces the average rMB to about zero per cent together with a significant reduction in the corresponding uncertainties in all radiation components. Though one would expect a bias-free result the adjustment algorithm does leave some minor remaining deviations due to inter-annual variations in solar radiation as presented in Table 3. Typical annual cycles in the correction factors applied are visible in most data sets. The magnitude differs

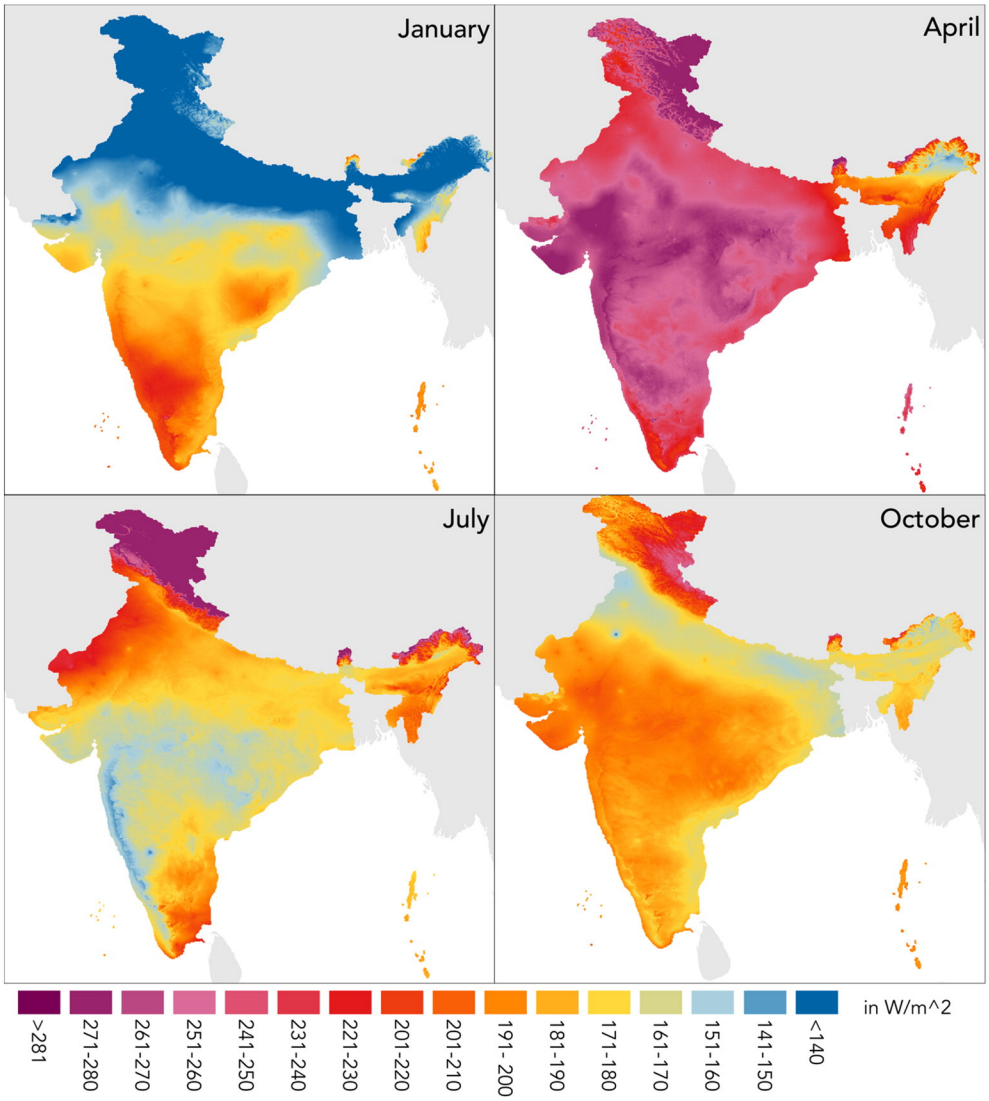

Fig. 7. Monthly average solar irradiance (GHI) for the period 1999 to 2014.

and short-term fluctuation might occur together leading to a non-zero monthly adjustment, i.e. the January of each year is corrected with the same factor and not individually. However, a higher representativeness of the correction factor and better results for application to long time series is assumed when using averaged values instead of individual values.

The designated validation sites were unaccounted for deriving the correction factors and can provide information on the quality of the new maps. For the GHI component the rMB is reduced to 0.8% on average over all months at all validation sites. The comparison to validations sites shows that the uncertainty of GHI maps decreases to 5.7%.

