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SOLAR RESOURCE AND PV POTENTIAL OF THE MALDIVES

SOLAR MODEL VALIDATION REPORT

September 2018

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This document is a **final output** from the above-mentioned project, and the content is the sole responsibility of the consultant authors. Users are strongly advised to exercise caution when utilizing the information and data contained, as this may include preliminary data and/or findings, and the document has not been subject to full peer review. Final outputs from this project will be marked as such, and any improved or validated solar resource data will be incorporated into the Global Solar Atlas.

SOLARGIS

Solar Model Validation Report

Regional adaptation of Solargis model based on 24 months solar measurement campaign

Republic of Maldives

No. **129-08/2018**

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Customer

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Acronyms

AOD	Aerosol Optical Depth
CFSR	Climate Forecast System Reanalysis. The meteorological model operated by the US service NOAA (National Oceanic and Atmospheric Administration)
CFSv2	Climate Forecast System Version 2 CFSv2 model is the operational extension of the CFSR (NOAA, NCEP)
DIF	Diffuse Horizontal Irradiation, if integrated solar energy is assumed. Diffuse Horizontal Irradiance, if solar power values are discussed
DNI	Direct Normal Irradiation, if integrated solar energy is assumed. Direct Normal Irradiance, if solar power values are discussed.
GFS	Global Forecast System. The meteorological model operated by the US service NOAA (National Oceanic and Atmospheric Administration)
GHI	Global Horizontal Irradiation, if integrated solar energy is assumed. Global Horizontal Irradiance, if solar power values are discussed.
GTI	Global Tilted (in-plane) Irradiation, if integrated solar energy is assumed. Global Tilted Irradiance, if solar power values are discussed.
MACC	Monitoring Atmospheric Composition and Climate – meteorological model operated by the European service ECMWF (European Centre for Medium-Range Weather Forecasts)
MERRA-2	Modern-Era Retrospective analysis for Research and Applications, Version 2
Meteosat IODC (MFG and MSG)	Meteosat First Generation and Meteosat Second Generation satellites operated by EUMETSAT organization. For this report the data from the Meteosat IODC are used. The satellite is positioned over the Indian Ocean.

Glossary

Aerosols	Small solid or liquid particles suspended in air, for example desert sand or soil particles, sea salts, burning biomass, pollen, industrial and traffic pollution.
All-sky irradiance	The amount of solar radiation reaching the Earth's surface is mainly determined by Earth-Sun geometry (the position of a point on the Earth's surface relative to the Sun which is determined by latitude, the time of year and the time of day) and the atmospheric conditions (the level of cloud cover and the optical transparency of atmosphere). All-sky irradiance is computed with all factors taken into account
Bias	Represents systematic deviation (over- or underestimation) and it is determined by systematic or seasonal issues in cloud identification algorithms, coarse resolution and regional imperfections of atmospheric data (aerosols, water vapour), terrain, sun position, satellite viewing angle, microclimate effects, high mountains, etc.
Clear-sky irradiance	The clear sky irradiance is calculated similarly to all-sky irradiance, but without considering the impact of cloud cover.
Long-term average	Average value of selected parameter (GHI, DNI, etc.) based on multiyear historical time series. Long-term averages provide a basic overview of solar resource availability and its seasonal variability.
P50 value	Best estimate or median value represents 50% probability of exceedance. For annual and monthly solar irradiation summaries it is close to average, since multiyear distribution of solar radiation resembles normal distribution.
P90 value	Conservative estimate, assuming 90% probability of exceedance (with the 90% probability the value should be exceeded). When assuming normal distribution, the P90 value is also a lower boundary of the 80% probability of occurrence. P90 value can be calculated by subtracting uncertainty from the P50 value. In this report, we apply a simplified assumption of normal distribution of yearly values.
Root Mean Square Deviation (RMSD)	Represents spread of deviations given by random discrepancies between measured and modelled data and is calculated according to this formula:

$$RMSD = \sqrt{\frac{\sum_{k=1}^{n}\left(X^{k}{}_{measured} - X_{modeled}^{k}\right)^{2}}{n}}$$

On the modelling side, this could be low accuracy of cloud estimate (e.g. intermediate clouds), under/over estimation of atmospheric input data, terrain, microclimate and other effects, which are not captured by the model. Part of this discrepancy is natural - as satellite monitors large area (of approx. 3.2 x 3.3 km for the satellite pixel), while sensor sees only micro area of approx. 1 sq. centimetre. On the measurement side, the discrepancy may be determined by accuracy/quality and errors of the instrument, pollution of the detector, misalignment, data loggers, insufficient quality control, etc.

Solar irradiance	Solar power (instantaneous energy) falling on a unit area per unit time [W/m^2]. Solar resource or solar radiation is used when considering both irradiance and irradiation.
Solar irradiation	Amount of solar energy falling on a unit area over a stated time interval [Wh/m^2 or kWh/m^2].
Uncertainty of estimate, U_{est}	Is a parameter characterizing the possible dispersion of the values attributed to an estimated irradiance/irradiation values. In this report, uncertainty assessment of the solar resource model estimate is based on a detailed understanding of the achievable accuracy of the solar radiation model and its data inputs (satellite, atmospheric and other data), which is confronted by an extensive data validation experience. The second source of uncertainty is ground measurements. Their quality depends on accuracy of instruments, their maintenance and data quality control. Third contribution to the uncertainty is from the site adaptation method where ground-measured and satellite-based data are correlated.

Executive summary

This report describes accuracy enhancement of Solargis solar resource data for Maldives based on the ground measurements collected at four solar meteorological stations across the country. These solar meteorological stations were installed and operated by Suntrace GmbH company (Germany), and commissioned by the World Bank over the years 2015 to 2018 under the same activity.

The data layers show long-term yearly and monthly averages of Direct Normal Irradiation (DNI) and Global Horizontal Irradiation (GHI), and they represent a period of the last 19 years, from 1999 to 2017. The data is calculated by aggregation of sub-hourly map-based time series calculated for the territory of Maldives with 1-km spatial resolution. The aggregated data layers are delivered in the format that is compatible with Geographical Information Systems (GIS). Additionally, printable maps are available in digital format and ready-to-use for large-format printing.

The accuracy of the data layers is enhanced by the regional adaptation of the Solargis model with use of ground measurements acquired at four high-standard solar meteorological stations located in Maldives. The measurements helped to reduce systematic deviation of the data inputs to the Solargis model as driving factors of the accuracy in this region. Individual improvements of the Solargis model at the stations in Maldives are shown in the table below. As a result of the regional adaptation of the Solargis model, the calculated GHI and DNI data are more accurate and with reduced uncertainty.

Table 0.1: Position of solar measuring stations in Maldives

Site	Site ID	Administrative atoll (district)	Latitude [°]	Longitude [°]	Elevation [metres a.s.l]
Hanimaadhoo	MVHAQ	Haa Dhaalu Atoll	6.7482	73.1696	2
Hulhulé	MVMLE	Kaafu Atoll	4.1927	73.5281	2
Kadhdhoo	MVKDO	Laamu Atoll	1.8599	73.5203	2
Gan	MVGAN	Addu Atoll	-0.6911	73.1599	2

Table 0.2: Results of regional adaptation for solar measuring stations in Maldives

Site	DNI original [kWh/m²]	DNI adapted [kWh/m²]	Difference to original [%]	GHI original [kWh/m²]	GHI adapted [kWh/m²]	Difference to original [%]
Hanimaadhoo	1522	1445	-5.1	2027	2009	-0.9
Hulhulé	1604	1487	-7.3	2042	2018	-1.2
Kadhdhoo	1667	1548	-7.1	2047	2025	-1.1
Gan	1700	1567	-7.8	2053	2029	-1.2

** All values in this table show results of the regional adaptation of Solargis time series, long-term average yearly values. GHI – Global Horizontal Irradiance, DNI – Direct Normal Irradiance. The data is derived from the GIS layers after disaggregation.*

Table 0.3: Uncertainty of yearly values for Maldives, for original and regionally-adapted Solargis model

Uncertainty of long-term annual values	**Acronym**	**Uncertainty of the original Solargis model**	**Uncertainty of the Solargis model after regional adaptation**	***Best achievable uncertainty***
Global Horizontal Irradiation	GHI	±6.0%	±3.5%	*±2.5%*
Global Tilted Irradiation	GTI	±6.0%	±4.0%	*±3.0%*
Direct Normal Irradiation	DNI	±12.0%	±6.0%	*±3.5%*

** Uncertainty only achievable by site-specific model adaptation based on many years of high quality measurements (values are shown as a model data reference)*

1 Overview of regionally adapted data layers

Solargis is a high-resolution global database that includes solar resource and meteorological parameters.

The regionally adapted solar model provides more accurate and reliable data on GHI and DNI solar resources for Maldives. This results in reduced uncertainty of derived parameters, such as Diffuse horizontal Irradiation (DIF), Global Tilted Irradiation (GTI) or Photovoltaic power potential (PVOUT), see Table 1.1. Lower uncertainty reduces financial risk and improves engineering quality of the solar power systems. For a project-specific site, the uncertainty can be further reduced by site adaptation.

This stage of the project delivers GIS data and maps for Maldives. These products include:

- Harmonized and accuracy-enhanced solar resource data: yearly and monthly long-term averages of GHI and DNI
- Solargis database is extensively validated and accuracy enhanced in the region
- The time series data for any location can be accessed online (http://solargis.com).
- Historical data represents the last 19 years (1999 to 2017) and it is available at high spatial and temporal resolution

Tables 1.1 and 1.2 describe the primary data layers GHI, DIF and DNI that have been processed by the regionally adapted solar model as part of the country data delivery. The other data layers, such as GTI and PVOUT were re-computed using the accuracy enhanced GHI, DIF and DNI.

