Accuracy of Solar Resource Assessments on the Basis of Publicly Available GHI Databases

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Abstract

The "true" long-term Global Horizontal Irradiation (GHI) for a given location is normally unknown. Thus, the selection of the most appropriate, publicly or commercially available dataset or the application of a corresponding data handling approach is a key challenge and task when assessing the site-specific GHI solar resource.

Based on reference data obtained from Baseline Surface Radiation Network (BSRN) as well as the German and Dutch national weather services, a database and approach benchmarking including 63 locations in Europe – mainly Germany and the Netherlands - and 1 location in North Africa has been conducted.

For publicly available databases and various arithmetic means, a typical relative Root Mean Square Error (RMSE) of the long-term annual GHI of ±1.8 % to ±7.2 % has been found. Regarding inter-annual variability, the corresponding range is ±0.4 % to ±4.0 %. In both cases, the arithmetic means typically achieve smaller relative RMSE, thus suggesting a greater reliability for Solar Resource Assessment purposes.

Keywords: Solar Resource Assessment, Global Horizontal Irradiation, Photovoltaic

1. Introduction

Accurate Solar Resource Assessments are essential for the success of both a single solar photovoltaic (PV) project and the energy transition towards renewable energies in general. For PV applications, the most important energy meteorological parameter is the Global Horizontal Irradiation (GHI).

There are several databases available that provide site-specific GHI from either ground observations and/or satellite information. The long-term average values obtained from these sources typically differ by a few percent. In addition, spatially-distributed, high-quality and high-accuracy long-term measurements are sparse, i.e. the "true" value of the GHI solar resource is normally unknown. The selection or application of the most appropriate dataset or approach is therefore one of the most important challenges and tasks when assessing the site specific solar resource.

A method that combines various datasets for site-specific GHI solar resource assessment was first published by Pagola et al. (2010). It includes database-related weights that account for the number of years of data, the quality of the information and the spatial resolution. Validation of the approach at five Spanish locations showed that the included five different databases individually exhibited a worse performance than the values obtained by the new methodology. The annual value bias of the combined datasets ranged from 0.42 % to 3.16 %, which results in an overall relative RMSE of ±1.7 %.

Similarly, in a global benchmarking effort that compared single database information as well as weighted means against 38 high-quality GHI reference datasets, Egler et al. (2017) found smaller overall relative RMSE for the combined datasets as well. The database-related weights utilized in this study were limited to the technical features, i.e. number of years of data and spatial resolution. Globally, the relative RMSE of the annual values for the weighted mean method was ±2.2 %, while the seven different, single databases achieved between ±2.6 % and ±5.3 %. Overall, it was concluded that combining different datasets for GHI solar resource assessment results in a more stable accuracy.

Comparably, for solar power forecasting it has been found that combination of discrete forecasts reduces the

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forecasting error. For day-ahead purposes, this has been shown, for example, by Bührer et al. (2018).

For PV Solar Resource Assessment, adequate averaging period is of relevance. Müller et al. (2014) concluded that applying the average of the last 10 years of historic data best meets the criteria of being an expedient predictor for the next 20 years. Accordingly, the commonly available recent period of 2007-2016 has been selected in the present benchmarking of various, publicly accessible GHI databases. In addition, arithmetic means, formed by the different datasets, have been included in the evaluation as well. The study area of the benchmarking is Europe and North Africa, with a reference data focus on Germany and the Netherlands. The aim of this work is to determine the accuracy of each single database and potential arithmetic means and to provide recommendations for accurate PV Solar Resource Assessments.

2. Database and approach benchmarking

2.1 Reference data and locations

Baseline Surface Radiation Network (BSRN) data are an ideal reference for GHI benchmarking, since its objective is to provide the best possible quality of solar irradiation data. However, for the considered study area and period, measurements of only eight BSRN locations are available. Therefore, datasets considered reliable – mainly, that is records being made utilizing Secondary Standard pyranometer – and obtained from the German and Dutch national weather services, Deutscher Wetterdienst (DWD) and Koninklijk Nederlands Meteorologisch Instituut (KNMI), at 24 locations in Germany and 32 in the Netherlands, have been included in the reference database as well. The data retrieval via the URLs presented in Tab. 1 mainly took place in June 2017 and August 2017.

