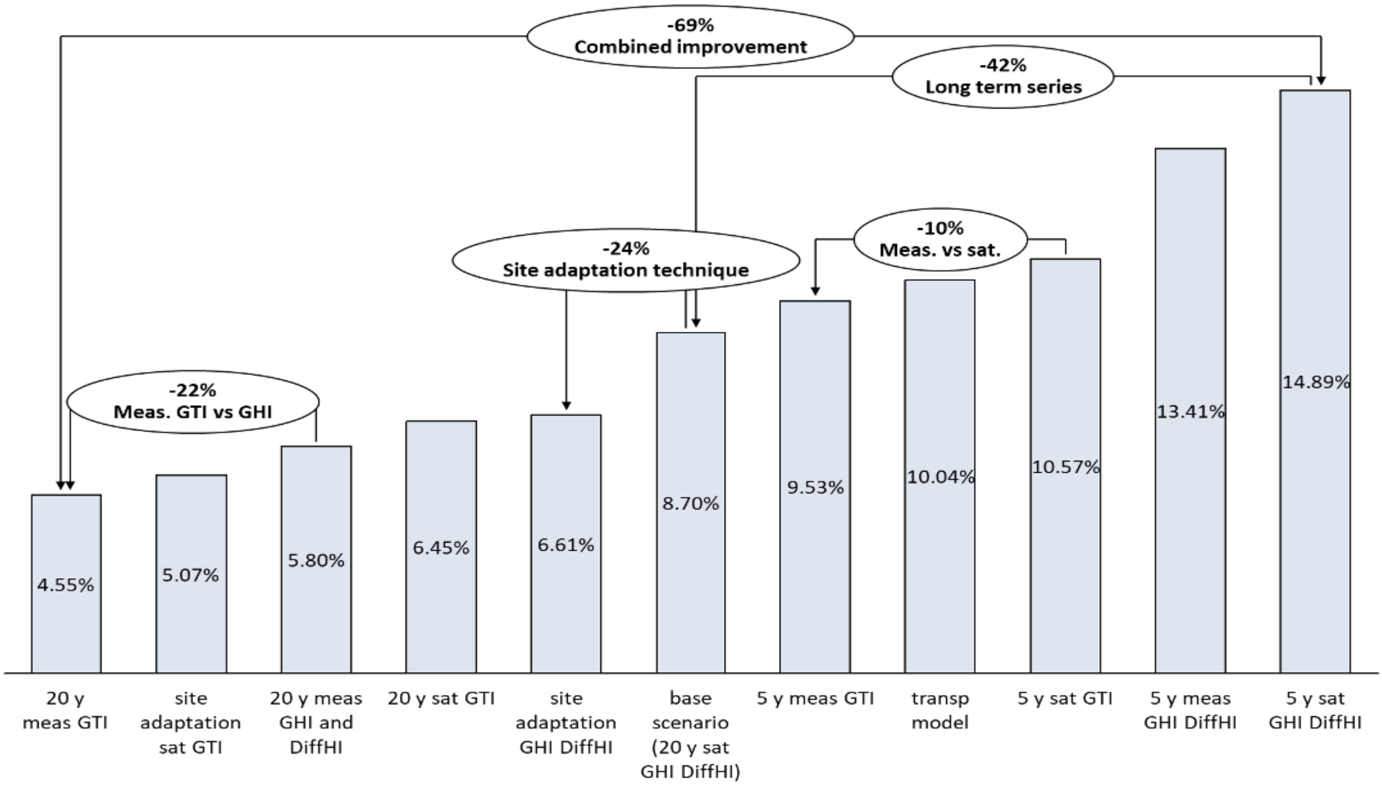
International Energy Agency
Photovoltaic Power Systems Programme



Task 13 Performance, Operation and Reliability of Photovoltaic Systems

PVPS

Uncertainties in Yield Assessments and PV LCOE

2020

Report IEA-PVPS T13-18:2020

What is IEA PVPS TCP?

The International Energy Agency (IEA), founded in 1974, is an autonomous body within the framework of the Organization for Economic Cooperation and Development (OECD). The Technology Collaboration Programme (TCP) was created with a belief that the future of energy security and sustainability starts with global collaboration. The programme is made up of 6.000 experts across government, academia, and industry dedicated to advancing common research and the application of specific energy technologies.

The IEA Photovoltaic Power Systems Programme (IEA PVPS) is one of the TCP's within the IEA and was established in 1993. The mission of the programme is to "enhance the international collaborative efforts which facilitate the role of photovoltaic solar energy as a cornerstone in the transition to sustainable energy systems." In order to achieve this, the Programme's participants have undertaken a variety of joint research projects in PV power systems applications. The overall programme is headed by an Executive Committee, comprised of one delegate from each country or organisation member, which designates distinct 'Tasks,' that may be research projects or activity areas.

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What is IEA PVPS Task 13?

Within the framework of IEA PVPS, Task 13 aims to provide support to market actors working to improve the operation, the reliability and the quality of PV components and systems. Operational data from PV systems in different climate zones compiled within the project will help provide the basis for estimates of the current situation regarding PV reliability and performance.

The general setting of Task 13 provides a common platform to summarize and report on technical aspects affecting the quality, performance, reliability and lifetime of PV systems in a wide variety of environments and applications. By working together across national boundaries we can all take advantage of research and experience from each member country and combine and integrate this knowledge into valuable summaries of best practices and methods for ensuring PV systems perform at their optimum and continue to provide competitive return on investment.

Task 13 has so far managed to create the right framework for the calculations of various parameters that can give an indication of the quality of PV components and systems. The framework is now there and can be used by the industry who has expressed appreciation towards the results included in the high-quality reports.

The IEA PVPS countries participating in Task 13 are Australia, Austria, Belgium, Canada, Chile, China, Denmark, Finland, France, Germany, Israel, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, Thailand, and the United States of America.

COVER PICTURE

Reduction in uncertainty of yield assessment depending on the quality of the insolation data. Courtesy of Eurac Research.

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INTERNATIONAL ENERGY AGENCY

PHOTOVOLTAIC POWER SYSTEMS PROGRAMME

IEA PVPS Task 13

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Uncertainty in Yield Assessments and PV LCOE

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LIST OF ABBREVIATIONS

AC	Alternating Current
BSRN	Baseline Surface Radiation Network
CAPEX	Capital Expenditures
DC	Direct Current
DKASC	Desert Knowledge Australia Solar Centre
DHI	Diffuse Horizontal Irradiance
DNI	Direct Normal Irradiance
EPC	Engineering, Procurement, Construction
FiT	Feed-in Tariff
GCM	Global Climate Models
GHI	Global Horizontal Irradiance
GTI	Global Tilted Irradiance
IAM	Incidence Angle Modifier
IEA	International Energy Agency
IRR	Internal Rate of Return
KPI	Key Performance Indicator
LCOE	Levelised Cost of Electricity
LTYP	Long-Term Yield Prediction
MCP	Measure Correlate Predict
NMOT	Nominal Module Operating Temperature
NPV	Net Present Value
O&M	Operation and Maintenance
OPEX	Operational Expenditures
PLR	Performance Loss Rate/s
POA	Plane of Array (irradiance)
PPA	Power Purchase Agreement
PR	Performance Ratio
RUL	Remaining Useful Lifetime
SLP	Service Life Prediction
SMHI	Swedish Meteorological and Hydrological Institute
TMY	Typical Meteorological Year
YA	Yield Assessment
WACC	Weighted Average Cost of Capital

EXECUTIVE SUMMARY

Yield assessments (YA) and Long-Term Yield Predictions (LTYP) are a prerequisite for business decisions on long term investments into photovoltaic (PV) power plants. Together with cost data (CAPEX, OPEX and discount rate), the output of a YA and LTYP (utilisation rate, performance loss rate and lifetime) provides to the financial investors the parameters needed for the calculation of the Levelised Cost of Electricity (LCOE) and to assess the cash flow model of an investment with relative Internal Rate of Return (IRR) and Net Present Value (NPV).

YA and LTYP outputs should be provided with a related exceedance probability. This gives the right tool to stakeholders involved in PV projects to take the best decision in terms of risk-aversion. A reduction in the uncertainty of the energy yield can lead to higher values for a given exceedance probability and hence a stronger business case. Various efforts in the literature show the importance of having a common framework that can assess the impact of technical risks on the economic performance of a PV project.

The most important parameter influencing the energy yield assessment is the site-specific insolation. Several aspects need to be considered: reliability of the database, interannual variability, long term trends.

Site adaptation techniques combine short-term measured data and long-term satellite estimates. Short periods of measured data but with site-specific seasonal and diurnal characteristics are combined with satellite-derived data having a long period of record with not necessarily site-specific characteristics. Upon completion of the measurement campaign, which is typically around one-year, different methodologies can be applied between the measured data at the target site, spanning a relatively short period, and the satellite data, spanning a much longer period. The complete record of satellite data is then used in this relationship to predict the long-term solar resource at the target site. Assuming a strong correlation, the strengths of both data sets are captured and the uncertainty in the long-term estimate can be reduced.

In Müller et al [1] an analysis on long-term trends for measured in-plane irradiance, Performance Ratio and energy yield for 44 rooftop installations in Germany was performed showing an average increase of in-plane irradiance of 1.1 %/year or about 11 %/decade over the period 2008 to 2018 for these systems. The increase in irradiance was especially higher than the observed Performance Loss Rate so that the energy yields of the systems analysed increased over the years with an average trend of 0.3 %/year.

The typical output of Yield Assessments should report the contribution to each derating factor, starting from the Global Horizontal Irradiation to the energy injected in the grid. The starting point of PR = 100 is considered after applying the horizon shading as this become the annual insolation seen by the PV modules. The following table shows a best practice in providing an overview of gains/losses along each modelling step and the related uncertainty. The uncertainty related to each modelling step can be provided already referred to the irradiation/yield value or to the parameter that is modelled. The value in the table for the specific yield (including its uncertainty) is to be understood as an average value over the entire operating period. The possible deviations between the yields for individual recorded years and the specific yield calculated can be assessed by including interannual variability.

