SASEC2015
Third Southern African Solar Energy Conference
11 – 13 May 2015
Kruger National Park, South Africa

ACCURACY-ENHANCED SOLAR RESOURCE MAPS OF SOUTH AFRICA

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ABSTRACT

The accuracy enhancement of two high-resolution solar maps for South Africa, Lesotho and Swaziland is based on regional adaptation of SolarGIS solar model with data measured at fourteen high-standard solar measuring stations.

SolarGIS is a global database of solar resource and meteorological parameters, developed and operated by GeoModel Solar. SolarGIS is updated daily by real-time satellite, atmospheric and meteorological data inputs. The maps show longterm yearly averages of Direct Normal Irradiation (DNI) and Global Horizontal Irradiation (GHI) with 1-km spatial resolution. They are calculated by aggregation of sub-hourly modeled time series, representing a period 1994 to 2013.

The accuracy-enhancement procedure is based on correlation of the ground measurements with the SolarGIS model. This reduced systematic deviation of the model input aerosol data, which is key factor determining the model data accuracy in Southern Africa. Ground measurements are sourced by Eskom, GeoSUN Africa, SAURAN, STERG and Ripasso Energy.

By regional adaptation of SolarGIS we achieved reduced uncertainty of the longterm estimate in the range of ±5% to ±7.5% for DNI, and ±3% to ±4% for GHI. The model now delivers more accurate high-resolution solar resource time series, which helps reducing financial risk and improving engineering quality of the solar power plants. The maps are accessible from http://www.sauran.net/. High resolution data can be accessed from http://solargis.info.

NOMENCLATURE AND ACRONYMS

CFSR	Climate Forecast System Reanalysis
GFS	Global Forecast System
MACC-II	Monitoring Atmospheric Composition and Climate
SAURAN	Southern African Universities Radiometric Network

AOD	[-]	Atmospheric Optical Depth
Bias	[W/m^2 or %]	Systematic model deviation
DNI	[kWh/m^2]	Direct Normal Irradiation
DIF	[kWh/m^2]	Diffuse Horizontal Irradiation
GHI	[kWh/m^2]	Global Horizontal Irradiation
KSI	[-]	Kolmogorov-Smirnoff Index
RMSD	[W/m^2 or %]	Root Mean Square Deviation (random deviation)

INTRODUCTION

Two principal approaches are used for monitoring solar resource: (i) calculation based on models using satellite and atmospheric data, and (ii) dedicated ground-based measuring equipment (Table 1). The fundamental difference between the modelled data and ground measurements is that while the model output is continuous in time and space (defined by the spatial resolution and sampling rate of the satellite and atmospheric data), the solar sensor mounted at a meteorological station provides pinpoint high-frequency measurements. Combination of both approaches is used for generating high quality and low uncertainty site-specific time series.

Professional monitoring assumes use of high accuracy measurements, consistent operation and maintenance of the equipment and rigorous data quality control. Low accuracy instruments and loose operation and maintenance practices deliver dubious outputs and data with high uncertainty.

Due to data inputs and algorithms, the satellite-based solar models have limited ability to accurately represent high-frequency changes of solar resource in a specific site. A natural mismatch occurs when comparing instantaneous values from the model and ground instrument, 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, which is also known as the "nugget effect" [1].

Table 1 Satellite and ground measured data – feature comparison

	Outputs from the SolarGIS satellite-based model	Ground measurements
Principle advantage	Spatial (map) data Long history	Site-specific data
Time resolution	15 and 30 minutes	Seconds to minutes
Time coverage	Up to 21+ years	Recent (rarely longer history)
Spatial resolution	3 to 7 km satellite 35 km water vapour 125 km aerosols	Less than 1 sq. centimeter
Radiometric and positional stability	High (based on preprocessing)	High (if calibrated and systematically controlled)
Continuity of measurements	High (occasional gaps are filled by inteligent algorithms)	Good (if well maintained)

Satellite images have resolution and information content that allow describing optical transmissivity of clouds only to limited extent. The coarse spatial resolution of aerosol and water vapour data does not allow capturing local patterns of the state of atmosphere. Thus limited spatial and temporal resolution of satellite and atmospheric data does not allow describing the inter-pixel variability in cases, where one pixel represents diverse natural conditions (e.g. fast changing patterns of fog, clouds, shading, land cover in mountains, urbanised areas or along the coast). Especially modelling DNI is very sensitive. The relation between uncertainty of global and direct irradiance is nonlinear: a negligible error in global irradiance may have high counterpart in direct irradiance.

