



Dornier Suntrace Solar Resource Assessment

## Combining several satellite-derived solar radiation datasets

Enhanced multi-source solar resource assessment

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## Glossary

| Term / Abbreviation | Definition                                                                                                                                                       |
|---------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| CPV                 | Concentrating Photovoltaic                                                                                                                                       |
| CSP                 | Concentrating Solar Power                                                                                                                                        |
| DSCR                | Debt Service Coverage Ratio                                                                                                                                      |
| GHI                 | Global Horizontal Irradiance – could be instantaneous measurement value, averaged over 1 min or several years, like a statistical climatological long-term value |
| GTI                 | Global Tilted Irradiance                                                                                                                                         |
| <i>i</i>            | Index: Natural integer number                                                                                                                                    |
| <i>n</i>            | Number of data sets                                                                                                                                              |
| PV                  | Photovoltaic                                                                                                                                                     |
| SRA                 | Solar Resource Assessments                                                                                                                                       |
| <i>u</i>            | Uncertainty – here typically used as relative uncertainty of $G = \delta G/G$                                                                                    |
| <i>w</i>            | Weight used for averaging data sets                                                                                                                              |

# Introduction

Solar resources account for a decisive share of uncertainty when determining the return on investment of utility-scale solar power plants. For instance, yield predictions and yield certificates mainly comprise of three components: Technical plant specifications, solar resource evaluation and estimation of changes in energy yield over the lifetime of the system (Müller et al., 2017). The required degree of solar data granularity can be adapted according to project progress, maturity, and budget. Uncertainty of yield calculation is caused by uncertainty of the input data and limitations of the yield model itself. Once the solar plant is properly specified irradiance conversion models and uncertainty of incoming irradiance have the highest influence on uncertainty of plant performance (Müller et al., 2007). To get an idea of the cost-benefit relationship, it is important to discuss some basic mechanisms of uncertainty reduction in solar resource assessments.

In our Solar Resource Assessments (SRA), we follow the methodology of Meyer et al. (2008) for deriving the long-term-average of solar irradiance at a site. This method assesses several satellite/model-derived solar resource data and combines data sets of good quality by quality-weighted averaging. Such quality-weighted average avoids accidental overestimation or underestimation, which happens at some sites, when relying only on a single data set.

However, among various datasets, a single source may provide lower uncertainty than others. Thus, it is necessary to assure that combining of multiple datasets does not lead to a higher overall uncertainty when considering the best estimate based on a weighted average in the process of project development.

Single satellite datasets can be assumed to be independent, uncorrelated sources since the mean bias between various satellite/model-derived long-term-averages from ground-correlated solar radiation datasets shows to be normally distributed (see Ineichen, 2014 and Forstinger et al., 2023). Thus, the Gaussian law of error propagation may be applied to determine the resulting uncertainty of the quality-weighted best estimate of solar irradiance at a site.

When combining several independent datasets of relatively high quality, not all information sources are created equal: Each data point carries its own degree of reliability, precision, and relevance. By assigning weights to different satellite-data sources based on their trustworthiness and accuracy, an even lower final uncertainty than the most accurate input dataset's uncertainty can be achieved. The multi-source approach may, therefore, not only provide more reliable best estimates, but can also show higher estimated yield when relying for example on the P90-value.

# The Multi-Source Approach

To meet the demands of engineering and financial tasks, highly detailed datasets, reflective of the specific geographical location, are indispensable. Therefore, an SRA serves as a key resource in providing an intricate analysis of solar radiation tailored to the site's particulars. This analysis encompasses time-series evaluations aimed at characterizing solar radiation intensity, typical variability, and ancillary meteorological data pertinent to the location.

The primary goal of the SRA is to derive accurate long-term averages of solar irradiance, specifically Global Horizontal Irradiance (GHI) for rooftop, ground-mounted or floating Photovoltaic (PV) ventures and Direct Normal Irradiance (DNI) for Concentrating Solar Power (CSP) projects, encompassing solar thermal power plants and Concentrating Photovoltaic (CPV) installations. These long-term averages are commonly expressed by the best estimate, as for example the P50-value. This P50-value, which should represent the most likely value for the site-specific long-term average of the respective irradiance component. Notably, engineering decisions, including site-specific power plant layouts and initial financial projections, hinge on the Typical Meteorological Year (TMY) dataset. This dataset should meticulously mirror the P50 values. Thus, the core objective of the assessment process is the generation of a TMY dataset, encompassing ancillary meteorological parameters such as ambient temperature, humidity, wind speed, and wind direction, all pivotal for site-specific engineering and yield estimates.