Fig. 1 gives a geographical overview of the reference locations included in this study.

Fig. 1: Map of reference locations with BSRN sites indicated by green, DWD by blue and KNMI by red dots.

Tab. 1: BSRN, DWD and KNMI reference data URLs

Network / Weather service	URL
BSRN	https://dataportals.pangaea.de/bsrn/?q=LR0100
DWD	ftp://ftp-cdc.dwd.de/pub/CDC/observations_germany/climate/hourly/solar/
KNMI	http://projects.knmi.nl/klimatologie/uurgegevens/selectie.cgi

Reference data density is greatest for Dutch territory, with approximately one reference site per 1,300 km². For Germany, the corresponding value is about 14,300 km².

The reference data are available in 1 min – BSRN – and hourly – DWD and KNMI – resolution. For the preparation of the long-term monthly and annual averages, each dataset is reviewed, and monthly daytime data availability calculated. Months featuring less than 95 % availability are excluded and all remaining are corrected for missing information. Correction is made on the assumption that the maximum 5 % lacking feature the same GHI per percent as the available data. This means the GHI sum of the corrected months include a fraction that is based on an extrapolation using the recorded GHI sum multiplied with the missing percent. Based on the reviewed dataset, long-term averages are calculated afterwards. Following this process, about half of the reference locations provide a complete dataset for the examined averaging period. For the remainder, the resulting data availability is displayed in Tab. 2.

Tab. 2: Reference locations featuring less than 100 % data availability in 2007-2016 period

Location name	Country	Database	Data Availability
Carpentras	FR	BSRN	81.7%
Palaiseau	FR	BSRN	87.5%
Tamanrasset	DZ	BSRN	98.3%
Cabauw	NL	BSRN	93.3%
Toravere	EE	BSRN	97.5%
Camborne	GB	BSRN	86.7%
Cener	ES	BSRN	73.3%
Lerwick	GB	BSRN	76.7%
Arkona	DE	DWD	88.3%
Braunschweig	DE	DWD	98.3%
Dresden-Klotzsche	DE	DWD	96.7%
Fichtelberg	DE	DWD	96.7%
Freiburg	DE	DWD	57.5%
Geisenheim	DE	DWD	60.0%
Görlitz	DE	DWD	96.7%
Hohenpeißenberg	DE	DWD	88.3%
List auf Sylt	DE	DWD	76.7%
Norderney	DE	DWD	97.5%
Potsdam	DE	DWD	99.2%
Rostock-Warnemünde	DE	DWD	98.3%
Saarbrücken-Ensheim	DE	DWD	99.2%
Schleswig	DE	DWD	99.2%
Stuttgart (Schnarrenberg)	DE	DWD	96.7%
Trier-Petrisberg	DE	DWD	87.5%
Weihenstephan-Dürnast	DE	DWD	80.0%
Weißenburg-Emetzheim	DE	DWD	75.8%
Würzburg	DE	DWD	98.3%
Fürstenzell	DE	DWD	98.3%
Valkenburg	NL	KNMI	94.2%
Wilhelminadorp	NL	KNMI	70.0%

To account for the data unavailability at these reference locations, the benchmarking is performed in a like-to-like way, i.e. only data points available in both the reference dataset and the databases are included.

A simple way to assess the quality or consistency of the DWD and KNMI reference datasets is cross-comparison. For this, the GHI of each reference location is estimated using the data of the surrounding reference locations, with the site of interest being excluded from the estimation but used as reference. By applying the 3-D inverse distance model introduced by Zelenka et al. (1992), with the additions of Lefèvre and Wald (2001), a relative RMSE for the long-term annual values of ±2.7 % for the German reference locations and ±2.2 % for the Dutch reference locations has been determined. According to Lorenz (2009) the BSRN target accuracy for GHI ground measurements is ±2 %, which means that the DWD and KNMI information can be considered as of comparable quality.

2.2 Databases and means

The databases considered in the benchmarking are all publicly available and provide data for the considered reference period as well as for all but two locations of the study area – PVGIS-CMSAF information for Toravere / EE and Lerwick / UK are unavailable.

Site-specific GHI data have been retrieved from PVGIS-CMSAF, PVGIS-SARAH, CAMS-RAD and NASA POWER via the URLs presented in Tab. 3. Data was mainly accessed between July and September 2017 as well as February 2018.