Annual values	**uncertainty**	**value**	**gains/loss**	**PR**
	%	kWh/m^2	%	%
global irradiation on horizontal plane	4.0	1248		
irradiation on module plane	2.5	1448	16.0	
shading				
horizon shading	0.5	1445	-0.2	100.0
row shading	2.0	1422	-1.7	98.3
object shading	3.0	1422	0.0	98.3
soiling	0.5	1414	-0.5	97.9
deviations from STC				
reflection losses	0.5	1376	-2.7	95.2
	%	kWh/kWp	%	%
spectral losses	0.5	1363	-1.0	94.3
irradiation-dependent losses	0.8	1342	-1.5	92.9
temperature-dependent losses	1.0	1309	-2.5	90.5
mismatch losses	0.5	1298	-0.8	89.8
DC cable losses	0.5	1287	-0.8	89.1
inverter losses	1.5	1272	-1.2	88.0
inverter power limitation	0.5	1272	-0.1	88.0
additional consumption	0.5	1270	-0.1	87.9
AC cable losses low voltage	0.5	1265	-0.4	87.5
Transformer medium voltage	0.5	1253	-0.9	86.7
AC cable losses medium voltage	0.5	1252	-0.1	86.6
Transformer high voltage	0.0	1252	0.0	86.6
total	**6.5**	**1252**		**86.6**

For example, for temperature-dependent losses, the value of uncertainty could be referred to the temperature variability of the profile used in the assessment or to the temperature model used in the assessment. The ambient temperature variability and the various temperature models will lead to a different contribution in terms of yield loss and in terms of uncertainty.

An emerging challenge in YAs is also due to the deployment of novel technologies (e.g. bifacial PV modules) with a contribution in terms of uncertainty that needs to be properly assessed.

Building upon the knowledge available in the literature and the previous IEA PVPS Task 13 report [2], in this report we have moved forward from the uncertainty framework in yield assessment to two real implementations of it and the impact that uncertainties can have on lifetime yield predictions, on the LCOE and on the cash-flow.

One of the most relevant question that we have tried to answer is also the following:

How reliable are YA's?

This is an apparently simple question; however, the answer is not equally simple. Typically, investors require one YA. In some cases, more YAs might be requested if results are unclear. The various YAs can be averaged to assign a purchase value to a given project. In any case the question remains unanswered: why different assessors obtain different answers? Is one YA more reliable than others?

Investors know that past performance is no guarantee for future results. This maxim also applies to long-term yield assessments and the LCOE that can be determined from these, also within the context of a changing climate. Yield Assessment is an essential step in a PV project, as it helps to determine whether a system will be funded or not. However, the YA is not only about the software used, it is mainly about the user. YAs may not be as reliable as expected, and in this report, we demonstrate how seven highly skilled specialists did not arrive at the same result, having been provided the same detailed inputs.

Independent yield assessors were in fact asked to provide YAs and LTYPs for two sites, namely, Bolzano in Italy and Alice Springs in Australia.

For the Bolzano site, the P50 ranged between 1095 and 1406 kWh/kWp, P90 ranged between 997 and 1274 kWh/kWp. The average value for the initial YAs is 1278 kWh/kWp with a STD (σ) of 9.7 %. Taking into account the estimated Performance Loss Rates of the LTYPs, the average annual energy yield over the time period the system is in operation (2010 to 2019) would be 1253 kWh/kWp. The measured average yield in the period is 1275 kWh/kWp.

For the Alice Springs site, the P50 ranged between 1757 and 1985 kWh/kWp and the P90 between 1631 and 1819 kWh/kWp. The average value for the initial YAs is 1878 kWh/kWp with a STD (σ) of 3.9 %. The system has been in operation since 2009 with an initial yield of 2075 kWh/kWp and 1926 kWh/kWp as 10-year average.

As seen from the YA exercises for Bolzano and Alice Springs, differences in these stem primarily from personal experience and assumptions by the modeler, of which

(i) the irradiance database selection and site adaptation (especially for mountainous terrain),
(ii) degradation/PLR assumption,
(iii) total modelling uncertainty values (as seen in the P50 and P90 ranges) and
(iv) soiling and far/near shading had the largest impact on the determined result.

The direct flow-on consequence from this is that LCOE values will also exhibit a variance, on top of the additional modelling assumptions that can be employed for LCOE calculations. Determining P50 and P90 values for LCOE results and highlighting the assumptions/modelling chain will be important. From an industry perspective, it would be beneficial if more “live” post-mortem analyses (i.e. comparison of the LTYP and measured data, at e.g. every 5 years of system life) would be made and published. These can then be used as crucial feedback and inputs for YA modelers, financiers, and insurers.

To conclude, we believe that together with the previous report [2], we have provided all the needed information to understand if one YA is more reliable than other and which input and output data must be provided by the assessor to reach this conclusion.

1 INTRODUCTION

Yield assessments (YA) and Long-Term Yield Predictions (LTYP) are a prerequisite for business decisions on long term investments into photovoltaic (PV) power plants. Together with cost data (CAPEX, OPEX and discount rate), the output of a YA and LTYP (utilisation rate, performance loss rate and lifetime) provides financial investors with the parameters needed for the calculation of the Levelised Cost of Electricity (LCOE) and to assess the cash flow model of an investment with relative Internal Rate of Return (IRR) and Net Present Value (NPV).

The preparation of a YA and LTYP report typically relies on numerical modelling and prediction of the expected energy yield, based on experience with previous PV power plants, laboratory measurements and knowledge gained in the PV community over the past years and decades. In the previous IEA PVPS TASK 13 report "Uncertainties in PV System Yield Predictions and Assessments" [2], we presented a comprehensive investigation of the uncertainties related to this task. The report collected some insights into the field of uncertainties of several technical aspects of PV system yield prediction and assessment investigating several of the modelling steps for gains and losses in a PV system: the solar resource — including long term trends, PV module properties, system output and performance.

The main challenge in YA and LTYP relates to the trustworthiness of site-specific information. In a global market it is in fact not uncommon to assess the yield of a PV plant to be located in areas which are not familiar for the yield assessor and local knowledge is thus of extreme importance.

Irradiation data derived from satellite images are increasingly used as input for long-term yield estimations and as the basis for reference yield calculations for monitoring and business reporting. Several authors have evaluated the quality of satellite-based irradiance data in the past, typical normalized root mean square errors for satellite-based irradiation reported in literature are situated between 4 % to 8 % for monthly and 2 % to 6 % for annual irradiation values.

Solar irradiation at the Earth's surface is not stable over time for all locations on earth but may undergo significant long-term variations for particular regions, which is referred to as "global dimming and brightening". Consequently, related uncertainties may not be considered to be negligible. In the presence of long-term trends, the question for solar resource assessments is no longer "what is the 'true' climatological value?", but "what is the best predictor for the project lifetime?". A suitable estimator should be a recent time period, that is long enough to filter the influence of single years with high anomalies, but which is short enough, to minimize the influence of past trends. For more insights about high quality solar resource assessments and in particular on the development of enhanced analysis of long-term inter-annual variability and trends in the solar resource, we invite the reader to look at the output of the IEA PVPS Task 16 "Solar resource for high penetration and large scale application" [3].

The direct current (DC) energy yield of a PV module depends on module characteristics as well as operating conditions. With respect to uncertainties, the different influencing effects (irradiance level, angle of incidence, operating temperature, etc.) are typically represented by one individual factor per effect. The influences are assumed to be independent. Furthermore, these factors are often used in integrated form, e.g. over one year.

In the previous report, a framework for the calculation of uncertainty for a complete long-term yield prediction was presented. As the simplified error propagation approach may not be suitable for a complex LTYP, a Monte-Carlo simulation was used instead as a methodology to improve the quality of the output.

The proposed approach was given as an effort to standardise the procedure for uncertainty calculation of predicted energy yields of PV systems in order to properly estimate financial investment risk.

In this report we will build upon the previous work by running benchmarking exercises in order to be able to quantify the differences between existing approaches. In Section 2, we will give an overall update about uncertainties in YA coming from the various modelling steps and derating factors.

In Section 3, several sites were selected in different climates and partners were asked to provide independent yield assessments and long-term yield predictions based on their best practices and/or their own developed simulation tools. The results were analysed, and uncertainty reduction scenarios were studied. The final aim is to link the uncertainty framework and the scenarios with cash flow models and LCOE calculations compared to real case studies.

The benchmarking yield assessment exercise was conducted by selecting sites with prominent features (e.g. soiling, shading, etc.). The first site we have selected is a PV plant in Bolzano, Italy, monitored by Eurac Research, leaving a high degree of freedom to the various yield assessors where only the following information were shared: details (including technical specifications) on the installed PV module technology and inverter type, coordinates, azimuth, tilt angle and shading diagram. The second selected site is located in Alice Springs, Australia, at the premises of the Desert Knowledge Australia Solar Centre (DKASC). The yield assessors were asked to send YAs for up to 3 PV technologies. From the Bolzano and Alice Springs exercises we gained insights on typical deviation from real performance data due to the peculiarities of the two sites (e.g. shading and snow loss, soiling).

In Section 4 we move from Yield Assessment to the calculation of LCOE using the data from Section 3 as input. The aim of the Section is to present a comparison between modelled LCOE and real LCOE using data coming from the field.

Finally, in Section 5 we define some take home messages in terms of best practices and guidelines.

2 HOW UNCERTAIN IS THE YIELD ASSESSMENT IN PHOTOVOLTAIC PROJECTS?

Exceedance probability is defined as the probability that a certain value will be exceeded. The exceedance probability of the energy yield and how this is influenced by the overall uncertainty is one of the key parameters to benchmark investments. A reduction in the uncertainties can lead to higher values of energy yield for a given exceedance probability and hence a stronger business case. Moser et al [4], Richter et al [5] and Reich et al. [6] estimated the combined overall uncertainty of the energy yield to fall in a range between 5 and 11 %; in another study, Müller et al [7] have calculated the variation of the overall uncertainty of the energy yield over the lifetime of a PV plant and compared the findings with data from a portfolio of 26 systems located in Germany and Spain. These efforts show the importance of having a common framework that can assess the impact of technical risks on the economic performance of a PV project.

