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Quantifying the amplified bias of PV system simulations due to uncertainties in solar radiation estimates

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Abstract

Solar radiation databases used for simulating PV systems are typically selected according to their annual bias in global horizontal irradiance (G_H) because this bias propagates proportionally to plane-of-array irradiance (G_{POA}) and module power (P_{DC}). However, the bias may get amplified through the simulations due to the impact of deviations in estimated irradiance on parts of the modeling chain depending on irradiance. This study quantifies these effects at 39 European locations by comparing simulations using satellite-based (SARAH) and reanalysis (COSMO-REA6 and ERA5) databases against simulations using station measurements.

SARAH showed a stable bias through the simulations producing the best P_{DC} predictions in Central and South Europe, whereas the bias of reanalyses got substantially amplified because their deviations vary with atmospheric transmissivity due to an incorrect prediction of clouds. However, SARAH worsened at the northern locations covered by the product (55-65°N) underestimating both G_{POA} and P_{DC} . On the contrary, ERA5 not only covers latitudes above 65° but it also obtained the least biased P_{DC} estimations between 55-65°N, which supports its use as a complement of satellite-based databases in high latitudes. The most significant amplifications occurred through the transposition model ranging from $\pm 1\%$ up to $+6\%$. Their magnitude increased linearly with the inclination angle, and they are related to the incorrect estimation of beam and diffuse irradiance. The bias increased around $+1\%$ in the PV module model because the PV conversion efficiency depends on irradiance directly, and indirectly via module temperature. The amplification of the bias was similar and occasionally greater than the bias in annual G_H , so databases with the smallest bias in G_H may not always provide the least biased PV simulations.

Keywords: satellite-based models; reanalysis; PV system simulation; PV system modeling

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Nomenclature

Δ	Variation of the statistics through the simulation
η_{rel}	relative energy conversion efficiency of the PV module
B	beam/direct irradiance
D	diffuse irradiance
G	global irradiance
G_{eff}	effective irradiance available for being converted by the PV the module
KT	clearness index
P_{DC}	direct current (DC) power of the PV module
R	reflected irradiance
T_{amb}	ambient temperature
T_{mod}	module temperature
U	absolute uncertainty
u	relative uncertainty
WS_{mod}	wind speed at module's height

Subscripts

d	daily
h	hourly
min	minutely
y	yearly/annual
H	horizontal plane
N	plane always normal to sun rays
POA	plane of array
STC	standard test conditions

Superscripts

$'$	variable normalized to STC
est	simulation using estimated irradiance from radiation databases
$meas$	simulation using irradiance measured at weather stations (reference simulation)

1. Introduction

The number of utility-scale and residential PV installations has exponentially increased in the latest years (Jäger-Waldau, 2017). The reasons are the strong cost reduction of PV technology and the appearance of economic incentive policies such as feed-in tariffs (FITs) and net-metering (NET) (Thevenard and Pelland, 2013). A higher penetration of solar PV is held back by the intermittency of the energy generated, which originates from the inherent variability of the solar resource. Part of this variability is caused by stochastic atmospheric processes such as cloud formation (Inman et al., 2013) that complicate PV system modeling and increase the uncertainty of estimations (Ela et al., 2013). The development of accurate simulations is therefore necessary

to minimize this uncertainty, helping in the deployment of PV systems globally (Thevenard and Pelland, 2013; Hansen and Martin, 2015).

PV simulations are used for *yield prediction*, i.e., the estimation of the total energy produced by a system during its lifetime. Yield predictions are essential in feasibility studies for selecting the best sites and estimating the financial risk of the investment (Müller et al., 2016; Goss et al., 2012). PV simulations are also part of *energy rating*, which consists of comparing the real performance of PV modules to that under standard test conditions (STC). Energy rating simulations are evaluated based on the performance ratio (PR) to assess the efficiency of a PV technology under different climatic conditions (Huld and Gracia Amillo, 2015; Huld et al., 2016; Dirnberger et al., 2015). Simulations made for yield prediction consider all specific details of the installation, such as electrical losses and the exact amount of irradiation at the location (including shading, soiling, and snow losses), whereas energy rating simulations are independent of these details. Thus, solar radiation data is more influential for yield predictions, where it is not only the most dominant factor (Cole et al., 2017; Müller et al., 2009) but it also accounts for around 50% of final uncertainty (Müller et al., 2007; Thevenard and Pelland, 2013; Müller et al., 2017; Richter et al., 2015). Still, uncertainties in irradiance data also affect energy rating simulations because the efficiency of the module under real conditions depends on irradiance.

Ground measurements are the most accurate source of radiation data for PV simulations (Urraca et al., 2018b). However, ground sensors are sparsely distributed and rarely close to the PV system location. The variable commonly measured at weather stations is global horizontal irradiance (G_H) using pyranometers. Few stations record the radiation components: diffuse horizontal irradiance (D_H) is measured with shaded pyranometers whereas beam horizontal irradiance (B_H) is determined from beam normal irradiance (B_N) recorded by pyrhemometers. In-plane irradiance (G_{POA}) measurements are even more rare. Therefore, most PV simulations use estimated irradiance (Urraca et al., 2017b), especially those made for feasibility studies requiring several years of data. Satellite-derived databases are the most common choice due to their great progress in the last years (Sengupta et al., 2017; Polo et al., 2016). These databases provide spatially continuous data and are integrated by some of the most popular online PV simulation tools: PVGIS (European Commission JRC, 2018), PVWATTS (NREL, 2018), pvPlanner (GeoModel Solar, 2018), and PV*SOL (Valentin Software, 2018), which use SARAHI, NSRDB, SolarGIS, and Meteonorm databases, respectively. Atmospheric reanalyses are another alternative to measurements. They have global coverage and estimate other climatic variables required for PV simulations such as wind speed and temperature. But even with the recent progress made in reanalysis, they generally have coarser spatial resolutions and larger uncertainties than satellite-based models (Urraca et al., 2018b, 2017c).

Solar radiation databases provide G_H , B_H , and D_H estimations, so most PV simulations use transposition models to calculate G_{POA} from horizontal irradiance variables. Radiation databases are generally selected according to their annual bias in G_H (Richter et al., 2015), and their suitability is rarely checked in terms of module power (P_{DC}) or G_{POA} due to the lack of measurements. The few validations published included a reduced number of locations (Müller et al., 2009, 2016; Ves, 2013; Roberts et al., 2017; Dobos, 2014; Axaopoulos et al., 2014; Freeman et al., 2014) and seldom compared radiation databases under a common simulation methodology. It would be interesting to clarify whether the databases with the least biased G_H estimations are always the ones most suited for PV system modeling by analyzing the propagation of the bias through simulations. Excluding the transposition model, simulation models are basically a series of multiplicative derating factors accounting for different types of losses (Thevenard and Pelland, 2013), so the bias in G_H propagates proportionally to G_{POA} and P_{DC} . However, the bias can change through the simulations because the parameters of some sub-models depend on irradiance; this is the case for transposition or power rating models. Cole

et al. (2017) estimated that the amplification of the bias may be around a $\pm 2\%$ using satellite-based data, but a more accurate quantification of these effects is needed to improve the selection of radiation databases. These secondary effects are rarely taken into account, but most of them may affect both yield predictions and energy rating simulations.