A more detailed statistical analysis can be derived from the corresponding boxplots in Fig. 9. For each data set a box gives information about the distribution of data points and their values. The edges of a box are located at the 25th and 75th percentile and the red line in between gives the median. The whiskers attached at both ends incorporate values up to about $\pm 2.7\,\sigma$ or 99.3% assuming normal distribution. Values beyond those bounds are considered to be outliers. For the new map the distribution of data points is slightly widened, but no outliers remain. The median is zero and 50% of the data points are located between −4 and +5% rMB.

In the direct component, we observe high deviations at numerous sites during the summer months. This was expected due to the fact that the typical monsoon circulation generates deep convection. In broken cloud situations estimating the direct sunbeam from a satellite platform is rather difficult and explains high uncertainties of satellite-derived maps. In addition, DNI is not only sensitive to clouds, but also highly affected by dust. In total the initial 37.9% rMB could efficiently be reduced to 7.1% for the corrected maps with a remaining uncertainty of 14.3%. The boxplot shows that no outliers are detected and the distribution of rMB values from single sites is shifted and more concentrated

Table 1
Raster statistics for monthly means of GHI.

Month	Min [W/m^2]	Max [W/m^2]	Mean [W/m^2]	Std dev [W/m^2]
Jan	94	247	160	31
Apr	146	346	255	23
Jul	136	391	196	44
Oct	139	273	192	16

Table 2
Statistical validation results for monthly values of GHI, DNI and DHI at site Rourkela.

Site Rourkela	Sat-derived map		Adjusted map	
	rMB [%]	Uncertainty [%]	rMB [%]	Uncertainty [%]
GHI	10.6	±3.9	1.3	±3.8
DNI	31.6	±29.5	2.3	±14.1
DHI	−0.3	±5.3	−1.6	±4.2

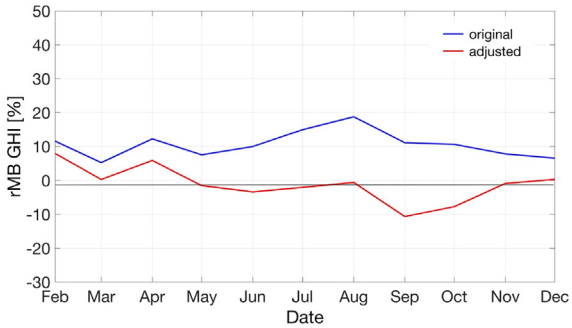

Fig. 8. Monthly relative mean bias of GHI for original map data (blue) and after applying the interpolated correction factors (red) at validation site Rourkela in southern India in 2014.

around zero per cent. High overestimations of the satellite product were significantly reduced. 50% of all data points are located within −5% and +16%, the median at 5% rMB is close to the average rMB.

Concerning DHI, the numbers in Table 3 suggest only a slight improvement. The negative rMB value of −1.1% indicates an underestimation of diffuse radiation on average. Also the median of the distribution is about −2%. The distribution of data points in Table 3 is symmetric around the median with 50% of the values in the interval from −7% to 3% rMB. Two values are categorized as outliers. However, the values are lower than the extent of the whiskers belonging to the original satellite-derived map. Thus, even if single values might be worse after the proposed map correction is applied, also the DHI maps are slightly improved on average.

Conclusions and policy implications

To conduct this study and to create solar resource maps for India, data from 51 ground measurement stations distributed over the whole country were used to derive site-specific correction factors. Correlation factors were transferred to the needed spatial extent using geospatial interpolation and used to adjust satellite derived data sets. Another 61 stations were used to validate the resulting maps of long-term monthly-averaged data sets. This study's findings show that the adjustment using monthly correlation factors significantly improves the quality of estimations from satellite derived sources. For the GHI component the rMB could be reduced to 0.8%, for DNI to 7.1% and for DHI to −1.1% on average over all months at all validation sites. In conclusion, a significant decrease of overestimations of the satellite product could be achieved by applying the described methodology. Largest improvements resulted from the adjustment of the averaged DNI component. The representation of GHI and DHI could be improved as well.

It is widely known that a precise knowledge of solar resource data is crucial to establish a solar project (Vignola et al., 2007). Nonetheless, most policies focus on the promotion of economic policy instruments and barriers that constrain the deployment of solar energy technologies.

Table 3
Statistical results for 51 sites used for adjustment based on SRRA L3 data (left column) and 61 sites used for validation (right column).