2.1 Definitions

Yield Assessment: Assessment of the expected energy yield (in kWh/kWp) of a defined PV system at a specified location. It can be calculated for the 1st year of operation (initial yield assessment), for a specific year or as an average over the lifetime of a PV project.

Irradiance: Irradiance is an instantaneous measurement of solar power over some area. The units of irradiance are watts per square meter.

Insolation: Insolation is a measurement of the cumulative energy measured over some area for a defined period of time (e.g. annual, monthly, daily, etc.). The common unit of insolation is kilowatt hours per square meter.

Uncertainty: defined as the contribution of each modelling step towards the overall uncertainty of a yield assessment. The overall uncertainty is typically calculated as the root mean square of the sum of the errors. Considering the standard deviation (σ), the lower threshold for the interval (E ± σ) is in correspondence of P84.1.

Long-term Yield Prediction: Yield Assessment calculated over the lifetime of a PV project including considerations about degradation of performance and the evolution of the uncertainty due to the reduction of site dependent variability (irradiation, temperature, etc.).

P_X: Exceedance probability defined as the X % probability that a certain value will be exceeded. A P90 value corresponds to a number that has 90 % probability of being exceeded.

LCOE: The Levelised Cost of Electricity is the cost of generating 1 kWh considering the initial investment (Capital Expenditures), the discounted Operational Expenditures and the discounted utilisation rate over the lifetime of the power plant.

NPV: The Net Present Value is the discounted difference between the present value of cash inflows and the present value of cash outflows over a period of time and it is used to analyse the profitability of an investment or project over its financial lifetime.

2.2 Typical uncertainties used in yield assessments

The topic of derating factors along the modelling chain of an yield assessment and related uncertainties has already been covered in the literature by several authors [4], [5], [8], [9] and organisations [2], [10]. The IEA PVPS Task 13 Report "Uncertainties in PV System Yield Predictions and Assessments" [2] already provides a detailed framework for the calculation of uncertainties in yield assessments. The aim of this section in the present report is to provide a short summary of and new insights in recent analysis and technologies.

2.2.1 Uncertainty in the long-term insolation estimation

The main source of uncertainty is certainly related to the insolation estimation. Various aspects need to be considered when assessing the insolation in a particular site. We will see in section 3 how previous experience of the assessor can play an important role during this step.

In Yield Assessment, the choice of the sources for long term insolation data is key with a direct impact on the P50 (median) value of the chosen distribution.

Any other P_X value (e.g. P90, P95) is affected by the variability of the annual insolation if it refers to the estimated annual yield for a specific year (e.g. year 0). For Yield Assessment values provided based on long-term predictions (i.e. as an average over a 20+ years' timeframe), the interannual variability is essentially cancelled out.

Other aspects that need to be considered are related to the presence and extrapolation of long-term trends (also known as global dimming or global brightening) which become important when assessing the yield over a 20+ year period.

A. Annual insolation variability

The solar resource variability or "year-to-year variability" is defined as the ratio of the standard deviation (σ) to the average global horizontal irradiation (GHI) over a long-term period of typically 10 to 20 years. As reported in literature, the solar resource variability in Europe, for example, can range from ca. ± 4 % up to ca. ± 7 % for more complex conditions like e.g. near coastal areas [11]. A month or a year with less solar irradiation than the long-term average also corresponds to a decrease of the solar park's production for the considered period with respect to the expected business model. Such variations over time are a well-known phenomenon and must be correctly accounted for in long-term yield assessment studies. Correctly calculated uncertainty scenarios (P90 figures calculated in the business model) should therefore sufficiently cover for these lower solar periods.

Recent developments like the Solar Index Maps[1] analyse the variability of the solar resource across continents and allows for improved assessments of how the solar resource varies compared with the expected long-term average values. The Solar Index Maps use 3E's satellite-based irradiation data (solardata.3e.eu) and generate detailed maps showing the percentage difference between the solar resource during the period of interest (e.g. last year or even last month), compared with the long-term average solar resource calculated over more than 10 years (data available from 2004 to date). The figure below (Figure 1), for example, shows the Solar Index Map of Europe for the year 2018 compared with the long-term average, where orange/red means higher irradiation than the P50 and green/blue means lower irradiation than the P50 (business model). This difference indicates natural fluctuations that directly impacted the generation of thousands of PV systems during 2018 across the region having direct effect in both the cash flow of the individual PV parks but also on the electricity grids at aggregated level.

[1] *https://www.3e.eu/solarpower-europe-3e-launch-solar-index-maps/*.

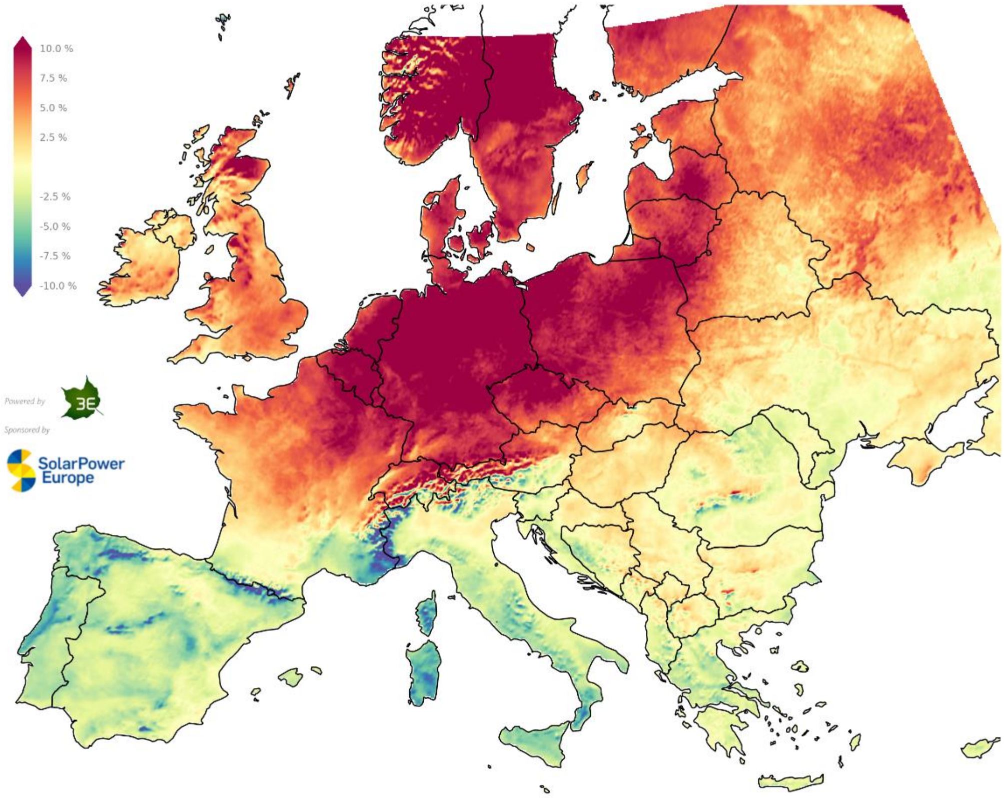


Figure 1: Yearly Solar Index Map of Europe for 2018 (source: https://solardata.3e.eu/maps/solarindex)

A closer look at multiple consecutive years is shown in Figure 2, where one can see that, for example, while 2016 was overall a very average year in terms of solar resource for most European countries, 2017 was a very good year for most of southern Europe with approx. 5 % more irradiation than the expected values (P50). However, 2017 was not a good year e.g. for western UK and Ireland, and particularly for some northern European areas with approx. 3 % to 5 % less than expected P50 values (e.g. Poland and northern Germany). Interestingly, 2018 had the opposite behaviour in terms of solar irradiation having very high irradiation values for most of northern European countries, UK and Ireland with over 8 % more irradiation than expected long-term average (P50) values in many countries while southern European countries such as e.g. Portugal, Spain and Italy experienced approx. 5% less yearly irradiation than their expected P50 values.

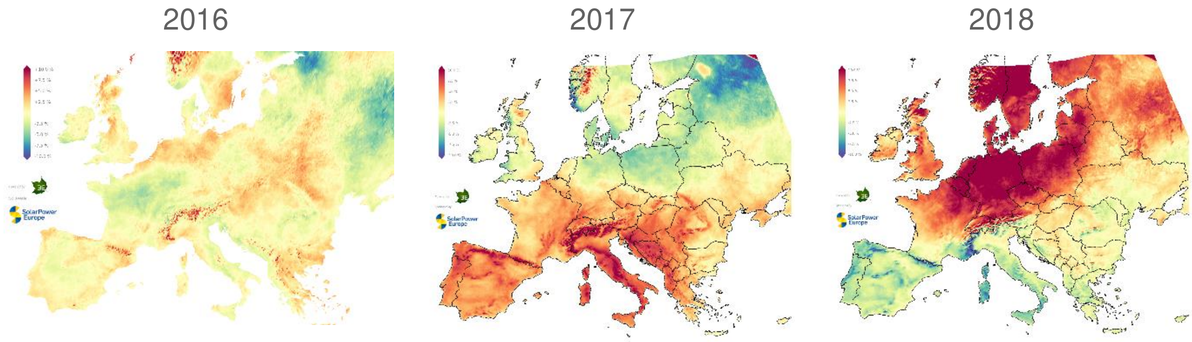


Figure 2: Yearly Solar Index Maps for Europe for 2016 (left), 2017 (middle) and 2018 (right) (source: https://solardata.3e.eu/maps/solarindex)

In the case of Africa (Figure 3), the Solar Index Maps show that while the variability of the solar resource over Africa is much lower than in Europe, still some important variations can occur like, for example, 2017 was not a very good year for some countries in the sub-Saharan region like Zambia and Mozambique where the irradiation over 2017 was approx. 6 % lower than the P50. On the contrary, 2016 was a much better year in terms of solar resource for all sub-Saharan countries.

