SATELLITE-BASED SOLAR RESOURCE DATA:
MODEL VALIDATION STATISTICS VERSUS USER’S UNCERTAINTY

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ABSTRACT

Accuracy of satellite-based model estimates is compared to the accuracy achievable by on-site ground measuring campaigns. Validation statistics is converted to probabilistic description of uncertainty and demonstrated for SolarGIS annual DNI and GHI values. The uncertainty is described in two ways: as (i) model uncertainty relative to the high-quality ground validation data, and as (ii) user’s uncertainty, where we consider also uncertainty of ground data. This work focuses only on the uncertainty of the estimate. The second component of the user’s uncertainty – data interannual variability – is not discussed here.

1. MEASUREMENTS AND SOLAR MODELS

In solar energy, Global Irradiance for Horizontal and Tilted plane (GHI and GTI) are two most important parameters for photovoltaics. The key solar parameter for Concentrated Photovoltaics and Concentrated Solar Power is Direct Normal Irradiance (DNI).

Solar resource can be modeled by satellite-based solar models or measured by ground-mounted sensors. Ground-mounted sensors are good in providing high frequency and accurate data (for well-maintained, high accuracy measuring equipment) for a given site. Satellite-based models provide data with lower frequency of measurement, but representing long history over larger territories. Satellite-models are not capable to produce instantaneous values at the same accuracy as ground sensors, but can provide robust aggregated values.

Systematic deviations in satellite model estimates may occur within certain range, and this is inherent feature given lower resolution of the atmospheric and satellite inputs. By correlation of satellite data with quality controlled ground-measured data, these systematic deviations can be reduced – by site adaptation or regional re-calibration of the model.

In the solar energy, some misconceptions can be seen:
- By default, estimates based on the measured data are considered as more accurate than modeled values. In many cases, satellite-based solar data offer the same or lower uncertainty when compared to the data from low accuracy ground sensors, or measured by equipment with little or no maintenance and no quality control.
- There are still industrial players who do not fully appreciate the fact that weather varies year-by-year, and this interannual variability may deviate actual performance of a solar power system from longterm expectation.

In this article we address (i) accuracy issues of solar resource data measured by ground-mounted sensors and by satellite-based models, and (ii) related user’s uncertainty for planning of solar power plants.

2. ACCURACY OF SATELLITE-BASED MODELS

Reliable solar models based on the use of satellite and atmospheric data exist today. A good description of the current approaches can be consulted in [1]. In brief, the state-of-the-art high-accuracy modelling approaches have the following features:
- Use of modern models based on sound theoretical grounds, which are regionally and temporally consistent and computationally stable.
- Use of the state-of-the-art input data: satellite, aerosols, water vapor, etc. These input data are systematically quality controlled and validated.
- Models and input data are integrated and regionally adapted to perform reliably at a wide range of geographical conditions.

Due to their complexity and numerous fine-tunings, it is no surprise that models based on the same theoretical principles perform very differently. The accuracy of the model depends on the underlying algorithms and quality of the input data and their optimized interaction. More advanced
models are usually adaptive to various non-standard situations (e.g. snow, desert areas or extreme aerosol situations). In the modern computing approaches, the input data come from global monitoring systems:

- Satellite data from geostationary satellites are used for monitoring of clouds. Currently at minimum five operational satellite missions are needed to cover the Earth’s surface between latitudes 60 degrees North and South. Spatial resolution of satellite data is approximately 3 to 5 km, depending on the location. Each satellite produces data in the range of 3 to 12 spectral bands at frequency of 15 and 30 minutes. Combined use of several spectral bands is the optimum approach for accurate detection of cloud properties.

- Aerosol and water vapor are used for modelling atmospheric properties. Data from global meteorological models are used. Spatial resolution of the modeled data is approx. 22 km to 125 km and their frequency of update is 3 and 6 hours. In case of aerosols, alternative to the models are data processed from satellite missions (e.g. MODIS, MISR, MERIS). Spatial resolution of these satellite-computed products is higher, but their availability and geographical coverage is irregular.

