UNCERTAINTY SOURCES IN SATELLITE-DERIVED DIRECT NORMAL IRRADIANCE: HOW CAN PREDICTION ACCURACY BE IMPROVED GLOBALLY?

Tomáš Cebecauer[1], Marcel Šúri[1] and Christian A. Gueymard[2]

[1] GeoModel Solar s.r.o., Pionierska 15, 831 02 Bratislava, Slovakia,
tomas.cebeceuer@geomodel.eu, marcel.suri@geomodel.eu

[2] Solar Consulting Services, P.O. Box 392, Colebrook, NH 03576, USA, Chris@solarconsultingservices.com

Abstract

This study analyzes the multiple factors affecting the accuracy of satellite-based direct normal irradiance (DNI) and global horizontal irradiance (GHI). The geographical and temporal aspects of the accuracy of the underlying models and input databases are addressed, with the goal of identifying the major sources of uncertainty in the end products. The complex effects and interactions of cloudiness, aerosol load, surface reflectance, terrain, and sun/satellite geometry are more specifically discussed. The recent improvements in the GeoModel SolarGIS algorithms are described. Some statistical properties (e.g., frequency distribution) and the interannual variability in the modeled DNI and GHI are discussed.

Keywords: DNI, irradiance, uncertainty, variability, satellite-derived solar data.

1. Introduction

With the recent progress in satellite-based solar radiation mapping, multiyear time series covering at least 12 years of irradiance data are available for almost any world location. Depending on the source of satellite data and their reduction method, the spatial resolution of solar resource databases can vary in the range 1–10 km, with temporal resolution between 15 minutes and 3 hours. Compared to ground irradiance measurements of direct normal irradiance (DNI) or global horizontal irradiance (GHI), the temporal availability of such data is very high, only limited by (rare) satellite/sensor downtimes.

This study analyzes the various factors affecting the accuracy and uncertainty of satellite-based solar resource data. Examples using GeoModel's SolarGIS v1.6 calculation scheme and its results are used to improve current knowledge in solar resource assessment, and to propose new avenues of research toward the development of more accurate solar resource datasets, which would benefit the whole CSP industry.

2. Satellite-derived solar radiation

Solar radiation can be calculated by various types of numerical radiative models, which use parameterizations of atmospheric extinction effects as affected by solar geometry, in conjunction with a set of inputs characterizing (i) terrain properties, (ii) state of the atmosphere, and (iii) cloud transmittance. The *clear-sky* radiative model is at the core of this process, as it calculates solar irradiance for any given sun position, state of the atmosphere, and terrain conditions. The performance of the clear-sky model depends on the physical soundness of its parameterizations, and their ability to deal properly not only with typical cases, but also with extreme values of the main inputs, such as high load of aerosols, extreme humidity conditions, high site elevation, low solar elevation, unusual surface reflectance patterns, or shading effects. A performance analysis of various clear-sky DNI models as affected by each of their inputs is detailed elsewhere [1]. A more recent study [2] analyzes the overall performance of 18 models commonly used to produce maps and datasets of both DNI and GHI. For SolarGIS, clear-sky irradiances are calculated with the simplified SOLIS model [3]. Its performance has been found to exceed that of most similar models [2]. Some performance degradation in DNI has been found under very hazy conditions, however.

The sun geometry is a deterministic parameter, which can be evaluated with satisfactory accuracy. The modeling of how topography affects the direct and diffuse radiation components is also deterministic, but more complex: the site's elevation determines the atmospheric pressure and the related extinction processes, whereas the surrounding terrain determines the possible shading of the sun and/or parts of the sky. However, terrain is still not routinely taken into account in most solar databases, since it considerably complicates calculations and requires a spatial resolution at least an order of magnitude better than the nominal resolution of the satellite images. In SolarGIS, a high-resolution Digital Elevation Model (DEM) data is used, allowing shading calculations and vertical scaling of atmospheric parameters with ground elevation [4]. In addition to the inherent complexity of this method, the vertical scaling of aerosols and water vapor, and their spatial variability at the mesoscale (within 100 km), are still large sources of uncertainty, owing to the possible site specificity of these processes. This is discussed further below.