2016 2017 2018

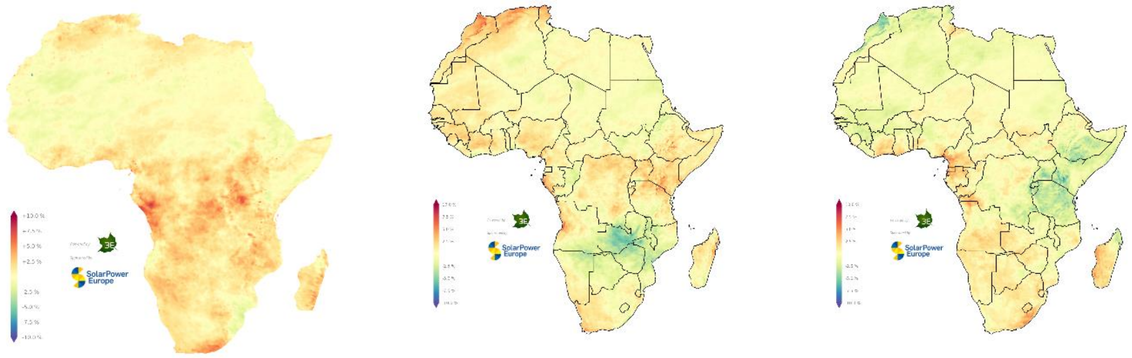


Figure 3: Yearly Solar Index Maps for Africa for 2016 (left), 2017 (middle), and 2018 (right) (source: https://solardata.3e.eu/maps/solarindex)

B. Long-term trends

Long-term trends of solar irradiance may have a significant influence on uncertainties of yield assessments [12]. While this influence may be close to zero or even negative for some regions of the world, there are regions where a strong brightening can be observed.

Figure 4: Analysis for 44 rooftop systems. Left: locations of the systems, Right: example system

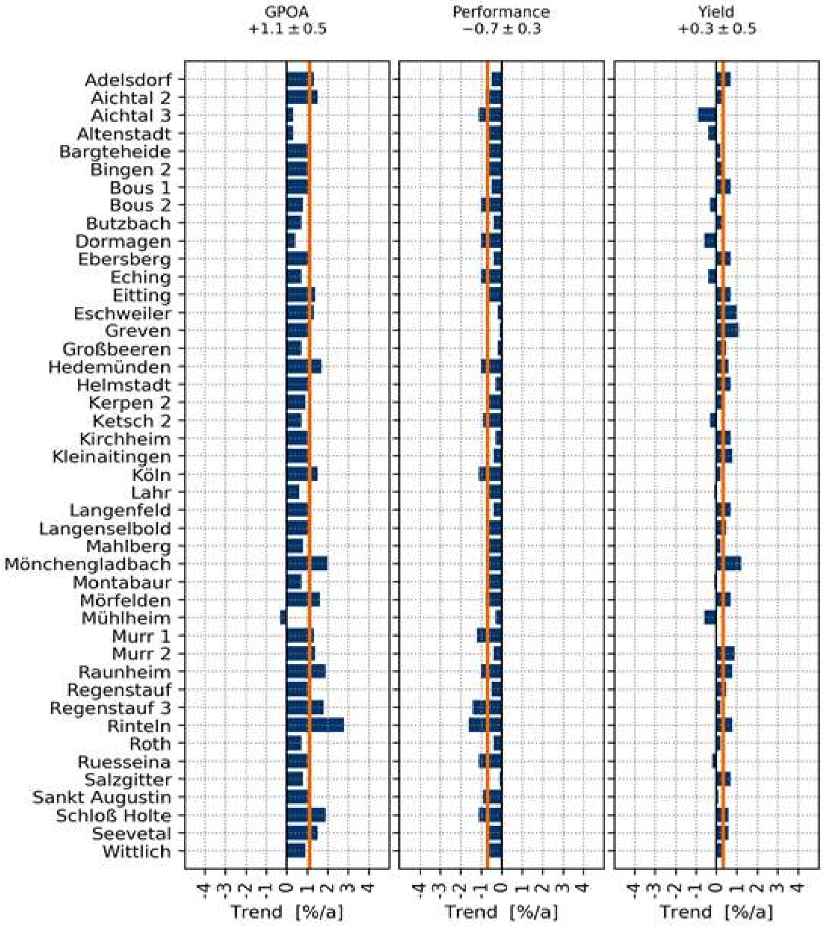


Figure 5: Trends for in-plane-irradiance (GPOA = GTI, left), Performance Loss Rate (Performance, middle) and annual energy yield (Yield, right)

In Müller et al [1] an analysis on long-term trends for measured in-plane irradiance, Performance Ratio and energy yield for 44 rooftop installations in Germany was performed (see Figure 4 for location of the PV plants). Figure 5 shows an average increase of in-plane irradiance (GTI) of 1.1 %/year or about 11 %/decade over the period 2008 to 2018 for these systems. While this strong positive trend is statistically influenced by the year 2018 which showed very high levels of irradiance in Germany (see Figure 2), still a continuing strong brightening effect can be assumed. The increase in irradiance is especially higher than the observed Performance Loss Rate (negative values means losses over time, see Section 2.2.2 for more information about the definition of Performance Loss Rate) so that the energy yields of the analysed systems increase over the years with an average trend of 0.3 %/year.

C. Long-term trends in Nordic countries

In Sweden, the Swedish Meteorological and Hydrological Institute (SMHI), is an expert agency under the Ministry of the Environment. SMHI uses the World Meteorological Organization WMO defined normal period 1961-1990 to define the “normal” weather. However, the temperature in Sweden and the solar irradiance in at least most of the southern part of Sweden have increased during the three last decades. At the SMHI stations near the coast of Sweden in Visby (southern Sweden), Stockholm, and Luleå (northern Sweden) the global horizontal irradiance showed an increase with 1.7 - 2.8 % from the period 1961-1990 to the average for the period 1991-2019, see Table 1. In contrast, the inland stations Karlstad, Östersund and Kiruna in the west, of which the two latter ones are in the northern half of Sweden close to the mountain area, and Umeå near the coast in the north showed a decreased irradiance with 0.9 - 3.1 % during the same period.

It can be noticed that there is a trend of increasing global irradiance for all stations in Table 1 during the period 1991-2019, as exemplified for Stockholm in Figure 6, although weak for the northern inland stations.

Table 1: Yearly average global horizontal irradiance for the periods 1961-1990 and 1991-2019 at SMHI weather stations in Sweden with measurements starting before 1961, sorted from south to north

Station	Latitude / Longitude (°)	Irradiance 1961-1990 (kWh/m^2)	Irradiance 1991-2019 (kWh/m^2)	Difference 1991-2019 vs 1961-1990
Visby	57.7 / 18.3	1067	1097	+2.8%
Stockholm	59.4 / 18.1	970	986	+1.7%
Karlstad	59.4 / 13.5	1011	1002	-0.9%
Östersund	63.2 / 14.5	933	904	-3.1%
Umeå	63.8 / 20.2	938	914	-2.5%
Luleå	65.5 / 22.1	876	894	+2.1%
Kiruna	67.8 / 20.4	817	802	-1.8%

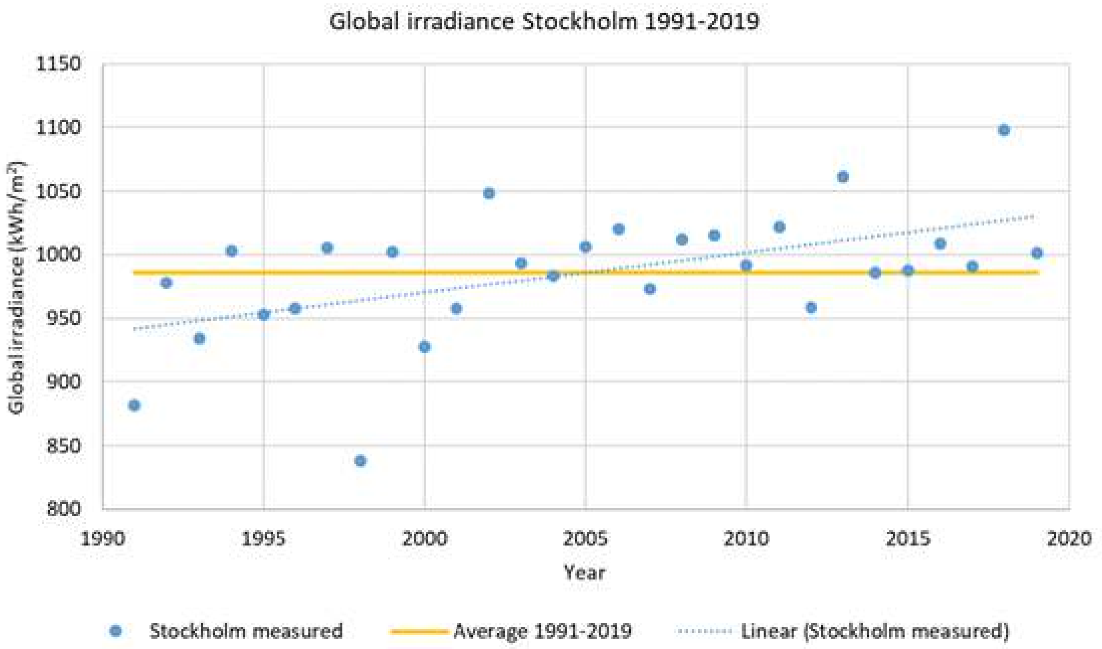


Figure 6: Yearly global horizontal irradiance measured in Stockholm for the period 1991-2019 [SMHI]. The yellow line shows the average for the period and the dotted blue line is linear trend line for the period

D. Long-term solar resource uncertainties

Sites where high-quality long-term ground-based measurements have been taken are rare, except for i) meteorological stations that belong to the BSRN [13] or national equivalents or ii) operational (utility-scale) PV systems. Having such long-term high-quality ground-based measurement data for new PV sites is extremely rare. Consequently, the use of satellite-derived irradiance data for long-term yield assessments is inescapable, yet as the satellite geographical resolution is often in the range of kilometres, the long-term dataset is best subjected to site adaptation methods [14].

