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Energy Sector Management Assistance Program

SOLAR RESOURCE AND PV POTENTIAL OF ZAMBIA

SOLAR MODEL VALIDATION REPORT

April 2019

This report was prepared by Solargis, under contract to the World Bank.

It is one of several outputs from the solar resource mapping component of the activity "Capacity Building for Renewable Energy Resource Mapping and Grid Integration in Zambia" [Project ID: P145271]. This activity is funded and supported by the Energy Sector Management Assistance Program (ESMAP), a multi-donor trust fund administered by the World Bank, under a global initiative on Renewable Energy Resource Mapping. Further details on the initiative can be obtained from the ESMAP website.

The content of this document is the sole responsibility of the consultant authors. Any improved or validated solar resource data will be incorporated into the Global Solar Atlas.

Attribution

Please cite the work as follows: World Bank. 2019. Solar resource and PV potential of Zambia: Solar Model Validation Report. Washington, DC: World Bank.

Solar Model Validation Report

Regional adaptation of Solargis model based on data acquired in 24-months solar measurement campaign

Republic of Zambia

No. 128-08/2019

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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 (MFG and MSG)	Meteosat satellite operated by EUMETSAT organization. MSG: Meteosat Second Generation; MFG: Meteosat First Generation

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: $$RMSD = \sqrt{\frac{\sum_{k=1}^{n}\left(X^{k}{}_{measured} - X^{k}_{modeled}\right)^{2}}{n}}$$ 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. 3.3 x 4.0 km for MSG 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 are 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 Zambia based on the ground measurements collected at six solar meteorological stations across the country. The accuracy-enhanced solar model makes it possible to calculate time series for any location with lower uncertainty. This effort results in more accurate solar resource and meteorological data, used in solar energy yield calculation and financial evaluation of a solar project to be developed in the region. The major benefit is higher confidence and lower costs of solar projects development.

The solar meteorological stations were installed and operated by GeoSUN Africa (South Africa) in collaboration with SGS Zambia. The stations are located within the premises of Zambia Meteorological Department (ZMD), Zambia Agriculture Research Institute (ZARI) and School of Agricultural Sciences at University of Zambia (UNZA) over years 2015 to 2017. The project was funded by the World Bank.

The output of the model calculation are aggregated data layers, in the data format that is compatible with Geographical Information Systems (GIS). The data represent long-term yearly and monthly averages of Direct Normal Irradiation (DNI) and Global Horizontal Irradiation (GHI), and they cover a period of the 24 years, from 1994 to 2017. The data is calculated by aggregation of sub-hourly map-based time series calculated for the territory of Zambia with 1-km spatial resolution. Additionally, printable maps are available in the 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 six high-accuracy standard solar meteorological stations located in Zambia. The measurements helped to reduce systematic deviation of the data inputs to the Solargis model as driving factors of the uncertainty in the region. Individual improvements of the Solargis model at the stations in Zambia are shown in the table below. As a result of the Solargis model adaptation, the calculated GHI and DNI data are available with reduced uncertainty.

Table 0.1: Position of solar measuring stations in Zambia

Site location	Nearest town	Latitude [°]	Longitude [°]	Elevation [metres a.s.l]	Measurement station host
Lusaka UNZA	Lusaka	-15.39463°	28.33722°	1263	UNZA
Mount Makulu	Chilanga	-15.54830°	28.24817°	1227	ZARI/ZMD
Mochipapa	Choma	-16.83828°	27.07046°	1282	ZARI/ZMD
Longe	Kaoma	-14.83900°	24.93100°	1169	ZARI
Misamfu	Kasama	-10.17165°	31.22558°	1380	ZARI/ZMD
Mutanda	Mutanda	-12.42300°	26.21500°	1316	ZARI/ZMD

Table 0.2: Model output changes, due to regional adaptation, at the solar measuring stations

Site	DNI original	DNI adapted	Difference to original	GHI original	GHI adapted	Difference to original
	[kWh/m²]	[kWh/m²]	[%]	[kWh/m²]	[kWh/m²]	[%]
Lusaka UNZA	2010	1870	-7.0	2113	2005	-5.1
Mount Makulu	2005	1849	-7.8	2106	1984	-5.8
Mochipapa	2108	1954	-7.3	2131	2019	-5.3
Longe	2096	1978	-5.6	2187	2069	-5.4
Misamfu	1915	1734	-9.5	2165	2024	-6.5
Mutanda	1896	1746	-7.9	2135	1991	-6.7

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

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

	Direct Normal Irradiation DNI		Global Horizontal Irradiation GHI		Global Tilted Irradiation GTI (fixed at optimum tilt)	
	Low	Medium	Low	Medium	Low	Medium
Original data	< ±9.0%	< ±13%	< ±6.5%	< ±8.0%	< ±7.0%	< ±9.0%
After adaptation	±5% to ±7%	< ±10%	±4% to ±5%	< ±6%	±4.5% to ±5.5%	< ±7%
Best-achievable*	±3.5%	-	±2.5%	-	±3.0%	

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

The accuracy-enhanced solar model makes it possible to calculate more accurate time series and derived data products. This project reduced substantially the uncertainty of primary solar parameters that are key inputs in calculation of solar electricity yield and financial prediction. Thus, results of this project increase confidence in the evaluation of technical design and performance of any solar power plant in the region, and it also increases reliability of financial estimates.

1 Overview of regionally adapted data layers

Solargis is a high-resolution global database which includes solar resource and meteorological parameters, important for development and operation of solar power plants. The regionally adapted solar model provides more accurate and reliable primary solar parameters for Zambia: Global Horizontal Irradiation (GHI) and Direct Normal Irradiation (DNI). This results in a reduced uncertainty of derived solar parameters, such as Diffuse horizontal Irradiation (DIF), Global Tilted Irradiation (GTI) and subsequently also Photovoltaic power potential (PVOUT), see Table 1.1. Lower uncertainty reduces financial risk and improves engineering quality of the design of solar power systems. For a project-specific site, the uncertainty can be further reduced by the model site adaptation and the use of local measurements.

This stage of the project delivers:

- Validated Solargis models for the region
- Historical aggregated solar data represents the last 24 years (1994 to 2017) and it is available at high spatial and temporal resolution.
- Harmonized and accuracy-enhanced solar resource data for Zambia: yearly and monthly long-term averages of GHI and DNI
- The accuracy enhanced model has been developed for the region. Compared to its original version, it can calculate time series data for any location at lower uncertainty.

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/m^2/year kWh/m^2/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/m^2/year kWh/m^2/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/m^2/year kWh/m^2/day	*Complementary parameter to GHI and DNI*	*Long-term yearly and monthly average of daily totals*
GTI	*Global Irradiation at optimum tilt*	kWh/m^2/year kWh/m^2/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

Table 1.1 describes 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.