Clear-sky atmospheric conditions are variable, both spatially and temporarily. These variations must be characterized and related to the changing concentrations of the main radiatively active atmospheric constituents, namely aerosols, water vapor and ozone. Routine remote-sensed observations or modeled data of these three atmospheric parameters are available globally, albeit not always at the fine spatial and temporal resolutions that would be ideally needed. The key factor determining the short-term (from seconds to hours) variability of the all-sky irradiance is cloudiness. In SolarGIS, as in most satellite-derived solar datasets, the extinction of clouds is expressed through a key variable called *cloud index* [5, 6], which is calculated from the upwelling radiance routinely observed by meteorological geostationary satellites. To evaluate the all-sky irradiance at each time step, the clear-sky GHI is coupled with the cloud index, which acts as a proxy for cloud transmittance. In most satellite-derived datasets (including SolarGIS), the cloud extinction of DNI is empirically derived from GHI whenever the cloud index indicates that cloudiness is present over the scene. This separation of the direct and diffuse components is the source of some bias, as well as substantial random errors at the hourly (or shorter) time scale [7].

3. Input parameters and underlying methods

Table 1 summarizes the time frequency and spatial resolution of the input data sets used in the SolarGIS calculation scheme. These inputs are further discussed in the next subsections.

Variable (source)	Time frequency	Spatial resolution*
Satellite data (EUMETSAT)	15 min (MSG: from 03/2004 onwards) 30 min (MFG: from 1994 to 02/2004)	3 km
Aerosol Optical Depth (ECMWF), 2003–present	Daily values (summarized from 6-hourly)	125 km
Aerosol Optical Depth (ECMWF), 1994–2002	Long-term monthly climate averages calculated from the daily data 2003–2010	125 km
Water vapor (NOAA-NCEP)	Daily values	30 km
Ozone (constant)	-	-
Terrain: elevation and horizon shading (SRTM-3)	-	90 m
SolarGIS solar resource data—resolution of the primary output parameters (GHI and DNI)	**15 minute and 30 minute**	**3 km**

Table 1. Input data to the SolarGIS computing chain. *Spatial resolution at the equator

3.1. Clouds

Clouds are normally the most influencing factor, with the ability to rapidly modulate the clear-sky irradiance, sometimes at high frequency. The radiative effect of clouds depends on their type and optical properties. Thick clouds completely obliterate DNI, whereas thin clouds (such as cirrus) can transmit a substantial fraction of it. The amplitude of cloud-induced irradiance variations is highest under broken clouds, when abrupt changes may trigger an attenuation of 60–70% in GHI and ≈100% in DNI. The sensitivity of GHI is lower since it compensates the loss of DNI by additional diffuse radiation from cloud reflections and scattering.

Clouds may have a highly regional or local nature, which can be depicted only by the use of high-resolution (≈1–3 km at the equator) satellite images, such as those obtained by Meteosat, GOES or MTSAT. Such meteorological satellites measure the radiance emanating from the atmosphere in one or more spectral channels. The cloud index is derived by relating the actual spectral radiance and actual surface reflectance as recorded by the satellite to the estimated values that these variables would take under cloudless conditions.

Satellite-based models are normally capable of reproducing most of the irradiance variability caused by clouds. However, the current satellite instruments have a limited spatial resolution, which is insufficient to accurately sense small broken clouds. The model then normally interprets the scene as a large thin cloud rather than a patchwork of small thick clouds, so that the modeled irradiance varies less and at lower frequency than what terrestrial instruments would record. Such situations are frequent, so that the uncertainty in the modeled instantaneous irradiance under intermittent cloudiness is higher than under cloudless or overcast conditions.