Table 1.1: Description of GIS data layers that were accuracy enhanced by regional model adaptation

Acronym	Full name	Unit	Type of use	Type of data layers
GHI	Global Horizontal Irradiation	kWh/m²/year kWh/m²/day	Reference information for the assessment of flat-plate photovoltaic (PV) and solar heating technologies (e.g. hot water)	Long-term annual and monthly averages
DNI	Direct Normal Irradiation	kWh/m²/year kWh/m²/day	Assessment of Concentrated PV (CPV) and Concentrated Solar Power (CSP) technologies. It is also important for simulation of flat-plate PV tracking technologies.	Long-term annual and monthly averages
DIF	*Diffuse Horizontal Irradiation*	kWh/m²/year kWh/m²/day	*Complementary parameter to GHI and DNI*	*Long-term yearly and monthly average of daily totals*
GTI	*Global Irradiation at optimum tilt*	kWh/m²/year kWh/m²/day	*Assessment of solar resource for PV technologies*	*Long-term yearly and monthly average of daily totals*
OPTA	*Optimum angle*	°	*Optimum tilt to maximize yearly PV production*	-
PVOUT	*Photovoltaic power potential*	*kWh/kWp/year kWh/kWp/day*	*Assessment of power production potential for a PV power plant with free-standing fixed-mounted c-Si modules, mounted at optimum tilt to maximize yearly PV production*	*Long-term yearly and monthly average of daily totals*

Note: in italics, we indicate data layer that have been accuracy enhanced indirectly from GHI and DNI

2 Solargis database

2.1 Solar resource data calculated by satellite-based solar model

Solar radiation is calculated by numerical models, which are parameterized by a set of inputs characterizing the cloud transmittance, state of the atmosphere and terrain conditions. A comprehensive **overview of the Solargis model** is made available in a recent book publication [1]. The methodology is also described in [2, 3]. The related uncertainty and requirements for bankability are discussed in [4, 5].

In the Solargis approach, the **clear-sky irradiance** is calculated by the simplified SOLIS model [6]. This model allows fast calculation of clear-sky irradiance from the set of input parameters. Sun position is a deterministic parameter and is described by the algorithms with satisfactory accuracy. Stochastic variability of clear-sky atmospheric conditions is determined by changing concentrations of atmospheric constituents, namely aerosols, water vapour and ozone. Global atmospheric data, representing these constituents, are routinely calculated by world atmospheric data centres:

- In Solargis, the new generation **aerosol data set** representing Atmospheric Optical Depth (AOD) is used. The calculation accuracy is strongly determined by quality of aerosols, especially for cloudless conditions. The aerosol data implemented by MACC-II/CAMS and MERRA-2 projects are used [7, 8, 9, 10].
- **Water vapour** is also highly variable in space and time, but it has lower impact on the values of solar radiation, compared to aerosols. The GFS and CFSR databases (NOAA NCEP) are used in Solargis, and the data represent the daily variability from 1999 to the present time [11, 12, 13, 14].
- **Ozone** absorbs solar radiation at wavelengths shorter than 0.3 μm, thus having negligible influence on the broadband solar radiation.

The clouds are the most influencing factor, modulating clear-sky irradiance. Effect of clouds is calculated from the satellite data in the form of a **cloud index** (cloud transmittance). The cloud index is derived by relating radiance recorded by the satellite in spectral channels and surface albedo to the cloud optical properties. In Solargis, the modified calculation scheme of Cano has been adopted to retrieve cloud optical properties from the satellite data [15, 16].

To calculate **all-sky irradiance** in each time step, the clear-sky global horizontal irradiance is coupled with the cloud index. Direct Normal Irradiance (DNI) is calculated from Global Horizontal Irradiance (GHI) using a modified Dirindex model [17]. Diffuse irradiance for tilted surfaces is calculated by the Perez model [18]. The calculation procedure also includes terrain disaggregation, while the spatial resolution is enhanced with use of the digital terrain model to 250 meters [19].

Solargis model version 2.1 has been used. Table 2.1 summarizes technical parameters of the model inputs and of the primary data outputs. This model was enhanced by regional adaptation based on the ground solar measurements (Chapter 4).

Table 2.1: Input data used in the Solargis model and related GHI and DNI outputs for Maldives

Inputs into the Solargis model	Source of input data	Time representation	Original time step	Approx. grid resolution
Cloud index	Meteosat MFG IODC Meteosat MSG IODC (EUMETSAT)	1999 to 2016 2017 to date	30 minutes 15 minutes	2.8 x 3.2 km 3.1 x 3.5 km
Atmospheric optical depth (aerosols)*	MACC/CAMS* (ECMWF) MERRA-2 (NASA)	2003 to date 1999 to 2002	3 hours 1 hour	75 km and 125 km 50 km
Water vapour	CFSR/GFS (NOAA)	1999 to date	1 hour	35 and 55 km
Elevation and horizon	SRTM-3 (SRTM)	-	-	250 m
Solargis primary data outputs (GHI and DNI)	**-**	**1999 to date**	**30 minutes**	**250 m**

** Aerosol data for 2003-2012 come from the reanalysis database; the data representing years 2013-present are derived from near-real time (NRT) operational model*

2.2 Combined use of satellite-based model and measurements

The fundamental difference between a satellite observation and a ground measurement is that signal received by the satellite radiometer integrates a large area, while a ground station represents a pinpoint measurement. This results in a mismatch when comparing instantaneous values from these two observation instruments, mainly during intermittent cloudy weather and changing aerosol load. Nearly half of the hourly Root Mean Square Deviation (RMSD) for GHI and DNI can be attributed to this mismatch (value at sub-pixel scale), which is also known as the "nugget effect" [20].

The satellite pixel is not capable of describing the inter-pixel variability in complex regions, where within one pixel, diverse natural conditions could vary (e.g. along the coast). In addition, the coarse spatial resolution of atmospheric databases such as aerosols or water vapour is not capable of describing local patterns of the state of the atmosphere. These features can be seen in the satellite GHI and DNI data by increased bias due to an imperfect description of aerosol load. Satellite data have inherent inaccuracies, which have a certain degree of geographical and time variability.

DNI is particularly sensitive to the variability of cloud information, aerosols, water vapour, and terrain shading. The relationship between the uncertainty of global and direct irradiance is nonlinear. Often, a negligible error in global irradiance may have a high impact on the direct irradiance component.

The solar energy projects require representative and accurate GHI and DNI time series. The satellite-derived databases are used to describe long-term solar resource for a specific site. However, their problem when compared to the high-quality ground measurements is a slightly higher bias and partial disagreement of frequency distribution functions, which may limit their potential to record the occurrence of extreme situations (e.g. very low atmospheric turbidity resulting in a high DNI and GHI). A solution is to correlate satellite-derived data with ground measurements to understand the source of the discrepancy, and subsequently, to improve the accuracy of the resulting time series.

The Solargis satellite-derived data are correlated with ground measurement data with two objectives:

- Improvement of the overall bias (removal of systematic deviations)
- Improvement of the fit of the frequency distribution of values.

Limited spatial and temporal resolution of the input data, and the simplified nature of the models results in the occurrence of systematic and random deviations of the model outputs when compared to the ground observations. The deviations in the satellite-computed data, which have a *systematic nature*, can be reduced by site adaptation or regional adaptation methods.

2.2.1 Site adaptation vs. regional adaptation

The terminology related to the procedure of improving the accuracy of the satellite data is not harmonized, and various terms are used:

- Correlation of ground measurements and satellite-based data;
- Calibration of the satellite model (its inputs and parameters);
- Site adaptation or regional adaptation of satellite-based data.

The term *site adaptation* or *regional adaptation* is more general and well explains the concept of adapting the satellite-based model (by correlation, calibration, fitting and recalculation) to the ground measured data.

- **Site adaptation** aims to adapt the characteristics of the satellite-based time series to the site-specific conditions described by local measurements.
- **Regional adaptation** aims to identify systematic patterns of deviation at the regional scale and correct them rather than focusing on a specific site.

In this study, we apply a **regional adaptation of the Solargis model** to improve its performance at the regional level. Its advantage is that the database in the given region has reduced uncertainty over the whole territory which has been assumed. To obtain the best accuracy for a specific location, it is preferred to apply the model site adaptation, as it focuses on matching the model outputs to the specific local climate conditions described by the ground measurements.

2.2.2 Conditions to be met

Four conditions are important for successful adaptation of the satellite-based model:

1. High quality DNI and GHI ground measurements for at least 12 months must be available; optimally data for 2 or 3 years should be used: for Maldives, the measurements are available for a period of 27+ months.
2. For regional-adaptation, the sites should be distributed over the whole territory, to provide information for the major climatic regions: for Maldives, four sites are selected to represent whole archipelago
3. High quality satellite data must be used, with consistent quality over the whole period of data: for Maldives, the quality of the measurements has been controlled in two steps.
4. There has to be a systematic difference identified between both data sources.

Systematic difference can be measured by two characteristics:

- Bias (offset)
- Systematic deviation in the distribution of hourly or daily values (in the histogram)

Systematic difference can be stable over the year or it can slightly change seasonally for certain meteorological conditions (e.g. typical cloud formation during a day, seasonal air pollution). The data analysis should distinguish systematic differences from those arising at occasional events, such as extreme storms. The episodically occurring differences may mislead the results of adaptation, especially if short period of ground measurements is only available.