This paper analyzes the importance of the mentioned secondary effects on the propagation of bias in G_H through simulations. For that, we studied separately this propagation in the transposition model (from G_H to G_{POA}) and the PV module model (from G_{POA} to P_{DC}). The three radiation databases implemented in PVGIS were used: (i) a satellite-based method (SARAH), (ii) a global atmospheric reanalysis (ERA5), and (iii) a regional atmospheric reanalysis (COSMO-REA6). The lack of G_{POA} and P_{DC} measurements was overcome by comparing simulations made with the radiation databases against a simulation made with station measurements. Simulations were made with crystalline silicon (c-Si) modules at the 39 locations of the weather stations. Deviations from the reference simulation can be attributed to the radiation database because all sub-models and remaining inputs (meteorological data and PV parameters) were kept constant in all simulations.

2. Solar radiation data on a horizontal plane

Radiation databases and weather stations were selected by taking into consideration the requirements for simulating PV systems: (i) sub-daily temporal resolution, and (ii) availability of estimations/measurements of both G_H and its components (B_H and D_H) to avoid using decomposition models (Gueymard and Ruiz-Arias, 2016). The three radiation databases selected are implemented in PVGIS and provide at least two out of the three horizontal irradiance variables (Table 1). An extensive validation of these databases can be found in Urraca et al. (2018a, 2017b, 2018b).

2.1. Ground measurements

Ground measurements were retrieved from 39 European weather stations distributed across different latitudes (Fig. 1). The stations belong to the Baseline Surface Radiation Network (BSRN) (BSRN, 2017), the German weather service (Deutscher Wetterdienst, DWD) (DWD, 2016), and the Finnish weather service (Finnish Meteorological Institute, FMI) (FMI, 2016) (Table 1). DWD stations only record G_H and D_H , thus B_H was obtained mathematically ($B_H = G_H - D_H$). The same procedure was followed at BSRN and FMI stations for homogenization, even though they measure B_N . Only those years from 2010 to 2015 with more than 7500 h of simultaneous measurements of G_H and D_H were used (Table A1). G_H and D_H were recorded with unshaded and shaded ventilated pyranometers, respectively. The majority of the stations were equipped with secondary standard Kipp&Zonen pyranometers, except for DWD-2928, which had PRM2 (Sonntag) pyranometers (shaded and unshaded) from 2010 to 2013, and DWD-4336 & DWD-4393, which used a Scanning Pyrheliometer/Pyranometer (SCAPP) (Becker and Behrens, 2012) for measuring D_H during 2010.

2.2. SARAH

SARAH is a satellite-based dataset produced by the Satellite Application Facility on Climate Monitoring (CM SAF) (CM SAF, 2015) for Europe, Africa, and Asia. SARAH uses images from Meteosat geostationary satellites limiting its spatial coverage to latitudes within $\pm 65^\circ$. Surface irradiance is estimated using a semi-empirical method based on the Heliosat algorithm. Reflectivity recorded by visible channels of radiometers on-board Meteosat satellites is used to calculate the effective cloud albedo or cloud index. Then, the cloud index is combined with the

Figure 1: Location of the stations used in this study. The stations surrounded by a black circle were used to analyze the influence of module inclination angle on bias propagation.

estimations of SPECMAGIC clear-sky model to obtain surface irradiance variables. A detailed description of the algorithm is available in [Müller et al. \(2015c\)](#).

Two main versions of SARAH are currently available from CM SAF data server for Europe: SARAH-1 ([Müller et al., 2015b](#)) and SARAH-2 ([Pfeifroth et al., 2016](#)). Besides, SARAH-East (SARAH-E) ([Gracia Amillo et al., 2014](#)) extends SARAH-1 coverage to Asia by using images from Meteosat East satellites. All versions have a spatial resolution of $0.05^\circ \times 0.05^\circ$ (Table 1). The version used in the present study is a combination of SARAH-1 and SARAH-E implemented by PVGIS ([European Commission JRC, 2018](#)). Compared to SARAH-1, this version covers Europe, Africa, and Asia, and it analyzes a single satellite image per hour providing instantaneous hourly estimations of G_H and B_H . Like SARAH-1, it uses monthly averages of water vapor from ERA-interim and monthly climatologies of aerosol optical depth from MACC ([MACC Reanalysis, 2015](#)). A detailed validation of this version can be found in [Urraca et al. \(2017b\)](#).

2.3. ERA5

ERA5 ([ECMWF, 2017](#)) is the newest global atmospheric reanalysis from the European Centre for Medium-range Weather Forecasts (ECMWF). ERA5 will replace ERA-Interim ([Dee et al., 2011](#)) as the main ECMWF operational reanalysis by the end of 2019, but up to now, only a preliminary release covering from 2010 to 2017 is available. ERA5 uses a 12-h 4DVar data assimilation system. The main improvements of ERA5 over ERA-Interim are the finer horizontal resolution (31 vs. 79 km), the finer vertical resolution (137 vs. 60 levels), the higher temporal frequency for surface irradiance variables (1 vs. 3 h), the greater amount of data assimilated, and the update of the numeric weather prediction (NWP) model (IFS Cycle 41r2). Surface irradiance variables do not assimilate ground measurements and are obtained with a radiative

transfer model (RTM) within the NWP model. The two short forecasts are initialized at 6:00 and 18:00 UTC every day. This study uses only the first 12 steps (first 12 h) of each short forecast. The variables retrieved are surface solar radiation downwards (*ssrd*) and total sky direct solar radiation at surface (*fdir*). Both provide the accumulated irradiation from the previous to the current step (1 h). Hourly G_H and B_H were calculated from *ssrd* and *fdir*, respectively, and are thus centered at half-hourly intervals (Table 1).

2.4. COSMO-REA6

COSMO-REA6 (Bollmeyer et al., 2015) is a regional reanalysis produced by the Hans-Ertel-Centre for Weather Research of Deutscher Wetterdienst (HErZ/DWD) for Europe with a resolution of about 6 km. It is generated using the operational NWP model of DWD (COSMO model). COSMO-REA6 implements a continuous nudging scheme, so it can assimilate data at different time intervals. ERA-Interim estimations are used as boundary conditions. The solar radiation scheme uses instantaneous data for clouds and water vapor. Aerosols are modeled with the Tanré climatology, which is known to provide too high aerosol optical thickness for Europe. However, it was kept in COSMO-REA6 because it was the standard input for COSMO NWP model (Frank et al., 2018). COSMO-REA6 provides instantaneous 15-min values for surface irradiance fields. The variables retrieved were instantaneous direct radiation (*SWDIFDS_RAD*) and instantaneous diffuse radiation (*SWDIRS_RAD*), which correspond to D_H and B_H , respectively.

Table 1: Summary of the radiation datasets used in this study (2010-2015).

Dataset	Provider	Spatial resolution	Temporal resolution ^b	Type	Variables
Weather stations (39) ^a	BSRN (6)	Point value	1 min	avg.	G_H, B_H, D_H
	DWD (25)		1 h (:30 LST)	avg.	G_H, D_H
	FMI (8)		1 h (:30 UTC)	avg.	G_H, D_H
SARAH PVGIS	CM SAF	$0.05^\circ \times 0.05^\circ$ (~5 km)	1 h (:55 UTC)	inst.	G_H, B_H
ERA5	ECMWF	$0.28^\circ \times 0.28^\circ$ (~31 km)	1 h (:30 UTC)	avg.	G_H, B_H
COSMO-REA6	HErZ/DWD	$0.055^\circ \times 0.055^\circ$ (~6.2 km)	15 min	inst.	B_H, D_H

^a Reference dataset. Values in brackets show the number of weather stations from each network.