Tab. 3: URLs of the databases included in the work

Database	URL
PVGIS-CMSAF/-SARAH	http://re.jrc.ec.europa.eu/pvg_tools/en/tools.html#MR
CAMS-RAD	http://www.soda-pro.com/en_GB/web-services/radiation/cams-radiation-service
NASA POWER	https://power.larc.nasa.gov/data-access-viewer/

The arithmetic means included in the benchmarking are labelled as follows: Mean-PVGIS, formed by both PVGIS databases; Mean-HighRe, formed by the high-resolution databases of PVGIS-CMSAF, PVGIS-SARAH and CAMS-RAD; Mean-All, which includes all databases; and Mean-All-2, which is a combination of PVGIS-SARAH, CAMS-RAD and NASA POWER.

In case of GHI benchmarking, first monthly average values are calculated using the corresponding long-term data provided by each database, before the annual sum of the respective arithmetic mean is determined. For inter-annual variability, the arithmetic mean values correspond to the average of the included database information.

2.3 Accuracy metrics and benchmarking

The site-specific monthly and annual long-term averages and inter-annual variabilities of each database and arithmetic mean are compared against the corresponding reference data. The comparison is made in a like-to-like way, i.e. only data points available in both reference and the databases are included in each respective long-term value or year-on-year variability figure. Finally, depending on the investigated parameter, various common accuracy metrics are calculated, with relative Root Mean Square Error (RMSE) being considered the most important in the context of the study.

Relative monthly and annual deviations (dev) between the database or arithmetic mean values and the reference information at each reference location (r) are determined. Subsequently resulting relative RMSE, relative Mean Bias Error (MBE) and relative Mean Absolute Error (MAE) over the full number of reference locations (N) are calculated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{r=1}^{N} dev_r^2} \quad \text{(eq. 1)}$$

$$MBE = \sum_{r=1}^{N} dev_r \quad \text{(eq. 2)}$$

$$MAE = \sum_{r=1}^{N} |dev_r| \quad \text{(eq. 3)}$$

3. Results

3.1 Long-term annual GHI

For the different databases and arithmetic means, the relative RMSE differentiated by reference sub-dataset, i.e. for BSRN, DWD and KNMI reference locations separately, is presented in Fig. 2.

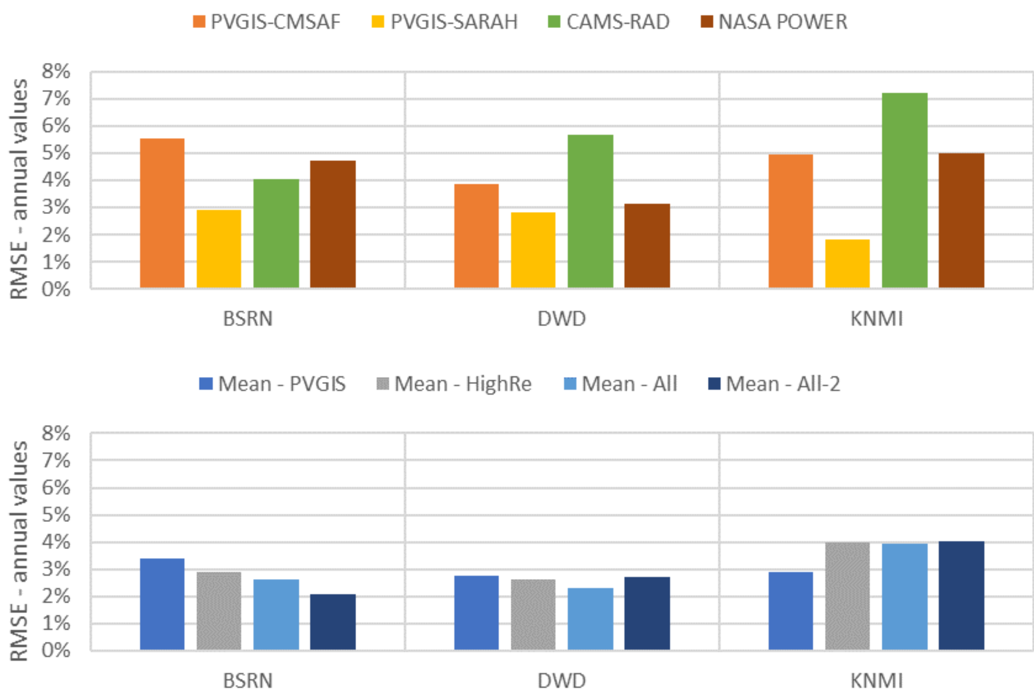

Fig. 2: Relative RMSE of annual values of different databases and arithmetic means as a function of reference sub-dataset