If one of the four above-mentioned conditions is not fulfilled, the model adaptation will not provide the expected results. In fact, such an attempt may provide even worse results.

For the quantitative assessment of the accuracy enhancement procedures, the following metrics are used:

- Metrics based on the comparison of all pairs of the hourly daytime data values: Mean Bias, Root Mean Square Deviation (RMSD) and histogram in an absolute and relative form (divided by the daytime mean DNI values);
- Metrics based on the difference of the cumulative distribution functions: KSI (Kolmogorov-Smirnov test Integral) [21]

The normalized KSI is defined as an integral of absolute differences of two cumulative distribution functions *D* normalized by the integral of critical value $a_{critical}$:

$$KSI\% = \frac{\int_{x\,min}^{x\,max} D_n dx}{a_{critical}} * 100$$

$$a_{critical} = V_c * (x_{max} - x_{min})$$

$$V_c = \frac{1.63}{\sqrt{N}}, \quad N \geq 35$$

where critical value depends on the number of the data pairs *N*. As the KSI value is dependent on the size of the sample, the KSI measure may be used only for the relative comparison of fit of cumulative distribution of irradiance values.

More about the Solargis site adaptation can be found in [22] and more general description is in [23].

3 Ground measurements in Maldives

3.1 Inventory of available solar meteorological stations and data

Data from the measuring stations in Maldives was collected and harmonized with the objective of acquiring reference solar radiation data for reducing the uncertainty of the solar models. The quality data from four meteorological stations were available for this assessment (Tables 3.1 and 3.2, Figure 3.1). Positions and detailed information about measurement sites is also available on the Global Solar Atlas website: http://globalsolaratlas.info/?c=5.224982,73.545227,8&s=5.419148,73.199158&e=1. The instruments are summarized in Tables 3.3 to 3.5.

Table 3.1: Summary of information for installed solar meteorological stations in Maldives

Project name	Solar Resource Mapping in Maldives
Project ID	7172111
Project framework	Energy Sector Management Assistance Program (ESMAP)
Project leader	Solargis s.r.o.
Data measurement points	4 stations (TIER 2)
Measurement service provider	Suntrace GmbH
Maintenance service provider	Renewable Energy Maldives

Table 3.2: Overview information on solar meteorological stations operated in Maldives

No.	Site name	Site ID	Latitude [°]	Longitude [°]	Altitude [m a.s.l.]	Measurement station host
1	Hanimaadhoo	MVHAQ	6.7482	73.1696	2	Hanimaadhoo International Airport
2	Hulhulé	MVMLE	4.1927	73.5281	2	Male International Airport
3	Kadhdhoo	MVKDO	1.8599	73.5203	2	Kadhdhoo Airport
4	Gan	MVGAN	-0.6911	73.1599	2	Gan International Airport

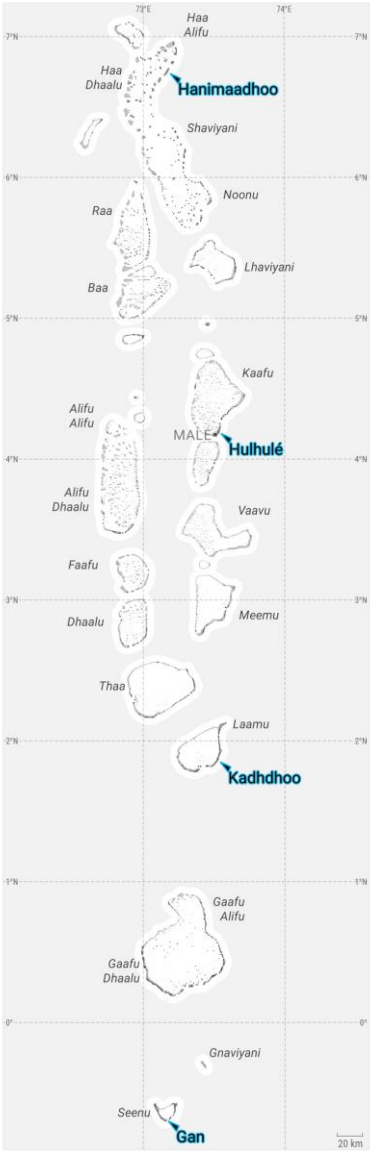

Figure 3.1: Position of the solar meteorological stations

Table 3.3: Instruments used for measuring solar radiation

No.	Site name	Site ID	Station type	DNI	GHI	DIF
1	Hanimaad hoo	MVHAQ	TIER 2	RSP 4G, Reichert GmbH	SR20-T1, Hukseflux RSP 4G, Reichert GmbH	RSP 4G, Reichert GmbH
2	Hulhulé	MVMLE	TIER 2	RSP 4G, Reichert GmbH	SR20-T1, Hukseflux RSP 4G, Reichert GmbH	RSP 4G, Reichert GmbH
3	Kadhdhoo	MVKDO	TIER 2	RSP 4G, Reichert GmbH	SR20-T1, Hukseflux RSP 4G, Reichert GmbH	RSP 4G, Reichert GmbH
4	Gan	MVGAN	TIER 2	RSP 4G, Reichert GmbH	SR20-T1, Hukseflux RSP 4G, Reichert GmbH	RSP 4G, Reichert GmbH

Table 3.4: Instruments installed at the solar meteorological stations

Parameter	Instrument	Type	Manufacturer	Uncertainty
GHI 1	Secondary standard pyranometer	SR20 - T1	Hukseflux	< ±2.0 % (daily)
GHI 2	Rotating Shadowband Irradiometer	RSP 4G	Reichert GmbH	Indicatively ±5 %
DIF	Rotating Shadowband Irradiometer	RSP 4G	Reichert GmbH	Indicatively ±8 %
DNI	Rotating Shadowband Irradiometer	RSP 4G	Reichert GmbH	Indicatively ±5 %
TEMP	Temperature probe	DKRF 400	Driesen und Kern	± 1.5 °C
RH	Relative humidity probe	DKRF 400	Driesen und Kern	± 3.5 % RH
WS	Wind speed sensor (WS at 3.0 m height)	First Class	Thies Clima	< ±1 %
AP	Barometric pressure sensor	Not provided	-	-
-	Data logger	blueberry	Wilmers GmbH	-

At all the stations (TIER 2 stations) solar radiation is measured by secondary standard pyranometers (for GHI, high quality and accuracy) and RSP 4G instruments for (GHI, DNI and DIF). Overview of the data availability, time step and measured parameters is shown in Tables 3.4, 3.5 and Figure 3.2.

Table 3.5: Overview information on solar meteorological stations operating in the region

No.	Site name	Site ID	Parameters	Time step	Period of data used in this study
1	Hanimaadhoo	MVHAQ	GHI, GHI2, DNI, DIF	1 min	11 Dec 2015 – 31 Mar 2018
2	Hulhulé	MVMLE	GHI, GHI2, DNI, DIF	1 min	09 Dec 2015 – 31 Mar 2018
3	Kadhdhoo	MVKDO	GHI, GHI2, DNI, DIF	1 min	15 Dec 2015 – 30 Apr 2018
4	Gan	MVGAN	GHI, GHI2, DNI, DIF	1 min	14 Dec 2015 – 30 Apr 2018

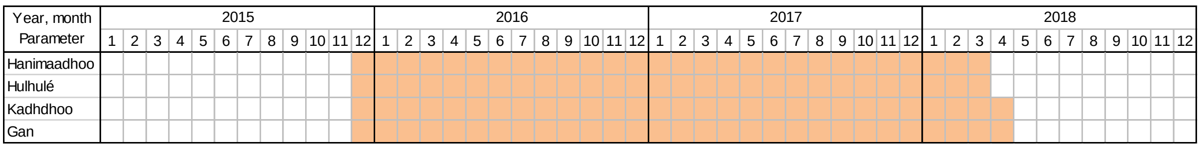

Figure 3.2: Availability of solar resource measurements (GHI, DNI and DIF).

3.2 Summary for solar meteorological stations

In this report, complete set of data from the measurement campaign is used for regional adaptation. As the measurement stations have been installed during December 2015, the regular envisaged period for the data analysis starts in January 2016 and ends in December 2017. The measurement campaign was extended by three to four months in year 2018, to recover data loss due to various technical issues during the two-year period. Thus, the data from extended period (from December 2015 to March/April 2018) is used to have the most representative ground reference data.

3.3 Quality control and harmonization of solar measurements

Prior to the comparison with satellite-based solar resource data, the ground-measured irradiance was quality-controlled by Solargis. Quality Control (QC) is based on methods defined in SERI QC procedures, Younes et al. and Long et al. [24, 25, 26, 27] and implemented in-house by the company Solargis. The tests are applied in two runs: (i) the automatic tests are run to identify the obvious issues; next (ii) by visual inspection we identify and flag inconsistencies, which are of a more complex nature. Visual inspection is an iterative and time-consuming process.

The quality control methods and results are in detail described in the report "*Annual Solar Resource Report for solar meteorological stations after completion of 24 months of measurements, Republic of Maldives, Report number: 129-07/2018*" [28], here we present only brief summary.