Ideally, on-site measurements are available to bolster the analysis and refinement of satellite-derived datasets. In cases where on-site measurements are lacking or possess a duration of less than six months, adjacent measurements are considered. Such proximal measurements

typically offer superior precision in ancillary meteorological data, thus augmenting the realism of the resultant TMY dataset.

TMYs generated solely from satellite-derived data may exhibit substantial differences in comparison to those based on ground-measured data. Satellite-derived solar radiation data, often diverge from ground-measured data concerning instant values, averages, frequency distribution, and representativeness. Mitigating these disparities necessitates the adjustment of satellite-derived data to align with ground-measured data. Dornier Suntrace has devised methodologies, including Schumann et al. (2011) and Mieslinger et al. (2014), that effectuate this alignment. These methodologies amalgamate the precision of ground-based measurements with the temporal breadth of satellite-derived datasets, facilitating data adjustment despite a general one-year temporal overlap between the two datasets. The utilization of Mieslinger et al. (2014) is particularly advantageous due to its tendency to nearly nullify biases in adjusted satellite-derived data concerning ground-measured data. Depending on geographic region, data duration, and quality, the employment of this adjustment method can curtail long-term average uncertainties to under 5% for DNI and under 4% for GHI.

TMYs are formulated using the adjusted satellite-derived solar radiation data, employing the methodology posited by Hoyer-Klick et al. (2009). These TMYs encapsulate the protracted monthly mean solar radiation, diligently approximating real-world conditions. A hallmark of our TMYs is their fidelity in representing the frequency distribution of solar radiation, an element of paramount significance in the design of solar power plants.

The accurate assessment of solar radiation is a critical enabler in the viability determination of

large-scale solar energy installations. Through the Full Solar Resource Assessment process, accurate long-term averages are derived, paving the way for optimal engineering decisions and precise financial projections. The adjustment of satellite-derived data augments the accuracy of

predictions and design considerations. As the world pivots towards renewable energy sources, the meticulous evaluation of solar irradiance becomes increasingly instrumental in shaping our energy landscape.

## Calculation of the quality-weighted average of solar radiation

The quality-weighted average of solar radiation, denoted as  $\bar{G}$ , is determined through a linear combination of various satellite- or model-derived solar radiation values  $G_i$ , each associated with an individual uncertainty  $u_i$ . According to Grossman et al. (2006) the weight  $w_i$  is inversely proportional to the square of its uncertainty:

$$w_i = 1/u_i^2 \text{ (Equation 1)}$$

Here,  $u_i$  signifies the uncertainty linked with each distinct dataset. Typically expressed as relative values, these uncertainties typically fall within the range of 3% to 10%, representing a 95% level of confidence. By assuming a normal distribution of uncertainties, the 95% confidence level equates to approximately 2-sigma values.

The quality-weighted average of solar radiation  $\bar{G}$  is calculated when the probability is maximized, yielding a more dependable value from satellite-model-derived data. This value is computed as follows:

$$\bar{G} = \frac{\sum (w_i \cdot G_i)}{\sum w_i} \text{ (Equation 2)}$$

The process of weighted averaging achieves best overall quality with the highest reliability<sup>1</sup>, as solar radiation data sets with much higher uncertainty than others will have a smaller weight than those with lower uncertainty.

Lastly, the determined best estimate is considering to be most accurate, since single data source

potentially over- or underestimating solar resource at site are excluded based on objective quantitative decisions.

Equation 2 represents an algebraic sum, alias geometric sum of the various satellite/model-derived solar radiation values. Following Gauss' law of error propagation, the uncertainty of  $\bar{G}$  according to Kallenrode (2005) is calculated by Equation 3:

$$u_{\bar{G}} = \sqrt{\frac{\sum (w_i \cdot u_i^2)}{\sum w_i}} \text{ (Equation 3)}$$

Using Equation 1, then results in

$$\begin{aligned} u_{\bar{G}} &= \sqrt{\frac{\sum (w_i \cdot u_i^2)}{\sum w_i}} \\ &= \sqrt{\frac{\sum (1/u_i^2 \cdot u_i^2)}{\sum 1/u_i^2}} = \sqrt{\frac{\sum 1}{\sum 1/u_i^2}} \\ &= \sqrt{\sum w_i} = \sqrt{\sum 1/u_i^2} = 1/\sqrt{\sum w_i} \end{aligned} \text{ (Equation 4)}$$

where  $u_{\bar{G}}$  is the uncertainty of  $\bar{G}$ . Applying Equation 4 for typical values of satellite/model-derived, Table 1 presents the combination of two independent satellite/model-derived sources in a spectrum from 1% to 8% uncertainty to each source. These results are displayed in Figure 1, additionally.