SATELLITE-BASED MODEL

In this study, time series from global solar radiation model SolarGIS are used [2, 3, 4]. SolarGIS includes models parameterizing atmospheric conditions and transmissivity by clouds. Sequentially, other models calculate solar irradiance components, deal with their transposition and terrain effects.

Simplified SOLIS atmospheric model [5] calculates clear-sky irradiance (i.e. irradiance without considering clouds) from three parameters that determine geographical and temporal variability of atmospheric conditions:

- Aerosols, represented by Atmospheric Optical Depth (AOD). In SolarGIS, AOD is derived from the global database MACC-II [6, 7]. The model uses daily aerosols to simulate the instantaneous DNI and GHI. Compared to approaches based using only monthly-averaged AOD, daily values reduce uncertainty, especially in regions with high and variable aerosol concentrations [8, 9].
- Water vapour is also highly variable, though it has lower impact on variability and reduction of DNI and GHI. Daily data are derived from CFSR and GFS databases for the whole historical period up to the present time [10, 11].
- Ozone has negligible influence on broadband solar radiation and it is considered by the model as a constant.

The SolarGIS cloud model estimates cloud attenuation of global horizontal irradiance. Data from the meteorological geostationary satellites are used to calculate a cloud index that relates radiance of the Earth's surface, recorded by the satellite in several spectral channels with an effect of optical attenuation by clouds. For Europe, Africa and Middle East, Meteosat satellite data are used [12]. Conceptually, the model is based on the modified Heliosat-2 calculation scheme [13], however it has a number of improvements dealing with identification of albedo, presence of snow, fog, ice, especially in tropical zone, high latitudes and in a complex terrain. Other support data are also used in the model, e.g. altitude and air temperature.

To calculate Global Horizontal Irradiance (GHI) for all atmospheric and cloud conditions, the clear-sky global horizontal irradiance is coupled with cloud index. From GHI, other solar irradiance components (direct, diffuse and reflected) are derived. Direct Normal Irradiance (DNI) is calculated by modified Dirindex model [14]. Model for simulation of terrain effects (elevation and shading) based on high resolution altitude and horizon data. Model by Ruiz Arias is used [15] to achieve enhanced spatial representation: the information based on the satellite resolution (3 to 4 km) is disaggregated to the resolution of 1 km in this project.

GROUND MEASUREMENTS

Solar measurements from fourteen meteorological sites were used for reducing the uncertainty of the SolarGIS model (Table 2). The measurement campaign has been conducted by four subjects: GeoSUN Africa, STERG, SAURAN and Eskom.

Table 2 Ground based measurements available for regional adaptation

ID	Site name	Latitude, Longitude	Altitude [m a.s.l.]
1	Aggeneys	-29° 17' 40", 18° 48' 56"	791
2	Bloemfontein	-29° 06' 39", 26° 11' 06"	1491
3	Durban	-29° 52' 16", 30° 58' 37"	150
4	Graaff-Reinet	-32° 29' 08", 24° 35' 09"	660
5	Helios	-30° 30' 04", 19° 33' 38"	905
6	Lephalale	-23° 35' 53", 27° 34' 11"	886
7	Port Elizabeth	-34° 00' 31", 25° 39' 55"	35
8	Pretoria	-25° 45' 11", 28° 13' 43"	1410
9	Sasolburg	-26° 46' 40", 27° 50' 14"	1468
10	Sonbesie	-33° 55' 41", 18° 51' 54"	144
11	Sutherland	-32° 13' 19", 20° 20' 52"	1318
12	Upington	-28° 30' 19", 21° 10' 07"	810
13	Vanrhynsdorp	-31° 37' 03", 18° 44' 18"	130
14	Vryheid	-27° 49' 41", 30° 30' 00"	1274

At all stations 1- and 5- minute GHI and DNI data are measured by secondary standard pyranometers and first class pyrheliometers mounted on a tracker. The measuremetns relate to years 2013 and 2014 or earlier, and at least 12 months of measurements were available at every station.