Based on the quality control results we conclude that the solar radiation measurements come from the high (SR20) and medium (RSP) accuracy equipment that is professionally operated and maintained. Some issues were identified during the data quality control of the whole period of ground measurement campaign:

- Occasional occurrence of incorrect DNI and DIF measurements due to shadowband malfunction. These data were flagged and excluded from further processing. Most influenced are measurements from Gan station, where ca 17.5% of DNI and DIF data was excluded due to this issue during the period of measurement campaign.
- Higher systematic difference between GHI from SR20 and form RSP (up to 7.4% in Hulhulé). The difference between the instruments is increasing with time at all stations (6.8% for 2016 and 8.1% for 2017 in Hulhulé). This is known effect that should relate mainly to GHI instrument calibration. Due to this issue, the GHI from RSP was not considered for site-adaptation. The effect of this issue on the measured DNI is unknown as the data from higher accuracy solar instrument was not available. It is expected that the effect will not be extremely high, because both initial measurements (GHI and DIF) used for the calculation of the DNI are affected in the same way and should at the end in some extent eliminate each other. Unfortunately, there is no direct proof for this behaviour. Therefore, a higher uncertainty of DNI measurements should be considered.
- The measurements at three stations are partially affected by morning or late afternoon shading from surrounding objects or threes. The measurements affected by these operation conditions were excluded from further analyses.

These issues have implication on the achievable uncertainty of ground measurements, and subsequently, on the results of the regional-adaptation of the Solargis data (Chapter 4).

In evaluation of the uncertainty of measurements several factors are considered:

1. Thermopile pyranometer CMP10 has lower nominal uncertainty than the Twin RSI instrument. Therefore us of CMP10 data has preference over RSI, in the regional adaptation.
2. The thermopile pyranometers are more susceptible to soiling. This is not so relevant for the geographical conditions of Maldives, where natural cleaning by rain occurs regularly.
3. Instruments are used in challenging environmental conditions (higher temperature, high humidity, sea salt in the air, etc.).

Table 3.6 summarises the finding of the quality control.

Table 3.6: Quality control summary

Description	Hanimaadhoo	Hulhulé	Kadhdhoo	Gan
Station description, metadata	Very good	Very good	Very good	Very good
Instrument accuracy	Good	Good	Good	Good
Instrument calibration	Very good	Very good	Problematic	Problematic
Data structure	Very good	Very good	Very good	Very good
Cleaning and maintenance information	Very good	Problematic	Very good	Very good
Time reference	Very good	Very good	Very good	Very good
Quality control complexity	Very good	Very good	Very good	Very good
Quality control results	Good	Sufficient	Sufficient	Problematic
Time period	Very good	Very good	Very good	Very good
Other issues	Not specified			

Legend: Quality flag

Very good	Good	Sufficient	Problematic	Insufficient	Not specified

4 Regional adaptation of Solargis model

Ground measurements from four solar meteorological stations in Maldives are used for the regional adaptation of the Solargis model (Figure 3.1). Ultimately, the model has been run to produce verified and accuracy enhanced solar model. This model has been used to generate a new version of GHI and DNI data layers and maps of Maldives.

4.1 Solargis method

Solargis regional model adaptation aims at reducing the mean bias (systematic deviation), RMSD (random deviation) and KSI (difference between frequency distribution of the measured and satellite-based data) at the level of all region.

The comparison of data produced by the original Solargis model to the ground measurements shows a very good fit of Global Horizontal Irradiance and small positive bias of Direct Normal Irradiance (with respect to achievable uncertainty of ground measurements).

The performance of the model is good under cloudy as well as cloudless conditions, during a situations of solar radiation intermittency, and also for the estimates of day-by-day variability. A deficiency in some sites is a small systematic overestimation of daily profiles for cloudless conditions (Figure 4.1). This indicates possible issues in the calculation of clear-sky model (cloudless conditions), which is mainly controlled by aerosol data input. Other sources of deviation, such as the accuracy of cloud identification, have a much lower impact on the model results. Therefore, we have decided to focus the regional adaptation on accuracy improvement of the model inputs, namely Aerosol Optical Depth (AOD).

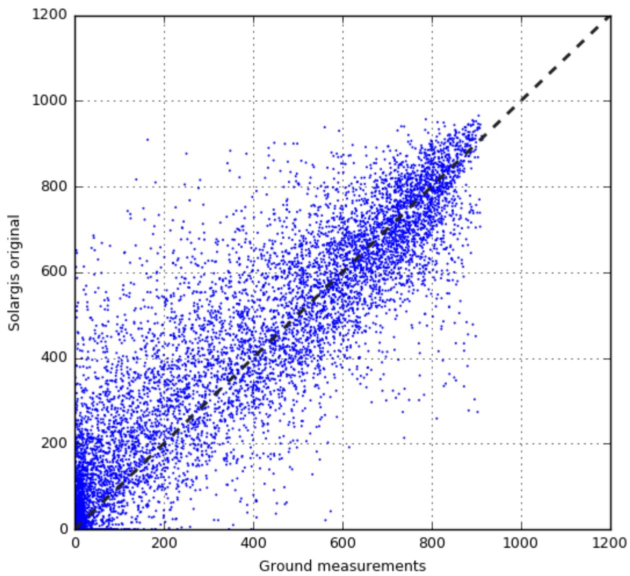

Figure 4.1: Comparison of hourly original satellite-model DNI with ground measurements. Model overestimates the measurements – Gan airport

The method was conducted in two steps:

1. Coefficients for adaptation of Aerosol Optical Depth were derived for individual ESMAP meteorological stations (Chapter 4.1.1)
2. Model adaptation coefficients were interpolated between the solar meteorological and AERONET sites to extend over the territory of Maldives (Chapter 4.1.2).

More about the Solargis site adaptation in [22].

4.1.1 Reduction of systematic deviation between satellite and measured data

Deviation between raw satellite-based data and ground-measurements was analysed individually for each site. We focussed on understanding of the following differences:

1. Deviation for the whole period of measurements
2. Seasonal patterns of deviation
3. Spread of deviations for various weather situations
4. Differences in the cumulative distribution of values.

Based on these results, **correction factors for AOD** (Atmospheric Optical Depth) values were proposed. They were developed by comparing the cloudless situations with theoretical clear-sky profiles. The input aerosols were corrected separately for low and medium to high aerosol load concentrations. For each group a separate set of monthly correction factors was identified.

In the next step, these **factors were harmonized** to avoid abrupt month-by-month changes that may be the result of insufficient representation of some situations by ground measurements, rather than a systematic problem in the data. In this phase, correction factors from the neighbouring sites were also compared to avoid issues in a spatial context, especially if sites are located in similar geographic conditions. In a case of nearby sites with contradicting deviations, the corrections for individual sites have to be balanced to avoid high spatial mismatch. The bias is removed only partially to maintain the spatial consistency of corrections. This approach helps to avoid steep changes of correction coefficients in the area. In the case of Maldives, the deviations in individual stations were spatially consistent and only small changes of correction coefficients were introduced by harmonization.

In the last step, the **satellite-based model was recalculated** using proposed aerosol correction factors and the results were again evaluated. Some residual deviations were removed in the second iteration of the same procedure.

For each site, the adaptation procedure results in a set of monthly correction values for low and medium AOD load. The correction was developed to respect the seasonal and spatial context of the data.

During the data evaluation, the availability and quality of ground measurements were considered, as the ground measurements may not provide a comprehensive representation of specific situations or may contain residual errors. The satellite data is available in 30-minute and 15-minute time steps; ground-measured data is available in 10-minute time step. To reduce the conceptual difference of point and satellite pixel measurements, all the measures are calculated using aggregated data in *hourly time step*.

After adaptation of AOD, the model is fully recalculated for the period of 19 years. Thus, the consistency of accuracy-enhanced GHI, DNI and DIF components is maintained.

The aerosol adaptation method removes the major source of discrepancies between satellite-model data and the ground measurements. Because of fundamental difference between the modelling using satellite data and ground measurements, even if bias was minimized, some mismatch between the data remains present in the data – mainly in the *frequency distribution* of values. The main focus of the regional adaptation is to determinate correction coefficients for individual sites that are used to remove seasonal and annual deviations in the regional context. The residual discrepancies present in the regionally adapted data can be removed only in the local context as they are sourced by locally specific features such as pollution in big cities. Such residual discrepancies cannot be extrapolated, and they can be only addressed in the model site adaptation.

4.1.2 Spatial interpolation of aerosol correction coefficients

The main objective of this step is to extend the correction coefficients identified in the previous stage (Chapter 4.1.1) at the sites to the territory of Maldives. To achieve this goal, an interpolation technique was used. The selection of interpolator is based on the assumption that the spatial distribution of aerosols is controlled by air mass movement.

Applying the spatial interpolation, we extended the validity of the correction factors from the solar (and aerosol) measuring stations to the whole territory of Maldives and neighbouring region. To maintain the stability of model in wider regional context, also effect of corrections from neighbouring regions (Pakistan, India) was introduced. The interpolation was applied separately for each month and two aerosol load conditions. The output of the interpolation is a set of 24 aerosol correction layers (2 layers per month).

Finally, aerosol correction layers were used for regional re-calibration of the Solargis model inputs and full recalculation of the 19-year database for the territory of Maldives.

4.2 Results and validation

4.2.1 Accuracy estimate of DNI and GHI at the solar measuring stations

The original Solargis data show a regional pattern of overestimation of DNI, compared to the ground measurements. The model adaptation, for the region, allowed to reduce a large proportion of the mismatch between satellite-based data and ground measurements.

Tables 4.1 to 4.4 summarize validation of the regional adaptation for all solar measuring stations. The original Solargis data represent output of the model, which is based on a standard calculation scheme without consideration of any corrections derived from the measurements available for Maldives. The regionally-adapted model includes also the correction factors calculated from the ESMAP project measurements in Maldives (Chapter 4.1). The GHI validation statistics (Table 4.2 and Table 4.4) show a comparison of the accuracy enhanced GHI to the measurements from SR20-T1 thermopile pyranometers. This type of instrument has lower nominal uncertainty and is more stable for various spectral irradiance conditions (Chapter 3.3). The DNI validation statistics (Table 4.1 and Table 4.3) show a comparison of the accuracy enhanced DNI to the measurements from RSP 4G instrument.