From Table 1 it is shown that when combining a dataset with  $u_1 = 1\%$  and the second dataset with  $u_2 < 4\%$ , we find an improvement of overall uncertainty compared to considering the most accurate data source only (1%). Analogue can be stated for  $u_1 = 2\%$ , but in this case, we find improvements for  $u_2 < 9\%$ . For values of  $u_1 \geq 3\%$  a general improvement on the uncertainty of satellite/model-derived data.

<sup>1</sup>If no ground data is available

Table 1: Combining 2 satellite/model-derived data sets with various assumptions on uncertainty. Green marked boxes indicate an improvement.

| uncertainty $u_2$ of additional data set | uncertainty $u_1$ of original data set |       |       |       |       |       |       |       |       |
|------------------------------------------|----------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|
|                                          |                                        | 1 %   | 2 %   | 3 %   | 4 %   | 5 %   | 6 %   | 7 %   | 8 %   |
|                                          | 1 %                                    | 0.7 % | 0.9 % | 0.9 % | 1.0 % | 1.0 % | 1.0 % | 1.0 % | 1.0 % |
|                                          | 2 %                                    | 0.9 % | 1.4 % | 1.7 % | 1.8 % | 1.9 % | 1.9 % | 1.9 % | 1.9 % |
|                                          | 3 %                                    | 0.9 % | 1.7 % | 2.1 % | 2.4 % | 2.6 % | 2.7 % | 2.8 % | 2.8 % |
|                                          | 4 %                                    | 1.0 % | 1.8 % | 2.4 % | 2.8 % | 3.1 % | 3.3 % | 3.5 % | 3.6 % |
|                                          | 5 %                                    | 1.0 % | 1.9 % | 2.6 % | 3.1 % | 3.5 % | 3.8 % | 4.1 % | 4.2 % |
|                                          | 6 %                                    | 1.0 % | 1.9 % | 2.7 % | 3.3 % | 3.8 % | 4.2 % | 4.6 % | 4.8 % |
|                                          | 7 %                                    | 1.0 % | 1.9 % | 2.8 % | 3.5 % | 4.1 % | 4.6 % | 4.9 % | 5.3 % |
|                                          | 8 %                                    | 1.0 % | 1.9 % | 2.8 % | 3.6 % | 4.2 % | 4.8 % | 5.3 % | 5.7 % |

Figure 1: Resulting uncertainty of various combinations of additional data sets characterized by uncertainty  $u_2$ .