- High-resolution digital terrain model is used for dealing with terrain shading and elevation effects. At a global scale, digital terrain model with spatial resolution up to 90 m (at the equator) can be routinely used (SRTM-3).

- Other databases such as land cover, temperature and snow are used as a support for modelling.

Information value of the input data used by these models is high, and most of it still remains unexploited, providing opportunities for future improvements. The following numerical models are used in a computing chain:

- Clear sky model for calculation of the state of the atmosphere. Such models read aerosol and water vapor data on the input. Optionally, ozone data can be used.

- Cloud model derives cloud attenuation effect on solar radiation, and the main inputs are satellite data.

- Models for calculation of solar radiation components (direct, diffuse and reflected) for different inclination and azimuth of the receiving surface.

Alternatively, fully coupled physically-based models integrating all components may be used. Advantages of satellite-based solar models are:

- Extensive geographical coverage, and long historical availability of the satellite data: in some regions, more than 20 years of data is available.

- Data continuity: for Meteosat satellites 99% of data is available, in other satellite missions, larger gaps are known. The shorter gaps in the data are filled-in by intelligent algorithms.

- Spatial and temporal stability: on condition that geometrical and radiometric quality of the input satellite and atmospheric data are systematically controlled.

It is clear that due to lower spatial and temporal resolution of input data and model limitations (most of the operational models have semi-empirical character), the model outputs feature systematic and random deviations. In case of sound models and input data, these deviations can be managed by regional calibration of the model (respecting specific geographical features) or adaptation of the solar model for the local conditions. For both cases high-quality ground measurements are needed.

The list below mentions some of the known issues in satellite-based solar models:

- High latitudes: due to limiting sun and satellite angles, cloud properties can be determined with lower accuracy at latitudes higher than 50 degrees, especially in winter.

- Edge of the satellite disc: for shallow viewing angles of the satellite sensor, the accuracy of cloud detection deteriorates close to the edges of the data image.

- High mountains: over ridges and valleys weather changes rapidly, clouds, shadows, snow and ice form complex and variable patterns, which are mixed with changing land cover. Thus, given the resolution of satellite and atmospheric data, the modelling is more challenging, especially at the boundary between high mountains and lowlands.

- Deserts: albedo detection over deserts and arid zones may occasionally suffer from surface reflections, abrupt albedo changes, and other effects.

- Snow: especially older satellite sensors with limited spectral resolution pose challenges in distinguishing different forms of snow and ice from clouds.

- Rapidly changing and high concentrations of aerosols. Large seasonal and daily variability is observed in some regions, e.g. in the Gulf region, West Africa, North India and Southwest China.

- Tropical humid seasons with occurrence of small and scattered clouds: these clouds may have frequency of changes in the range of seconds to minutes and this intermittency may not be properly captured by satellite data.
• Regions and seasons with constant occurrence of clouds. Such situation makes it difficult to accurately identify the ground albedo and cloud properties.
• Mosaic of water and land: coastal zone, especially in a close proximity to mountains may feature dramatic change of climate over short distances, which may not always be captured by atmospheric and occasionally also satellite data. Similar effect can be seen in rapidly changing landscape (mountains, lowlands, water bodies, urbanization, islands, etc.)
• Small and medium size islands, especially mountainous.
• Satellite missions: Meteosat satellite data are the most accurate and stable.
• Regions with little or no ground-based solar measurements: due to limited empirical knowledge of the interaction of the modeled data with local geography, the uncertainty of the model outputs is higher. This is a situation in some regions of Africa, Asia, Pacific and Latin America.

3. ACCURACY OF GROUND MEASUREMENTS

Global Horizontal Irradiance (GHI) is typically measured by (i) thermocouple junction based pyranometers or (ii) silicon photodiode cells. For development and monitoring of solar power plants, it is advised to use high-standard meteorological pyranometers to achieve the highest possible accuracy and stability of measurements.