Site adaptation techniques combine short-term measured data and long-term satellite estimates. Short periods of measured data but with site-specific seasonal and diurnal characteristics are combined with satellite-derived data having a long period of record with not necessarily site-specific characteristics. Upon completion of the measurement campaign, which is typically around one-year, different methodologies can be applied to the measured data at the target site, spanning a relatively short period, and the satellite data, spanning a much longer period. The complete record of satellite data is then used in this relationship to predict the long-term solar resource at the target site. Assuming a strong correlation, the strengths of both data sets are captured and the uncertainty in the long-term estimate can be reduced.

Two main approaches for site adaptation of satellite-derived data are identified in literature: an adaptation to the input data of the model to better fit the local irradiation measurements and, empirical adjustments of the model output estimates by comparison with the on-site measurements. The study conducted by [14] concluded that each site would likely require a specific initial assessment to design the proper method for data adaptation. Moreover, the site-specific method may be a combination of the different approaches. Furthermore, it is highlighted in the study that the optimum duration of the overlapping period between ground observations and model estimates has not been widely studied.

In [15], the authors validated the application of a Measure Correlate Predict (MCP) methodology, a rather simple site adaptation technique, on 32 meteorological stations in the Netherlands. The study concluded that the MCP methodology can yield high accuracies with uncertainties below 2 % (bias) if the common reference period used is at least one year. However, if the bias of the satellite is not constant over the year, the application of the MCP methodology based on periods shorter that one year can have considerably lower accuracy. This can be improved by using more advanced site adaptation methods as proposed e.g. in [14].

Historically, solar resource assessments have been judged to have lower uncertainty as the timespan included in the dataset increases [16], although this assumption ignores i) that long-term insolation trends may be subject to brightening or dimming, in which case using the most recent ten years of data is recommended [17], ii) that significant changes to satellite instrumentation can result in older data being of much lower quality, to the extent that many commercial meteorological data providers only provide insolation data from 2006 onwards for the Pacific region covering Japan and Australia [18] as the newer satellites came online [19].

E. Projections of future trends

A growing number of publications is using data from global climate models (GCM's) to assess the influence of climate change and dimming and brightening effects on PV system performance [20]–[23]. In [24], the ambient temperature and irradiance towards 2100 for the SSP5-8.5 scenario are processed [25]–[27] for several locations worldwide. Using a simplified PV yield model for crystalline silicon technology, the authors present the trends of maximal PV module temperature and Performance Ratio (see Figure 7). Under the SSP5-8.5 projected scenario, Ljubljana-Slovenia will increase both ambient temperature and irradiance, and for this reason, the rise of PV module temperature will lead to decrease in the PR. Minnesota-USA is showing the fastest PR reduction due to the fast rising temperature. In Jos-Nigeria, GHI drops significantly, limiting the decrease of PR only to 1.8% in 2100.

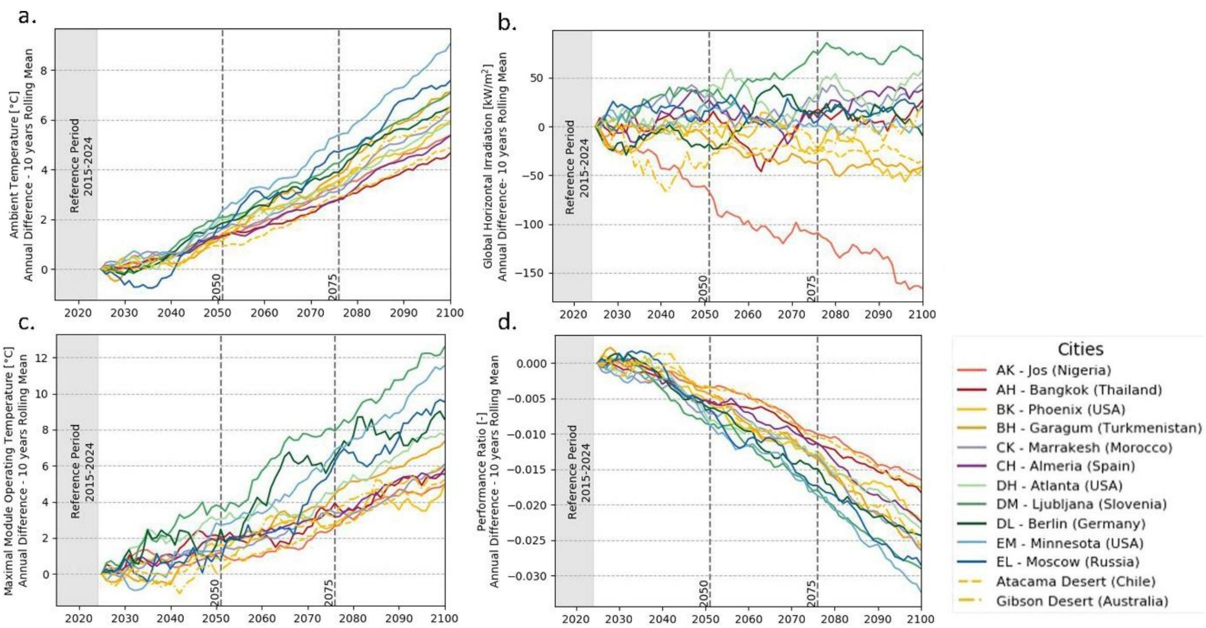


Figure 7: Evolution of relevant PV performance indicators for c-Si PV modules under the SSP5-8.5 climate change scenario. Annual differences of 10 years rolling mean for: (a) Ambient Temperature, (b) Global Horizontal Irradiation, (c) Maximal Module Operating Temperature and (d) Performance Ratio. (source: [24])

Even though some results are already published, further research is needed to establish methods to include more information from GCM's into yield assessments. While the direct usage of time series data derived from GCM's for yield assessments is proved to be possible, the regional analysis and more realistic PV performance modelling including uncertainties need further exploration.

2.2.2 Uncertainties in degradation and performance loss models available

In the IEA PVPS Task 13 report "Assessment of Performance Loss Rate of PV Power Systems" [28], the authors focused their efforts on the determination of reliable Performance Loss Rate (PLR) calculation approaches. PLR is defined as the sum of losses on system and module level and include both reversible and irreversible effects. The term degradation instead is often used to verify an irreversible loss on module level stemming from appearing degradation modes. In general, PLR calculations follow a strict order of steps, which includes input data acquisition, data filtering, performance metric selection and the application of statistical methods to obtain the final PLR, which is given in %/year. In order to understand which approaches and calculation step combinations yield reliable results, and which should be discarded, 31 different filter/metric/method combinations have been applied to 19 different real PV systems and several more digital systems (data for digital systems are generated based on a physical model of a PV plant and the PLR is introduced as a known parameter). The outcome is that there is no outperforming combination, rather the authors suggest that one should apply several combinations to the same dataset to find an average value for PLR which might approximate best the "true" value (which remains unknown). However, certain filter/metric/statistical method combinations should be avoided as they produce PLR values with high deviations from the "true" value.

An uncertainty evaluation across different approaches turned out to be impossible as related uncertainties depend on the methodology used for the calculation of PLR and the chosen approach selected by the analyst. Most statistical methods for PLR determination are based on regression. For regression-based PLR uncertainty, it is recommended to evaluate the variance of the linear model to the selected performance metric trend over time. If time series decomposition approaches have been used the residuals component should be added back to the trend to ensure comparable conditions. Another tested, and widely used, statistical method for PLR determination is the Year-on-Year approach, where the differences between one data-point in a calendar year with the data-point at the same position in the subsequent year are accumulated. The method is available in the RdTools Python package [29]. Here, the uncertainty determination is standardised by using the probability distribution of the individual PLR results to represent the uncertainty. It thereby inevitably deviates from the regression-based uncertainty determination.

2.2.3 Uncertainties in parameters used in power calculation

The power calculation in PV modelling software not only depends on the software's algorithms, it also requires that components (modules, inverters) have been correctly parametrised and is available as input into the software [30]. While the modeller can input or translate datasheet values for use in, for e.g., PVsyst, typically module (PAN files) or inverter (OND files) data sets are provided by the manufacturer, yet no reliance is given by most manufacturers as to the accuracy of these key inputs. The uncertainties on (sub)components in the PV power modelling chain [31] are often relatively low through the implementation of peer-reviewed methods. However, modelling risks can occur through errors in module or inverter files, which can negatively affect the yield, and with it, the financial viability of PV plants. Therefore, it becomes more and more the common industry standard that PV modules or inverters are subjected to additional characterisation by independent laboratories upon instruction by investors to ensure that the power plant model is bankable. Special care must be taken during this phase in terms of number of modules to be tested and selection procedure (look at Section 2.2.1 in [2]) in order to obtain a reliable mean value of electrical parameters to be used in power calculation.

2.2.4 Estimation of Array DC losses

A. Soiling

In many countries, the impact of soiling (including snow losses) has an important impact in the yield assessment. There is always a certain degree of uncertainty from a yield assessor perspective in evaluating typical soiling losses for different countries/regions and in assigning uncertainties related to their estimation. The presence of point sources should be verified and avoided whenever possible.

Li et al recently reported on the global reduction of solar power generation efficiency due to aerosols and PV module soiling [32]. They reveal that in case of precipitation-only removal and no cleaning, PV generation in heavily polluted and desert regions is reduced by more than 50 % by particulate matter. A cost-effective cleaning schedule must be considered with a positive impact in terms of yield and an increase in Operation and Maintenance (O&M) costs.