The range of relative RMSE of the publicly accessible databases is ±1.8 % to ±7.2 %, and the corresponding values of the arithmetic means are ±2.1 % to ±4.0 %.

Fig. 3 provides the long-term annual relative MBE results over each reference sub-dataset.

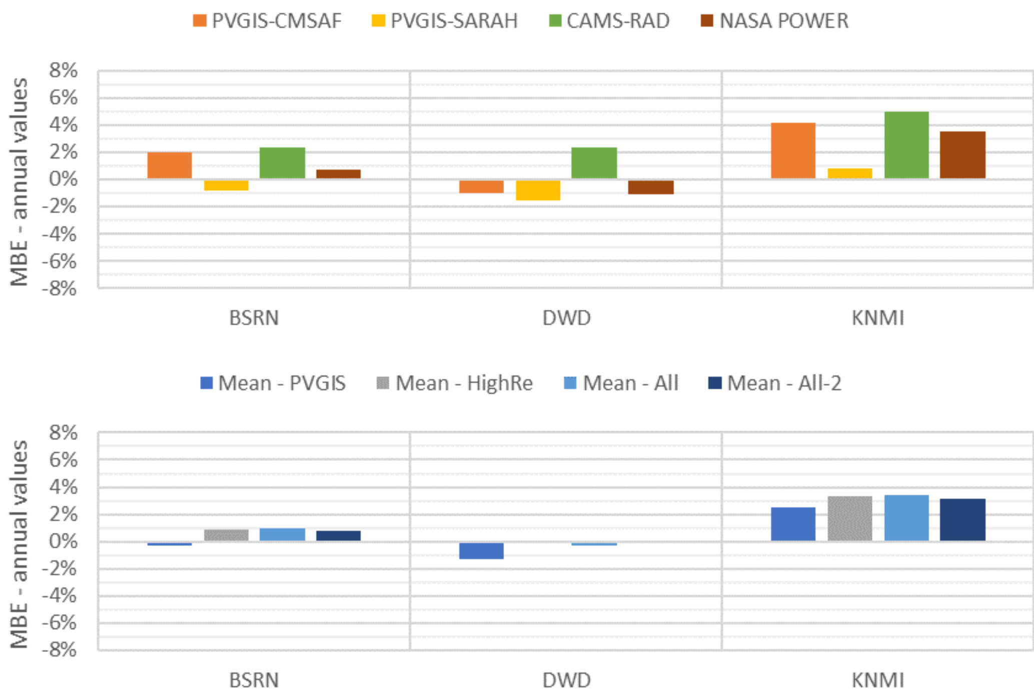

Fig. 3: Relative MBE of annual values of different databases and arithmetic means as a function of reference sub-dataset

The publicly available databases exhibit a relative MBE range of -1.6 % to +5.0 %, the arithmetic means of -1.3 % to 3.4 %. Of note, while for BSRN and DWD both negative and positive numbers occur, this is not the case when looking at KNMI reference sub-dataset. For KNMI, only positive relative MBE are determined.

Overall, both accuracy metric results indicate that typically arithmetic means show less deviation and thus provide more reliable, site-specific GHI estimates than selecting a single database. The scatter plots presented in Fig. 4 further visualize this finding by showing the respective MAE determined for each individual reference location.