Prior to correlation with satellite-based time series, the ground-measured irradiance was quality-controlled by GeoModel Solar. Quality control (QC) was based on methods defined by SERI QC procedures, Younes et al. [16, 17] and also the in-house tests were used. The measurements were inspected also visually, mainly for identification of shading and other data error patterns. The most typical errors identified in the data are: missing values, morning or evening shading and short periods of inconsistency between the solar components. The data values with identified issues are flagged and excluded from the regional adaptation of the SolarGIS model.

REGIONAL ADAPTATION

By regional adaptation we aim to reduce bias (systematic deviation), RMSD (random deviation) and KSI (difference between frequency distributions of the measured and satellite data). The comparison of raw SolarGIS data with ground measurements shows good fit for various weather situations: cloudy and cloudless skies as well as for intermittent cloudiness. Bias showing systematic underestimation or overestimation of the daily profiles of cloudless conditions indicates that correction is needed in the clear-sky atmospheric model, especially in the aerosol data input. Other source of systematic deviation comes from the cloud model, however it has lower impact on the model results. Therefore we focused on accuracy improvement of Aerosol Optical Depth (AOD) derived from the MACC–II aerosol database. The method was conducted in two steps:

- Determination of AOD correction coefficients for individual ground stations in order to reduce the systematic deviation of the modelled data compared to ground measurements.
- Adaptation of AOD based on site-specific correction coefficients was extended from individual sites to the whole territory of South Africa by spatial interpolation.

Reduction of systematic deviation at meteorological stations

The satellite data is available in 15- and 30-minute time step; ground-measured data are available in different time steps. To reduce the conceptual difference of point and satellite pixel measurements, all the measures are calculated using aggregated data in hourly time step.

Deviations between original model data and ground measurements were analysed for each site with focus on:

- Deviation for the whole period of available measurements seen as a systematic feature and as seasonal patterns;
- Deviation patterns for various weather situations, especially for cloudless sky;
- Differences in the cumulative distribution of hourly values between the modelled and measured data.

The monthly AOD correction factors are calculated from comparison of measured and modelled data for cloudless sky [18]. The correction factors were harmonized to achieve smooth month-by-month changes; in this phase, the neighbouring sites are also compared in a spatial context. Next, the satellite-based model was recalculated with correction factors and validated. Larger residuals are removed in the second iteration of this procedure. Even if bias was minimized, some mismatch between the measured and modelled data is still present, mainly in the frequency distribution of values.

For each site the adaptation procedure results in a set of monthly correction factors, which respect seasonal and spatial context of the data. The aerosol adaptation method removed major source of discrepancies between satellite data and ground measurements. Important benefit of this approach is that it maintains the consistency of GHI, DNI and DIF components.

Spatial interpolation of correction coefficients

The objective of the second step was to extend the correction factors, identified at individual sites, to the territory of South Africa. A complex interpolation technique, incorporating orographic barriers, was used. The algorithm assumes that spatial distribution of aerosols is controlled by air mass movement influenced by orography (digital terrain model). The correction factors were interpolated separately for each month. Finally, aerosol correction layers were used for regional re-calibration of the AOD input and recalculation of the 20 years data for the territory of South Africa.

RESULTS AND VALIDATION

The regional-adaptation of the SolarGIS model removed large part of systematic mismatch between the satellite-based data and ground measurements.

Table 3 Direct Normal Irradiance: bias and KSI before and after regional model adaptation

Meteo station	Original DNI		After regional adaptation	
	Bias [%]	KSI [-]	Bias [%]	KSI [-]
Aggeneys	-4.9	203	0.3	99
Bloemfontein	-5.2	120	-0.1	43
Durban	-9.7	187	-0.4	80
Helios	-4.9	270	0.6	167
Lephalale	-2.4	119	0.0	77
Port Elizabeth	-2.0	75	1.8	64
Pretoria	0.0	51	0.2	48
Sasolburg	-0.8	77	-0.2	70
Stellenbosch	-4.2	292	0.5	196
Sutherland	-2.8	91	0.3	59
Upington	-9.2	302	-0.7	89
Vryheid	1.3	88	0.4	89
Vanrhynsdorp	-4.6	162	-0.1	114
Graaff-Reinet	-5.5	131	0.1	79
Mean	-3.9	155	0.2	91
St. deviation	3.1		0.6	

In semi-arid and desert conditions, the clouds have lower importance and it is mainly AOD, which determines the mismatch between ground-measured and satellite data. Therefore more accurate results (reduction of bias, RMSD and KSI) were achieved by adaptive adjustment of the AOD values.