^b Values in brackets give the interval midpoint of average values (avg.), and the exact time of instantaneous values (inst.). LST = local solar time.pl

3. PV modeling chain

3.1. Preprocessing horizontal irradiance data

Hourly means were calculated at BSRN stations, which were the only ones with sub-hourly temporal resolution (1-min). 15-min averages were calculated if at least 5 samples were available, and hourly means were obtained by averaging 15-min means if all four 15-min values were valid. All night values (solar elevation $< 0^\circ$) were set to 0. The BSRN tests (Long and Dutton, 2002) were used to quality control (QC) hourly ground records. Samples falling out the physically possible and extremely rare limits for G_H and D_H were considered as not available (NA). A second and more restrictive QC method was applied to all ground measurements. This QC method flags those samples that show a deviation against several radiation databases out of the typical intervals for the time of the year and location (Urraca et al., 2017a). All samples passed the second QC test.

The three radiation databases provide estimations as raster files. In databases with a rather fine spatial resolution (SARAH and COSMO-REA6), the values used were those of the pixel

containing the station location. In ERA5, the values of the four nearest pixels to the station location were interpolated using inverse distance weighting (IDW). While reanalysis data do not have missing values and their coherence has been already verified, SARAH has missing values at low solar elevation angles (set to -1) and may contain inconsistencies. Thus, SARAH data was preprocessed by setting night values (solar elevation $< 0^\circ$) and missing values at low solar elevation angles ($G_H = -1$, $B_H = -1$) to 0 for the validation of G_H , B_H and D_H . All missing values of SARAH were reconstructed for the simulations using averages of the same hour/-day/month in different years. The missing horizontal irradiance variable in each database was calculated based on solar geometry.

3.2. Transposition model

Most PV systems have the modules installed at an angle to the horizontal plane to maximize the radiative energy that arrives at the modules. However, both measured and estimated irradiance data are available on the horizontal plane. The transposition model calculates the irradiance on the plane of array (POA) from horizontal irradiance variables by transposing each radiation component separately and subsequently adding them:

$$G_{\text{POA}} = B_{\text{POA}} + D_{\text{POA}} + R_{\text{POA}}, \quad (1)$$

where B_{POA} , D_{POA} , and R_{POA} are the beam, diffuse, and reflected components on the plane of array. B_{POA} is determined based on solar geometry, and R_{POA} was calculated from G_H assuming an isotropic distribution and a constant ground albedo ($\rho_g = 0.2$). This is the common procedure used in most PV simulations, which typically differ in the type of transposition model for the diffuse component. In this study, we used Muneer's model (Muneer, 1990), which considers the anisotropic diffuse irradiance coming from the horizon and that coming from the circumsolar region. This model compares well with other inclined-plane models (Gracia and Huld, 2013). However, the choice of the inclined-plane model is not critical to the present study because Muneer's model was included in both simulations using radiation databases and those using station measurements. All simulations will predict a decrease in diffuse radiation with increasing inclination (as more and more of the sky will shine on the back of the plane), and an increase in direct radiation from horizontal up to an optimum angle which depends on latitude and the seasonal variation in climate.

3.3. PV module model

PV module models can be split into (Fig. 2): (i) the calculation of the effective irradiance (G_{eff}), i.e., the portion of G_{POA} available for being converted into electrical current, and (ii) the calculation of instantaneous P_{DC} as a function of G_{eff} and module temperature (T_{mod}). G_{eff} is calculated from G_{POA} by applying several correction factors accounting for different types of losses:

$$G_{\text{eff}} = (f_{\text{AOI}} \cdot f_{\text{spec}} \cdot f_{\text{snow}} \cdot f_{\text{soiling}} \cdot f_{\text{shading}}) \cdot G_{\text{POA}} \approx f_{\text{AOI}} \cdot G_{\text{POA}}. \quad (2)$$

Spectral losses (f_{spec}) were neglected because only SARAH provides spectrally resolved irradiance data. Losses due to the accumulation snow (f_{snow}), accumulation of dirt and dust (f_{soiling}), and shadows (f_{shading}) were also ignored because their impact is independent of the radiation database used. Therefore, the only losses accounted for in this study were the angle of incidence (AOI) effects (f_{AOI}).

3.3.1. Angle of incidence (AOI) effects

Some of the light hitting the PV modules will be reflected away from the module surface, and the fraction of light reflected depends on the angle between the module surface and the incoming light. AOI losses were calculated using [Martin and Ruiz \(2001\)](#) model with a value of $a_r = 0.16$. This model has been included in the Part 2 of the IEC 61853 standard on PV module energy rating ([IEC, 2016](#)).

3.3.2. Model for PV power dependence on temperature and irradiance

Figure 2: Description of the modeling chain used for the PV system simulations.

The instantaneous power of PV modules at conditions different from those at STC depends on effective in-plane irradiance (G_{eff}) and module temperature (T_{mod}). T_{mod} was calculated from G_{POA} , ambient temperature (T_{amb}), and wind speed at module's height (WS_{mod}) with the model proposed by [Faiman \(2008\)](#):

$$T_{mod} = T_{amb} + \frac{G_{POA}}{u_0 + u_1 \cdot WS_{mod}}, \quad (3)$$

where u_0 and u_1 are empirical coefficients. In this case, the values proposed by [Koehl et al. \(2011\)](#) for c-Si modules were used.

The conversion efficiency of PV modules for irradiance and temperature values different from STC was determined with the model suggested by [Huld et al. \(2011\)](#) as

$$P'_{DC}(G'_{eff}, T'_{mod}) = G'_{eff} \cdot \eta_{rel}(G'_{eff}, T'_{mod}) = G'_{eff} \cdot (1 + k_1 \cdot \ln G'_{eff} + k_2 \cdot \ln^2 G'_{eff} + k_3 \cdot T'_{mod} + k_4 \cdot T'_{mod} \cdot \ln G'_{eff} + k_5 \cdot T'_{mod} \cdot \ln^2 G'_{eff} + k_6 \cdot (T'_{mod})^2), \quad (4)$$

where η_{rel} is the relative energy conversion efficiency of the module, and coefficients $k_1 \dots k_6$ are those reported by [Huld et al. \(2011\)](#) for c-Si modules. All variables in this model are normalized to STC:

$$P'_{DC} = P_{DC} / P_{STC} \quad \text{with} \quad P_{STC} = \text{nominal power} \quad (5)$$

$$G'_{eff} = G_{eff} / G_{STC} \quad \text{with} \quad G_{STC} = 1000 \text{ W/m}^2 \quad (6)$$

$$T'_{mod} = T_{mod} - T_{STC} \quad \text{with} \quad T_{STC} = 25^\circ\text{C} \quad (7)$$

3.4. Additional meteorological data

Ambient temperature (T_{amb}) and wind speed at module's height (T_{mod}) are required to calculate PV module temperature (T_{mod}). Both variables were obtained from ERA-Interim (Dee et al., 2011), which estimates 10 m E-W wind component, 10 m N-S wind component, and 2 m temperature with a spatial resolution of $0.75^\circ \times 0.75^\circ$ (~ 81 km) and a temporal frequency of 3 h. T_{amb} was assumed to be equal to 2 m temperature. WS_{mod} was obtained by adding in quadrature the two wind components and using the power law (Chen et al., 1998) to estimate WS variation with height:

$$WS_{mod} = WS_{10m} \cdot (z_{mod}/10)^\alpha, \quad (8)$$

where z_{mod} is the module's height and α is the power law index, an empirically derived coefficient that depends on terrain roughness and atmospheric stability. In this case, z_{mod} and α were assumed to be 2 m and 0.2, respectively. Linear interpolation was used to obtain hourly WS_{mod} and T_{amb} from the 3-h ERA-Interim estimates. Besides, T_{amb} estimates were downscaled using the procedure described in Huld and Pinedo (2015) to account for the local terrain variations.