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 1994 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 Zambia

Inputs into the Solargis model	Source of input data	Time representation	Original time step	Approx. grid resolution
Cloud index	Meteosat MFG and MSG satellites (EUMETSAT)	1994 to 2004 2005 to date	30 minutes 15 minutes	2.8 x 3.3 km 3.3 x 4.0 km
Atmospheric optical depth (aerosols)*	MACC/CAMS* (ECMWF) MERRA-2 (NASA)	2003 to date 1994 to 2002	3 hours 1 hour	75 km and 125 km 50 km
Water vapour	CFSR/GFS (NOAA)	1994 to date	1 hour	35 and 55 km
Elevation and horizon	SRTM-3 (SRTM)	-	-	250 m
Solargis primary data outputs (GHI and DNI)	**-**	**1994 to date**	**15 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 a 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 geographical conditions vary (e.g. along the coast, near mountains). 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 higher bias of the satellite GHI and DNI due to an imperfect description of aerosol load, as well as identification of local specific cloud properties from satellite data. 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 Zambia, the measurements are available for a period of 24+ months.
2. For regional-adaptation, the sites should be distributed over the whole territory, to provide information for the major climatic regions. For Zambia, six sites are selected to represent geography of the entire country.
3. High quality satellite data must be used, with consistent quality over the whole period of data. Solargis model fulfils this condition.
4. Systematic difference should be 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 during occasional events, such as extreme storms. The episodically occurring differences may mislead the results of adaptation, especially if a 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 GHI or 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 solar irradiance values.

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

3 Ground measurements in Zambia

3.1 Solar meteorological stations: specifications and data

Data from the measuring stations in Zambia 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 six meteorological stations were available for this assessment (Tables 3.1 and 3.2, Figure 3.1). Position and detailed information about the measurement sites is also available in the Global Solar Atlas website: https://globalsolaratlas.info/?c=-13.025966,28.19087,6&s=-13.795406,29.531537&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 Zambia

Project name	Solar Resource Mapping in Zambia
Project ID	P145271
Project framework	Energy Sector Management Assistance Program (ESMAP)
Project leader	Solargis s.r.o.
Data measurement points	6 stations (1x TIER 1 and 5x TIER 2)
Measurement service provider	GeoSUN Africa, assisted by SGS Zambia
Maintenance service provider	Zambia Meteorological Department/ Zambia agriculture Research Institute and School of Agricultural Sciences at University of Zambia (trained by GeoSUN Africa)

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

No.	Site name	Latitude [°]	Longitude [°]	Altitude [m a.s.l.]	Measurement station host
1	Lusaka UNZA	-15.39463°	28.33722°	1263	UNZA
2	Mount Makulu	-15.54830°	28.24817°	1227	ZARI/ZMD
3	Mochipapa	-16.83828°	27.07046°	1282	ZARI/ZMD
4	Longe	-14.83900°	24.93100°	1169	ZARI
5	Misamfu	-10.17165°	31.22558°	1380	ZARI/ZMD
6	Mutanda	-12.42300°	26.21500°	1316	ZARI/ZMD

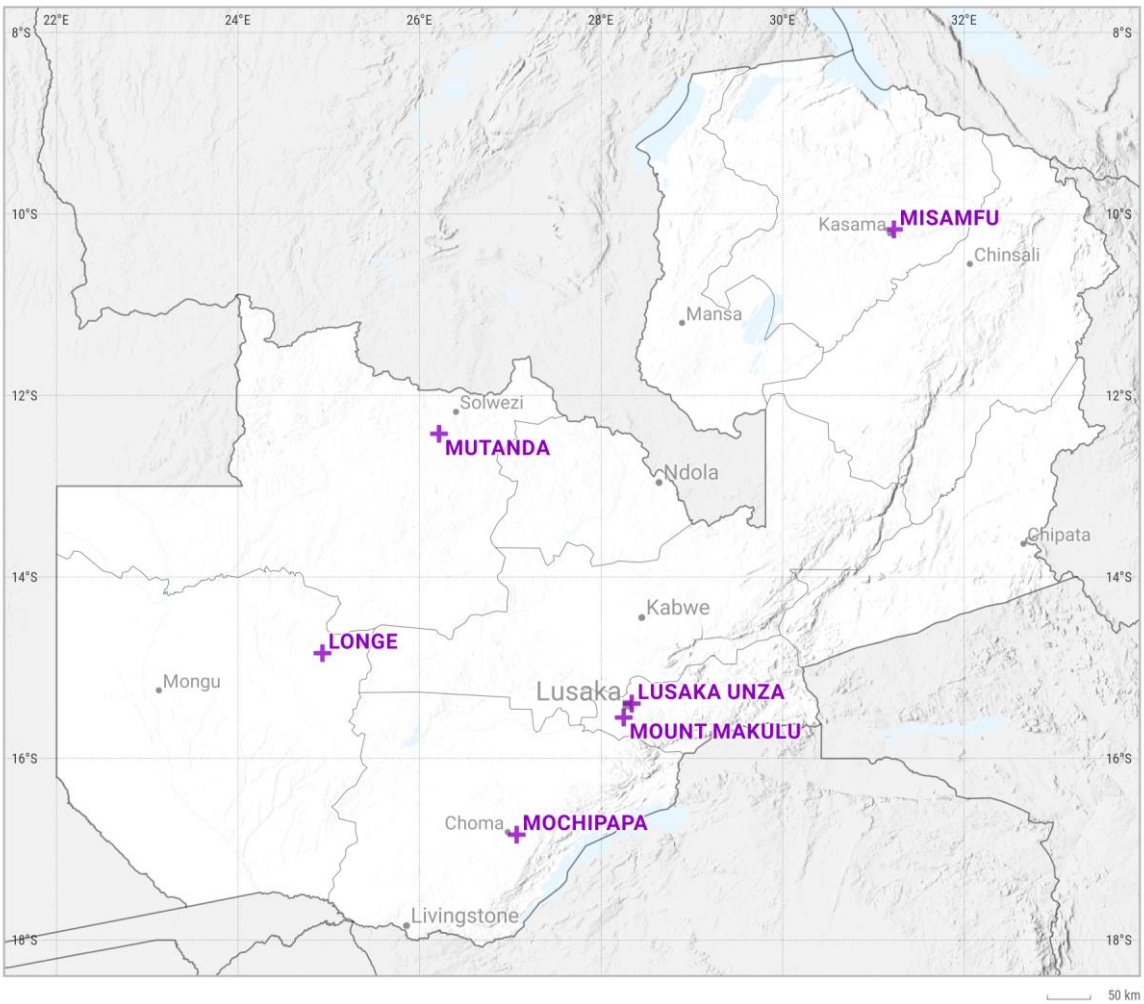

Figure 3.1: Position of the solar meteorological stations

Table 3.3: Instruments used for measuring solar radiation

No.	Site name	Station type	DNI	GHI	DIF
1	Lusaka UNZA	TIER 1	CHP 1, Kipp & Zonen	CMP 10, Kipp & Zonen	CMP 10, Kipp & Zonen
2	Mount Makulu	TIER 2	RSR 2, Irradiance Inc.	CMP 10, Kipp & Zonen RSR 2, Irradiance Inc.	RSR 2, Irradiance Inc.
3	Mochipapa	TIER 2	RSR 2, Irradiance Inc.	CMP 10, Kipp & Zonen RSR 2, Irradiance Inc.	RSR 2, Irradiance Inc.
4	Longe	TIER 2	RSR 2, Irradiance Inc.	CMP 10, Kipp & Zonen RSR 2, Irradiance Inc.	RSR 2, Irradiance Inc.
5	Misamfu	TIER 2	RSR 2, Irradiance Inc.	CMP 10, Kipp & Zonen RSR 2, Irradiance Inc.	RSR 2, Irradiance Inc.
6	Mutanda	TIER 2	RSR 2, Irradiance Inc.	CMP 10, Kipp & Zonen RSR 2, Irradiance Inc.	RSR 2, Irradiance Inc.