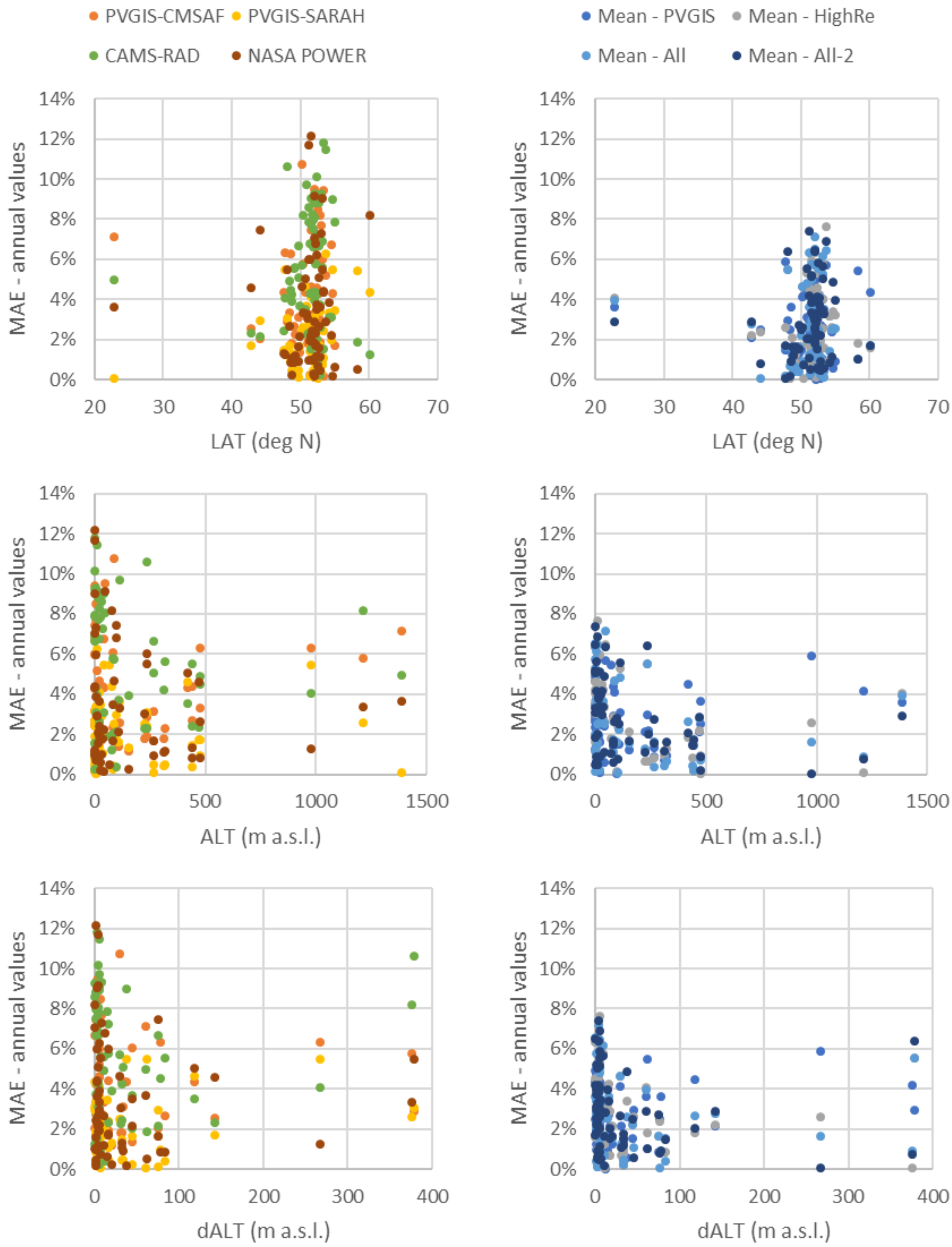

Fig. 4: Scatter plots of relative MAE of annual values for each database and arithmetic mean

In addition to this general observation, the most stable performance over the DWD, KNMI and BSRN reference sub-dataset has been found for PVGIS-SARAH database.

Fig. 5 and Fig. 6 show the resulting relative RMSE and relative MBE numbers when sorting the reference locations by geographic characteristics. There, location class Coastal / Island includes locations on small islands and less than approximately 20 km from the sea, while Flat, Hilly and Mountainous is differentiated by altitude variability of the spatial resolved information – less than 30 m, between 30 m to 100 m and more than 100 m – of the surrounding terrain, as provided by SoDa's "altitude of a point" service (http://www.soda-pro.com/en_GB/web-services/altitude/altitude-of-a-point).