4. Validation

4.1. Evaluation of bias propagation through the simulation

The PV simulations were made at the locations of the 39 weather stations from 2010 to 2015, using c-Si modules with a nominal power of 1 kW ($P_{STC} = 1$ kW) and an inclination angle of 45° . Results were independent of P_{STC} because the analysis was based on relative metrics. The deviations between simulations using estimated irradiance (subscript 'est') and the simulation using station measurements (subscript 'meas', reference simulation) were calculated for each radiation database (Eq. 9). The presence of uncertainty in the reference values was emphasized by using the term "deviation" instead of "error" (Gueymard, 2014), and it is further discussed in Appendix B. Even though the simulations were made with hourly values, hourly deviations could not be calculated because hourly intervals were defined differently in radiation databases and weather stations (Table 1). Thus, deviations were calculated with the daily irradiance means as

$$deviation_d(X) = X_d^{est} - X_d^{meas} \quad X \in (G_H, B_H, D_H, G_{POA}, P_{DC}), \quad (9)$$

where the daily means (X_d) were obtained by averaging hourly values if at least 21 values per day were available (max NAs = 3). This procedure gives the "true error" only for horizontal irradiance variables (G_H, B_H, D_H) because these are the only ones for which X^{meas} is actually measured data. In G_{POA} and P_{DC} , X^{meas} is the prediction obtained with the simulation based on ground measurements, so the deviations show the difference between predictions using estimated irradiance and that using station measurements.

The annual relative bias ($bias_y[\%]$) of daily deviations was calculated to analyze the suitability of each solar radiation database for PV simulations because the feasibility of PV systems is commonly evaluated based on annual yield predictions (Müller et al., 2017).

$$bias_y(X)[\%] = \frac{\frac{1}{N_d} \sum_{n=1}^{N_d} (X_d^{\text{est}} - X_d^{\text{meas}})}{\frac{1}{N_d} \sum_{n=1}^{N_d} X_d^{\text{meas}}} \cdot 100 \quad X \in (G_H, B_H, D_H, G_{\text{POA}}, P_{\text{DC}}), \quad (10)$$

where N_d is the number of days per year with available values for both the simulation based on estimations and the reference simulation. The annual bias was calculated only if $N_d > 312$ days (≈ 7500 h) to guarantee that the bias was representative of irradiance conditions throughout the whole year.

The influence of the intra-annual distribution of deviations on the propagation of the bias was evaluated with the scatter plots of daily relative deviations ($deviation_d[\%]$) against clearness index (KT). Relative deviations were obtained by dividing absolute daily deviations by the annual mean of X in the reference simulation instead of by its daily value:

$$deviation_d(X)[\%] = \frac{X_d^{\text{est}} - X_d^{\text{meas}}}{\frac{1}{N_d} \sum_{n=1}^{N_d} X_d^{\text{meas}}} \cdot 100 \quad X \in (G_H, B_H, D_H, G_{\text{POA}}, P_{\text{DC}}). \quad (11)$$

Thereby, $deviation_d[\%]$ shows the actual contribution of each daily deviation to the $bias_y[\%]$ eliminating the dependence of relative daily metrics on the seasonal variation of the solar resource. The KT , which is a common indicator of the atmospheric transmissivity, was calculated as

$$KT = \frac{G_H}{E_H}, \quad (12)$$

where E_H is the extraterrestrial irradiance received on a horizontal plane.

The use of relative metrics enabled the comparison of the values obtained in the different steps of the simulation chain. Therefore, the propagation of the bias in the transposition model (from G_H to G_{POA}) and the PV module model (from G_{POA} to P_{DC}) were obtained as

$$\begin{aligned} \Delta bias_y(\text{trans.model}) &= bias_y(G_{\text{POA}}) - bias_y(G_H) \\ \Delta deviation_d(\text{trans.model}) &= deviation_d(G_{\text{POA}}) - deviation_d(G_H) \end{aligned} \quad (13)$$

$$\begin{aligned} \Delta bias_y(\text{PVmod.model}) &= bias_y(P_{\text{DC}}) - bias_y(G_{\text{POA}}) \\ \Delta deviation_d(\text{PVmod.model}) &= deviation_d(P_{\text{DC}}) - deviation_d(G_{\text{POA}}). \end{aligned} \quad (14)$$

Note that in the present study, both positive and negative changes of the bias through the simulation have negative connotations regardless of whether the absolute value of the bias decreases.

4.2. Influence of the module inclination angle on bias propagation

The influence of the module inclination angle on bias propagation was analyzed by varying the inclination angle from 0° to 65° in 5° intervals. These simulations were made only at three locations (Fig. 1): (i) BSRN-CAR (Carpentras), a low-latitude station (44.08°) situated in a sunny region with a high frequency of clear conditions, (ii) DWD-662 (Branuschweig), a mid-latitude station (52.29°) located in a cloudy region, and (iii) FMI-4714 (Sotkamo), a high-latitude station (64.11°) located in a region with seasonal snow and low solar elevations during winter.

5. Results and discussion

5.1. Propagation of the bias through PV simulations

The annual bias in G_H and G_{POA} was analyzed separately below and above 55°N (Fig. 3) because the performance of radiation databases changes in high latitudes due to seasonal snow, low solar elevation angles, and low satellite viewing angles. SARA obtained the smallest annual bias in G_H below 55°N ($bias_y = -0.06\%$). It showed a decreasing bias with increasing latitude, obtaining negative biases in Northern Germany and particularly in the Nordic countries ($bias_y = -4.87\%$). SARA-1 and SARA-E underestimate near the edge of satellite images due to an overestimation of cloud thickness because satellites view clouds at very shallow angles (Müller et al., 2015a; Gracia Amillo et al., 2014). This issue has been addressed in SARA-2 with an empirical correction of the cloud index as a function of the satellite zenith angle, but it has not been implemented in SARA PVGIS yet. The negative bias was stronger in winter (Fig. 6), which may be related to an over-prediction of clouds over snow-covered surfaces (Müller et al., 2015a). COSMO-REA6 showed the largest bias by underestimating G_H across all latitudes (-4.99% and -5.98%). This is a well-known problem of COSMO-REA6 caused by the use of an aerosol climatology that introduces a too high aerosol content (Frank et al., 2018). The most homogeneous distribution of the annual bias in G_H over Europe (Fig. 3a) corresponded to ERA5, with a moderate overestimation of G_H below 55°N ($bias_y = +1.67\%$) and a low underestimation in high latitudes ($bias_y = -1.43\%$). Thus, ERA5 was the database with the smallest bias above 55°N , while the smallest bias below 55°N corresponded to SARA.