Table 4.5 shows the difference between yearly GHI and DNI values before and after the model adaptation.

Terms are explained in Glossary. Absolute values of bias are calculated for daytime hours only.

Table 4.1: Direct Normal Irradiance: bias and KSI before and after regional model adaptation

Meteo station	Original DNI model data			DNI after regional adaptation		
	Bias [kWh/m²]	Bias [%]	KSI [-]	Bias [kWh/m²]	Bias [%]	KSI [-]
Hanimaadhoo	19	5.3	104	1	0.4	90
Hulhulé	31	8.4	149	4	1.0	107
Kadhdhoo	29	7.5	148	2	0.5	129
Gan	33	8.4	159	-1	-0.2	151
Mean	28.0	7.4	140	1.7	0.4	129
Standard deviation	6.2	1.5		2.5	0.6	

Table 4.2: Global Horizontal Irradiance: bias and KSI before and after regional model adaptation

Meteo station	Original GHI model data			GHI after regional adaptation		
	Bias [kWh/m²]	Bias [%]	KSI [-]	Bias [kWh/m²]	Bias [%]	KSI [-]
Hanimaadhoo	3	0.7	49	-1	-0.2	45
Hulhulé	0	0.0	50	-6	-1.1	52
Kadhdhoo	3	0.7	52	-2	-0.4	51
Gan	7	1.4	67	1	0.2	55
Mean	3.3	0.7	55	-2.0	-0.3	51
Standard deviation	2.9	0.5		2.9	0.6	

Table 4.3: Direct Normal Irradiance: RMSD before and after regional model adaptation

Meteo station	RMSD of original DNI data			RMSD of DNI after regional adaptation		
	Hourly [%]	Daily [%]	Monthly [%]	Hourly [%]	Daily [%]	Monthly [%]
Hanimaadhoo	31.8	17.7	6.6	31.3	17.2	3.9
Hulhulé	35.2	20.0	9.1	34.2	18.9	3.9
Kadhdhoo	35.6	19.3	8.1	34.7	18.5	2.7
Gan	35.8	20.1	9.3	35.1	19.4	4.3
Mean	34.6	19.3	8.3	34.7	18.9	3.6

Table 4.4: Global Horizontal Irradiance: RMSD before and after regional model adaptation

Meteo station	RMSD of original GHI data			RMSD of GHI after regional adaptation		
	Hourly [%]	Daily [%]	Monthly [%]	Hourly [%]	Daily [%]	Monthly [%]
Hanimaadhoo	15.3	6.6	2.3	15.2	6.6	2.1
Hulhulé	16.4	7.2	1.8	16.4	7.3	2.0
Kadhdhoo	16.7	7.1	1.3	16.7	7.2	1.2
Gan	16.2	7.2	2.2	16.1	7.1	1.7
Mean	16.2	7.0	1.9	16.1	7.0	1.7

As a result, at the level of individual sites in Maldives, the mean bias of the adapted GHI values stays close to zero, which means that the model is well balanced to simulate all type of weather and geographical conditions. The standard deviation of bias values is 0.6% for both DNI and GHI, which is very low compared to the inherent uncertainty of ground sensors.

A significant improvement was achieved for Direct Normal Irradiance (DNI; Tables 4.1 and 4.3). The average bias of DNI for all stations dropped from 7.4% to 0.4% and the standard deviation considerably reduced from1.5% to 0.6% by regional adaptation. This confirms removal of specific regional problems where the DNI bias of original data for two stations reached 8.4%. The spread of DNI values and fit of cumulative distributions expressed by RMSD and KSI also improved.

The average Global Horizontal Irradiance (GHI) bias for all stations after adaptation is -0.3% with standard deviation of 0.6% (Table 4.2). There is a small increase of the bias compared to original data in Hulhulé station, but the change is below the uncertainty of ground measurements used for adaptation. This increase is the result of the regional adaptation method where the consistency of DNI and GHI data is preserved. The RMSD of GHI regionally adapted data is very similar to that of original model (Table 4.4).

The regionally-adapted model values better represent the geographical variability of DNI and GHI solar resource and they also improve the distribution and match of hourly values. Some residual discrepancies still remain in the output data, but their removal is beyond the possibilities of the regional adaptation. The residuals can only be removed for the locations of the meteorological stations in the context of the site-adaptation. Moreover, the residual discrepancies should be evaluated within the context of the quality and accuracy of ground measurements (Chapter 3.3).

Table 4.5: Comparison of long-term average of yearly summaries of original and regionally-adapted values

Meteo station	DNI annual values*			GHI annual values*		
	Original [kWh/m^2]	Adapted [kWh/m^2]	Difference [%]	Original [kWh/m^2]	Adapted [kWh/m^2]	Difference [%]
Hanimaadhoo	1522	1445	-5.1	2027	2009	-0.9
Hulhulé	1604	1487	-7.3	2042	2018	-1.2
Kadhdhoo	1667	1548	-7.1	2047	2025	-1.1
Gan	1700	1567	-7.8	2053	2029	-1.2

** Values represent GIS data layers, which may slightly deviate from the site-specific data values due to spatial resolution and disaggregation.*

The coefficients of the regional adaptation were derived for the period with the overlap between the ground data and the model data. These coefficients were implemented to the model to recalculate the full-time series of solar radiation.

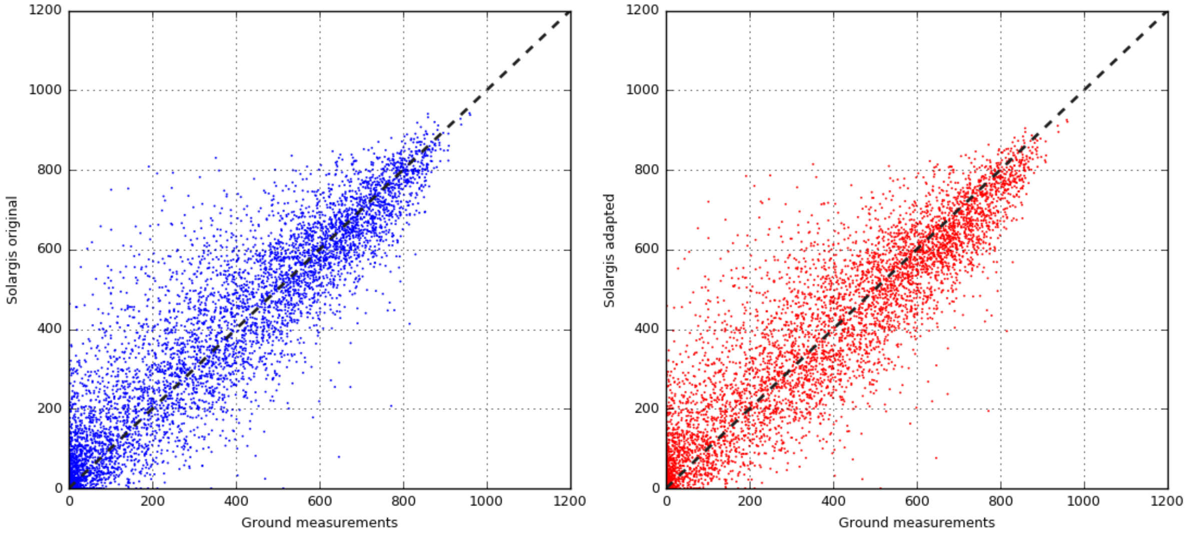

Figure 4.2: Adaptation of DNI hourly values for Hanimaadhoo
Left: original Solargis data, right: regionally adapted Solargis data.
The X-axis represents the measured DNI and the Y-axis represents the satellite-derived DNI.

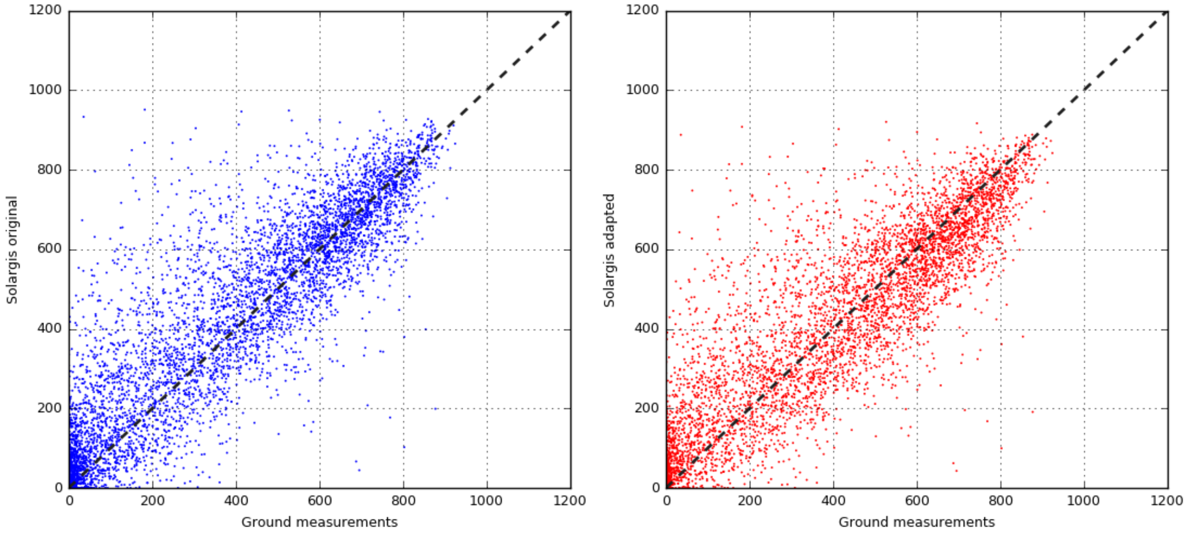

Figure 4.3: Adaptation of DNI hourly values for Hulhulé
Left: original Solargis data, right: regionally adapted Solargis data.
The X-axis represents the measured DNI and the Y-axis represents the satellite-derived DNI.