Direct Normal Irradiance (DNI) is measured by pyrheliometers, where the instrument always aims directly at the sun by continuously sun tracking mechanism. Optionally DNI can be measured by Rotating Shadowband Radiometer (RSR) or by integrated pyranometer such as Sunshine Pyranometer (e.g. SPN1).

Diffuse Horizontal Irradiance (DIF) is measured by (i) pyranometers, which obscure the direct radiation with a sun-tracking disk or an adjustable fixed shadow ring, or (ii) by RSR equipped with rotating shadow band. Diffuse radiation can be also calculated as a difference between global and direct components. However, this method is not ideal because it increases uncertainty compared to a dedicated measurement, and does not allow full quality testing of measurements.

The experience shows that a combination of high accuracy instruments for measuring GHI, DNI and DIF provides best means for reliable data:
• Secondary standard pyranometers for GHI.
• Secondary standard pyranometers with shading disc for DIF.
• First class pyrheliometers on a sun-tracker for DNI.

The most accurate instrumentation is more expensive and needs more dedicated maintenance. However, if cleaning and maintenance routines are rigorously followed, the system works reliably, delivering data within the expectation and with low uncertainty.

An option for remote areas and harsh conditions is the use of RSR. In such a case, at least one redundant measurement is needed for crosschecking consistency of GHI, DNI and DIF components. A good option is to install one secondary standard pyranometer for measuring GHI. Using solely RSR does not allow for cross-validation of GHI, DNI and DIF, which results in higher measurement uncertainty.

Theoretical uncertainties of the main instruments used in solar industry are summarized in Tabs. 1 and 2 [2, 3, 4]. According to [5, 6] uncertainty in outdoor conditions is higher – it depends strongly on installation, maintenance, calibration and data quality control.

TAB. 1: THEORETICAL UNCERTAINTY OF DAILY DNI SUMMARIES*

<table>
<thead>
<tr>
<th>Pyrheliometers</th>
<th>RSR**</th>
<th>SPN1</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNI</td>
<td>±0.5%</td>
<td>±4.5%</td>
</tr>
</tbody>
</table>

* At 95% confidence level in laboratory conditions
** After post processing

TAB. 2: THEORETICAL UNCERTAINTY OF DAILY GHI SUMMARIES*

<table>
<thead>
<tr>
<th>§</th>
<th>Pyranometers</th>
<th>RSR**</th>
<th>SPN1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Secondary</td>
<td>First</td>
<td>Second</td>
<td></td>
</tr>
<tr>
<td>standard</td>
<td>class</td>
<td>class</td>
<td></td>
</tr>
<tr>
<td>DNI</td>
<td>±2%</td>
<td>±5%</td>
<td>±10%</td>
</tr>
</tbody>
</table>

* At 95% confidence level in laboratory conditions
** After post processing

Utilization of the state-of-the-art instruments does not alone guarantee good results. All measurements are subject to uncertainty. Sensors exhibit different specific features that
must be considered, and appropriate correction techniques applied to obtain correct results.

Besides use of high accuracy instruments, proper operation and maintenance are key factors for sustainable quality and bankability of ground measurements:

- Systematic cleaning and calibration of instruments, logging of all service and maintenance works.
- Routine control of mounting and functioning of all equipment: data logger, battery, modem, and other components of a meteo station.
- Systematic validation and quality control of the measured data, optimally in real time to reduce failure intervals, application of error-flagging procedures.

Solar measuring stations are often operated by non-professionals, with limited experience and knowledge. The experience shows that only data measured by dedicated and trained teams offer acceptable quality.

From the viewpoint of validation of satellite-based solar models, the only option is to use high-accuracy instruments with at least one redundant sensor to measure additional GHI, DIF or DNI component(s). If no redundant measurements are available, validation is less reliable.