Annual biases in P_{DC} differed from those obtained in G_H at some locations. SARA obtained the most stable bias through simulations (Fig. 3b), with $\Delta bias_y$ within $\pm 1.8\%$ in the transposition model and a negligible $\Delta bias_y$ within $\pm 0.1\%$ in the PV module model. In the transposition model, the bias got more positive below 55°N ($\Delta bias_y = +1.8\%$) and more negative in the Nordic countries ($\Delta bias_y = -1.46\%$). COSMO-REA6 presented a similar propagation pattern to that of SARA in the transposition model, but COSMO-REA6 obtained a non-negligible $\Delta bias_y$ of $+0.92\%$ in the PV module model. The increase in bias below 55°N canceled out the negative bias in G_H leading to a moderate bias in P_{DC} , whereas the decrease of bias in high latitudes accentuated the negative bias in P_{DC} . The largest bias amplification was obtained by ERA5 below 55°N , with $\Delta bias_y = +6.09\%$ in the transposition model and $\Delta bias_y = +1.52\%$ in the PV module model. This led to a large bias in P_{DC} ($+9.29\%$) despite the moderate bias in G_H ($+1.67\%$) obtained by ERA5. ERA5 performance sharply changed in Northern Europe becoming the best radiation database in terms of G_H and the one showing the most stable bias through simulations ($\Delta bias_y = +1.44\%$). Therefore, ERA5 was the best performing database in high latitudes with an annual bias in P_{DC} of $+0.01\%$, whereas SARA remained as the database with the smallest annual bias in P_{DC} below 55°N ($+1.64\%$).

The interpretation of the results is constrained by the uncertainty in the reference simulation (see Appendix B). Annual biases of horizontal irradiance variables were greater than the uncertainty of the reference simulation at the majority of stations (Table 2). The exceptions were found in SARA below 55°N and ERA5 above 55°N , where around half of the stations were within the uncertainty limits because of the low deviations of both databases in those regions. For G_{POA} and P_{DC} , the number of stations within the uncertainty limits increased because both variables were not measured but estimated by feeding horizontal irradiance measurements to the simulation model. However, values shown in Table 2 are the worst-case scenario. The true number of biases greater than the uncertainty in the reference simulation should be considerably larger because test and reference simulations used the same transposition and PV module model. Thus, systematic deviations introduced by these models cancel out. Nonetheless, G_{POA} and P_{DC} deviations were still significant for ERA5 below 55°N and COSMO-REA6 above 55°N .

Figure 3: **(a)** Distribution of the annual bias in G_H and P_{DC} . **(b)** Distribution of the propagation of the annual bias in the transposition model (from G_H to G_{POA}) and the PV module model (from G_{POA} to P_{DC}). Values in the box represent the mean bias at locations over and under $55^\circ N$.

even in this worst-case scenario. Concerning the uncertainties at DWD and FMI stations, we did not observe any significant difference between the results obtained at BSRN stations and those obtained at FMI or DWD. This suggests that the variations of uncertainty between stations were negligible and did not interfere significantly in the interpretation of the results.

Table 2: Percentage of annual biases greater than the annual uncertainty of the reference simulation.

	Database	G_H	B_H	D_H	G_{POA}^*	P_{DC}^*
Latitude < 55°	SARAH	57	42	62	30	24
	COSMO-REA6	91	75	74	34	20
	ERA5	60	96	100	73	77
Latitude > 55°	SARAH	62	91	81	38	34
	COSMO-REA6	82	95	75	70	52
	ERA5	30	34	64	11	11

* In the reference simulation, G_{POA} and P_{DC} are estimated using the irradiance measurements as inputs to the PV simulation model.

These results evidence that, despite the bias in G_H is the main driver of the bias in P_{DC} , the bias significantly changes through the simulations. Deviations observed were exclusively due to the source of radiation data, so changes in the bias through the simulations were caused by secondary effects of uncertainties in estimated irradiance on the modeling chain. The magnitude and sign of these changes varied between databases and locations, and in some cases, they were even greater than the magnitude of the annual bias in G_H . Therefore, the best radiation database in terms of G_H does not assure the least biased PV estimations, so the bias in G_H alone may not be an adequate criterion to select radiation databases. For example, the annual bias in G_H of ERA5 was smaller than that of COSMO-REA6 (+1.67 vs. -4.99%), but the amplification of ERA5 bias through the simulations made that its annual bias in P_{DC} was greater than that of COSMO-REA6 (+9.29 vs. -2.79%). In the following sections, we analyze the root of these variations by studying independently the bias propagation through the transposition model (Subsection 5.2) and the PV module model (Subsection 5.3).

5.2. Propagation of the bias through the transposition model

The propagation of the bias in the transposition model was studied based on the distribution of daily deviations against KT (Fig. 4), the deviations of B_H and D_H (Fig. 5), and the intra-annual distribution of these deviations (Fig. 6). The role of radiation components in the transposition model is essential because they are transposed separately (Fig. 2), and the contribution of each component varies with the inclination angle: the contribution of beam irradiance increases up to the optimum inclination angle whereas the contribution of diffuse irradiance decreases (Subsection 3.2). Therefore, an unbalanced estimation of radiation components ($bias_y(G_H) \neq bias_y(D_H) \neq bias_y(B_H)$) will be accentuated through the transposition model leading to large errors in G_{POA} . The bias in G_{POA} will get more negative when B_H is underestimated ($bias_y(B_H) < bias_y(G_H)$) and more positive when B_H is overestimated ($bias_y(B_H) > bias_y(G_H)$) because beam irradiance plays a dominant role close to the optimum inclination angle. Regarding reflected irradiance, the relative bias in R_{POA} will be proportional to that in G_H because R_{POA} was calculated from G_H assuming a constant ground albedo. However, the contribution of R_{POA} to G_{POA} is substantially smaller than that of beam or diffuse irradiance, so R_{POA} is not analyzed in this section.

The bias of SARAH slightly changed through the transposition model below 55°N ($\Delta bias_y = +1.8\%$) because of a balanced estimation of the radiation components ($bias_y(B_H) = -0.91\%$,

Figure 4: (a) 2D density plot of daily deviations in G_H and G_{POA} between radiation databases and station measurements. (b) 2D density plot of the change of daily deviations through the transposition model.

$bias_y(D_H) = +0.97\%$ (Fig. 5). The increase of the bias may be partly explained by the presence of missing values at low solar elevations. These values were set to 0 for the validation of horizontal irradiance while they were reconstructed for PV simulations, introducing a small negative bias in G_H , B_H and D_H when compared to G_{POA} and P_{DC} . The $\Delta bias_y$ was more negative with an increasing latitude (Fig. 3b) due to the greater underestimation of B_H (Fig. 5a) that canceled out the overestimation caused by missing values. Therefore, $\Delta bias_y$ was -1.46% above $55^\circ N$ driven by the strong imbalance between the radiation components ($bias_y(B_H) = -14.91\%$, $bias_y(D_H) = +8.18\%$). The underestimation of SARAH in G_H and G_{POA} was strong under clear conditions in winter and spring (Fig. 6), which may be related to the known limitations of SARAH on detecting snow (Müller et al., 2015a). SARAH detects clouds solely with images from the visible channels of radiometers on-board geostationary satellites. These images are not sufficient to robustly distinguish between snow and clouds because both have high reflectivity, leading to an over-prediction of clouds over snow-covered surfaces. In high latitudes, the imbalance between B_H and D_H (positive bias in D_H , negative bias in B_H) was also large in summer under clear conditions (Fig. 6), which may be related to other issues such as aerosols or the overestimation of cloud thickness at shallow satellite viewing angles.