Table 3.4: Instruments installed at Tier 1 and Tier 2 solar meteorological stations

Parameter	Instrument	Type	Manufacturer	Uncertainty
GHI	Secondary standard pyranometer	CMP 10	Kipp & Zonen	< ±2 % (daily)
DIF	Secondary standard pyranometer	CMP 10	Kipp & Zonen	< ±2 % (daily)
DNI	First class pyrheliometer	CHP 1	Kipp & Zonen	< 1 % (daily)
GHI 2	Rotating shadowband radiometer with LI200	RSR 2	Irradiance Inc.	Indicatively ±5 %
DIF 2	Rotating shadowband radiometer with LI200	RSR 2	Irradiance Inc.	Indicatively ±8 %
DNI 2	Rotating shadowband radiometer with LI200	RSR 2	Irradiance Inc.	Indicatively ±5 %
WS	TIER 1 station wind speed sensor (at 10 m)	05103	R.M. Young	±0.3 m/s
	TIER 2 station wind speed sensor (at 3 m)	03002	R.M. Young	±0.5 m/s
WD	TIER 1 station wind direction sensor (at 10 m)	05103	R.M. Young	±3 °
	TIER 2 station wind direction sensor (at 3 m)	03002	R.M. Young	±5 °
TEMP	Temperature probe (at 2 m)	CS215	Campbell Scientific	±0.9°C
RH	Relative humidity probe	CS215	Campbell Scientific	±4% RH
AP	Barometric pressure sensor	PTB110	Vaisala	±1.5 hPa
PWAT	Tipping-bucket rain gage	TE525	Texas Instrument	±1%
-	Data logger	CR1000	Campbell Scientific	± (0.06% of reading + offset)

At the TIER 2 stations, solar radiation is measured by secondary standard pyranometers of high quality and accuracy (GHI), and by RSR 2 instruments (GHI, DNI and DIF). At TIER 1 station, secondary standard pyranometers (GHI and DIF) and a first class pyrheliometer (DNI) were used. 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	Parameters	Time step	Period of data used in this study
1	Lusaka UNZA	GHI, DNI, DIF	1 min	7 November 2015 – 31 December 2017
2	Mount Makulu	GHI, GHI2, DNI2, DIF2	1 min	13 November 2015 – 31 December 2017
3	Mochipapa	GHI, GHI2, DNI2, DIF2	1 min	5 November 2015 – 31 December 2017
4	Longe	GHI, GHI2, DNI2, DIF2	1 min	10 November 2015 – 31 December 2017
5	Misamfu	GHI, GHI2, DNI2, DIF2	1 min	18 November 2015 – 31 December 2017
6	Mutanda	GHI, GHI2, DNI2, DIF2	1 min	21 November 2015 – 31 December 2017

In this report, a complete set of data from the measurement campaign is used for regional adaptation. As the measurement stations have been installed in November 2015, the regular envisaged period for the data analysis starts in December 2015 and ends in December 2017.

Year, month	2015												2016												2017											
Station	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12
Lusaka UNZA																																				
Mount Makulu																																				
Mochipapa																																				
Longe																																				
Misamfu																																				
Mutanda																																				

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

3.2 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 "24 Months *Solar Resource Report, Republic of Zambia, Report number: 128-07/2018*" [28], here we present only a brief summary.

Based on the quality control results we conclude that the solar radiation measurements come from the high accuracy (CMP10, CHP1) and medium accuracy (RSR2) equipment that is professionally operated and maintained. Some issues were identified during the data quality control of the whole period of ground measurement campaign:

- Several periods of inconsistency between independent GHI, DNI and DIF measurements is seen in the data. This might be a result of different measurement technologies.
- Effect of dew on CPM10 instruments in the morning hours (all stations).
- The measurements are partially affected by morning or late afternoon shading from surrounding objects or trees. The measurements affected by these operation conditions were excluded from further analyses.

The issues above have implication on the uncertainty of ground measurements. Therefore, the affected data values had to be excluded so that they do not impact the results of the Solargis model adaptation (Chapter 4).

In evaluation of the measurement uncertainty several factors are considered:

1. Thermopile pyranometer CMP10 has lower nominal uncertainty than the RSR2 instrument. Therefore, use of CMP10 data has preference over RSR2, in the regional adaptation.
2. The thermopile pyranometers are more susceptible to soiling; however no significant issues with the soiling were identified in the data by quality control.
3. Instruments are used in challenging environmental conditions (higher temperature, high humidity, higher dew, etc.), and their possible impact was evaluated, and the measured data values excluded.

Table 3.6 summarises the finding of the quality control.

Table 3.6: Quality control summary

Description	Lusaka UNZA	Mount Makulu	Mochipapa	Longe	Misamfu	Mutanda
Station description, metadata						
Instrument accuracy						
Instrument calibration						
Data structure						
Cleaning and maintenance information						
Time reference						
Quality control complexity						
Quality control results						
Time period						
Other issues						

Legend: Quality flag

Very good	Good	Sufficient	Problematic	Insufficient	Not specified

4 Regional adaptation of solar model for Zambia

Ground measurements from six solar meteorological stations in Zambia are used for the regional adaptation of the Solargis model (Figure 3.1). In addition, the measurements from Kasungu and Mzuzu stations in Malawi were used to improve regional adaptation of the model in the East. After adapting the model for the region, it was run to produce accuracy enhanced time series. By aggregating the time series, for every grid cell, the model has been used to generate a new version of GHI and DNI data layers and maps of Zambia.

4.1 Solargis method

Solargis regional model adaptation aims at reducing the bias (systematic deviation) at the level of the region. Bias reduction improves also RMSD (Root Mean Square Deviation, i.e. random deviation) and KSI (Kolmogorov Smirnov Index, i.e. difference between frequency distribution of the measured and satellite-based data).

The original Solargis data show a regional pattern of overestimation, compared to the ground measurements, for both GHI and DNI. The highest difference is seen at Mutanda station, where the systematic deviation between the ground measurements and the satellite data exceeds 9% for yearly values GHI. Such discrepancy is beyond uncertainty usually seen in Solargis satellite data in this region, as typical expectation of the satellite data systematic error is within ±6 to ±8% for GHI. The detailed inspection of the ground measurements and satellite data indicates two possible sources (and their combination) of this deviation:

- Ground measurements at the Mutanda site are affected to some extent by local shading (trees and buildings nearby the station) and higher occurrence of morning dew on instruments.
- Performance of current satellite models is less accurate in conditions of high occurrence of scattered clouds and persistent clouds in the tropical regions.

Similar features can be found at some extent also in the data from other sites in this climate zone.