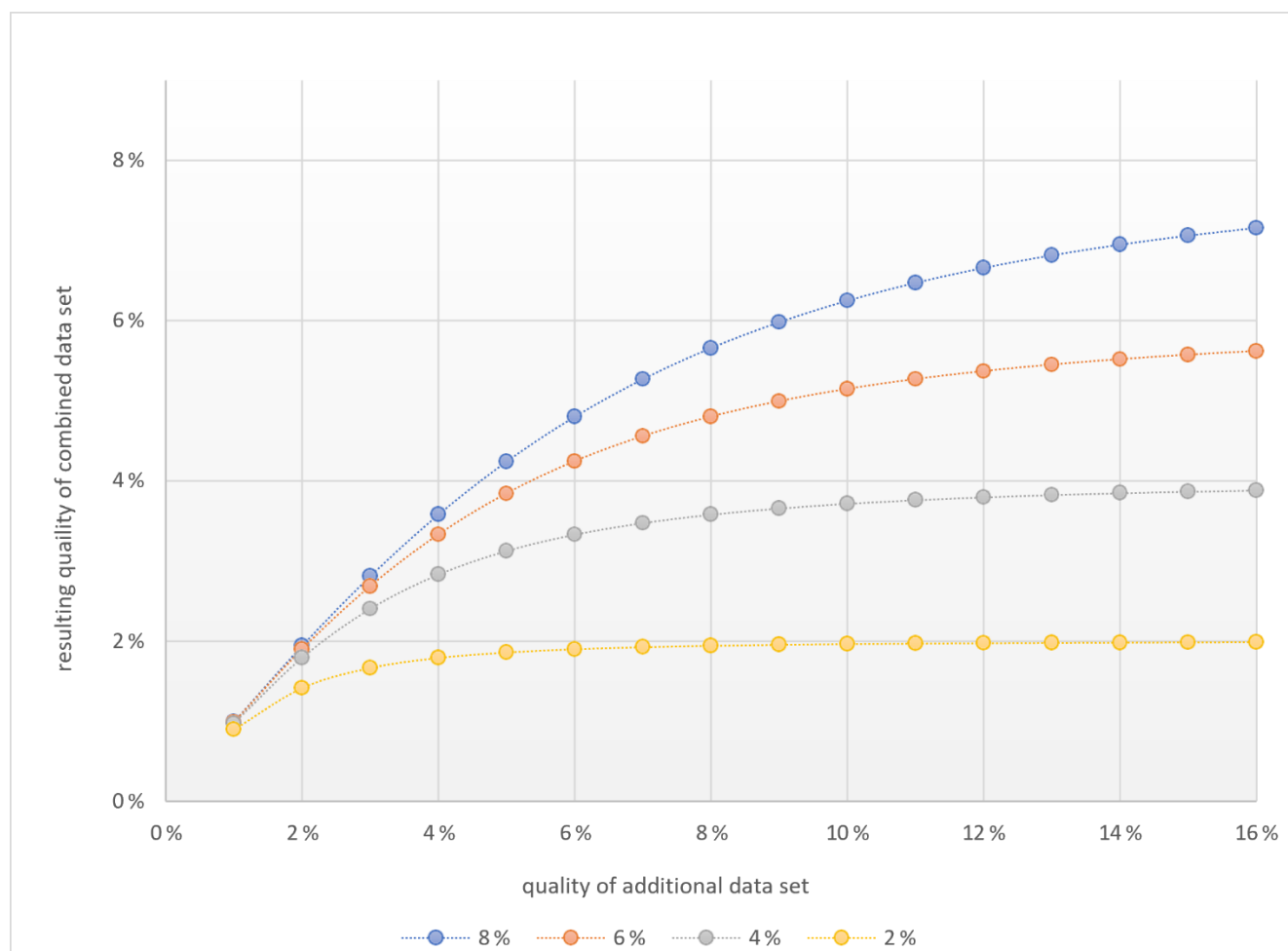


Table 2 shows a case where three datasets of various quality are combined. The table shows the resulting uncertainty by combining uncertainty levels  $u1$  and  $u2$  with a base-uncertainty  $u3$  of 3%. The results indicate that by combining more than two datasets of typical<sup>2</sup> uncertainty level a general improvement of data uncertainty can be found. Here, the uncertainty of

the average would only be spoiled, when combining high-quality data with poor quality data. In Table 2 we recognize that combining a base dataset with  $u3 = 3\%$  the reliability of the weighted average improves for all displayed cases. For such situation a better reliability of the weighted average is reached.

Table 2: Combining 3 satellite/model-derived data sets with varying level of uncertainty for  $u1$  and  $u2$ , whilst  $u3$  is set to 3%. Green marked boxes indicate an improvement of overall uncertainty.

| uncertainty $u2$ of additional data set | uncertainty $u1$ of original data set |       |       |       |       |       |       |       |       |
|-----------------------------------------|---------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|
|                                         |                                       | 1 %   | 2 %   | 3 %   | 4 %   | 5 %   | 6 %   | 7 %   | 8 %   |
|                                         | 1 %                                   | 0.7 % | 0.9 % | 0.9 % | 0.9 % | 0.9 % | 0.9 % | 0.9 % | 0.9 % |
|                                         | 2 %                                   | 0.9 % | 1.3 % | 1.5 % | 1.5 % | 1.6 % | 1.6 % | 1.6 % | 1.6 % |
|                                         | 3 %                                   | 0.9 % | 1.5 % | 1.7 % | 1.9 % | 2.0 % | 2.0 % | 2.0 % | 2.1 % |
|                                         | 4 %                                   | 0.9 % | 1.5 % | 1.9 % | 2.1 % | 2.2 % | 2.2 % | 2.3 % | 2.3 % |
|                                         | 5 %                                   | 0.9 % | 1.6 % | 2.0 % | 2.2 % | 2.3 % | 2.4 % | 2.4 % | 2.4 % |
|                                         | 6 %                                   | 0.9 % | 1.6 % | 2.0 % | 2.2 % | 2.4 % | 2.4 % | 2.5 % | 2.5 % |
|                                         | 7 %                                   | 0.9 % | 1.6 % | 2.0 % | 2.3 % | 2.4 % | 2.5 % | 2.6 % | 2.6 % |
|                                         | 8 %                                   | 0.9 % | 1.6 % | 2.1 % | 2.3 % | 2.4 % | 2.5 % | 2.6 % | 2.7 % |