The bias of COSMO-REA6 got more positive through the transposition model below $55^\circ N$ ($\Delta bias_y = +1.27\%$) and more negative in high latitudes ($\Delta bias_y = -2.67\%$). Compared to SARAH, COSMO-REA6 presented an uneven distribution of the deviations (Fig. 4), underestimating under clear sky and overestimating under cloudy conditions as reported by the own HERZ/DWD (Frank et al., 2018, 2017). Negative deviations under clear sky are caused by the well-known overestimation of Tanré aerosol climatology, which leads to the underestimation of B_H , G_H and B_H in mid and low latitudes. These deviations are more visible during the central months of the year (Fig. 6). Conversely, positive deviations for $KTs < 0.5$ are caused by the prediction of

Figure 5: **(a)** Distribution of the annual bias in B_H and D_H . **(b)** 2D density plot of daily deviations in B_H and D_H between radiation databases and station measurements against the daily clearness index (KT_d^{meas}). Values in the box represent the average bias at locations over and under 55°N .

optically too thin or too few clouds (Frank et al., 2018) and lead to the overestimation of B_H and the underestimation of D_H (Fig. 5). Below 55°N , both effects virtually balance each other (Fig. 5b). The bias of COSMO-REA6 slightly got more positive due to the overestimation of B_H under cloudy conditions and the predominantly high-cloudiness at the sites evaluated below

Figure 6: Heatmap of monthly-aggregated relative bias ($bias_m$) in G_H , D_H and B_H . Stations are sorted from left to right by increasing latitude.

55°N. Above 55°N, the overestimation of B_H under cloudy conditions was somehow mitigated. Therefore, the underestimation of B_H under clear conditions prevailed leading to a negative $\Delta bias_y$ through the transposition model of -2.67%. The bias became more negative as well at southern locations because the underestimation of B_H caused by the excess of aerosol content was accentuated by the high frequency of clear conditions (Fig. 5). Overall, both SARA and COSMO-REA6 presented a similar propagation pattern in the transposition model, with a moderate positive $\Delta bias_y$ below 55°N and a large negative $\Delta bias_y$ in high latitudes, though the causes of these changes differed in each database.

ERA5 showed a significantly positive $\Delta bias_y$ of +6.09% through the transposition model below 55°N, which may be explained by the great imbalance between beam and diffuse irradiance ($bias_y(B_H) = +17.81\%$, $bias_y(D_H) = -14.15\%$) (Fig. 5). Similarly to COSMO-REA6, ERA5 overestimated and underestimated G_H for low and high KT, respectively. However, the overestimation of G_H under cloudy conditions was substantially more accentuated in ERA5 than in COSMO-REA6 (Fig. 4a). This is related to different failures in the prediction of clouds such as false prediction of clear-sky situations, underestimation of the cloud fraction, optically too thin clouds, or incorrect cloud properties (cloud phase or liquid/ice water content), among others (Urraca et al., 2018a). These defects led to an overestimated B_H for KT < 0.5 (Fig. 4b), and thus, to an overestimated G_{POA} . The performance of ERA5 completely changed in the Nordic countries because of a reduced overestimation of B_H under cloudy conditions, leading to a better balanced estimation of radiation components (Fig. 5). The overestimation of B_H for KT < 0.6 canceled the underestimation of B_H for KT > 0.6, producing a moderate $\Delta bias_y = +0.86\%$. Thus, ERA5 presented the smallest $\Delta bias_y$ through the transposition model above 55°N, which contrasts with its poor performance below 55°N where it obtained the largest $\Delta bias_y$ overall.

The bias of reanalysis databases was substantially amplified through the transposition model due to the uneven performance of these models with the atmospheric transmissivity. Reanalyses underestimate and overestimate G_H under clear and cloudy conditions, respectively. This pattern may be related to random errors in cloud placement because even the best solar radiation models will show clouds under clear conditions and vice versa. Typically, these random errors do not affect the annual bias because they cancel out, but they still lead to an incorrect estimation of beam and diffuse irradiance amplifying the bias through the simulations. Besides, in this case, random errors were not fully averaged out. COSMO-REA6 showed a negative bias due to the overestimation of aerosols under clear skies, whereas ERA5 showed a positive bias due to the strong underestimation of clouds under cloudy conditions. Conversely, the performance of SARA was uniform under different atmospheric conditions, especially below 55°N. We conclude that the principal limitation of reanalyses when simulating PV systems is the high intra-annual variability of their bias caused by cloud-related errors.

5.3. Propagation of the bias through the PV module model

The PV module model comprises the estimation of G_{eff} from G_{POA} and the estimation of η_{rel} for temperature and irradiance values different from those under STC (Fig. 2). In this study, the estimation of G_{eff} only accounted for AOI losses, which depend on solar geometry and are virtually independent of the radiation database. Therefore, variations of the bias through the PV module model primarily occurred in the estimation of η_{rel} , and they were caused by second-order effects of irradiance errors on the model that calculates η_{rel} . These effects are two-fold because η_{rel} depends on irradiance directly (Fig. 7a) and indirectly via module temperature (Fig. 7b). Irradiance and temperature were the predominant factors at low and high irradiances, respectively. Therefore, η_{rel} increases with irradiance until a value of around 400 W/m², after which it decreases due to the heating of the cell (Fig. 7c) (Huld et al., 2008).

Figure 7: Relative energy conversion efficiency (η_{rel}) of c-Si modules **(a)** as a function of irradiance for constant module temperature, **(b)** as a function of module temperature for constant irradiance, **(c)** and as a function of irradiance for constant ambient temperature.

Figure 8: **(a)** 2D density plot of daily deviations in G_{POA} between simulations using radiation databases and that using station measurements against G_{POA} . **(b)** 2D density plot of the change of daily deviations through the PV module model against G_{POA} .