The accuracy of the cloud detection algorithm described above is influenced by the sun-satellite geometry and by the local surface albedo. At low solar elevations, the uncertainty in the cloud index generally increases, because of complex 3D reflection effect off the sides of clouds, and parallax effects in the case of high clouds. Additionally, a high surface albedo (e.g., salt depressions or white sand in arid zones, or snow-covered areas) lowers the contrast of the signal recorded by the satellite and introduces errors in the cloud index. Use of multispectral information for cloud detection improves results [8–10]. A related problem is caused by inhomogeneous reflectance properties of the surface or increased backscattering, which often vary over time during the day. For some specific sun-satellite geometrical conditions, the signal recorded by the satellite sensor may be high due to augmented reflectance from the surface, and may be misinterpreted as a passing cloud by the model. A backscatter correction can adequately solve this issue [9].

In SolarGIS, a modified version of the Heliosat-2 calculation scheme [6] has been adopted to obtain the cloud index. The main improvements are described below:

- Higher-resolution images are used to better map local patterns of fog, clouds and snow, particularly over complex terrain;
- Four spectral bands (in the visible and infrared) are now used to better separate clouds from high-albedo surfaces;
- A multivariate and multidimensional statistical treatment of pseudo-albedo (i.e., the apparent albedo related to a specific sun-satellite-scene geometry) is adopted to improve the long-term radiometric stability of the albedo reference;
- An adaptive algorithm for the calculation of the surface's pseudo-albedo is devised to improve cloud-index calculations under rainy tropical climates;
- Bidirectional and variable reflectance patterns are considered for the surface albedo, especially in case of high-reflectance surfaces.

The fundamental difference between a satellite observation and a ground measurement is that the signal received by a satellite sensor describes the average radiance over a grid cell with a significant area (1x1 to 10x10 km), whereas a ground station records a pinpoint measurement. This fundamental difference results in a mismatch when comparing 15-min or hourly values from these two data sources, mainly during intermittent cloudy weather. It is considered that nearly half of the resulting hourly Root Mean Square Deviation (RMSD) can be attributed to this mismatch, also known as the "nugget effect" [8]. The remaining differences mainly result from a simplified quantification of the attenuation effect of complex (multilayer) cloud formations, which are very variable in physical properties, time and space. If the cloud model fails to distinguish between snow, ice and clouds (which is the case of models relying only on the use of the satellite sensor's visible channel), increased errors are unavoidable. These can be extremely large under unfavorable conditions [11].

The uncertainty in the estimated cloud index is lower in sunny regions or during situations with stable cloudiness (e.g., fog). Higher uncertainties are observed under rapidly changing and intermittent clouds, particularly over mountains, snow-covered areas, coastal zones, and regions with complex topography. All satellite models have difficulties at low sun angles (which might also be the case of ground radiometers measuring GHI), and over regions that are close to the limits of the satellite's field of view. As with other phenomena, many random-like prediction errors compensate each other by averaging over time, so that mean daily or monthly data have a much lower uncertainty (although they might still have a systematic bias).

3.2. Aerosols

Aerosols (particles of smaller size than those in clouds) are, after clouds, the second most important factor determining DNI's magnitude, and to a lesser extent, GHI's magnitude. Under clear skies, aerosols become the main source of extinction for DNI. Large errors in aerosol data are frequent and may result in DNI uncertainties in the range of 15–20% and up to 8% for GHI on a mean annual basis [12, 13]. A variable called *aerosol optical depth* (AOD) is used to characterize the overall radiative effect of aerosols. Because of fluctuations in aerosol sources and in the meteorological and chemical conditions governing their transport and evolution, aerosols have a high spatial and temporal variability in both composition and quantity. The variability in AOD is high, but its radiative effect is not as abrupt as that of the cloud index. Up to very recently, long-term monthly-average AOD data were most generally used in solar radiation modeling. A serious drawback of such an approach is that long-term averages artificially remove the natural daily fluctuations, thus resulting in skewed frequency distributions of DNI and in failure to represent extreme events (see Section 4.2).