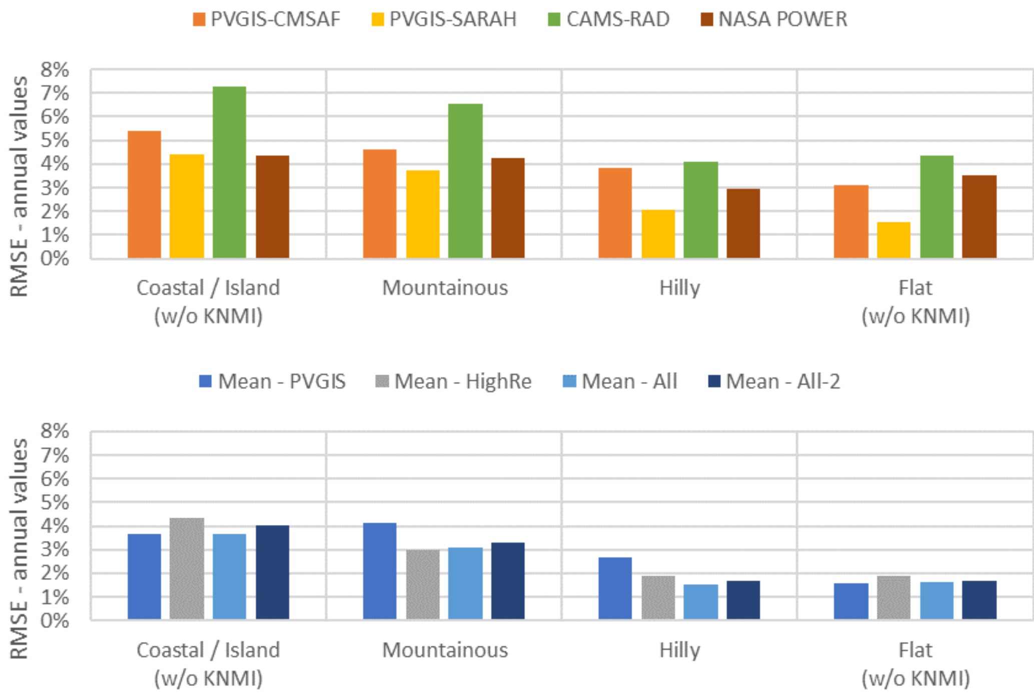

Fig. 5: Relative RMSE of annual values of different databases and arithmetic means as a function of location class

Fig. 6: Relative MBE of annual values of different databases and arithmetic means as a function of location class

Because the accuracy metric results obtained for KNMI reference sub-dataset differs from both BSRN and DWD and to achieve relatively equal numbers of reference locations in each class, all KNMI locations have been excluded in above analysis. If included, relative RMSE values change by up to ±1.5 % for Coastal / Island and up to ±3 % for Flat.

Considering the different situations of the locations, varying performances can be observed. This is in line with expectations, which say that for more complex geographic environment greater deviations likely occur.

3.2 Long-term monthly GHI

For the benchmarking of long-term monthly GHI database or arithmetic mean performance, the respective monthly deviations at each reference location is used to calculate relative RMSE before an average over each reference sub-dataset is determined. Fig. 7 presents the resulting numbers.