The $\Delta bias_y$ through the PV module model can be explained by the interaction of curves shown in Fig. 7c with the distribution of daily deviations with irradiance (Fig. 8a). SARAH exhibited a negligible $\Delta bias_y$ in the PV module model within $\pm 0.1\%$ because its deviations were evenly distributed with irradiance (Fig. 8a). Conversely, a positive $\Delta bias_y$ was obtained in the PV module model with both reanalyses: $+0.92\%$ and $+0.14\%$ for COSMO-REA6, and $+1.52\%$ and $+0.58\%$ for ERA5, for locations below and above $55^\circ N$, respectively. As discussed above, this is because both products present an unbalanced error distribution showing positive deviations under cloudy conditions (low irradiance days) and negative deviations under clear

conditions (primarily high irradiance days). Irradiance effects dominate η_{rel} in low irradiance days, so an overestimated irradiance leads to an overestimated η_{rel} , and hence to a positive $\Delta bias_y$. On the other hand, temperature effects dominate η_{rel} in high irradiance days. Here an underestimated irradiance leads to a too low module temperature, and as a consequence, an overestimated η_{rel} that results in a positive $\Delta bias_y$ as well. The combination of both effects results in the banana-shaped curves obtained in Fig. 8b, explaining why the bias got more positive in the PV module model. In COSMO-REA6, the positive $\Delta bias_y$ was mostly driven by an underestimated temperature in days with high irradiance (above 250 W/m^2) due to the excess of aerosols (Fig. 8b), whereas the positive $\Delta bias_y$ of ERA5 is primarily caused by an overestimated irradiance in days with low irradiance (below 200 W/m^2) due to the underestimation of clouds (Fig. 8b). As in the transposition model, the bias was amplified through the PV module model in simulations based on reanalyses due to the intra-annual variation of their deviations with the atmospheric transmissivity.

5.4. Propagation of the bias with different module inclination angles

The propagation of the bias through the transposition model showed a clear dependence on the module inclination angle. The $\Delta bias_y$ grew linearly with the inclination angle up to the optimum inclination at each location (Fig. 9). This trend was common to all databases and locations regardless the sign of $\Delta bias_y$, driven by the increasing contribution of beam irradiance with the inclination angle. $\Delta bias_y$ increased more rapidly for databases with an imbalanced estimation of beam and diffuse components, such as ERA5 in Germany (DWD-662) and COSMO-REA6 in high latitudes (FMI-4714). In general, the trend in bias continued at a smaller rate beyond the optimum angle. This may be related to the fact that for an interval above the optimum angle B_{POA} still increases while D_{POA} continues to fall. Thus, the trend in bias caused by an imbalance of B and D will continue.

Figure 9: Influence of module inclination angle on bias propagation. The dashed line shows the optimum inclination angle at each location.

The $\Delta bias_y$ in the PV module model was small and virtually constant along different inclination angles because the inclination angle does not directly affect the PV module model. The changes of the bias observed were side effects of the propagation of the bias in the transposition model. A large $\Delta bias_y$ in the transposition model accentuates the defects in the radiation databases, leading to a more irregular distribution of errors in G_{POA} . This alters the calculation of the energy conversion efficiency of the module, explaining the amplification of the bias in the PV module model.

6. Conclusions

PV system simulations using radiation databases (SARAH, ERA5, and COSMO-REA6) were compared against a simulation using ground measurements to analyze the propagation of the bias in G_H through the PV modeling chain. As the rest of the parameters involved were similar between simulations, the changes in the bias observed from G_H to P_{DC} may be only caused by the source of radiation data used.

Significant differences were observed between geographic areas and databases. In mid and low European latitudes, the bias of COSMO-REA6 and ERA5 substantially changed through the simulations because their deviations in G_H varied with the atmospheric transmissivity. ERA5 especially overestimates under cloudy conditions due to an underestimation of cloud coverage, while COSMO-REA6 particularly underestimates under clear sky due to an excess of aerosols. This problem was particularly severe in ERA5 which showed a $\Delta bias_y$ of +7.61% through the simulations. On the other hand, the satellite-based SARAH showed the smallest annual bias in G_H and the most stable bias through the simulations. This confirms that SARAH is the best database to simulate PV systems in Central and South Europe.

The performance of SARAH and COSMO-REA6 changed dramatically in Northern Europe. The annual bias of both databases became more negative through the transposition model caused by an underestimation of beam irradiance ($\Delta bias_y = -1.46\%$ in SARAH, $\Delta bias_y = -2.67\%$ in COSMO-REA6). In the case of SARAH, this may be related to the shallow satellite viewing angles and snow detection problems. Conversely, ERA5 showed the smallest $\Delta bias_y$ and the best annual bias in both G_H and P_{DC} . ERA5 not only complements SARAH above $65^\circ N$ but also outperforms it between $55^\circ N$ and $65^\circ N$. These are promising results for using ERA5 as a complement of satellite-based databases in regions not covered by geostationary satellites such as Northern Europe. Nonetheless, ERA5 still shows large intra-annual deviations in high latitudes due to cloud-related errors, so users should keep in mind that the uncertainty of yield predictions from ERA5 in high latitudes may be larger than that from SARAH in Central Europe.

The bias in G_H is the traditional metric for selecting radiation databases because it is the main driver of the bias in P_{DC} . However, the bias can significantly change through the PV modeling chain due to secondary effects of uncertainties in estimated irradiance on sub-models that depend on irradiance. The greatest amplifications occurred through the transposition model ranging from $\pm 1\%$ up to $+6\%$. Their magnitude increased linearly with the inclination angle, and they were related to an incorrect estimation of beam and diffuse irradiance. The amplification of the bias through the PV module model was around $+1\%$. It was caused by the effects of high intra-annual errors in G_H on module efficiency, which depends on irradiance directly, and indirectly via module temperature. Overall, the annual bias was substantially amplified in simulations using reanalysis databases because their daily deviations vary with the atmospheric transmissivity due to an incorrect prediction of clouds. These second-order effects cannot be neglected when selecting a radiation database for PV system simulations because databases

showing the smallest annual bias in G_H do not always provide the least biased yield predictions. Besides, the amplification of the bias also affects energy rating studies because they alter the estimated real efficiency of the modules, and hence the performance ratio.

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Appendix A. Weather stations

Table A1: List of weather stations and years of data used in the study.

Network	ID	Location	Longitude [°]	Latitude [°]	Altitude [m]	Years
BSRN	CAB	Cabauw	4.93	51.97	0	10-15
BSRN	CAR	Carpentras	5.06	44.08	100	10-15
BSRN	CNR	Cener	-1.60	42.82	471	10-15
BSRN	PAL	Palaiseau	2.21	48.71	156	10-15
BSRN	PAY	Payerne	6.94	46.81	491	10
BSRN	TOR	Toravere	26.46	58.25	70	10-15
DWD	183	Arkona	13.43	54.68	42	10-15
DWD	662	Braunschweig	10.45	52.29	81	10-15
DWD	691	Bremen	8.80	53.05	4	10-15
DWD	853	Chemnitz	12.87	50.79	418	10-15
DWD	1048	Dresden-Klotzsche	13.75	51.13	227	10-15
DWD	1358	Fichtelberg	12.95	50.43	1213	10-15
DWD	1684	Görlitz	14.95	51.16	238	10-15
DWD	1975	Hamburg-Fuhlsbüttel	9.99	53.63	11	10-15
DWD	2290	Hohenpei_enberg	11.01	47.80	977	10-15
DWD	2712	Konstanz	9.19	47.68	443	10-15
DWD	2928	Leipzig-Holzhausen	12.45	51.32	138	14-15
DWD	3015	Lindenberg	14.12	52.21	98	10-15
DWD	3631	Norderney	7.15	53.71	11	10-15
DWD	3668	Nürnberg	11.05	49.50	314	10-15
DWD	3987	Potsdam	13.06	52.38	81	10-15
DWD	4271	Rostock-Warnemünde	12.08	54.18	4	10-15
DWD	4336	Saarbrücken-Ensheim	7.11	49.21	320	10-15
DWD	4393	Sankt Peter-Ording	8.60	54.33	5	15
DWD	4466	Schleswig	9.55	54.53	43	10-15
DWD	4642	Seehausen	11.73	52.89	21	10-15
DWD	4928	Stuttgart (Schnarrenberg)	9.20	48.83	314	10-15
DWD	5100	Trier-Petrisberg	6.66	49.75	265	10-15
DWD	5404	Weihestephana-Dürnast	11.69	48.40	477	10-11,13-15
DWD	5705	Würzburg	9.96	49.77	268	10-15
DWD	5856	Fürstentzell	13.35	48.55	476	10-15
FMI	2	Utö	21.37	59.78	9	10-15
FMI	301	Helsinki-Vantaa	24.96	60.33	51	10-15
FMI	339	Helsinki-Kumpula	24.96	60.20	24	10,15
FMI	1201	Jokioinen	23.50	60.81	104	10-15
FMI	2401	Jyväskylä	25.68	62.40	139	10-15
FMI	4714	Sotkamo	28.34	64.11	161	13-15
FMI	7501	Sodankylä	26.63	67.37	179	10-15
FMI	9603	Utsjoki	27.01	69.76	107	13-15