The current version of SolarGIS makes use of a new generation of aerosol data, using operational calculations from an advanced chemical-transport model, known as GEMS/MACC [14]. An important feature of this AOD dataset is that it captures the variability of aerosols with a 6-hour resolution, thus precisely tracking aerosol plumes with large AOD, for instance. Moreover, the AOD is calculated for all grid cells at each time increment, hence guaranteeing the absence of missing data. This is a significant advantage over satellite observations, which cannot be made everywhere or all the time. A daily AOD input to the SolarGIS radiative model reduces the uncertainty in instantaneous estimates of GHI and especially DNI, and thus yields improved statistical distributions of irradiance values. It has been shown that the current GEMS/MACC data correctly represent the magnitude of the aerosol variability over both time and space [15], even though some bias has been identified in regions with high aerosol loads. The reported issues will be dealt with in the next version (MACC2) of the aerosol chemical-transport model. At present, the daily GEMS/MACC AOD data exist only since 2003. SolarGIS still uses monthly long-term averages for older periods. The spatial resolution of the GEMS/MACC data is 1.15 arc-degree (≈125 km at the equator). A higher spatial resolution would be desirable, of course. Another important improvement would be the additional determination of the Ångström exponent, which would allow better evaluations of DNI, in particular.

3.3. Water vapor and ozone

Like aerosols, water vapor is highly variable over space and time. It typically induces uncertainties in the range of 3–5% for DNI or GHI. Monthly values (based on, e.g., the NVAP database) were traditionally used, although daily values are now available as well, from, e.g., reanalysis data. The daily GFS and CFSR values (from NOAA) are used in SolarGIS, thus representing the daily variability in water vapor since 1994, with a 30-km spatial resolution.

Ozone has only a small impact on broadband DNI [1], and thus a climatological value is sufficient to obtain correct monthly-average DNI and GHI. For added accuracy, daily data from TOMS/OMI or GOME could be used. This is contemplated in future versions of SolarGIS.

3.4. Spatial resolution and terrain

The database's spatial resolution determines its ability to deal with microclimate and terrain features. For plain regions, the spatial resolution of satellite imagery (most typically ≈3–5 km) usually provides good results. In general, therefore, the use of high-resolution satellite data (≈1 km)—such as from HRV on-board Meteosat MSG—cannot be justified, since it would result in only a slightly lower RMSE in modeled results, while imposing substantially higher costs and other technical problems, e.g., processing high volumes of data for positional accuracy or dealing with more intense reflections from cloud edges. Conversely, a high-resolution DEM is critical for the proper vertical scaling of atmospheric parameters, and for accurate modeling of horizon shading over complex terrain. High-performance disaggregation algorithms (e.g., [4]) evaluate the effect of shading on both the direct and diffuse components. It is thus possible to obtain realistic high-resolution maps or time series. In SolarGIS, the SRTM-3 DEM is implemented with the above-mentioned advanced algorithm [4] and a primary spatial resolution of 3 arc-seconds (about 90 m at the equator). Over complex terrain and mountains, the use of such high-resolution elevation data results in better irradiance predictions. For example, under moderate aerosol load conditions (such as those found in Europe), DNI typically varies by 0.7–1.2% for an elevation differential of 100 m.

4. Accuracy, interannual variability and geographical aspects

4.1. Bias and RMSD statistics

Bias between the predicted and measured irradiance, as summarized by the mean bias difference (MBD) statistics, may result from systematic features in the radiative model (e.g., drawbacks in the clear-sky part of the model under extreme aerosol situations, or failure to differentiate clouds from high-albedo surfaces). Other common sources of bias are regional inconsistencies embedded in the input data (mostly aerosols or water vapor). Well-tuned solar radiation models produce a small bias under any climatic condition, typically within ±3% for GHI and ±7% for DNI on an annual basis.