Under assumption of frequent cleaning of instruments, data from high-quality pyranometers and pyrheliometers have lower uncertainty compared to RSR instruments (Tabs. 1 and 2). In dusty and polluted environments and conditions of less-frequent cleaning, the uncertainty of pyrheliometers and pyranometers may be comparable to RSR.

Climate conditions influence performance of ground sensors, such as extreme temperature, humidity, snow, frost, dust and aerosols. In many regions, the weather conditions may exceed the standard operating conditions, for which the uncertainty given by a manufacturer applies. Example of extreme conditions may be extreme deserts, high elevation, humid tropical climate and regions with high atmospheric pollution.

For those who measure, it is not often known that the measured data have to be quality-controlled before further use. Some QC algorithms can be operated automatically but a number of procedures are based on visual control. Some of the issues, which can be detected in the ground measured data during quality control [7, 8]:

- Stability of mounting (levelling, tracking)
- Shading by nearby objects or terrain features
- Radiometric stability
- Cleaning issues
- Issue in the data logger, battery, solar power and modem
- Time shifts, missing data
- Unrealistic values given by reflections or shading, strange patterns, etc.

In most cases, the issues found in the measured data are due to the following reasons:

- Primary savings: for the sake of saving on capital investment, cheaper sensors (lower class or silicon-based sensors) and equipment is installed, which does not comply with the expectations for the uncertainty and data quality.
- Personnel with limited knowledge and experience run measurement campaign.
- Sensors are incorrectly positioned (shading, local air pollution)
- Systematic maintenance, cleaning, and calibration is not implemented.
- There are issues and gaps in the data due to failures.
- Importance of quality control of the measured data is often undervalued or completely neglected.

The lowest possible uncertainties of solar measurements are essential for accurate determination of solar resource. Uncertainty of measurements in outdoor conditions is always higher than the one declared in the technical specifications of the instrument, and it may dramatically increase in extreme operating conditions and in case of insufficient maintenance.

4. MEASURES OF ACCURACY

The performance of satellite-based models, for a given site, is characterized by the following indicators [9]:

1. Bias characterizes systematic model deviation at a given site.
2. Root Mean Square Deviation (RMSD) and Mean Average Deviation (MAD), which indicate spread of error for instantaneous values.
3. Correlation coefficient.
4. Kolmogorov-Smirnoff index (KSI) characterizes representativeness of distribution of values.

Only quality-controlled measurements from high-standard sensors should be used for reliable validation of satellite-
based solar models. Any issues in the ground measured data result in skewed evaluation.

Typically, bias is considered as the first indicator of the model accuracy, however the interpretation of the model accuracy should be done analyzing all measures. While knowing bias helps to understand a possible error of longer-term estimate, MAD and RMSD are important for estimating the accuracy of energy simulation and operational calculations (monitoring, forecasting). KSI may indicate issues in the model’s ability to represent various solar radiation conditions, which is important for accurate CSP modelling as the response of these systems is non-linear to irradiance levels.

Even if bias of different satellite-based models is similar, other accuracy characteristics (RMSD, MAD and KSI) may indicate substantial differences in their performance.

Validation statistics such as bias, RMSD, MAD or KSI, for one site may not provide representative picture of the model performance in the given geographical conditions. The reason is that such site may be affected by a local microclimate or by hidden issues in the ground-measured data. Therefore, the ability of the model to characterize long term annual GHI and DNI values should be evaluated at several validation sites, using two measures [10]:

- **Mean bias deviation**, which indicates whether the model has overall tendency to overestimate or to underestimate the measured values.
- **Standard deviation of biases**, which shows the range of deviation of the model estimates (statistically one standard deviation characterizes 68% probability of occurrence).

Good satellite models are consistent in space and time, and thus the validation at several sites within one geography provides a robust indication of the model accuracy in geographically comparable regions elsewhere.