Appendix B. Uncertainty of the reference simulation

The uncertainty of the reference simulation is smaller in horizontal irradiance variables (G_H , B_H , D_H), which are measurements, than in G_{POA} and P_{DC} , which include the uncertainty of measured irradiance plus that of simulation models. This uncertainty can be reduced by using G_{POA} and P_{DC} measurements as well, which is the common approach for validating PV simulation models, but those are available only at a few sites. On the contrary, our goal is to analyze the suitability of radiation databases for simulating PV systems. Thus, having a spatially uniform group of weather stations to feed simulations and evaluate radiation databases across

Europe was more important than having high-quality but sparsely distributed G_{POA} and P_{DC} measurements.

The uncertainty analysis was made following the Guide to the Expression of Uncertainty in Measurement (GUM) (JCGM 100:2008, 2008; JCGM 104:2009, 2009), using the expanded uncertainty (u) with a 95% confidence level (coverage factor of 1.96 for normally distributed variables). The uncertainty of annual values was analyzed because this is the temporal resolution used to calculate the uncertainty of yield predictions (Thevenard and Pelland, 2013; Huld and Gracia Amillo, 2015; Müller et al., 2016). Annual uncertainties were estimated from values reported by previous studies applying the uncertainty propagation rules, due to the lack of high-quality collocated data to calculate u statistically.

The uncertainty of measured variables (G_H , D_H) depends on the quality of the sensor and the operating conditions at the stations. In the present study, most stations use secondary standard pyranometers (shaded and unshaded), which have a typical uncertainty of $\pm 3\%$ and $\pm 2\%$ for hourly and daily values, respectively (Sengupta et al., 2017). These values do not include additional uncertainties due to calibration and operational defects. However, the presence of significant operational errors in the weather stations used is unlikely. All stations are maintained by organizations that implement strict measuring protocols. For instance, BSRN follows the most stringent guidelines among all the networks used and has an accuracy target of 2% for G_H and D_H (1-min values) (Vuilleumier et al., 2014). Besides, all measurements have passed the BSRN QC tests and a QC procedure based on the analysis of the stability of deviations between measurements and satellite-based estimations (Urraca et al., 2017a). This second method was able to detect operational errors and some equipment errors related to sensor miscalibrations at several European (Urraca et al., 2017b) and Spanish (Urraca et al., 2018b) stations, but it did not find any defect in the current group of weather stations.

Based on this, we assumed an uncertainty in annual G_H and D_H of $\pm 2\%$ and $\pm 3.5\%$ for stations below and above 55°N , respectively. The uncertainty of annual values is lower than that of daily values due to the compensation of seasonal deviations. We assumed a higher uncertainty at high-latitude stations because the difficult measuring conditions, such as the high frequency of hours with low solar elevation angles, aggravate the equipment errors of pyranometers. These values are rough estimates just for the analysis of uncertainty propagation through the simulations. A more detailed analysis, such as those made by Reda (2012), Vuilleumier et al. (2014), or Habte et al. (2015), would require the evaluation of the particular conditions of the stations such as the specific pyranometer model used, dates of sensor replacement and re-calibrations. Besides, uncertainty also varies spatially with latitude and temporally from season to season due to changes in the incoming irradiance and solar elevation angles (Habte et al., 2015). Uncertainty fluctuations due to changes in either equipment or operating conditions are more likely at FMI or DWD than at BSRN. A couple of DWD stations were temporally equipped with SCAPP sensors, which simultaneously measure B_N and D_H using a silicon detector. The uncertainty of SCAPP measurements is higher due to the limited spectral response of silicon, among other issues. Besides, the uncertainty in D_H is not homogeneous between FMI stations due to variations in the equipment (sorted by increasing accuracy): (i) shading ring (up to 2012), (ii) Delta-T SPN1 multipyranometer (2012-), (iii) shading ball on solar tracker.

The uncertainty increases for B_H , because this variable was calculated as the difference between G_H and D_H . In sums and differences, absolute uncertainties (U) add in quadrature,

$$y = x_1 \pm x_2 \quad \rightarrow \quad U(y) = \sqrt{U^2(x_1) + U^2(x_2)}, \quad (\text{B.1})$$

so the uncertainty in B_H is estimated as

$$U(B_H) = \sqrt{U^2(G_H) + U^2(D_H)}. \quad (\text{B.2})$$

Absolute uncertainties (U) were transformed into relative ones (u) by using the annual averages for all stations below 55°N ($\overline{G_H} = 130 \text{ W/m}^2$, $\overline{B_H} = 66 \text{ W/m}^2$, $\overline{D_H} = 64 \text{ W/m}^2$) and for all stations above 55°N ($\overline{G_H} = 104 \text{ W/m}^2$, $\overline{B_H} = 56 \text{ W/m}^2$, $\overline{D_H} = 48 \text{ W/m}^2$).

The uncertainty propagation through simulations was estimated assuming that the PV simulation model is a series of multiplicative factors that transform incoming irradiance into P_{DC} (Thevenard and Pelland, 2013). The only part of the modeling chain that is not strictly a multiplicative factor is the transposition model, but it is usually treated as if it were. In multiplications, relative uncertainties add in quadrature,

$$y = A \cdot x_1 \times B \cdot x_2 \rightarrow u(y) = \sqrt{u^2(x_1) + u^2(x_2)}, \quad (\text{B.3})$$

so the uncertainty in G_{POA} and P_{DC} is

$$u(G_{\text{POA}}) = \sqrt{u^2(B_H) + u^2(\text{trans.model})} \quad (\text{B.4})$$

$$u(P_{\text{DC}}) = \sqrt{u^2(B_H) + u^2(\text{trans.model}) + u^2(\text{PVmod.model})}. \quad (\text{B.5})$$

$u(B_H)$ was considered the initial uncertainty for the transposition model because B_H had the largest uncertainty among the three horizontal irradiance variables. An annual uncertainty of 3% was assumed for both transposition and PV module models based on the studies made by Müller et al. (2016) and Thevenard and Pelland (2013).

Figure B.1: Estimated annual uncertainty in the reference simulation (a) below 55°N and (b) above 55°N .