Irradiance component		Adjustment sites		Validation sites	
		Avg(rMB) [%]	Std(rMB) [%]	Avg(rMB) [%]	Std(rMB) [%]
GHI	Original	8.3	±6.1	9.3	±7.1
	Adjusted	0.3	±1.7	0.8	±5.7
DNI	Original	24.2	±19.3	37.9	±27.3
	Adjusted	−0.4	±2.3	7.1	±14.3
DHI	Original	3.8	±6.0	2.5	±9.6
	Adjusted	−0.0	±1.3	−1.1	±8.5

Key instruments established and extensively analyzed for India include feed-in-tariffs, government mandates and regulatory provisions, subsidies, and public investment (Shrimali and Rohra, 2012; Timilsina et al., 2012; Ummadisingu and Soni, 2011). It is often neglected that robust and transparent solar resource data is crucial to secure financing for solar projects. Measuring solar data is expensive and time consuming and requires at least one complete year of measurements covering all seasons, referring to seasonality of solar resource data. In early stages of project development bankability is about managing risk and understanding uncertainty. Deciding on a suitable site requires a high degree of confidence that solar irradiation will meet a certain minimum level. Consequently, making solar data available for solar companies and customers in early stages of the project development is essential to establish an investor-friendly market and policy planning environment, and to step towards data-driven policy making. In this context, the resulting maps of long-term averages are made available to the public and updated frequently.

Besides the availability for private stakeholders the maps can be used to support policy makers to direct future policies to mitigate or aggravate upcoming problems. For instance, the first intention of the JNNSM policy was to give equal emphasis to both solar photovoltaic (SPV) as well as concentrated solar power (CSP) technologies under Phase-I of the JNNSM policy. This resulted from the assumption that DNI was expected to be higher in certain areas than received. During the bidding developers had to rely on satellite modeling data giving overestimated DNI values. Consequently, projects had to be reengineered substantially to achieve expected performance. This illustrates the value reliable and consistent solar resource data has for both, private and public stakeholders in a complex policy landscape driven by market growth. Based on this data reasonable shares and solar technologies can be chosen and policy instruments applied. Prospects for solar energy are particularly good as costs of solar electricity generation are decreasing making them competitive in different energy markets. Solar deployment can be further enhanced by assessing the projects capital structure from early stages of project development by providing solar resource data with high accuracy.

In conclusion, a significant increase in accuracy for long-term averages of all three irradiance components could be achieved by correcting satellite derived model results with spatially interpolated correction factors from measurements. While the advantages are important, it should be noted that the value of the solar resource data can be enhanced by frequently improving the spatial maps. First, solar measurements continue under the SRRA campaign and their integration in updates of the solar maps will improve their accuracy. Moreover, locations of the network were chosen due to results of previous studies. Based on insights from this study establishing new or replacing existing ground stations, even if operated over short-term campaigns, can add a value to the spatial maps. Second, despite the results of this study more complex methodological approaches could be of advantage. The study of Davy et al. (2016) for example shows that improvement over satellite-derived radiation time series is achieved by combining those with irradiance values from a Numerical Weather Prediction (NWP) model. For the Australian domain, this method leads to the best solar irradiance estimates next to an increase in accuracy. In addition, Davy et al. find a dependency of their model correction on weather. Thus, a separate correction according to clear and cloudy sky conditions might lead to further improvements. Moreover, no reassessment of reached targets considering constrains and the availability of long-term averages for solar irradiance components have been conducted so far.

However, this could lead to a deeper insight into the role of the provided solar atlas. Results could indicate if higher spatial or temporal resolution data can provide additional value for private and public stakeholder. India's solar industry is growing fast. India's Tamil Nadu Project is the currently largest solar plant with a 648 MW capacity, indicating that implementation of solar policies in India is already showing first signs of success.

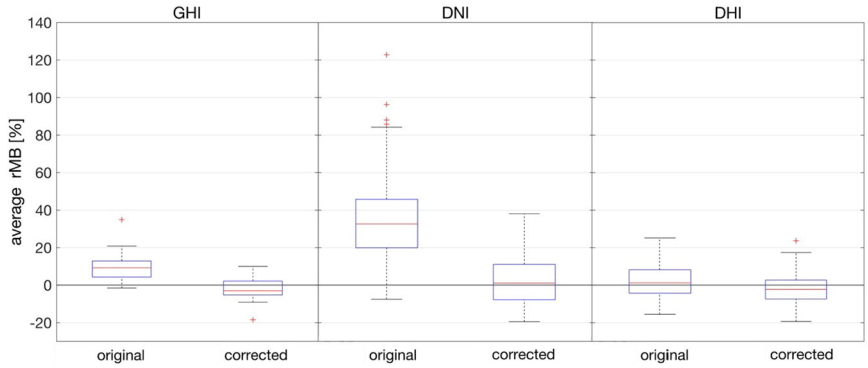

Fig. 9. Statistical validation results for GHI, DNI and DHI. Displayed are relative mean bias values calculated from 61 validation sites.

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