The performance of the satellite model shows higher discrepancies in conditions of high intermittency of solar irradiance. The DNI is overestimated mostly for lower irradiance (Figure 4.1, left) while GHI is overestimated mainly in whole range from low to high irradiance values (Figure 4.1, right).

This indicates insufficiencies (i) in the clear-sky model (quantifying the cloudless conditions), which is mainly controlled by aerosol data input as well as (ii) limitations of the cloud model. In regional adaptation, we have focused on (i) accuracy improvement of the model inputs, namely Aerosol Optical Depth (AOD), and (ii) on reducing the overestimation by de-biasing the GHI and DNI values.

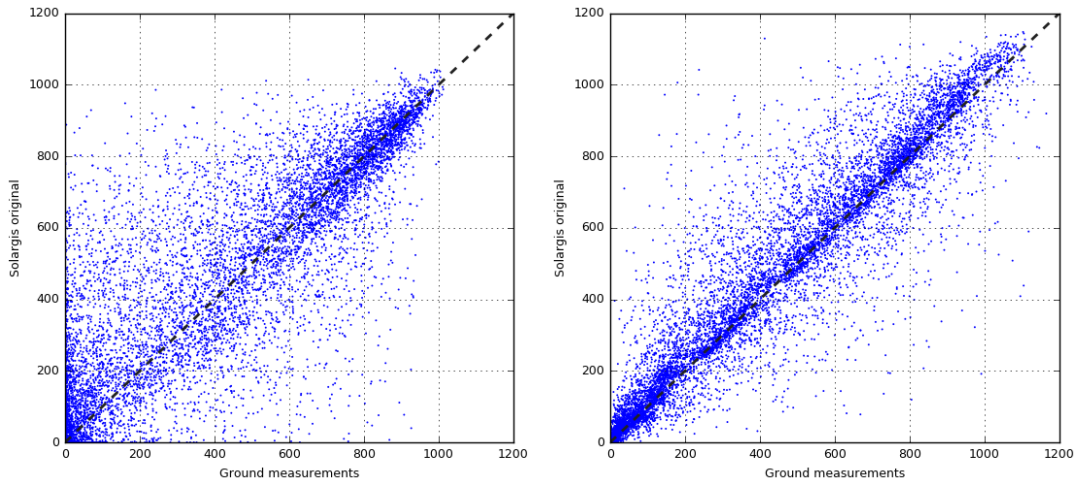

Figure 4.1: Comparison of hourly original satellite-model DNI and GHI with ground measurements.
Model systematically overestimates the measurements – UNZA Lusaka
Left: DNI, Right: GHI

More about the Solargis site adaptation method in [22].

4.1.1 Reduction of systematic deviation between satellite and measured data

Deviation between the original satellite model output and ground-measurements was analysed individually for each site. We focussed on understanding of the following differences:

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

Understanding of discrepancies and their sources was determining factor for the selection of appropriate methods for reduction of systematic deviation between satellite-based calculation and measured data.

The reduction was conducted in two steps:

1. **Regional aerosol correction**. Coefficients for adaptation of Aerosol Optical Depth (ADO) were derived for individual ESMAP meteorological stations (Chapter 4.1.1). Aerosol adaptation coefficients were interpolated between the solar meteorological sites to extend over the territory of Zambia (Chapter 4.1.2). Adapted (accuracy enhanced) aerosol values were used for the recalculation of the satellite model outputs.
2. Regional GHI and DNI de-biasing. Larger **residual discrepancies were reduced** between the ground measurements and the AOD corrected model, in the second step, by regional de-biasing of the GHI and DNI layers. GHI and DNI de-biasing correction factors derived for the ESMAP stations were spatially interpolated and applied to calculate the final GHI and DNI data layers.

4.1.2 Regional aerosol correction

Based on the comparison of satellite model data and ground measurements, **correction factors for AOD** (Atmospheric Optical Depth) values were calculated. 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.

Next, these **factors were harmonized** to avoid abrupt month-by-month changes that might be rather a representation of specific weather situations, rather than a systematic problem in the model. 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 case of Zambia, the deviations in individual stations were spatially consistent and only small changes of correction coefficients were introduced by harmonization. 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.

The main objective of **spatial interpolation of aerosol correction coefficients** is to extend the correction coefficients identified at the sites to the territory of Zambia and a wider region. 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 identified at the solar meteorological stations to the entire territory of Zambia and neighbouring areas. To maintain the stability of model in a wider regional context, also effect of corrections from neighbouring regions (Malawi) 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).

In the last step, the **satellite-based model was recalculated** using aerosol correction layers for the full period of 24 years for the entire territory of Zambia. Thus, the consistency of accuracy-enhanced GHI, DNI and DIF components is maintained.

The aerosol adaptation method removes one important 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 to a large extent reduced, some mismatch is still present in the data after the AOD correction. The discrepancies are expressed by higher bias of the original data. The residual bias was reduced by regional de-biasing of GHI and DNI.

4.1.3 Regional DNI and GHI de-biasing

The residual differences of AOD corrected model data were analysed at the measurement stations and the **yearly GHI and DNI correction (de-biasing) factors** were derived. The proposed reduction of the bias is applied within the regional context, where the representativeness of the individual stations within the given region (Chapter 4.1), and quality of measurements (Chapter 3.3) are considered. By applying the correction factors, we aim to reduce regional patterns of systematic deviation, rather than the specific microclimatic features. Therefore, for individual stations a small residual bias at the level of solar meteorological stations can be expected.

Similarly to AOD correction factors, the GHI and DNI de-biasing factors derived for measurement stations were interpolated for the entire territory. Also, for this correction factors the information from neighbouring regions (Malawi) was included in the interpolation scheme to maintain stability and continuity in a wider context. As a result, two correction layers were derived, one for GHI and one for DNI.

In the final step the correction factors were used to de-bias GHI and DNI data for the whole territory. Final corrected GHI and DNI data layers were used for spatial analysis of solar resource in Zambia, and for calculation of secondary data layers: diffuse horizontal irradiation (DIF), global radiation on optimally tilted surface (GTI) and potential photovoltaic production (PVOUT).

The main focus of the regional adaptation is to determinate correction coefficients for individual sites that are used to remove seasonal and annual systematic deviations in the regional context. The residual discrepancies present in the regionally-adapted data can be further removed only in the local context as their source are locally-specific features such as pollution in cities. Such residual discrepancies cannot be extrapolated, as they can only be addressed in the model site adaptation.

The coefficients of the regional adaptation were derived for the period with the overlapping ground measurements and model data. These coefficients were implemented in the model to recalculate the more accurate full-time series of solar radiation.

4.2 Results and validation

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

Comparing original Solargis data to the ground measurements shows a regional model overestimation pattern for both GHI and DNI. The model adaptation, for the region, allowed reducing a large proportion of the systematic mismatch between satellite-based data and ground measurements.