If a number of validation sites, within a specific geography (e.g. arid and semiarid conditions of Southern Africa), shows bias and RMSD consistently within certain range of values, one can assume that the model will behave consistently also in regions with similar geography where validation sites are not available. Thus, for example, if geographical analogy to South African deserts can be found in Australia and South America, it is very likely that the model will deliver outputs within comparable uncertainty.

The above arguments are documented for the case of the model SolarGIS [1], which has been validated for 189 sites worldwide. Fig. 1 shows a GHI world map as a reference. Figs. 2 and 3 show distribution of validation sites and the identified GHI and DNI bias in five categories. Fig. 4 shows a scatterplot of GHI and DNI bias values for all sites.

Even though distribution of validation sites is irregular, Figs. 2 to 4 indicate stable and predictable performance of SolarGIS across various climate regions. Range of bias values for DNI is approximately two times higher compared to GHI. In most cases, bias (systematic deviation) of yearly GHI approaches uncertainty limits of lower-accuracy solar sensors. Due to higher complexity of the model, bias of satellite-based DNI is higher than that of solar sensors.

For a 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. The most required value by project developers, technical consultants and finance industry is the uncertainty of the longterm yearly GHI or DNI estimate.

One way of evaluating the user’s uncertainty is to calculate standard deviation of bias values for all sites available in the region and to apply confidence intervals for estimating its probabilistic nature. This works for a simplified assumption of normal distribution of deviation between the model and the measured values. As an example, Tab. 3 shows probabilistic nature of uncertainty calculated from standard deviation (STDEV) of bias values for two cases:

- 80% occurrence of values, which is the equivalent to 90% exceedance, or P90 (use of this confidence interval became a standard in solar resource assessment); calculated as 1.282*STDEV
- 95% occurrence of values, which is the equivalent to 97.5% exceedance, or P97.5 (this confidence interval is used in the standards for meteorological instruments); calculated as 1.960*STDEV

5. USER’S UNCERTAINTY – CASE OF SOLARGIS

As with any other measuring approaches, a user cannot expect zero uncertainty for satellite-based solar models. However, if the physics represented by the algorithms is correctly implemented, one can expect robust and uniform behavior of the model for the geographical conditions, for which it has been calibrated and validated.
Validation statistics and uncertainty can be considered from two viewpoints:

- Uncertainty relative to the measurements (model uncertainty), which relates uncertainty of satellite model to the measured data, and ignores fact that the measurements also include the uncertainty component.
- Absolute uncertainty (user’s uncertainty), which includes also the uncertainty of ground measurements.

The user’s uncertainty $Uncert_{user}$ in this study is calculated from the model uncertainty of the SolarGIS model estimate $Uncert_{model}$ and from the uncertainty of the measurements $Uncert_{measurements}$:

$$Uncert_{user} = \sqrt{Uncert_{model}^2 + Uncert_{measurements}^2}$$

Estimate of the longterm uncertainty of ground measurements ($Uncert_{measurements}$) can be a bit subjective – it can be based on combination of the theoretical uncertainty of the instrument, results of quality control procedure and comparison of the redundant measurements.

According to [11], for carefully maintained instruments, the values from Tabs. 1 and 2 could serve as a good starting point for assessing annual uncertainty of solar instruments. It is known from other comparisons [5,6], that these values could be exceeded in standard operating conditions.

The user’s uncertainty of SolarGIS GHI and DNI yearly summaries for 80% of observations (at P90) is within the range of approx. ±4.4% and ±7.7% (±6.3% and ±11.7% for 95% of observations, i.e. at P97.5), respectively. In complex geographies and extreme cases, uncertainty of GHI and DNI yearly summaries can be higher than ±8% and ±15%, respectively.

Similar analysis on the regional basis shows, that regions where lower SolarGIS uncertainty (below ±4% for yearly GHI and ±8% for DNI) can be typically expected: most of Europe and North America below latitude approx. 50° (see exceptions below), South Africa, Chile, Brazil, Australia, Japan, Morocco, Mediterranean region and Arabian Peninsula (except the Gulf region). Lower uncertainty is also expected in regions with good availability of high-quality ground measurements.