DNI derived from current satellite-based radiative models is only marginally sensitive to imperfections in the clear-sky model, if it is well chosen. DNI is rather primarily sensitive to inaccuracies in the input data. For any particular site, a bias of about ±9% is still considered a good result. Under adverse conditions (e.g., high aerosols around the Sahara), it may increase to ±15% or more on an annual basis [13]. If a larger bias is observed at a particular site where experimental DNI measurements are available, this may indicate:

- Inconsistencies in the measured data, such as miscalibration or lack of cleaning of the instruments;
- Local issues (complex terrain, costal zone, mountains, urban area with high local pollution) that are not well represented in the low-resolution atmospheric data;
- Issues with high-albedo surfaces that are sporadically or regularly misinterpreted as clouds.

In contrast, the long-term bias is normally less affected due to error cancelations over time, except over some regions (e.g., around the Sahara), due to large potential errors in current AOD datasets [13]. When short-term high-quality ground DNI and GHI measurements are available, the long-term bias in satellite-based DNI and GHI irradiance time series can be reduced a posteriori by correlating them together [12]. Correcting the satellite-derived data by using on-site measurements can reduce the overall model bias to the level of uncertainty in the available DNI measurements, which may be as low as ±2% for well-maintained instruments.

The root mean square difference (RMSD) is a statistical measure of the random-like differences in pairs of individual observed and modeled data points. Typical sources of mismatch between them are as follows:

- Ground (pinpoint) observations are compared to area-averaged values derived from satellite cloud data (3–5 km) and atmospheric data (100–200 km);
- Poor time and/or spatial description of the local variability in atmospheric or cloud data;
- Inability of the cloud index to exactly quantify the transmittance of certain types of clouds (high cirrus clouds, complex structures, multiple layers, intereflections, etc.);
- Experimental errors, such as inadvertent shading or malfunction.

The achievable RMSD for hourly DNI predictions is typically in the range 16–30%, but larger errors (up to 45%) can be encountered, essentially for the same reasons as discussed above for the bias.

4.2. Frequency distribution statistics

All older satellite-derived databases that use long-term monthly-average AOD data have difficulties with the DNI frequency distribution, since extreme aerosol conditions (and thus DNI values) are incorrectly smoothed out. For instance, these databases may show a maximum DNI frequency at ≈800 W/m^2, while occurrences of very clear conditions with DNI over 900 W/m^2 may be missing (Fig. 1). This issue has a large impact on energy simulations. Using daily AOD data significantly improves the dynamics of the predicted DNI [16].

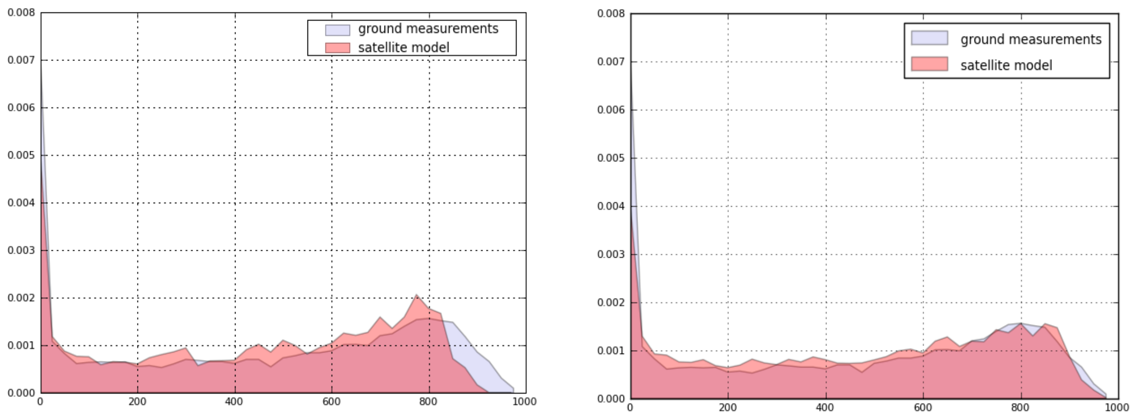

Fig. 1. Frequency distributions of hourly DNI (W/m^2) for Valladolid (Spain). Left: results based on long-term monthly averages of AOD and water vapor. Right: results based on daily values.