Table 4 Global Horizontal Irradiance: bias and KSI before and after regional model adaptation

Meteo station	Original GHI		After regional adaptation	
	Bias [%]	KSI [-]	Bias [%]	KSI [-]
Aggeneys	-2.1	50	-1.3	38
Bloemfontein	-1.6	26	-0.7	14
Durban	-3.3	70	-1.7	54
Helios	-2.1	52	-1.3	43
Lephalale	0.6	22	0.9	24
Port Elizabeth	-2.3	21	-1.7	17
Pretoria	1.1	20	1.1	21
Sasolburg	4.3	76	4.4	78
Stellenbosch	-1.2	49	-0.6	36
Sutherland	-2.5	44	-2.1	37
Upington	-1.6	38	-0.4	22
Vryheid	0.7	13	0.5	13
Vanrhynsdorp	-0.8	23	-0.1	19
Graaff-Reinet	-0.3	11	0.5	11
Mean	-0.8	37	-0.2	31
St. deviation	2.0		1.7	

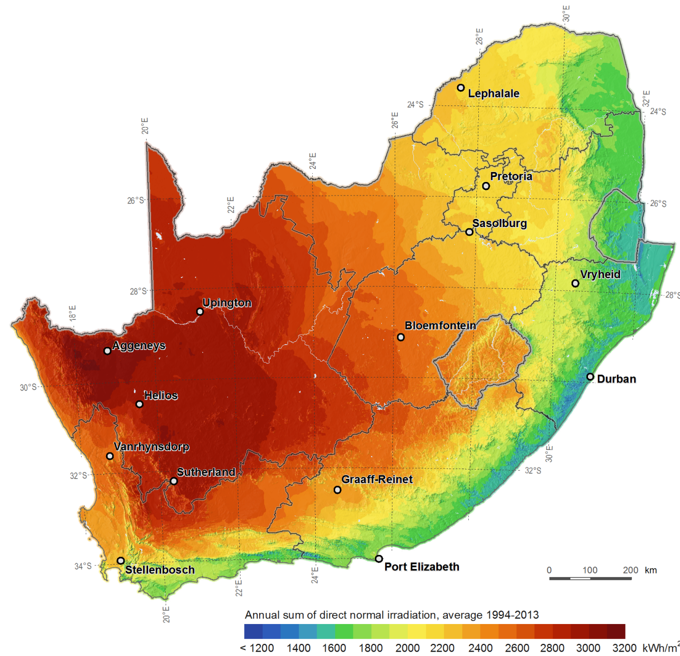

Figure 2 Accuracy enhanced DNI map

At the level of individual sites, mean bias of site-adapted values from the ground measurement is close to zero (typically within ±1% for DNI, and ±2% for GHI), which corresponds to the expected uncertainty of the measuring instruments (Tabs. 3 and 4). RMSD and KSI parameters are also reduced (due to limited space, RMSD is not shown in this paper). The only exception from this trend is found in Sasolburg meteo station, where GHI deviation exceeds the expected uncertainty. This is probably an effect of residual measurement errors that were not identified in data quality control.