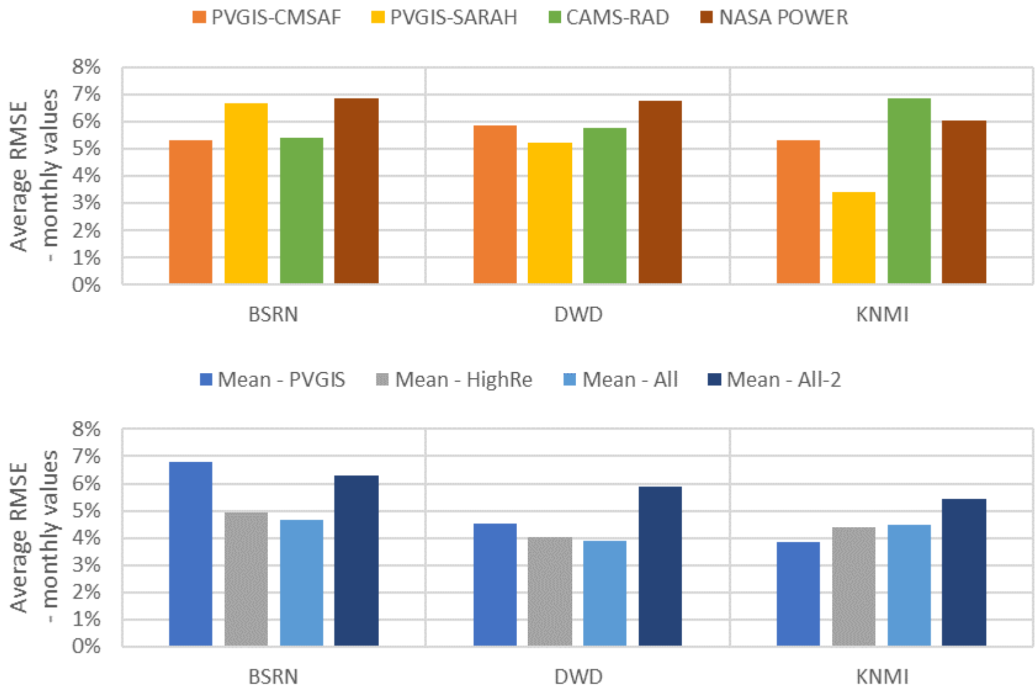

Fig. 7: Average of relative RMSE of monthly values of different databases and arithmetic means as a function of reference sub-dataset

The average relative RMSE for monthly values of the individual databases ranges from ±3.4 % to ±6.9 %, the corresponding values for the arithmetic means are ±3.9 % to ±6.8 %. Except for the greater numbers and some changes in the ranking relative to each other, the results are similar to the ones obtained for long-term annual values, as the combined datasets typically give more accurate estimates.

3.3 Inter-annual GHI variability

Overleaf Fig. 8 and Fig. 9 show the relative RMSE and relative MBE with regard to inter-annual variability, differentiated by reference sub-datasets.

In contrast to the GHI benchmarking of both long-term monthly and annual values, performance of NASA POWER database is significantly worse than those of the other three databases and the arithmetic means when considering year-on-year variations. Even for the combination of datasets a negative influence can be observed. The strong deviation of NASA POWER against the reference datasets is likely caused by multiple changes affecting this database during the 2007-2016 period.

Considering inter-annual GHI variability, the differences between individual database and arithmetic mean performances are smaller than within the long-term data benchmarking, but still combined datasets provide more reliable estimates. Overall, the relative RMSE ranges from ±0.6 % to ±1.9 % for arithmetic means and from ±0.4 % to ±4.0 % for the databases. Excluding NASA POWER, the results are ±0.6 % to ±1.1 % and ±0.4 % to ±1.6 %. In terms of relative MBE, all but one number – PVGIS-CMSAF with 0.2 % – are negative. For the databases the MBE results are between +0.2 % and -3.9 %, or between +0.2 % and -1.2 % if NASA POWER is excluded. The arithmetic means achieve relative MBE ranging from -0.2 % to -1.8 % including NASA POWER or -0.2 % to -0.8 % excluding NASA POWER dataset.