Tables 4.1 to 4.2 summarize validation of the regional adaptation for all six solar meteorological stations. The original Solargis data represent output of the model, which is based on a standard calculation scheme without considering any corrections derived from the measurements. The regionally-adapted model includes the effect of correction factors calculated from the ESMAP project measurements in Zambia (Chapter 4.1). The GHI validation statistics (Table 4.2) show a comparison of the accuracy-enhanced GHI to the measurements from secondary standard CMP10 thermopile pyranometers. The DNI validation statistics (Table 4.1) shows a comparison of the accuracy enhanced DNI to the measurements from CHP1 (Lusaka UNZA) and RSR2 (all other stations) instruments. The measurements from RSR2 instrument have higher nominal uncertainty. Terms are explained in Glossary. Absolute values of bias are calculated for daytime hours only.

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

Meteo station	Original DNI data		DNI after regional adaptation	
	Bias [kWh/m²]	Bias [%]	Bias [kWh/m²]	Bias [%]
Lusaka UNZA	44	10.5	8	2.0
Mount Makulu	42	9.9	3	0.7
Mochipapa	41	9.0	2	0.4
Longe	32	6.9	3	0.6
Misamfu	44	10.1	-1	-0.2
Mutanda	43	10.5	5	1.2
Mean	41	9.5	3	0.8
Standard deviation	5	1.4	3	0.7

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

Meteo station	Original GHI data		GHI after regional adaptation	
	Bias [kWh/m²]	Bias [%]	Bias [kWh/m²]	Bias [%]
Lusaka UNZA	32	6.8	6	1.2
Mount Makulu	30	6.4	1	0.2
Mochipapa	26	5.4	-1	-0.2
Longe	33	6.6	4	0.8
Misamfu	32	6.4	-3	-0.5
Mutanda	46	9.5	10	2.0
Mean	33	6.9	3	0.6
Standard deviation	7	1.4	5	0.9

As a result, at the level of individual sites in Zambia, the mean bias of the adapted GHI and DNI values stays below ±1.0% for Mount Makulu, Mochipapa, Longe and Misamfu stations. For Lusaka UNZA and Mutanda station it is slightly higher but still below or equal ±2.0% for both DNI and GHI. The standard deviation of bias values, considering all six stations, is 0.7% and 0.9% for the DNI and GHI respectively, which is comparable to the inherent uncertainty of ground sensors.

Table 4.3 shows the comparison of long-term annual averages of GHI and DNI derived from the original and regionally-adapted GIS data layers. Both the GHI and DNI values from the accuracy-enhanced model are lower, which indicates that the original model has trend of systematic overestimation in the region.

Table 4.3: Comparison of long-term average of yearly summaries of original and regionally-adapted values

Meteo station	DNI annual values*			GHI annual values*		
	Original [kWh/m²]	Adapted [kWh/m²]	Difference [%]	Original [kWh/m²]	Adapted [kWh/m²]	Difference [%]
Lusaka UNZA	2010	1870	-7.0	2113	2005	-5.1
Mount Makulu	2005	1849	-7.8	2106	1984	-5.8
Mochipapa	2108	1954	-7.3	2131	2019	-5.3
Longe	2096	1978	-5.6	2187	2069	-5.4
Misamfu	1915	1734	-9.5	2165	2024	-6.5
Mutanda	1896	1746	-7.9	2135	1991	-6.7

** Values represent GIS data layers, and they may slightly deviate from the version of the point model that calculates site-specific time series. This difference is due to spatial resolution and method of terrain disaggregation in the grid model.*

A significant improvement was achieved for both Direct Normal Irradiance (DNI) and Global Horizontal Irradiance (GHI). The average bias of DNI for all stations dropped from the range of 6.9% to 10.5% to the range of -0.2% to 2.0%, and the standard deviation was reduced from 1.4% to 0.7% by regional adaptation. The average Global Horizontal Irradiance (GHI) bias for all stations after adaptation is 0.6% with standard deviation of 0.9% (Table 4.2). High bias of original data, in the range of 5.4% to 9.5% was reduced to the range of -0.5% to 2.0% by regional

adaptation. The higher residual bias at Mutanda station is a result of lower representativeness of the measurements from this station (Chapter 4.1) in the regional context. Therefore, in this station, the adaptation correction coefficients were calculated with higher freedom than for the other stations.

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

4.2.2 Accuracy-enhanced DNI and GHI maps

Regionally adapted DNI and GHI long-term averages are lower in the entire region, compared to the original data (Figure 4.2 and 4.3). The absolute change of DNI is higher for most of the territory, as DNI is more sensitive to changes of aerosol load introduced in the first step of the regional adaptation.

The change of GHI and DNI values due to regional adaptation is most visible in the region East of Misamfu station; close to the border with Malawi. The correction in this region is partly influenced by Mzuzu station in Malawi. In general, correction level for both DNI and GHI decreases towards the West and Southwest of the country.