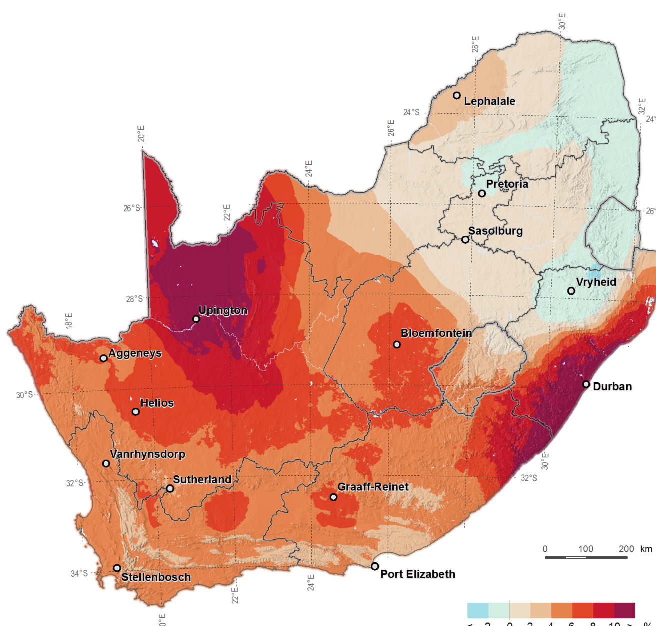

Figure 1 Map of differences between original and adapted DNI

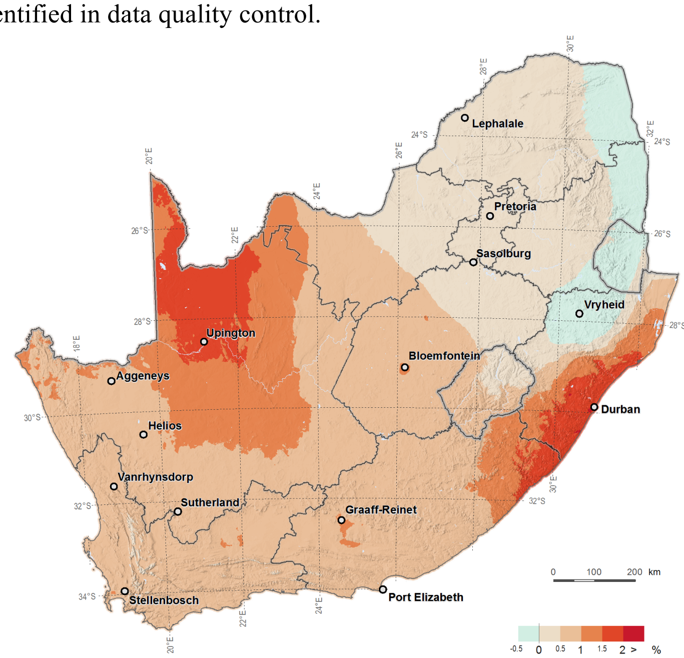

Figure 3 Map of differences between original and adapted GHI

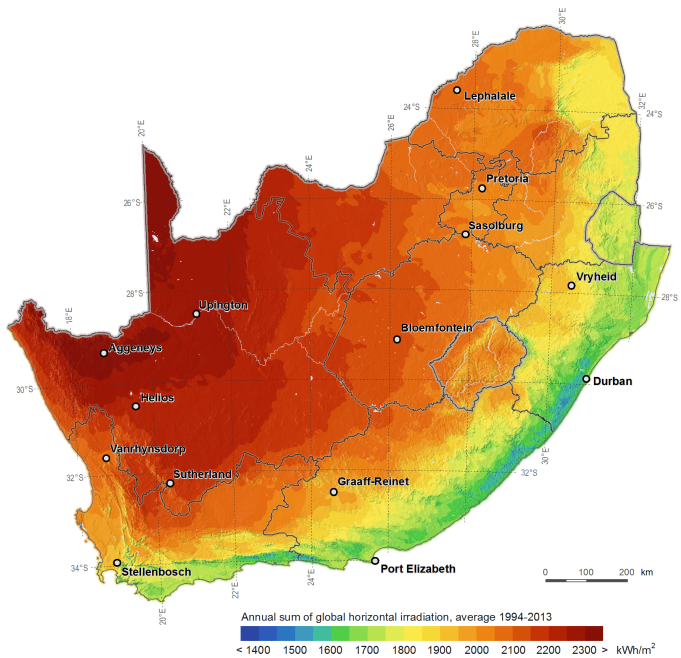

Figure 4 Accuracy enhanced GHI map

After regional adaptation of the model was validated, the model was recalculated and full time series representing a period of 1994 to 2013 were aggregated into longterm DNI and GHI yearly averages (Figs. 1 to 4). Adaptation of the model helped reducing systematic and also random deviations at all sites. The maps of correction effect on GHI and DNI shows difference between regionally adapted and original data.