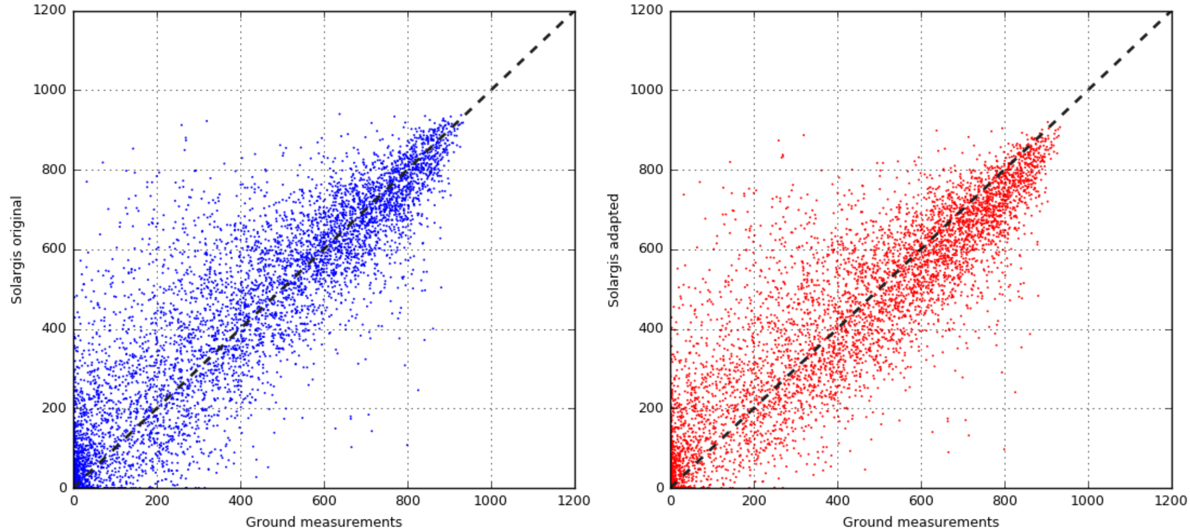

Figure 4.4: Adaptation of DNI hourly values for Kadhdhoo
Left: original Solargis data, right: regionally adapted Solargis data.
The X-axis represents the measured DNI and the Y-axis represents the satellite-derived DNI.

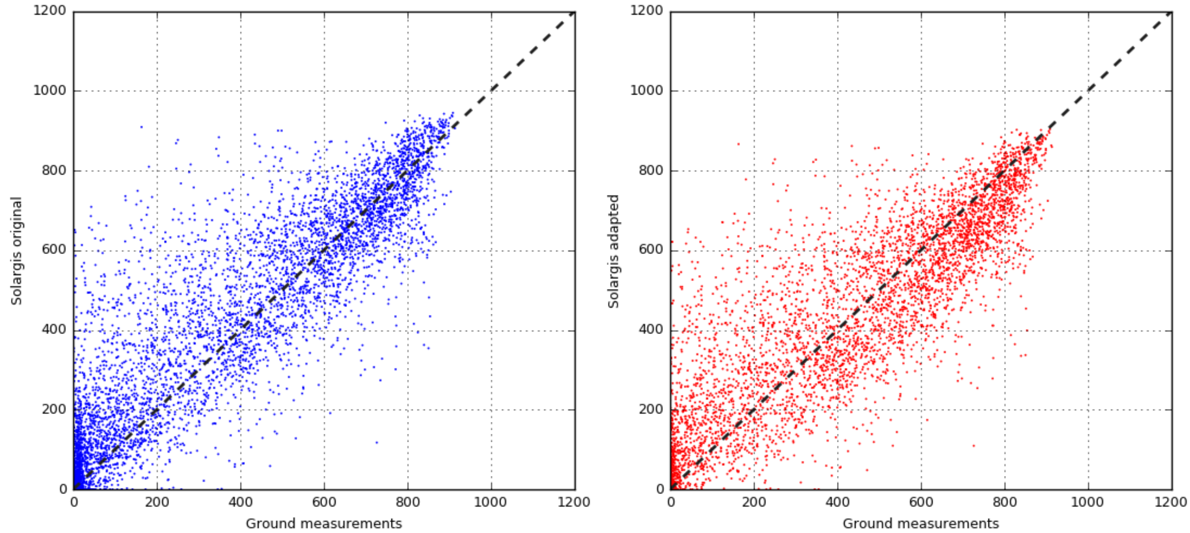

Figure 4.5: Adaptation of DNI hourly values for Gan
Left: original Solargis data, right: regionally adapted Solargis data.
The X-axis represents the measured DNI and the Y-axis represents the satellite-derived DNI.

4.2.2 Accuracy-enhanced DNI and GHI maps

Regionally adapted DNI and GHI long-term averages are higher in the majority of the area, compared to the original data (Figure 4.6 and 4.7). The absolute change of DNI is higher, compared to GHI, as DNI is more sensitive to changes of aerosol load introduced in the first step of the regional adaptation.

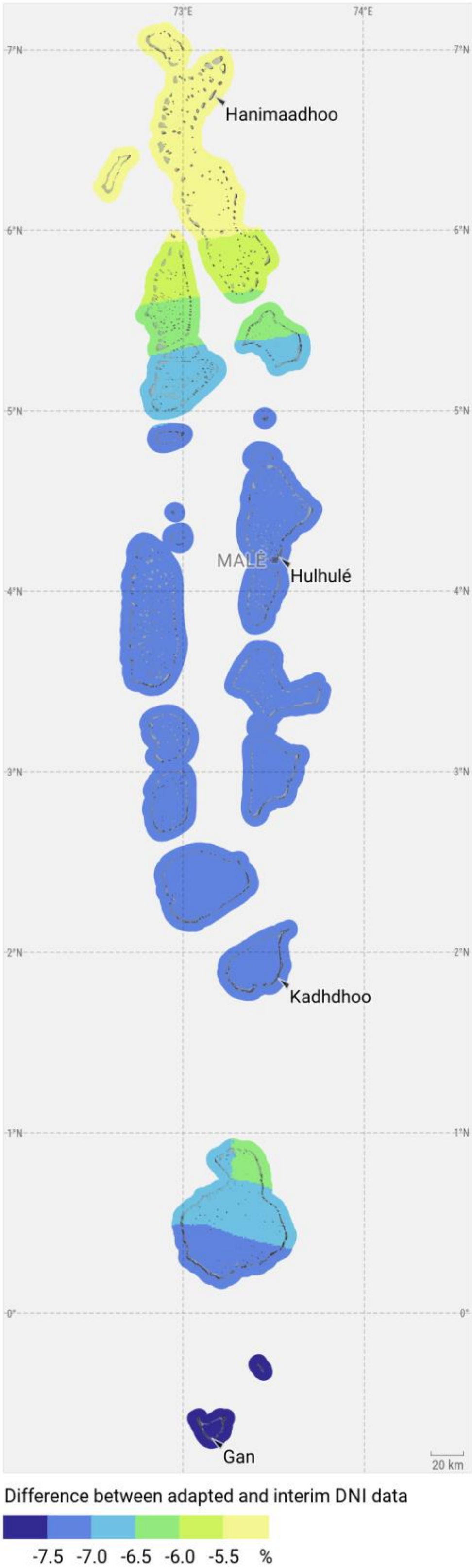

Figure 4.6: Map of differences in yearly DNI between the original and adapted model outputs

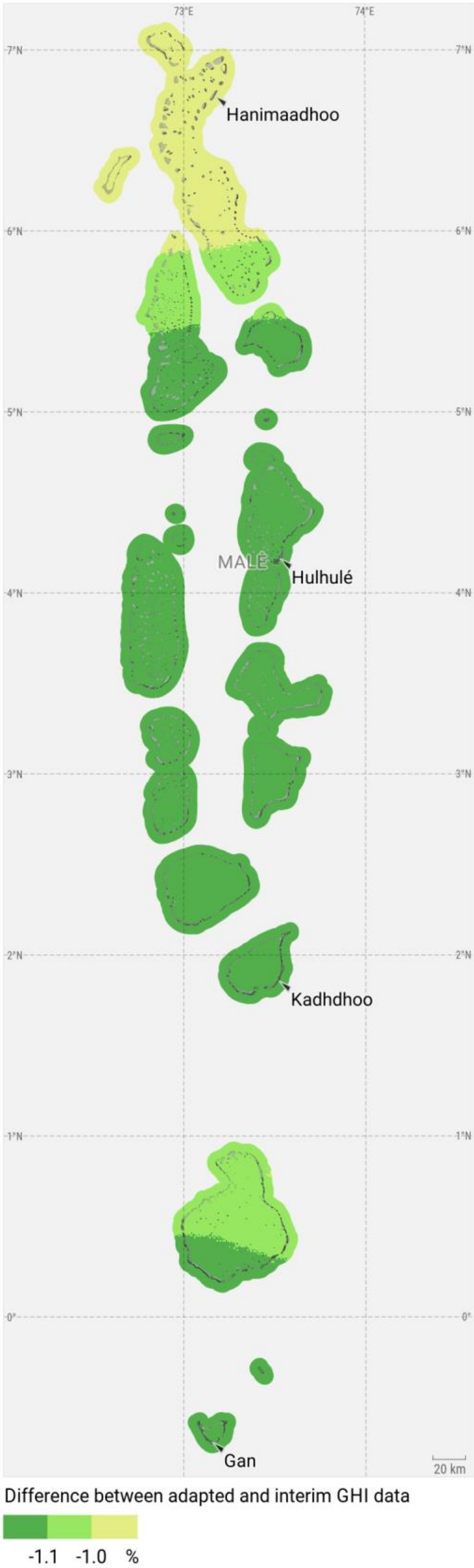

Figure 4.7: Map of differences in yearly GHI between the original and adapted model outputs