<sup>2</sup> Typical level of uncertainty as to be found for satellite-based solar irradiance data



## Suntrace Solar Resource Services

For PV, floating PV & CSP yield, the strongest impact on uncertainty originates from solar resource uncertainty. During the early stages of project development, the solar resource uncertainty of an initial estimation can reach 10 % and more. Through our step-wise approach by assessing multiple satellite sources for long-term best-estimates and considering highly accurate ground-based measurements, we significantly reduce this uncertainty. In turn, this mitigative approach establishes a reliable and trustworthy base that is crucial for bankability and investment of the project. A thorough assessment in combination with high-quality on-site measurements may reduce uncertainty down to 2 % - and in turn will increase the P90 best estimate by about 2.5 %. Such an improvement may increase Net Present Value by up to 200 kEUR each 10 MW. By offering both on-site measurement campaigns and independent SRA, Suntrace is your ideal partner for all activities related to your project.

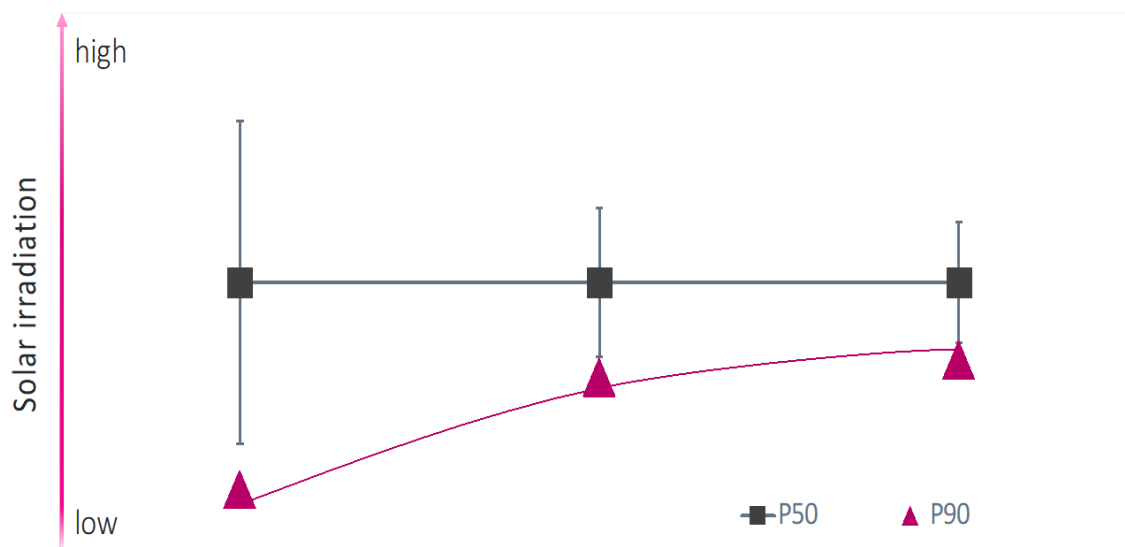
- ✓ Site Screening & Selection
- ✓ Solar Resource Assessments
- ✓ On-site Measurement Solutions



# Conclusion

In the pursuit of sustainable energy solutions, the evaluation of sites suitable for solar energy facilities is a crucial aspect in project development. For yield and return calculations, investors usually use the average, most probable solar resource conditions. These are typically described by the P50 value. Lenders, however, rather rely

on P90 values for their debt sizing i.e. the solar irradiance value that is expected to be exceeded to 90 %. Given that the P50 or mean value does not change substantially, more precise measurements will increase the P90 value as illustrated below.



Pre-feasibility

Feasibility & Site qualification

Due diligence

The investor can demonstrate a higher cash flow to lenders, who, in turn, would allow a higher share of debt to the project, generally resulting in lower capital cost. Lender's may further reduce the Debt Service Coverage Ratio (DSCR) threshold or offer lower interest rates. These yield a higher real return on investment.