Another recent study (2019) reports on the techno-economic assessment of soiling [33]. They determined the optimal trade-off between losses and cleaning events using reported soiling rates from 20 countries. The soiling rate varies widely: Italy shows a range between 0.02 % and 0.2 % per day, Spain 0.01 % - 1 %, UAE 0.1 % - 1 %, China 0.06 % - 3 %, just to give some examples.

Uncertainties related to soiling estimation can arise from various reasons: uncertainty on measurement, uncertainty on the impact of soiling on various PV technologies [34], spatial non-uniformity of soiling over PV modules within the same system. Even within a single site, variations in soiling data can be observed [35]. Typical measurement related uncertainties can be of the order of 1 % [36].

Report [37] presents in details all the aspects related to soiling losses determination and uncertainties.

B. Snow losses

The presence of snow has a double effect with a negative impact in terms of performance losses and a positive impact in terms of increase in albedo. Yield assessment carried out in high latitude regions should pay special attention to the overall impact of snow on the yield. As for soiling, the choice in system layout and in PV module technology can decrease the losses, e.g. frameless modules.

Pawluk et.al. [38] states that annual losses due to snow coverage are less than 10% in most climates. This is also confirmed in studies made in Sweden by RISE Energy Technology Center [39].

For more information see report [37], [40].

2.2.5 Further uncertainty sources for emerging PV technologies

Emerging PV module and system technologies promise to significantly increase the power output of PV systems in various ways. Bifacial PV modules enable the collection of reflected light by the rear surface of the solar cells and sun-tracking PV systems enhance the collection of direct light by following the sun’s trajectory through dynamically adapting the PV system geometry (see more in [41]). As such technologies will increasingly contribute to worldwide renewable energy generation, it is important to identify the associated yield assessment uncertainty sources. Moreover, the worldwide cost-competitiveness of PV electricity generation extends the range of financially viable PV projects to sites with increased complexity, where e.g. variations of terrain topography need to be considered.

A. Bifacial demonstration setup

The additional uncertainty sources for bifacial PV systems are explained with the help of an example bifacial PV system depicted by Figure 8. It consists of 24, 60-cell PV modules installed in landscape orientation. Modules are arranged in 4 rows and 6 columns on a single, South-facing PV stand, which is tilted by 30˚. The mounting structure elements are positioned under the module frames to minimize rear-side shading.

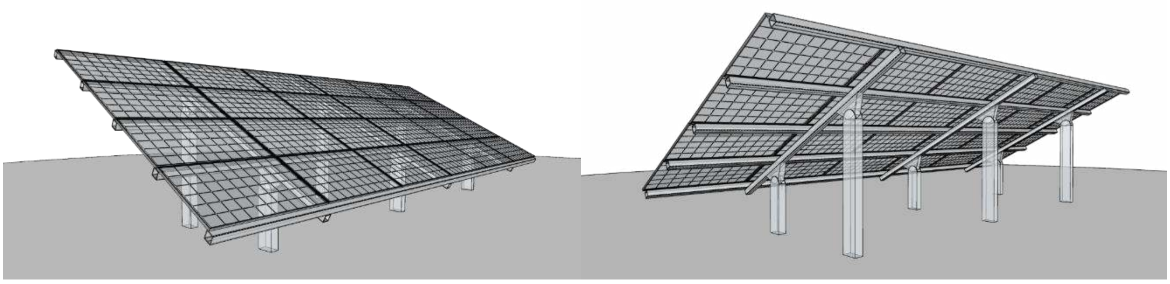


Figure 8: Illustration of the example bifacial PV system from front and rear views. All elements are artificially made transparent to expose the details of the geometry.

The PV module geometry model is inspired by an industrial, 60 cell bifacial, glass-glass, framed PERC module. The module frame cross section and the junction boxes are also modelled, to best represent rear-side light collection. The cross sections of the long and short edges of the module are shown in Figure 9, where the junction box location is also shown.

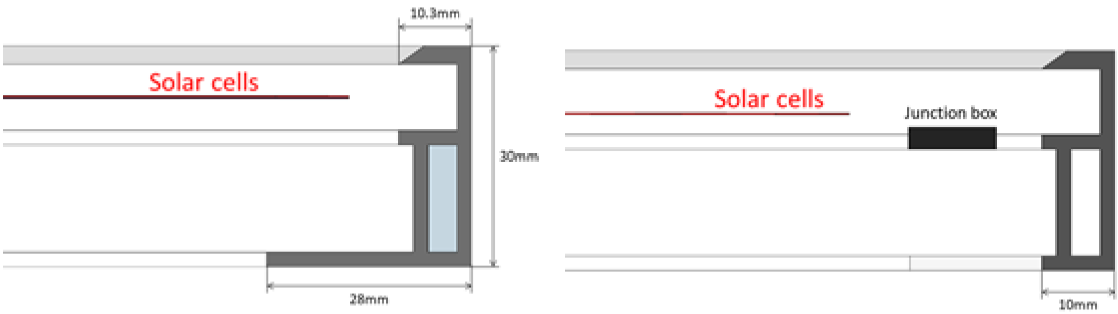


Figure 9: Module cross-sections taken on the long edge (left) and short edge (right)

As shown above, the long edge module frame, which is designed to provide structural rigidity, protrudes above the solar cells creating rear-side shading, therefore its inclusion in the model is important. The short edge frame is much further away from the solar cells, although it can be observed on Figure 9 (right) that the junction boxes will limit light transmission through the modules, causing a minor reduction of rear irradiance.

The introduced test system is placed in a sunny climate, where the South orientation and 30˚ tilt angle represents an optimal configuration for traditional, monofacial PV systems.

The 24 modules of the demonstration array are all connected in series and they represent one string.

B. Bifacial irradiance

During yield assessment, irradiance modelling for monofacial, unshaded PV systems is achieved by transforming standard irradiance measurements Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI) to the collector plane using an all-weather sky model. However, when the amount of irradiance received by the modules is affected by their surroundings through shading or reflections, additional phenomena need to be considered.

In recent years, a significant amount of scientific contributions has addressed the problem of calculating bifacial irradiance and two main approaches emerged: ray tracing and view factors [41]. Published errors compared to in-plane irradiance measurements range from 5 % to 40 % showing that both methods have high accuracy potential if appropriately implemented. Nevertheless, compared to uniformly illuminated, monofacial PV systems, increased in-plane irradiance uncertainty is expected.

It is well documented in literature that ground albedo affects bifacial PV energy yield, thus accurate, on-site albedo measurements are needed for reducing bifacial PV yield assessment uncertainty. It is however a challenging task to obtain such measurements as albedo (as seen by a horizontally mounted albedometer) shows ground cover-dependent, intra-day and seasonal variations. Intra-day variations may be caused by anisotropic ground reflectivity and forward-scattering effect, while seasonal variations can be caused by changing vegetation, ground moisture and snow cover.

One such example of on-site albedo measurements is presented by Figure 10 showing both intra-day and seasonal variations. In morning and evening hours albedo values as high as 0.4 and more are recorded, as opposed to the daily mean value of 0.2. Analysing noon-time values throughout the year reveals seasonal variations between 0.1 and 0.22, whereas lower albedo values are measured during winter.

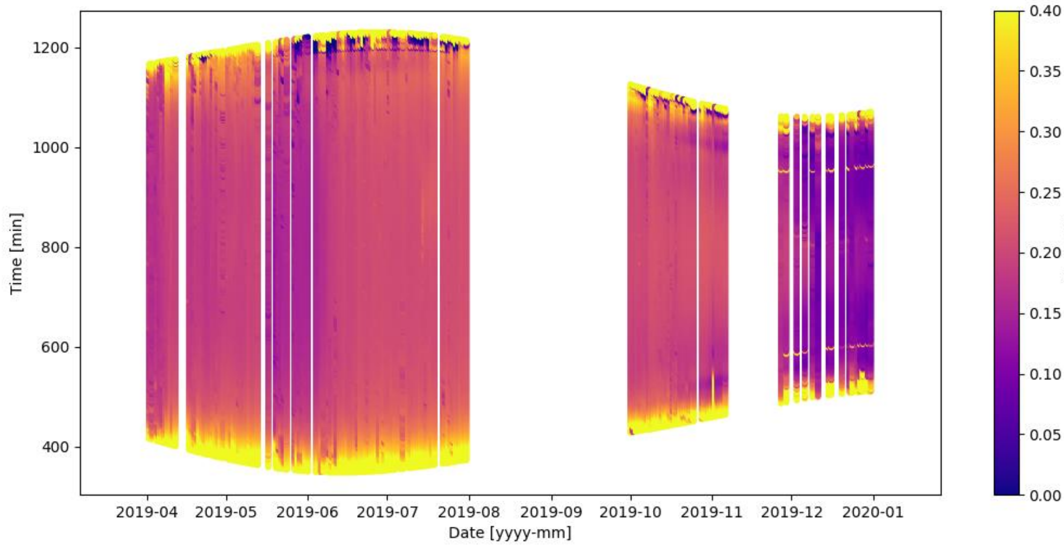


Figure 10: on-site albedo measurements of a bifacial experimental installation

Analysing the sensitivity of bifacial gain (for the presented PV system) to albedo reveals that an albedo difference of 0.1 results in an approx. 1 % bifacial gain difference, however this value can be significantly higher in systems optimized for rear-side light collection.

C. Non-uniformity and mismatch losses

Non-uniform irradiance patterns lead to different shading scenarios, causing varying amounts of losses, which strongly depend on the electrical layout of the system. While shading losses can be minimized by an appropriate system design, non-uniform irradiance is inevitable in bifacial PV systems. In such systems typically 5 – 15 % of the energy output originates from indirect illumination falling on the rear-side of the modules. Typical sources of indirect irradiance are diffuse sky, ground reflection and reflections off mounting structure and other nearby objects. Figure 11 illustrates the magnitude of rear-irradiance variations throughout a bifacial PV array. The graph shows results of a ray tracing simulation, where front- and rear irradiance of each individual solar cell has been calculated for a clear-sky and cloudy day.