5 Solar resource maps of Maldives

5.1 Accuracy enhanced maps of DNI and GHI

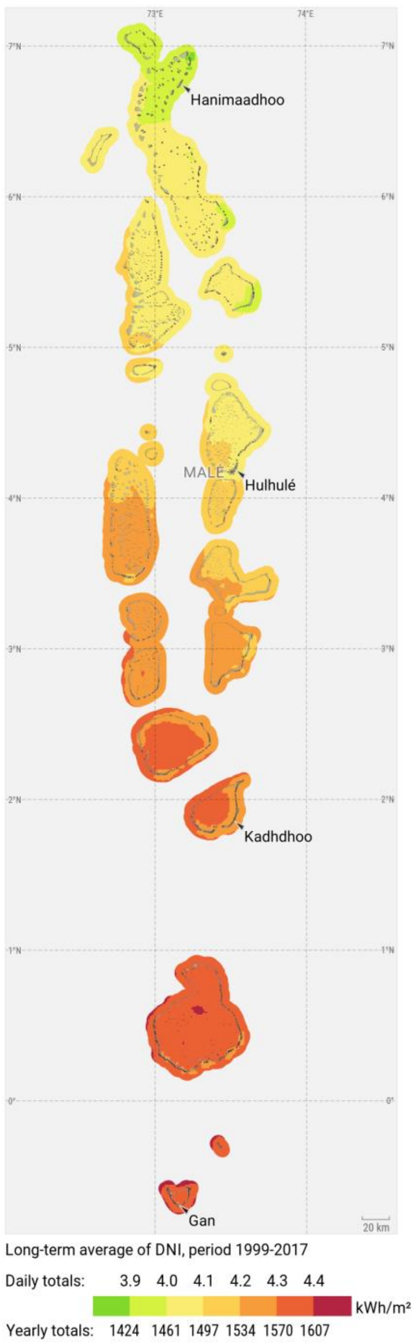

Figure 5.1: Accuracy-enhanced DNI yearly long-term average

After the regional adaptation of the Solargis satellite model, full time series representing a period of 19 years (1999 to 2017) are aggregated into long-term yearly averages of DNI and GHI (Figure 5.1 and 5.2). Important outcomes of this exercise are two maps with reduced uncertainty (Chapter 5.2).

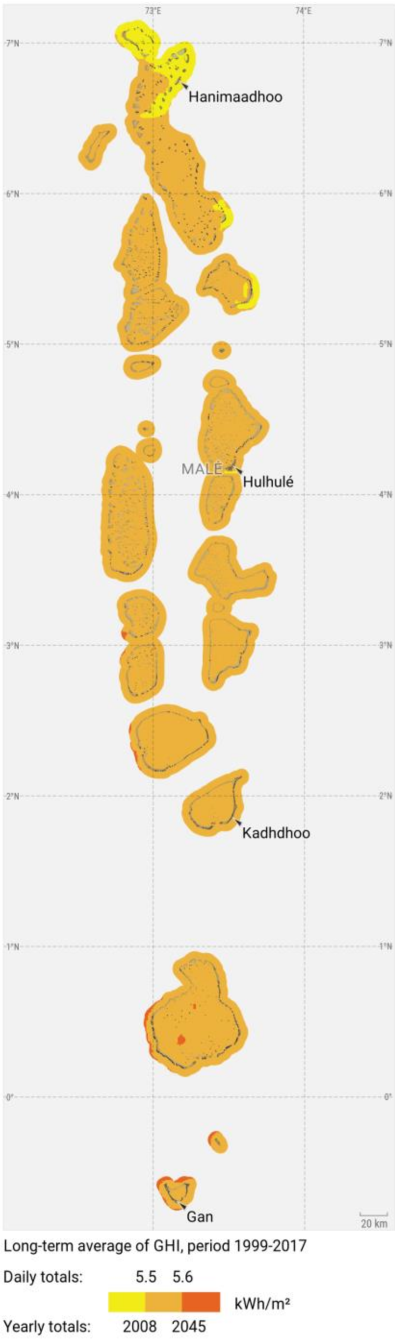

Figure 5.2: Accuracy-enhanced GHI yearly long-term average

5.2 Uncertainty of solar resource maps

Solargis model is based on the use of the best available algorithms and input data, and it has been calibrated and validated for all geographies. Therefore, the model has robust and uniform behaviour in all conditions. Validation sites in Maldives show consistent bias and RMSD within the expected range. Bias (systematic deviation) of yearly GHI and DNI is found within acceptable limits of accuracy, in the majority of cases close to the uncertainty that is typical for long-term estimates calculated from medium quality measuring instruments. After the model adaptation the bias and RMSD values are even lower (Tables 4.1 to 4.4).

For practical use, the statistical measures of accuracy have to be converted into uncertainty, which better characterizes probabilistic nature of a possible error of the model estimate. Uncertainty is based on the assumption of normal distribution of solar radiation model errors, which is a simplification given by availability of validation data and limited geographical knowledge.

Typically, a long-term yearly average estimate is required, often denoted as P50 value (in case of normal distribution equivalent to median). Besides P50, project developers, technical consultants and the finance industry inquire about uncertainty of long-term yearly GHI or DNI. P90 values are calculated by subtracting uncertainty from P50 value.

The uncertainty in this report is calculated for 80% probability of occurrence, thus P90 value shows an estimate at 90% probability of exceedance.

The **uncertainty of regionally adapted satellite-based DNI and GHI** is determined by uncertainty of the model, ground measurements, and the model adaptation method. More specifically it depends on [29]:

1. Parameterization and adaptation of **numerical models integrated in Solargis** for the given data inputs and their ability to generate accurate results for various geographical and time-variable conditions:
    - Data inputs into Solargis model: accuracy of Meteosat satellite data, MACC-II/CAMS and MERRA-2 aerosols and GFS/CFSR/GFS water vapour
    - Solis clear-sky model and its capability to properly characterize various states of the atmosphere
    - Simulation accuracy of the Solargis cloud transmittance algorithms, being able to properly distinguish different states of various surface types, albedo, clouds and fog
    - Diffuse and direct decomposition by Perez model
    - Transposition from global horizontal to in-plane irradiance (for GTI) by Perez model
    - Terrain shading and disaggregation by Ruiz-Arias model
2. Uncertainty of the **ground-measurements**, which is determined by:
    - Accuracy of the instruments
    - Maintenance practices, including sensor cleaning, service and calibration
    - Data post-processing and quality control procedures.
3. Uncertainty of the **model adaptation** at regional scale and residual uncertainty after adaptation

The uncertainty of the estimate $Uncert_{est}$ in this study is estimated from the model uncertainty of the Solargis model $Uncert_{model}$, the uncertainty of the measurements $Uncert_{meas}$, and the uncertainty of the model adaptation method $Uncert_{adapt}$:

$$Uncert_{est} = \sqrt{Uncert_{model}{}^2 + Uncert_{meas}{}^2 + Uncert_{adapt}{}^2}$$

Combined uncertainty of the yearly estimate $Uncert_{est}$ is estimated empirically, based on the experience and accuracy evaluation of the model and measurements (Chapter 3 and Chapter 4.2.1). We consider it to have probabilistic nature and is estimated based on the statistical measures calculated for four solar measuring stations. The expert estimate of the combined user uncertainty in this report assumes 80% probability of occurrence of values, i.e. 90% probability of exceedance. Tables 5.1 summarize the estimated uncertainty.

The uncertainty from the interannual variability of solar resource is not considered in this study.

Based on today's knowledge and experience, we assume that the lowest achievable uncertainty (assuming uncertainty of the model and measurements at P90) of satellite-based long-term estimates is indicatively ±2.5% for GHI and ±3.5% for DNI. The uncertainty at best possible limits can only be achieved if the following conditions are met:

- Best available models and approaches are applied
- Input data (satellite, atmospheric, etc.) are quality controlled and homogenized
- Satellite model is adapted for local geography by high quality ground measurements, available for a period of at least 3 to 4 years
- Ground measurements are available for GHI, DNI and DIF, measured by high-standard meteorological instruments and equipment, applying best operation and maintenance practices.

The lowest uncertainty levels can only be achieved by site-adaptation for a very local region around meteorological stations with site-specific microclimatic conditions recorded in ground measurements. In the case of the regional adaptation used in this study, the uncertainty is usually higher because it describes uncertainty of any selected location in the broader region.

Moreover, a residual discrepancy between ground measurements, and the model data can be found after regional adaptation (Tables 4.1 and 4.2). This adaptation approach is designed to correct only regional discrepancy patterns, not to resolve site-specific issues.