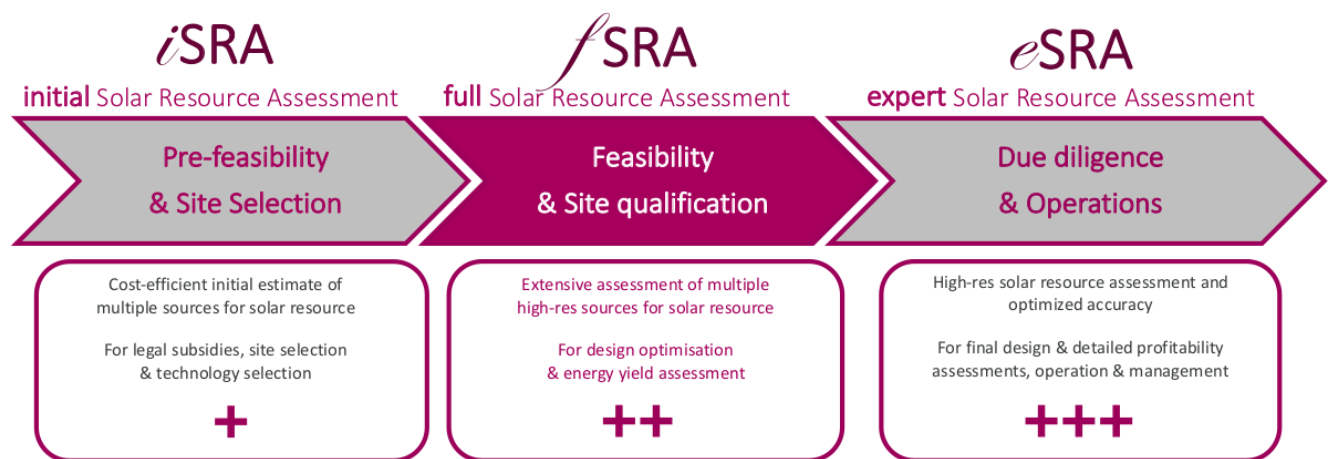
A second effect of more accurate measurement is that the investor can price the bid in a Power Purchase Agreement (PPA) negotiation more accurately with lower risk deductions. Accordingly, the investor can price the tariff with a higher certainty on the solar fuel factor.

Several sources of uncertainty require such risk deductions. P50 values always differ between different measurements, and this difference can be substantial. Further, the calculation of uncertainties itself is a source of uncertainty as is the difference in frequency distributions of auxiliary data (Bohny, 2016). Using not only multiple data sets but also adding the precision of on-site measurements allows reducing this risk deduction and in turn will lead to more favourable financing conditions and hence a change in real returns.

The depicted P90-effect assumes that the general estimate of a resource distribution is fairly

accurate, indicated by an overall good overlap of resource distribution. Yet, the higher uncertainty associated with satellite-only data does not allow for more optimistic yield predictions. Opposed to that the Risk Deduction Effect assumes that without multi-source analysis and on-site data you cannot even be sure about the accurateness of the position of your resource distribution<sup>3</sup>.

Reaching higher accuracy may, however, require enhanced efforts when conducting a solar re-source assessment. Thus, Dornier Suntrace recommends a stepwise multi-source approach to provide a feasible, yet reliable best estimate. Assessing multiple sources shows to reduce overall uncertainty while by mitigating potential over or underestimation of single data sources. In this process, an expert review of individual datasets is indispensable to consider only representative and accurate data of the envisaged region.



<sup>3</sup>The position of resource distribution is given by the P50 value. Depending on the region, satellite- i.e. modelled data potentially over- or underestimates the solar resource and with it the position of resource distribution.

# About Dornier Suntrace

Suntrace was established 2009 in Hamburg, Germany's largest renewable energy cluster of firms. Today, Suntrace provides essential elements to develop renewable energy projects for clients all over the world. The range of services reaches from renewable energy resource assessments over owner's engineering to project implementation. In addition to the full engineering, Suntrace also provides financial advisory and project development management. Having a portfolio of over 7.5GW of installed solar in 135 projects over more than 46 countries, Suntrace with its strong team has established itself in renewable energy market. From concept to full realization, Suntrace has expertise in solar, wind and storage hybrid system with conventional power systems. Suntrace is part of Dornier Group with approx. 100 Mio EUR turnover and more than 2.000 staff.

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