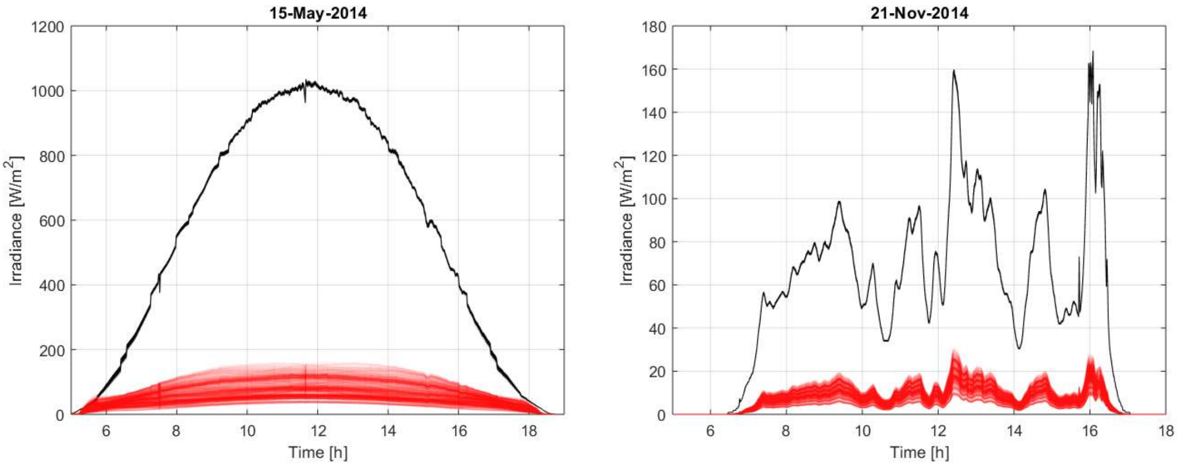


Figure 11 - Cell-by-cell front (black trace) and rear (red trace) irradiance of a bifacial PV array in clear sky (left figure) and cloudy (right figure) conditions. Using semi-transparent traces allows to visualize the aggregation of the irradiance curves, indicating possible representatives.

According to Figure 11, superposing front and rear irradiance results in 10 – 15 % irradiance variability throughout the PV array. Consequently, non-uniformity needs to be taken into account either by correctly choosing a representative location or by spatially resolving the entire PV array.

The presence of mounting structure and module frame is commonly omitted by bifacial PV system simulation approaches, in order to simplify computations. Simulating three different scenarios can give an indication about the significance of this simplification. The three chosen scenarios are: model including mounting structure, module frame and solar cells; model including only module frames and solar cells and a model including only solar cells. All simulations are performed by assuming a ground reflectivity of 0.5.

The results are presented by Figure 12, where the energy yield estimation corresponding to the above three cases is compared. It is found that excluding the mounting structure causes 4.6 % erroneous increase of energy yield prediction and excluding module frames will add a further 1.6 % error. Simplified geometries thus can result in overestimating the energy yield of bifacial PV systems; however, the magnitude of this effect strongly depends on the specific PV system design.

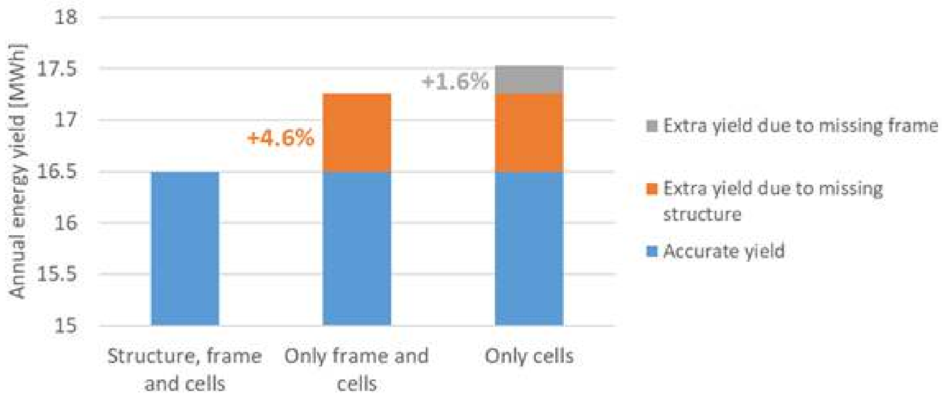


Figure 12: Annual energy yield prediction influence of neglecting mounting structure and module frames

D. PV systems installed on complex terrain

Installing PV power plants on sites characterized by uneven terrain represent both a construction and yield assessment challenge. Depending on the chosen installation technique, it is more, or less difficult to ensure that all module mounting structures assume an optimal module tilt and orientation angle. The following figures (Figure 13) present the distribution of structure tilt and azimuth angles for such a PV installation.

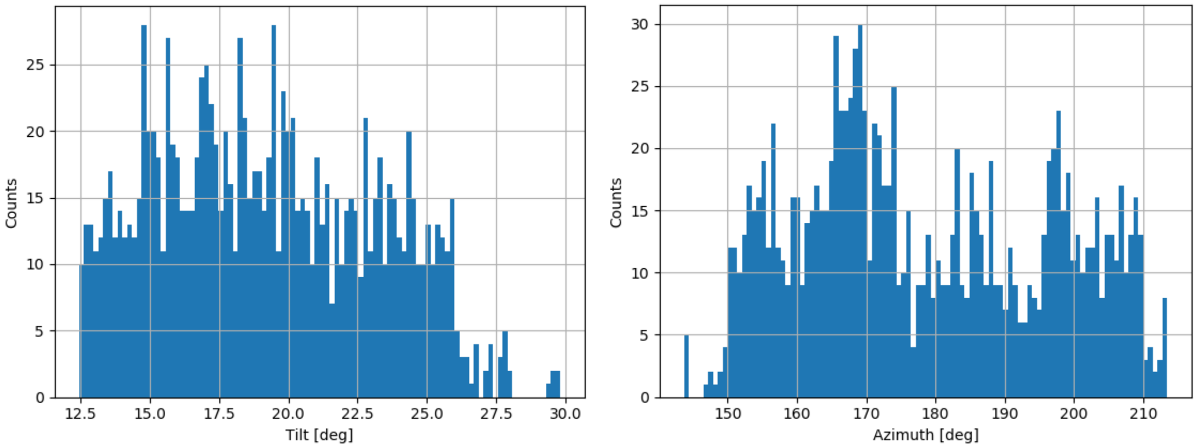


Figure 13 - Distribution of mounting structure tilt (left) and azimuth (right) angles for a PV system installed on a site characterized by uneven terrain

The above figures show that the both tilt and azimuth angles may vary within the same PV power plant, causing a variability of in-plane irradiance between modules installed on different mounting structures. Assuming that 20° tilt and 180° (South) orientation maximize annual in-plane insolation for the above PV site, the difference between highest and lowest annual module insolation will be approximately 1.6 %. The yield assessment accuracy of such PV installations can be improved upon taking the tilt and azimuth angle distributions into account. Optimizing the angular step size is required to achieve a reasonable trade-off between computing costs and accuracy. Using the average value of angles should be avoided because in-plane insolation (therefore energy output) is a non-linear function of the tilt and azimuth angles, especially near the maximum point.

2.2.6 Availability

PV power plant effective availability can be split into two components: a portion which can be influenced by the PV asset owner through its O&M contractor (such as ensuring that all power-producing equipment is "available" to generate power through appropriate procedures), and the portion which cannot be controlled, such as availability of the grid to accept power, or grid operator signals to curtail power.

Recent O&M contractor guaranteed availability values typically are 99% or higher [40], with exceptions for PV plants in remote regions. The influence of O&M expenditures on availability and other Key Performance Indicators (KPIs) was shown by [42], where the availability for one plant ranged between 92% and 99.5% over 8 years, and even higher availability rates of 99.7% were found in [43], with [44] reporting an average effective availability of 99.5% for 27 plants. [15] reported a mean yearly unavailability of the analysed portfolio (41 rooftop PV plants) of around 2 % ± 2 %.

A more detailed analysis has been carried out extracting the mean monthly availability of a portfolio of 533 PV plants installed mostly in Belgium, Germany and Switzerland (see Figure 14). The monitored data show the highest mean unavailability of 6.85% in February, followed by 4.28% in March and 3.48% in January, which coincide with harsher weather conditions (snow, winds, etc.) during the European winter. For the rest of the year, the mean monthly unavailability ranges from 1.16% to 1.81%. Furthermore, it has been seen that unavailability has decreased over time, possibly based on improved O&M protocols.

Figure 14: Statistical indicators of mean monthly unavailability of 533 PV plants in 2019 (majority installed in Belgium, Germany and Switzerland)

One discrepancy that is near-impossible to remove from LTYP and its use in financial models is the assumption that the PV plant will start operation at a certain scheduled date and operate at the rated capacity from then onwards. The recent experience from Australia saw ARENA-funded utility-scale PV projects experiencing a ramp-up period to full generation of 28 weeks (more than 6 months), while the projects reached practical completion 38 weeks behind schedule (nearly 9 months) [45]. This reduced yield, or availability of active inverters, thus affects the availability in the initial period of the PV plant. Similarly, curtailment or other grid operator signals (on top of forced outages) can reduce the availability of the grid for established PV plants.

Uncertainties in availability values thus can have a long tail: while typical values are 99 % availability ±1 % (assuming a suitable O&M contract and contractor), PV plants in areas with constrained grids can have availabilities below 90% for weeks (e.g. during spring/autumn shoulder periods with high PV production and low demand, or due to grid strength issues) [46].

2.2.7 Typical output of Yield Assessments

The typical output of Yield Assessments shows the contribution to each derating factor, starting from the Global Horizontal Irradiation to the energy injected in the grid. Figure 15 shows the impact of each modelling step to the Performance Ratio. The starting point of PR = 100 is considered after applying the horizon shading as this become the annual insolation seen by the modules. Table 2 shows a best practice in providing an overview of gains/losses along each modelling step and the related uncertainty. The uncertainty related to each modelling step can be provided already referred to the irradiation/yield value or to the parameter that is modelled. The value in the table for the specific yield (including its uncertainty) is to be understood as an average value over the entire operating period. The possible deviations between the yields for individual recorded years and the specific yield calculated can be assessed by including interannual variability.