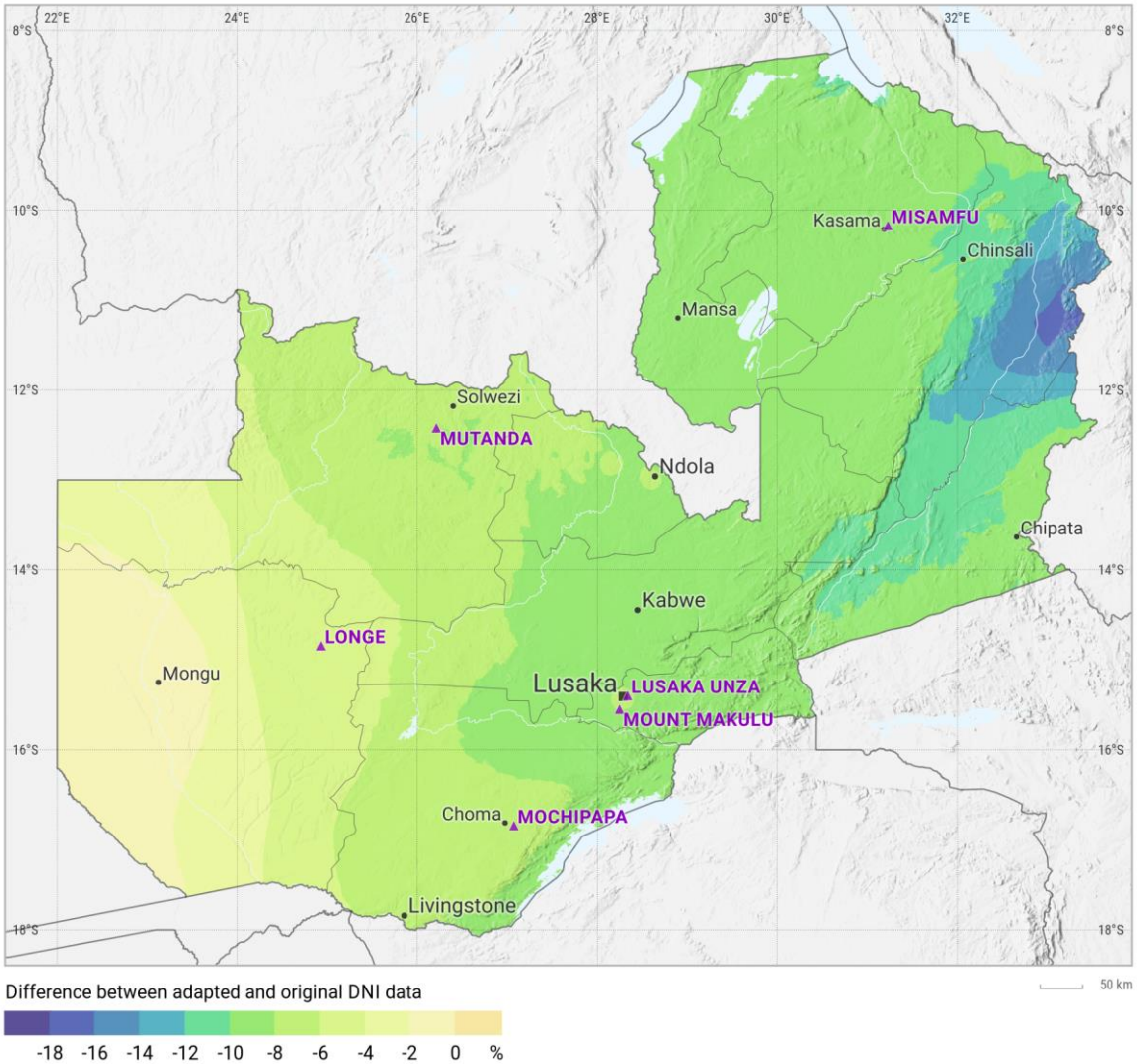

Figure 4.2: Map of differences in yearly DNI between the original and regionally adapted model

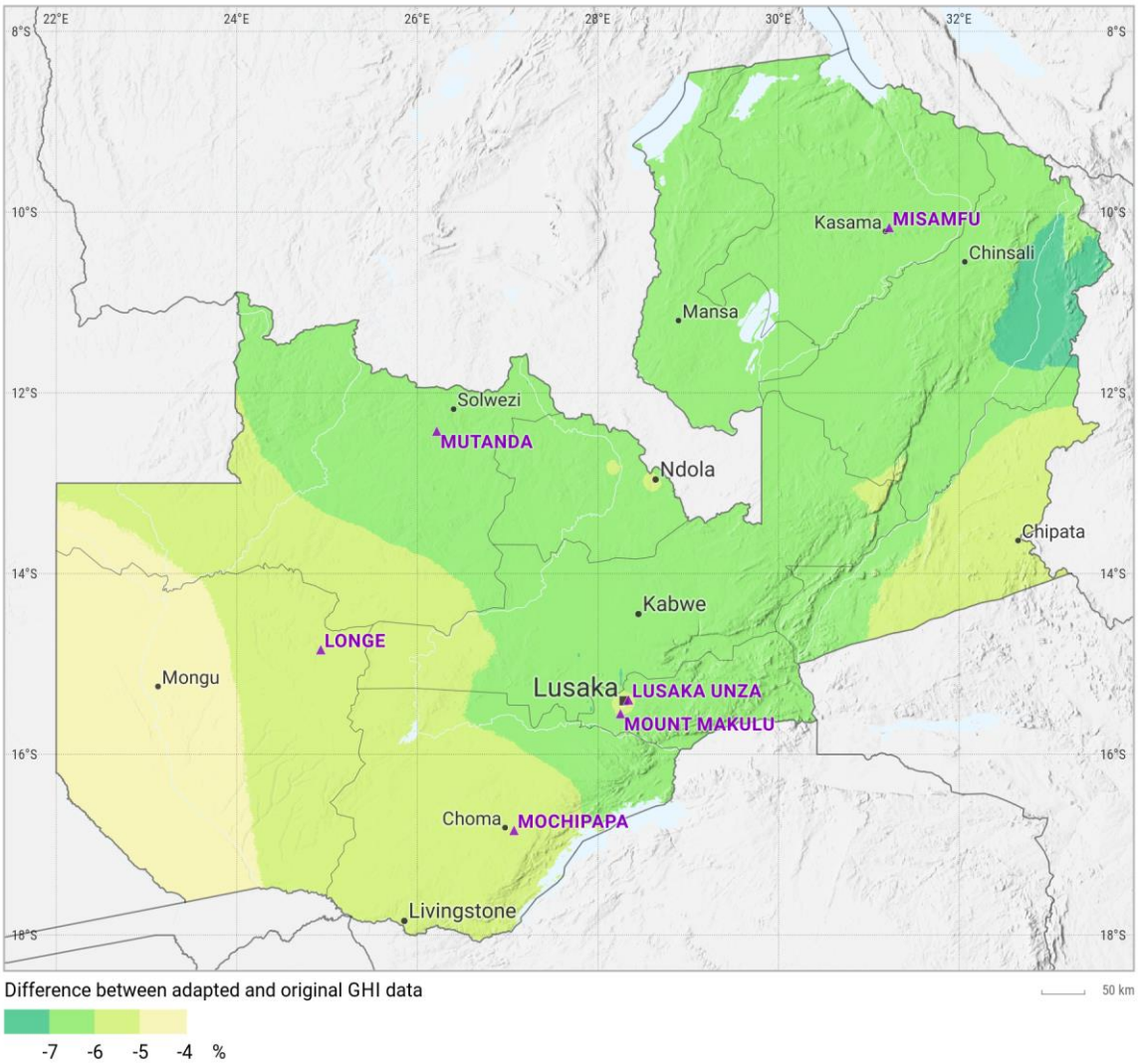

Figure 4.3: Map of differences in yearly GHI between the original and regionally-adapted model