UNCERTAINTY OF SOLAR RESOURCE MAPS

SolarGIS model shows robust and uniform behaviour in South Africa, which is consistent with our experience worldwide [4, 19]. Validation shows bias and RMSD within expected range of values. Due to higher computational complexity, bias for DNI is approximately two times higher compared to GHI.

For practical use, the statistical measures of accuracy are converted into uncertainty, which better characterizes probabilistic nature of possible errors. Uncertainty is based on the assumption of normal distribution of solar radiation values, which has to be considered as simplification given by limited availability of data and current knowledge.

Typically, the best estimate of GHI and DNI longterm yearly average is required, often denoted as P50 value (in case of normal distribution equivalent to median). Besides P50, project developers, technical consultants and finance industry inquire about uncertainty of longterm estimates [20]. P90 values are calculated where the uncertainty is calculated for 80% probability of occurrence, thus P90 value indicates an estimate at 90% probability of exceedance. Often other probabilities of exceedance also are requested (e.g. P75, P95).

The user's uncertainty $Uncert_{user}$ in this study, denoted also as *combined uncertainty*, is calculated from the uncertainty of the SolarGIS model estimate $Uncert_{model}$, the uncertainty of the ground measurements $Uncert_{meas}$ and from the interannual weather variability $Uncert_{var}$:

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

Uncertainty of the model and measurements

The accuracy of SolarGIS model is mainly determined by parameterization of the atmosphere (especially the qualitative and quantitative properties of aerosols) and by cloud model. The uncertainty of regionally adapted satellite-based DNI and GHI is determined by:

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 aerosols and GFS/CFSR water vapour
   - Solis clear-sky model and its capability to properly characterize different state of the atmosphere
   - Simulation accuracy of the SolarGIS cloud transmittance algorithms, being able to properly distinguish different state of various surface types, albedo, clouds and fog
   - Diffuse and direct decomposition
   - Terrain shading and disaggregation 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.

SolarGIS model is compared to the high-quality measurements. All measuring stations are equipped with high-quality sensors, and in general the accuracy of measured data passing quality control is good. In this study we estimate SolarGIS model uncertainty $Uncert_{model}$ relative to the measurements from high-standard instruments. Estimate of the yearly uncertainty of ground measurements ($Uncert_{meas}$) is a bit subjective. According to [21], for carefully maintained instruments, the yearly uncertainty of 1% for first class pyrheliometers and 2% for secondary standard pyranometers can be achieved. Although, it is known [22] that the uncertainty of instruments can be higher in challenging operating conditions. Most of analyzed ground-measurements in South Africa, after quality control, are of good quality and their uncertainty is included in the estimate of the model uncertainty.

The uncertainty of SolarGIS model before and after regional adaptation is shown in Tab. 5, and its geographic distribution is discussed in Tab. 6. For comparison, **best achievable uncertainty of the satellite-based longterm estimates** is approximately 2.5% for GHI and 3.5% for DNI (assuming uncertainty at P90). This level of uncertainty can be achieved if the following conditions are met:

- Best available solar 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.

Table 5 Uncertainty of the **SolarGIS model estimate** for annual GHI and DNI – original values, and after adaptation. As a reference, the best-achievable values are shown for site-adapted satellite data.

DNI	Lower	Higher	Very high
Original data	8.0	9.5	11.0
After adaptation	5.0	5.8	7.4
Best-achievable	*3.5*	-	-
GHI	Lower	Higher	Very high
Original data	3.5	4.0	5.0
After adaptation	3.0	3.5	4.0
Best-achievable	*2.5*	-	-

Table 6 Geographic distribution of the model uncertainty

Uncertainty of DNI and GHI	
Lower	Approximately 80% of country
Higher	Coastal zone. Regions with higher occurrence and variability of clouds and fogs. Urban and industrial areas. Fast changing terrain and landscape (land cover). For DNI, higher variability of aerosols triggers higher uncertainty.
Extreme	Large urban and industrial areas, high mountains and complex geographies

Uncertainty due to weather variability

Weather changes in cycles and has also stochastic nature. Therefore annual solar radiation in each year can deviate from the long-term average in the range of few percent. The uncertainty of DNI and GHI prediction is highest if only one single year is considered, but when averaged for a longer period, weather oscillations even out and approximate to the long-term average.