4.3. Interannual variability

Solar radiation changes over long time periods because of global climate cycles and various weather factors. Some interannual variability is inherent to any solar radiation data series, and is a reason why a single year of measured or modeled data cannot adequately represent the local solar radiation climate. Ideally, 30 years of data would be necessary to represent the interannual climate variability. Data from the 1980s and 1990s include episodes of large volcanic eruptions that significantly affected DNI [17], but unfortunately modeled DNI datasets at high resolution are rarely available for that period.

The uncertainty in irradiance variability tends to decrease when a longer dataset is considered. For GHI, this uncertainty is 2–4% over 10 years of data, and only 2% for a 20-year dataset [18]. Based on existing studies [11, 17, 19], it is expected that the magnitude of the DNI variability be at least twice as much at any site. These figures do not consider the larger anomalies due to extreme volcanic eruptions, however.

Figure 2 shows how the interannual variability in DNI may differ regionally. It is calculated here for six locations in India over the period 2003–2010 (during which daily aerosol data were used by SolarGIS). For each year of that period, the variability is defined as an anomaly (in percent) relative to the "long-term" annual DNI defined here as the 2003–2010 average. The top plot refers to the all-sky DNI, whereas the bottom plot refers to the ideal clear-sky DNI. Some interesting features can be observed in Fig. 2: (i) During some years (2004 and 2005), most of the variability in all-sky DNI is a result of that in the clear-sky DNI, which means that in such cases the key factor was AOD; (ii) the anomaly can be high during some years, and can substantially differ between one year and the next (e.g., 2009 vs. 2010); (iii) the large anomalies during 2009 and 2010 appear to result from changes in cloud regime, which can be expected in such monsoon-prone areas; (iv) depending on year and location, the aerosol and cloud effects in DNI can cumulate or counteract each other; and (v) the largest changes in clear-sky DNI occur over those regions with the largest AOD [20].

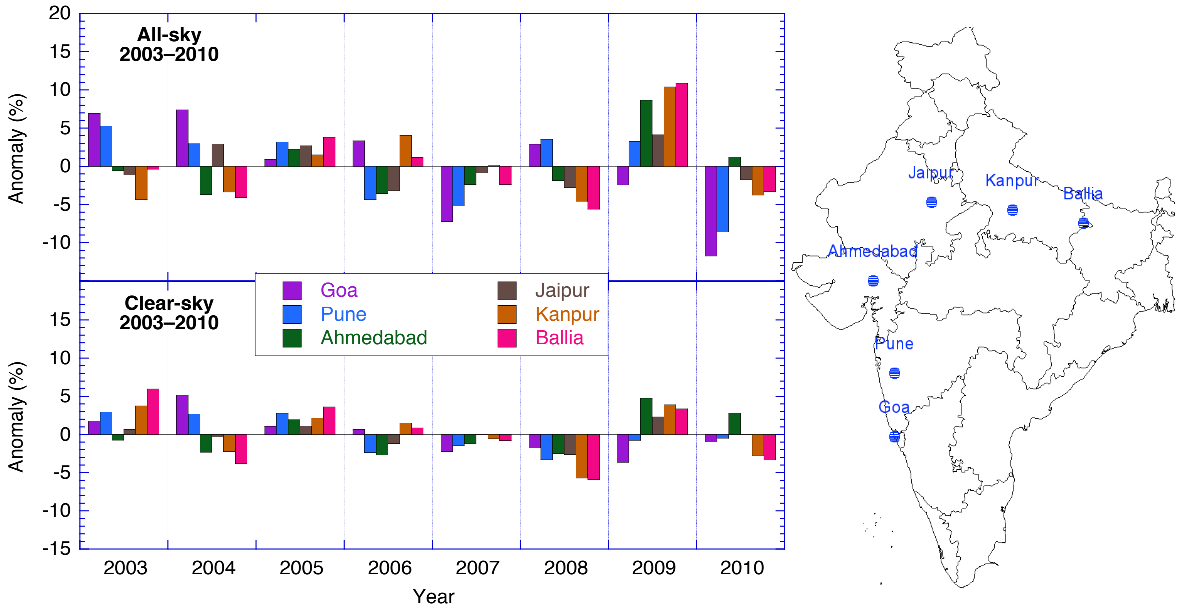

Fig. 2. Interannual variability of the all-sky DNI (top) and ideal clear-sky DNI (bottom) for six Indian locations (shown on the right plot) over the period 2003–2010.