5 Solar resource maps of Zambia

5.1 Accuracy enhanced maps of DNI and GHI

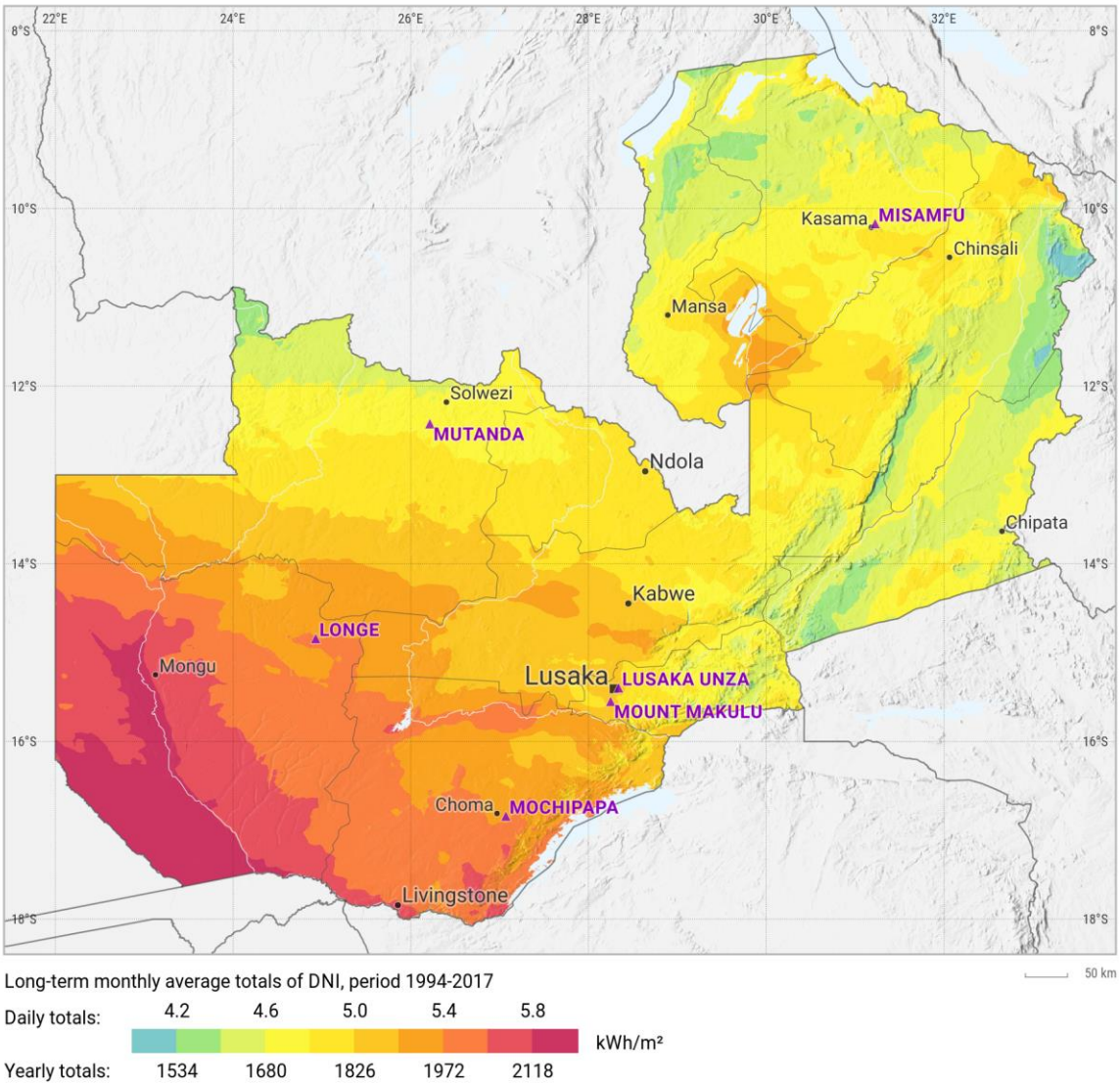

Figure 5.1: Accuracy-enhanced DNI yearly long-term average

After the regional adaptation of the Solargis satellite model, full time series representing a period of 24 years (1994 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).

The spatial (grid) resolution of the output maps is 1 km.

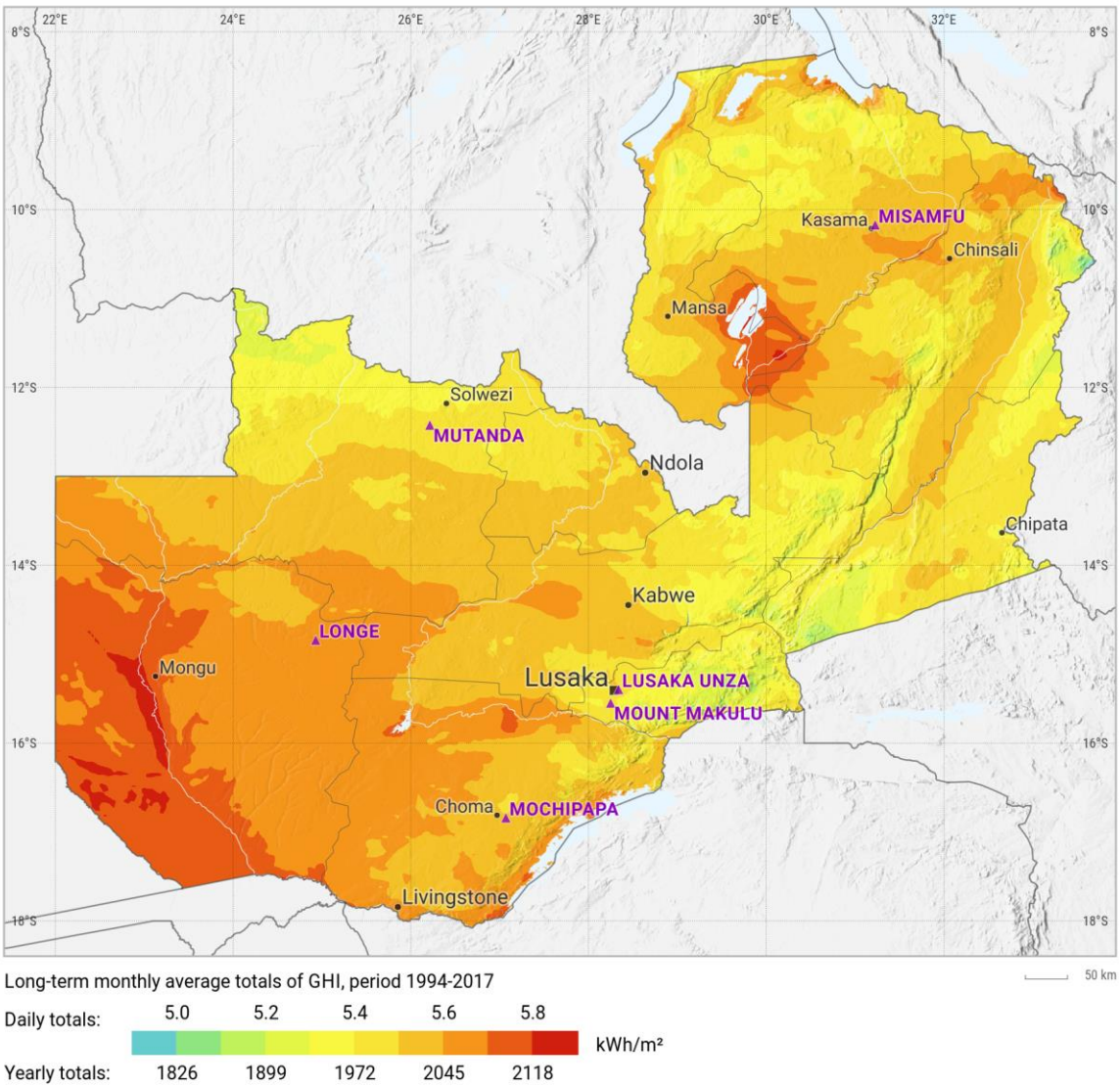

Figure 5.2: Accuracy-enhanced GHI yearly long-term average

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 behaviour in all conditions. Validation sites in Zambia show consistent bias. The bias is higher, but in most cases still within the expected range (except of GHI in Mutanda station). The results reflect specific local conditions as well as limitations of the Solargis model. The regional adaptation reduced these discrepancies (Chapter 4.1.3). The adaptation was applied to remove systematic model deviations, not the discrepancies coming from specific microclimate. After the model adaptation the bias values are significantly lower (Tables 4.1 and 4.2).

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 errors of solar radiation model, which is a simplification given by availability of validation data and limited geographical knowledge.