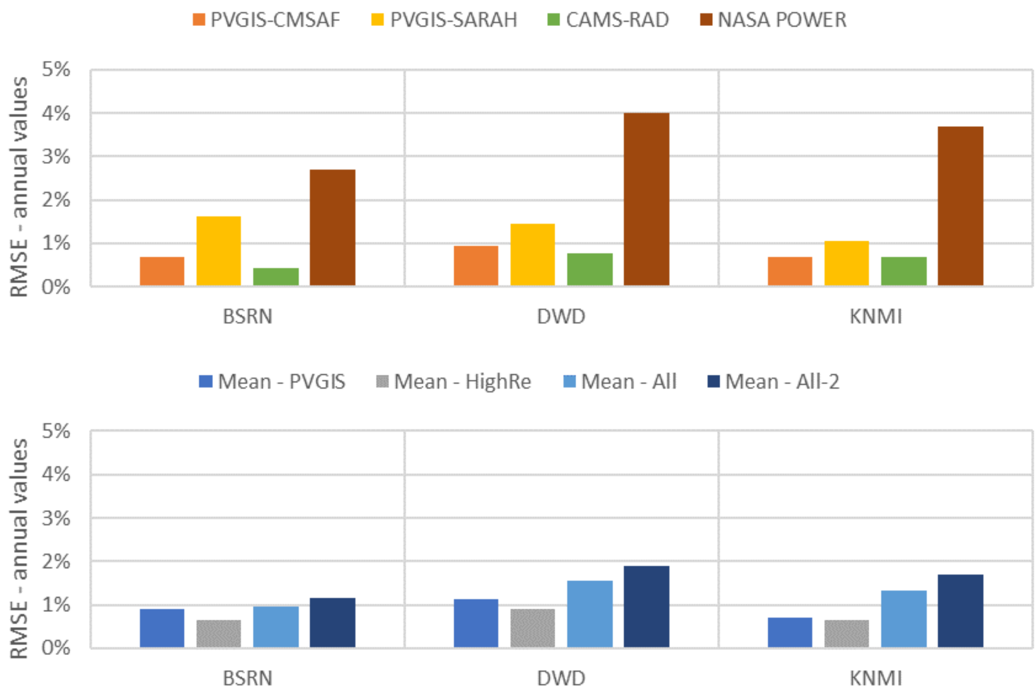

Fig. 8: Relative RMSE of annual values of different databases and arithmetic means as a function of reference sub-dataset

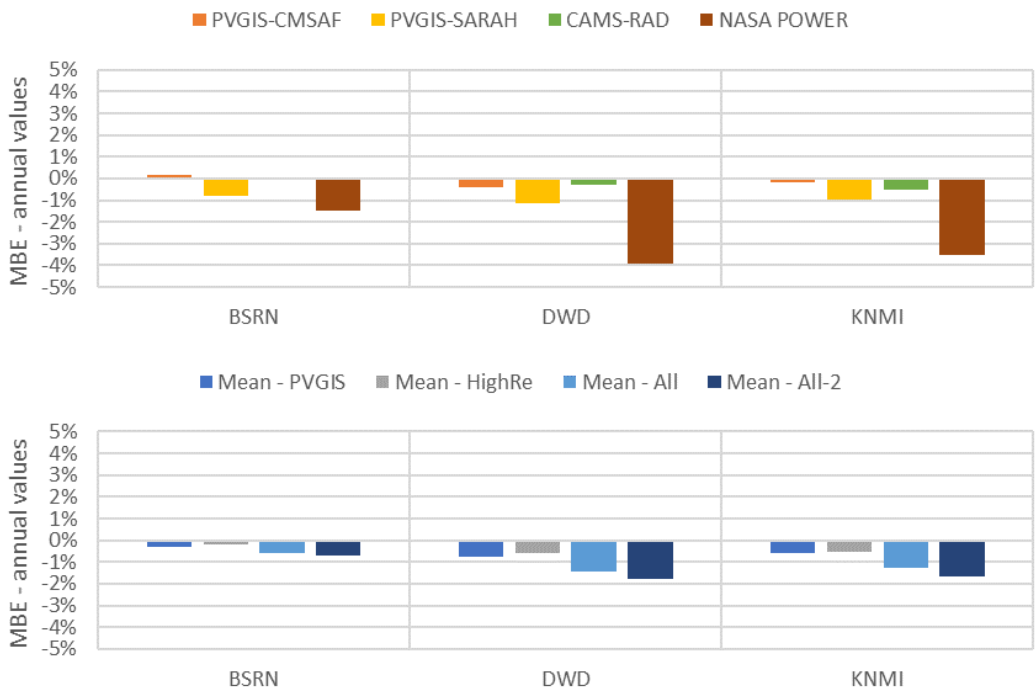

Fig. 9: Relative MBE of annual values of different databases and arithmetic means as a function of reference sub-dataset

4. Conclusion

The performance in terms of relative RMSE and relative MBE of individual databases and different combinations or arithmetic means formed using this information has been analysed. The values obtained have been benchmarked against reliable reference information. The results indicate that for both long-term GHI averages and their inter-annual variability, arithmetic means typically provide more accurate estimates than single databases. Thus, it is concluded that an approach which combines database information is more reliable than selection of an individual dataset for Solar Resource Assessment purposes. However, the actual performance of the arithmetic means depends on the selection of the databases included in the combining and therefore requires a continuous benchmarking, particularly when entering new markets. Finally, individual information is not generally outperformed and might be equal or slightly better choice in specific regions.

5. References

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