5. Geographical aspects of irradiance uncertainty

Many factors determine the quality of satellite-derived data products. From a technical standpoint, the pre-processing of data and their preliminary cleaning have an impact on the quality of the final products:

- The positional accuracy of each satellite image has to be corrected using rectification algorithms, particularly for older satellite platforms;
- The multiyear radiometric stability of each satellite sensor has to be established using radiometric ancillary data and statistical methods. Any radiometric error in imagery must also be detected at this stage;
- Spatial interpolation between grid cells may be necessary to remove blocky features and artificial steps in the data. This is specially important in the case of atmospheric data;
- To be optimally combined with high-frequency cloud data, and to remove most artificial features in the resulting time series, lower-frequency atmospheric inputs should be time interpolated.

Geographic differences in DNI and GHI uncertainty reflect the complex interactions of individual factors, as discussed in what follows.

5.1. Equatorial and tropical regions

Over equatorial regions, the major challenge is to properly estimate the cloud index. This is because the sky is most often cloudy, with only short periods during which the background surface albedo can be evaluated. This problem can be partially solved by using multidimensional statistics.

5.2. Arid and semiarid regions

Over arid and semiarid zones, AOD determines the magnitude of DNI and (to a smaller extent) GHI. This is especially the case of regions with high aerosol loads (e.g., Sahara, North India, China, or the Persian Gulf) with high daily variability and seasonal changes. Geographic patterns of uncertainty in DNI and GHI due to AOD and its variability can be obtained with the help of the *aerosol variability index* (AVI) [17]. As discussed above, high-albedo surfaces can be easily mistaken with clouds. For SolarGIS, new algorithms have been developed to limit this effect as much as possible [9].

5.3. Temperate climates and high latitudes

At latitudes above 45°, the uncertainty in modeled irradiance is driven mainly by inaccuracies in the cloud index and cloud attenuation. The major challenge here is to correctly attribute any high radiance value retrieved from satellite imagery to either a cloud scene or a high-albedo surface. The use of multispectral satellite images, and of multivariate statistics aided by ancillary data, can substantially improve results. Normal degradation of accuracy can be expected at low sun angles. Uncertainties are thus higher during winter months. The use of high-resolution terrain data allows shading calculations (which may be high at low sun angles), hence substantially improving results over complex terrain.

5.4. Other issues

Over mountains, solar radiation is strongly driven by elevation and terrain shading. A complex topography reduces accuracy in the calculation of cloud index as well as in the proper vertical scaling of AOD and water vapor Such topography-induced effects are not well-known in general and often have local overtones, which cannot be resolved with current simple models.

Snow, ice, and fog can be differentiated from each other only by calculating snow indexes from multispectral satellite data, with help from ancillary data and historical multivariate statistics. Although significant progress has been made in the SolarGIS algorithms, snow will remain a challenging phenomenon when trying to further reduce modeling uncertainty, similarly to the case of arid high-albedo areas. When snow is present, the overall surface albedo increases as a function of snow depth, since not all surfaces are not necessarily covered. (For instance, a deciduous forest—which is leafless in winter—might look relatively dark from above until the snow cover reaches some minimum depth.) This means that an observed high radiance may be caused either by a cloud over a shallow snow cover, or by a deep snow cover under clear skies.

Over coastal areas, particularly wherever complex patterns of land, sea, and possibly mountains do exist, DNI and GHI depend on local patterns of cloud formation, and on rapid changes in sea salt concentrations in the air. Similarly, higher uncertainties can be observed over small islands, because they are often of volcanic origin, thus having steep topography and sharply carved coastal lines.