Typically, in the industry, a long-term yearly average estimate is required, often denoted as P50 value (in case of normal distribution this is equivalent to median). Besides P50, project developers, technical consultants and the finance industry request the uncertainty of long-term yearly GHI or DNI and P90 estimate, that is more conservative and it is calculated by subtracting the 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 MFG and MSG 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 surfaces, and properties of 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 it is derived primarily from the statistical measures calculated at six solar meteorological 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. Table 5.1 summarizes 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 of the 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 4 to 5 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 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). The model adaptation approach, described in this study, is designed to remove 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 for the majority of Zambia territory the regionally-adapted model has uncertainty of yearly values at the level of ±4% to ±5% for GHI, and ±5% to ±7% for DNI. We expect higher uncertainty in regions with more complex geography, which is partly a result of uncertainty of ground measurements, distribution of measurement stations throughout country and inherently higher model uncertainty in regions with specific micro-climate (e.g. occurrence of convective clouds close to steep slopes). These uncertainties can be reduced by the use of longer period of high-quality ground measurements and by installing more meteorological stations in the region.

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

	Direct Normal Irradiation		**Global Horizontal Irradiation**		**Global Tilted Irradiation**	
	Low	Medium	Low	Medium	Low	Medium
Original data	< ±9.0%	< ±13%	< ±6.5%	< ±8.0%	< ±7.0%	< ±9.0%
After adaptation	±5% to ±7%	< ±10%	±4% to ±5%	< ±6%	±4.5% to ±5.5%	< ±7%
Best-achievable*	±3.5%	-	±2.5%	-	±3.0%	

The expected model uncertainty in the regions of Zambia is presented in Table 5.2 and Figure 5.3. The map is derived by expert evaluation of the distribution and the quality of ground measurements within the context of regional geography and capability of regional adaptation method.

Table 5.2: Geographic distribution of the model uncertainty

Model uncertainty for yearly estimates	Region	DNI	GHI	GTI
Low	Flat and monotonous terrain	±5% to ±7%	±4% to ±5%	< ±4.5% to 5.5%
Medium	Complex terrain	< 10%	< ±6%	< ±7 %

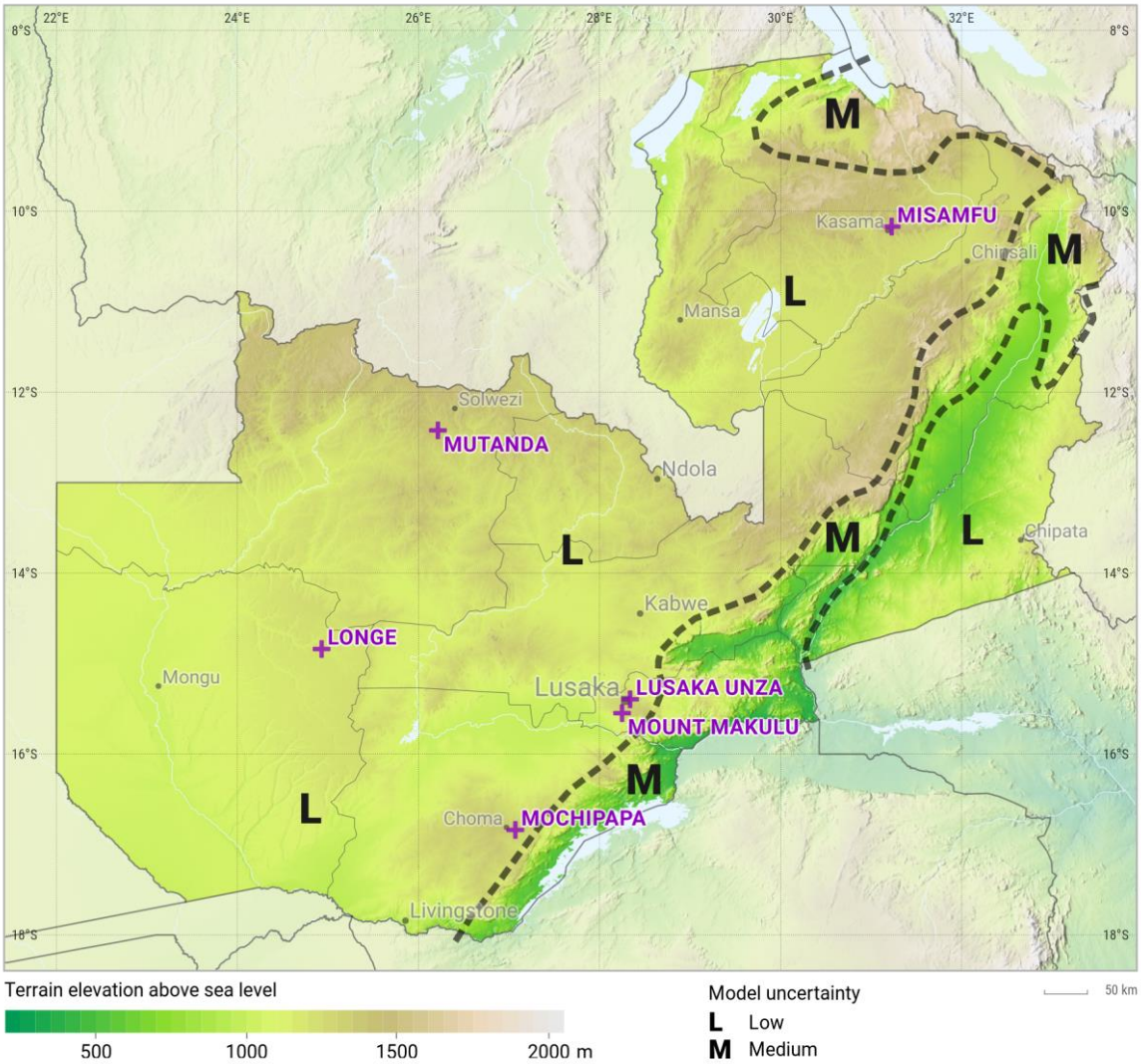

Figure 5.3: Geographic distribution of the model uncertainty in Zambia
L: low; M: medium

6 Conclusions

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

It benefits form the systematic and diligent 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 ±9% to ±13% (exceptionally even higher in some regions) for **DNI** yearly values to the range of ±5% to ±7% (exceptionally ±10.0%) for accuracy enhanced values. For yearly **GHI** the uncertainty reduction is seen from the original range of ±6.5% to ±8.0% to the range of ±4.0% to ±5.0% (exceptionally ±6.0%) for the accuracy enhanced values. The expected uncertainty in Zambia is split into low and medium uncertainty regions.

Besides reducing systematic deviation (bias), the regional model adaptation also results in the indirect 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). There is direct benefit in using higher-quality DNI and GHI data in the solar energy yield estimation, which in turn is used for optimising a technical design and for calculation of financial parameters of a project.

Role of solar measuring stations in maintaining sustainable solar data infrastructure

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

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

- For new sites, relevant to any larger solar power project, it is important to install and operate a solar meteorological station with objective of reducing uncertainty of **long-term estimates** to achievable minimum (see Table 5.1)**.**
- 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 evaluation** of solar power plants in the region.
- Keeping solar measuring stations in operation is of strategic importance to maintain the quality of satellite-based solar models and of models for solar power **forecasts**.

7 List of figures

8 List of tables

9 References

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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 19 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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Reference No. (Solargis): 128-08/2018

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