The range of values, assuming possible variation for any single year in South Africa is between ±2.9% and ±9.9% for DNI and ±1.3% to ±5.9% for GHI. The uncertainty due to weather variability decreases over the time with square root of the number of years, thus assuming data covering 20 years, the range of uncertainty is reduced in the range between 0.7% and ±2.2% for DNI and ±0.3% and ±1.3% for GHI.

This analysis is based on the data representing a history of year 1994 to 2013, and on the expert extrapolation of the related weather variability. The assumptions may not reflect possible man-induced climate change or occurrence of extreme events such as large volcano eruptions in the future [23, 24].

Combined uncertainty

The combined (user's) uncertainty of the yearly DNI and GHI values is quantified, considering P90 case. Two components of uncertainty have to be considered: (i) uncertainty of the model estimate in relation to high accuracy meteorological instruments and (ii) interannual variability due to changing weather.

The two above-mentioned uncertainties combine in the conservative expectation of the minimum GHI, and DNI for N years (Tab. 7). Assuming a simplified case of normal distribution of the annual values, probability of exceedance can be calculated at different confidence levels.

Table 7 Combined user's uncertainty for annual GHI and DNI in South Africa, assuming 20 years of data – original values and after adaptation. As a reference, the best-achievable values are shown for site-adapted satellite data.

DNI	Lower	Higher	Very high
Original data	8.0	10.0	11.5
After adaptation	5.0	6.0	7.5
Best-achievable	*3.5*	-	-
GHI	Lower	Higher	Very high
Original data	3.5	4.0	5.0
After adaptation	3.0	3.5	4.0
Best-achievable	*2.5*	-	-

CONCLUSIONS

This work reduced uncertainty of longterm DNI and GHI solar resource maps for South Africa, Lesotho and Swaziland.

It is a result of systematic development and maintenance of solar measuring network of ground-based high-standard equipment and systematic work on implementation of the best practices in operation and maintenance of solar equipment. Well-linked to this infrastructure is satellite-based solar radiation model SolarGIS, which has proven quality of map based outputs as well as site-specific data products.

The typical uncertainty of the SolarGIS model estimate has been reduced from the 8% to 9.5% range for the original DNI yearly values to the range 5% to 6% for accuracy enhanced values. For GHI the reduction is seen from the range 3.5% to 4% for original values to 3% to 3.5% for accuracy enhanced values. Thus, regional adaptation helped to reduce average systematic bias by more than 3% for DNI and by about 1% for GHI.

Besides reducing systematic deviation (bias), the regional model adaptation results also in significant improvement in other data quality indicators: reducing random deviation (measurable by Root Mean Square Deviation) and improving probability distribution of hourly values (measureable by Kolmogorov-Smirnoff Index). Higher-quality DNI and GHI improve accuracy of energy simulation and financial predictions.

There is still a room for reduction of uncertainty in the range of 1.5 to 2.5% for DNI and 1 to1.5% for GHI, and this can be achieved at a local level by use of high accuracy ground measured data for site-specific adaptation of SolarGIS multiyear time series.

Deployment of a number of measuring stations enables to maintain control over quality of satellite-based estimates, as well as they help to improve understanding of the dynamics of solar resource in regions of South Africa as a country with very divers climate and geography. Even though regional adaptation reduced uncertainty, it is still important to maintain in operation solar measuring stations:

- For new sites, relevant to any larger solar power project, it is important to operate a measuring station to reduce uncertainty to a achievable minimum of site-specific longterm model estimates;
- For existing sites, measuring 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 plant

Keeping solar measuring stations is of strategic importance to maintain quality of satellite models and of solar power forecast systems.

ACKNOWLEDGEMENT

We would like to thank the following organisations:

- The German Government, through their agency the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), which made funding available.
- The companies Eskom, Sasol, Exxaro and Ripasso for providing access to their solar measurements
- The universities who are participating on the Southern African Universities Radiometric Network (SAURAN) for supply of data and support.

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