The uncertainty levels of regionally adapted data (Table 5.1) are higher than the best achievable results by site-specific adaptation. It is estimated that the majority of Maldives territory has uncertainty of the regionally-adapted model yearly values at the level of ±3.5% for GHI and ±6.0% for DNI. Due to specific monotonous geographical conditions without any topographic barriers, we expect that the four meteorological stations sufficiently represent the territory and the quality of regional adaptation predominantly homogeneous over the whole Maldives. Therefore, we do not expect occurrence of regions with increased uncertainty due to insufficient amount reference solar meteorological stations.

Table 5.1: Uncertainty of the model estimate for original and regionally-adapted annual GHI and DNI and how does it compare to the best-achievable uncertainty case.

Uncertainty of long-term annual values	Acronym	Uncertainty of the original Solargis model	Uncertainty of the Solargis model after regional adaptation	*Best achievable uncertainty*
Global Horizontal Irradiation	GHI	±6.0%	±3.5%	*±2.5%*
Global Tilted Irradiation	GTI	±6.0%	±4.0%	*±3.0%*
Direct Normal Irradiation	DNI	±12.0%	±6.0%	*±3.5%*

6 Conclusions

This project reduced the uncertainty of the DNI and GHI solar resource database and the resulting yearly and monthly maps representing the territory of Maldives.

It is the result of systematic work on (i) setting up a network of solar meteorological stations with high-standard equipment and on (ii) implementation of rigorous practices in operation and maintenance of solar equipment. Well-linked to this infrastructure is satellite-based solar radiation model Solargis, which has proven quality and reliability of time series, and derived site-specific data products and map-based outputs.

Reduced uncertainty

The typical uncertainty of the Solargis model estimate has been reduced from the original range of ±12.0% for **DNI** yearly values to the range of ±6.0% for accuracy enhanced values. For yearly **GHI** the uncertainty reduction is seen from the original range of ±6.0% to the range of ±3.5 for the accuracy enhanced values. The reductions is homogeneous for the whole territory of Maldives.

Besides reducing systematic deviation (bias), the regional model adaptation also results in the improvement of other data quality indicators such as reducing random deviation (quantified by Root Mean Square Deviation) and by improving the probability distribution of hourly values (quantified by Kolmogorov-Smirnoff Index). Higher-quality DNI and GHI data have substantial benefits in energy simulation, which can in turn be used for more reliable technical design and financial predictions.

Role of solar measuring stations in maintaining sustainable solar data infrastructure

Receiving data from a number of high-quality measuring stations enables an improved understanding of the geographical and temporal variability of solar resource in regions of Maldives.

Even though regional adaptation reduced uncertainty, it is important to maintain the operation of the solar meteorological stations, with special focus on the following cases:

- For new sites, relevant to any larger solar power project, it is important to operate a solar meteorological station to reduce uncertainty to an achievable minimum (see Table 5.1) of the site-specific **long-term estimates.**
- For existing sites, the meteorological stations together with satellite data make it possible to maintain high quality and bankability of solar resource and meteorological data for sustainable **performance assessment** of solar power plants in the region.
- Keeping solar measuring stations in operation is of strategic importance to maintain quality of satellite models and of solar power **forecasts**.

7 List of figures

8 List of tables

9 References

[1] Perez R., Cebecauer T., Šúri M., 2013. Semi-Empirical Satellite Models. In Kleissl J. (ed.) Solar Energy Forecasting and Resource Assessment. Academic press.

[2] Cebecauer T., Šúri M., Perez R., High performance MSG satellite model for operational solar energy applications. ASES National Solar Conference, Phoenix, USA, 2010.

[3] Šúri M., Cebecauer T., Perez P., Quality procedures of Solargis for provision site-specific solar resource information. Conference SolarPACES 2010, September 2010, Perpignan, France.

[4] Cebecauer T., Suri M., Gueymard C., Uncertainty sources in satellite-derived Direct Normal Irradiance: How can prediction accuracy be improved globally? Proceedings of the SolarPACES Conference, Granada, Spain, 20-23 Sept 2011.

[5] Šúri M., Cebecauer T., 2014. Satellite-based solar resource data: Model validation statistics versus user's uncertainty. ASES SOLAR 2014 Conference, San Francisco, 7-9 July 2014.

[6] Ineichen P., A broadband simplified version of the Solis clear sky model, 2008. Solar Energy, 82, 8, 758-762.

[7] Morcrette J., Boucher O., Jones L., Salmond D., Bechtold P., Beljaars A., Benedetti A., Bonet A., Kaiser J.W., Razinger M., Schulz M., Serrar S., Simmons A.J., Sofiev M., Suttie M., Tompkins A., Uncht A., GEMS-AER team, 2009. Aerosol analysis and forecast in the ECMWF Integrated Forecast System. Part I: Forward modelling. Journal of Geophysical Research, 114.

[8] Benedictow A. et al. 2012. Validation report of the MACC reanalysis of global atmospheric composition: Period 2003-2010, MACC-II Deliverable D83.1.

[9] Cebecauer T., Šúri M., Accuracy improvements of satellite-derived solar resource based on GEMS re-analysis aerosols. Conference SolarPACES 2010, September 2010, Perpignan, France.

[10] Cebecauer T., Perez R., Súri M., Comparing performance of Solargis and SUNY satellite models using monthly and daily aerosol data. Proceedings of the ISES Solar World Congress 2011, September 2011, Kassel, Germany.

[11] GFS model. http://www.nco.ncep.noaa.gov/pmb/products/gfs/

[12] CFSR model. https://climatedataguide.ucar.edu/climate-data/climate-forecast-system-reanalysis-cfsr/

[13] CFSv2 model http://www.cpc.ncep.noaa.gov/products/CFSv2/CFSv2seasonal.shtml

[14] Molod, A., Takacs, L., Suarez, M., and Bacmeister, J., 2015: Development of the GEOS-5 atmospheric general circulation model: evolution from MERRA to MERRA2, Geosci. Model Dev., 8, 1339-1356, doi:10.5194/gmd-8-1339-2015

[15] Meteosat satellites MFG and MSG, EUMETSAT. http://www.eumetsat.int/website/home/Satellites/CurrentSatellites/Meteosat/index.html

[16] Cano D., Monget J.M., Albuisson M., Guillard H., Regas N., Wald L., 1986. A method for the determination of the global solar radiation from meteorological satellite data, Solar Energy, 37, 31-39.

[17] Perez R., Ineichen P., Maxwell E., Seals R. and Zelenka A., 1992. Dynamic global-to-direct irradiance conversion models. ASHRAE Transactions-Research Series, pp. 354-369.

[18] Perez, R., Seals R., Ineichen P., Stewart R., Menicucci D.,1987. A new simplified version of the Perez diffuse irradiance model for tilted surfaces. Solar Energy, 39, 221-232.

[19] Ruiz-Arias J.A., Cebecauer T., Tovar-Pescador J., Šúri M., 2010. Spatial disaggregation of satellite-derived irradiance using a high-resolution digital elevation model. Solar Energy, 84,1644-57.

[20] Zelenka A., Perez R., Seals R., Renne D., 1997. Effective Accuracy of Satellite-Derived Hourly Irradiances. Theoretical Appl. Climatology, 62, 199-207.

[21] Espinar B., Ramírez L., Drews A., Beyer H. G., Zarzalejo L. F., Polo J., Martín L., 2009. Analysis of different comparison parameters applied to solar radiation data from satellite and German radiometric stations. Solar Energy, 83, 1, 118-125.

[22] Cebecauer T., Suri M., 2016. Site-adaptation of satellite-based DNI and GHI time series: overview and Solargis approach. SolarPACES conference, September 2016, Cape Town, South Africa.

[23] Polo J., Wilbert S., Ruiz-Arias J.A., Meyer R., Gueymard C., Šúri M., Martín L., Mieslinger T., Blanc P., Grant I., Bolan J., Ineichen P., Remund J., Escobar R., Troccoli A., Sengupta M., Nielsen K.P., Renné D., Geuder N., Cebecauer T., 2016. Preliminary survey on site-adaptation techniques for satellite-derived and reanalysis solar radiation datasets. Solar Energy, 132, 25–37.

[24] NREL, 1993. User's Manual for SERI_QC Software-Assessing the Quality of Solar Radiation Data. NREL/TP-463-5608. Golden, CO: National Renewable Energy Laboratory.

[25] Younes S., Claywell R. and Munner T, 2005. Quality control of solar radiation data: Present status and proposed new approaches. Solar Energy 30, 1533-1549.

[26] Long C.N., Dutton E.G., 2002. BSRN Global Network recommended QC tests, V2.0. Rapport technique BSRN. http://epic.awi.de/30083/1/BSRN_recommended_QC_tests_V2.pdf

[27] Long C.N., Shi Y., 2008. An automated quality assessment and control algorithm for surface radiation measurements. Open Atmos. Sci. J., 2, 23-37.

[28] Suri at el, 2018. Annual Solar Resource Report for solar meteorological stations after completion of 24 months of measurements, Republic of Maldives. Solargis report No.129-07/2018, delivered for the World Bank.

[29] Šúri M., Cebecauer T., 2014. Satellite-based solar resource data: Model validation statistics versus user's uncertainty. ASES SOLAR 2014 Conference, San Francisco, 7-9 July 2014

Support information

Background on Solargis

Solargis is a technology company offering energy-related meteorological data, software and consultancy services to solar energy. We support industry in the site qualification, planning, financing and operation of solar energy systems for more than 18 years. We develop and operate a new generation high-resolution global database and applications integrated within Solargis® information system. Accurate, standardised and validated data help to reduce the weather-related risks and costs in system planning, performance assessment, forecasting and management of distributed solar power.

ISO 9001 LL-C (Certification) Solargis is ISO 9001:2015 certified company for quality management.

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