Tab. 3 shows model and user’s uncertainty of yearly GHI and DNI for the SolarGIS model considering that the absolute majority of the validation data have been collected using high-accuracy instruments, applying the best measurement practices and strict quality control procedures.

<table>
<thead>
<tr>
<th>Annual value</th>
<th>Model uncertainty ±%</th>
<th>User’s uncertainty ±%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GHI</td>
<td>DNI</td>
</tr>
<tr>
<td>Uncert. of instruments*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Number of sites</td>
<td>189</td>
<td>134</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>3.0</td>
<td>6.0</td>
</tr>
<tr>
<td>Uncertainty (probability of occurrence)</td>
<td>80%</td>
<td>P90</td>
</tr>
<tr>
<td></td>
<td>90%</td>
<td>P95</td>
</tr>
<tr>
<td></td>
<td>95%</td>
<td>P97.5</td>
</tr>
<tr>
<td></td>
<td>99%</td>
<td>P99.5</td>
</tr>
</tbody>
</table>

* Theoretical daily uncertainty can serve as good starting point for longterm annual estimates [11] though in outdoor conditions achieving these values is more than challenging.

Regions where higher SolarGIS uncertainty can be expected (higher than ±4% for yearly GHI and higher than ±8% for DNI): high latitudes (approx. above 50°, high mountains, regions with regular snow and ice coverage, high-reflectance deserts, urbanized and industrialized areas, regions with high and dynamically changing concentrations of atmospheric aerosols (Northern India, West Africa, Gulf region, some regions in China), coastal zone (approx. up to 15 km from water) and countries in humid tropical climate (e.g. equatorial regions of Africa, America and Pacific, Philippines, Indonesia and Malaysia). Higher uncertainty is also assumed in regions with limited or no availability of high-quality ground measurements.

Systematic deviations between on-site measurements and satellite-modeled GHI and DNI can be corrected by site-adaptation or regional adaptation. However, even if local bias is reduced to zero, the uncertainty of site-adapted longterm estimate can (at the best) only approximate to the uncertainty of ground measurements combined by the length of on-site measuring campaign.

Site adaptation and regional adaptation of satellite-based solar data is a topic, which goes beyond the scope of this work.
Fig. 1: Longterm average of yearly sum of Global Horizontal Irradiation by SolarGIS.

Fig. 2: Bias for SolarGIS yearly GHI values at validation sites (in percent)

Fig. 3: Bias for SolarGIS yearly DNI values at validation sites (in percent)
6. CONCLUSIONS

Validation statistics are good for measuring the accuracy of model estimates at individual sites. However, the solar industry prefers working with uncertainty, the nature of which is probabilistic. We present an approach for an uncertainty estimate of longterm annual GHI and DNI that is based on multiplying values for standard deviation of bias with different levels of confidence.

The use of high quality measurements for a model evaluation is general practice. Uncertainty of such measurements, after rigorous quality control, is low and affects the user’s total uncertainty only marginally (Tab. 3). Therefore, model uncertainty is often considered an equivalent to the user’s uncertainty.

In some cases, ground measurements of dubious quality are used, which leads to lack of correspondence with the solar model. The resulting discrepancies are then unfairly attributed to the satellite-based models. Such practice does not lead to objective findings and hence use of low quality ground measurements for the model validation is strongly discouraged.

We demonstrate that the accuracy of well-designed satellite-based solar model can be stable over various geographies. Uncertainty of annual DNI is about 2-times higher compared to GHI. These findings are consistent with an independent evaluation [10].

Regions of higher uncertainty can be identified based on understanding of limits of the underlying models (clear-sky, cloud, DNI, transposition), satellite and atmospheric input data and on-site measurements.

More ground-measuring campaigns are needed over vast regions, which show interest in developing solar power. Programs, such as ESMAP by World Bank, and other initiatives help improving uncertainty of world’s solar resource maps.

7. REFERENCES