Regions with high urban or industrial pollution may differ from each other due to topography-induced variations in pollutant dispersion, rapid changes in the aerosol mixing layer, etc. It is therefore difficult to address such site-specific features with a generic algorithm.

An important determinant of the modeled irradiance uncertainty is the spatial resolution of the input parameters. For instance, the relatively coarse spatial resolution of aerosol or water vapor data prevents a detailed rendering of local small-scale patterns, particularly over complex terrain. The cloud index algorithm, choice and adaptation of the clear-sky model, treatment of input parameters, and their processing scheme, are important sources of differences in the accuracy of different modeled databases. These differences are also a function of the region for which they have been developed and (hopefully) validated. Significant differences in the predicted solar irradiance data series and their uncertainty are observed when intercomparing the irradiance predictions from various data providers, while comparing them to ground measurements too [13]. This can be easily explained by the number of algorithms and data sources involved, whose combination may result in either cancelations or multiplications of errors, at least locally. In the case of SolarGIS, Table 2 summarizes the sources of uncertainty and their relative importance throughout its computational chain. These estimates are the key components that contribute to the overall RMSD of hourly DNI values. For the hourly GHI values, the magnitude of the effects is about 2–3 times lower.

Variable	Clear sky	Scattered clouds	Cloudy/Overcast
Elevation and shading	+	+	+
Clear-sky model	++	+	+
Aerosols	++++	++	+
Water vapor	++	+	+
Cloud index	++	+++	+

Table 2. Sources of uncertainty in hourly SolarGIS radiation predictions for three different sky conditions (+ very low; ++ low; +++ moderate; ++++ high).

Similarly to Table 2, Table 3 indicates the sources and magnitude of uncertainty in GHI to consider when evaluating the potential bias (MBD) in their annual values. The magnitude of the effects of all these variables on DNI follows the pattern shown in Table 3, even though it can be several times larger than for GHI. Some entries for "Snow or ice" are marked N/A (not applicable) because they are actually considered in other columns.

Variable	Humid Tropics	Arid & semi-arid	Temperate climate	Steep terrain	Snow or ice	Coastal zones	Polluted areas
Elevation, shading	+	+	+	++	N/A	+	+
Clear-sky model	+	+	+	+	++	+	++
Aerosols	++	++++	++	+++	N/A	++	++++
Water vapor	+	+	+	++	N/A	+	+
Cloud index	+++	++	+++	++	+++	++	++

Table 3. Sources of bias in annual SolarGIS radiation predictions, considering various types of climate and terrain (+ very low; ++ low; +++ moderate; ++++ high).

6. Conclusions

Based on a detailed account of the various possible sources of uncertainty in radiation modeling, it has been shown that the main causes of uncertainty in DNI and (to a lesser extent) in GHI are related to clouds and aerosols. For sunny areas, using daily aerosol data can significantly reduce the uncertainty in DNI and improve its cumulative frequency distribution. Significant biases in DNI may be observed over regions affected by large aerosol loads.

For intermittent cloud situations, the major part of the observed random errors (as evaluated by the RMSD statistics) is driven by inadequacies in cloud-related parts of the radiative algorithms. In regions of complex topography and/or at high latitudes, the modeling accuracy is reduced and often depends on a combination of factors, such as steep terrain, high pollution, dynamic patterns of cloud formations, significant shading, low sun angles, etc.

Significant improvements have been incorporated into the latest version (1.6) of the SolarGIS algorithms, including daily aerosol data, high-resolution satellite imagery, high-resolution terrain description with a 90-m digital elevation model, shading calculations for both the direct and diffuse components, better determination of the presence of snow or ice on ground, and more detailed handling of variable or spurious ground reflectance patterns. A part of the remaining uncertainty in predicted irradiance is attributed to processes that are highly site or terrain specific, and which therefore cannot be fully described by generic models. More research would be necessary on these aspects. More importantly, improvements can still be made in the “cloud index” method to better describe complex cloud formations, side reflections, parallax effects, etc.

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