For example, for temperature-dependent losses, the value of uncertainty could be referred to the temperature variability of the profile used in the assessment or to the temperature model used in the assessment. The ambient temperature variability and the various temperature models will lead to a different contribution in terms of yield loss and in terms of uncertainty.

Table 2 provides a value of uncertainty for temperature dependent losses of 1 %. The range of uncertainty for temperature dependent losses due to ambient temperature variability can vary from 0.4 to 2 %, and due to the use of different models from 0.1 to 1.2 % [47]. These values would impact on the overall uncertainty yielding a range of 7.25 % to 7.5 %.

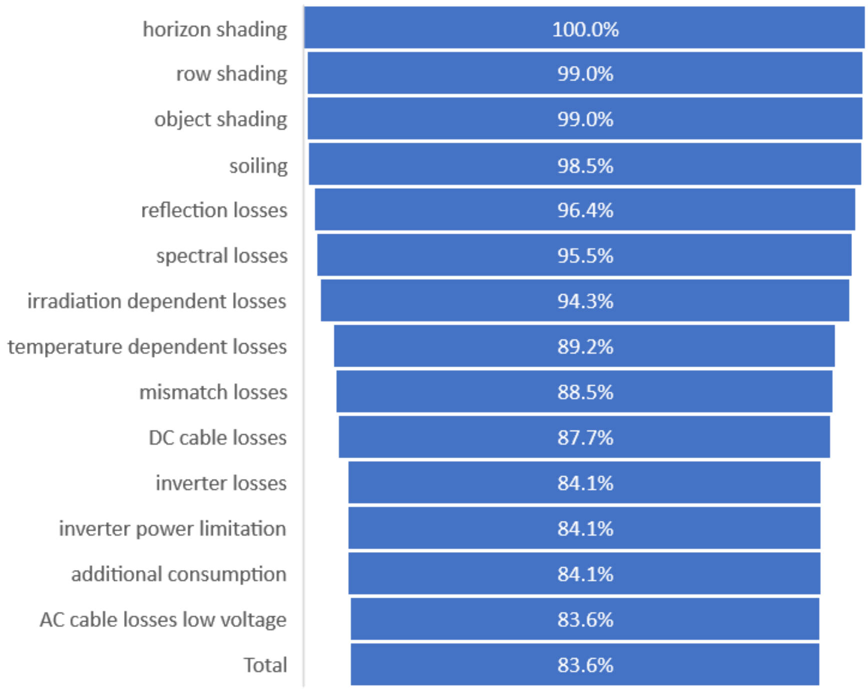


Figure 15: Example of waterfall plot showing the impact of each modelling step to the PR in a yield assessment

Table 2: Summary table for a Yield Assessment with the contribution of each factor along the modelling chain and relative uncertainty (courtesy of Fraunhofer ISE)

Annual values	**uncertainty**	**value**	**gains/loss**	**PR**
	%	kWh/m^2	%	%
global irradiation on horizontal plane	4.0	1248		
irradiation on module plane	2.5	1448	16.0	
shading				
horizon shading	0.5	1445	-0.2	100.0
row shading	2.0	1422	-1.7	98.3
object shading	3.0	1422	0.0	98.3
soiling	0.5	1414	-0.5	97.9
deviations from STC				
reflection losses	0.5	1376	-2.7	95.2
	%	kWh/kWp	%	%
spectral losses	0.5	1363	-1.0	94.3
irradiation-dependent losses	0.8	1342	-1.5	92.9
temperature-dependent losses	1.0	1309	-2.5	90.5
mismatch losses	0.5	1298	-0.8	89.8
DC cable losses	0.5	1287	-0.8	89.1
inverter losses	1.5	1272	-1.2	88.0
inverter power limitation	0.5	1272	-0.1	88.0
additional consumption	0.5	1270	-0.1	87.9
AC cable losses low voltage	0.5	1265	-0.4	87.5
Transformer medium voltage	0.5	1253	-0.9	86.7
AC cable losses medium voltage	0.5	1252	-0.1	86.6
Transformer high voltage	0.0	1252	0.0	86.6
total	**6.5**	**1252**		**86.6**

Typical output tables or diagrams in yield assessment show the contribution in losses along the modelling chain for each factor described in Section 2. Only rarely is uncertainty provided. Table 2 shows an example provided by Fraunhofer ISE of a yield assessment where also uncertainties are stated. The overall uncertainty equal to 6.5 % is the result of the sum of the root mean square error of the relative uncertainty of each step. This is an approximation as it is only valid if all distributions are assumed as normal and independent from each other.

2.2.8 Uncertainty in Long-term Yield Prediction

A typical yield assessment refers to an initial year with an associated initial specific yield. The assessment over a certain period is referred to a long-term yield prediction (LTYP).

Some yield assessors provide an initial specific yield and an average annual specific yield over a certain period (e.g. 20 years). The average annual specific year will include degradation (or Performance Loss Rates). In the report two values will thus be provided, the initial and the average specific yield with a reduction compared to the first year. As the yield assessor is providing an average value, the interannual variability is not included.

Another way to report an LTYP, is to assess the yield at regular intervals (e.g. every year, or every 5 years). The uncertainty assigned to every time interval will decrease due to the averaging of the interannual variability, with the highest value assigned to the initial specific yield (with interannual variability and solar resource uncertainties) and the lowest at the end of the period. The evolution of the P50 value will depend on the chosen degradation/PLR value, while the P90/P50 ratio will decrease due to the decrease in uncertainty.

2.3 Uncertainty scenarios

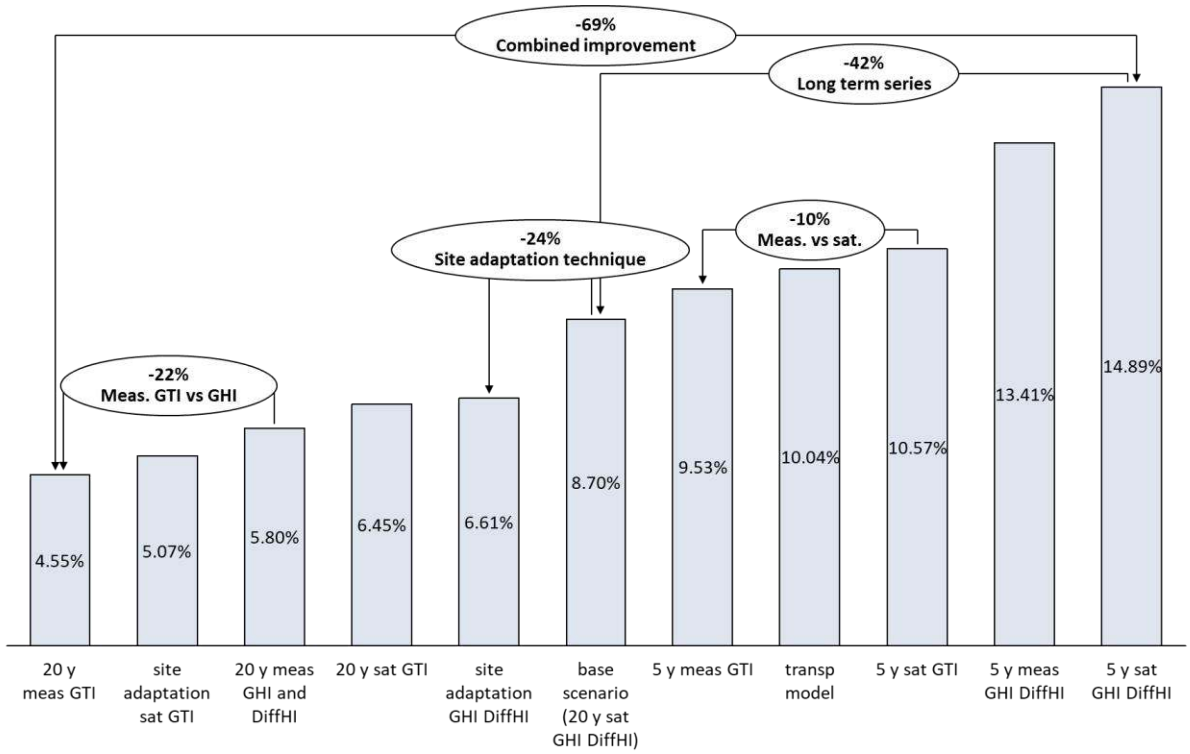


Figure 16: Reduction of uncertainty in case of improvement of the quality of irradiation source. Taken from [47], courtesy of Eurac Research

Figure 16 shows an example on how uncertainty in yield assessment can be reduced considering improvements in the most important parameter, e.g. irradiation. The reference scenario is defined for the case of 20 years of satellite data on the horizontal plane (20 y sat GHI DiffHI) with an uncertainty of 8.7%. Uncertainty increases in case of shorter time series (up to 14.9%) and decreased when reliable measured data on the plane of array are available. The use of the best transposition model and of site adaptation techniques can also have an important effect on uncertainty reduction (site adaptation GHI DiffHI).

When the best possible information is available to the assessor, the uncertainty can be as low as 4.55 % (20 y measured GTI). This has a high impact on the exceedance probability with P90 values which could be up to 20 % higher for the case with reduced uncertainty and thus a much more favourable business model. At the same time, the availability of reliable measurement of GTI is extreme rare and usually available only at existing sites; this could be an important available resource in revamping / repowering projects.

A similar analysis is shown in Figure 17 using the values from Table 2 as reference scenario and by applying the highest possible uncertainty for each derating factor. The uncertainty increases from 6.5 % to around 14 %. The impact on the P90 value is of a 10 % reduction which is in line with what was already reported by Moser et al in [48]. An even higher impact can be seen in case of P50 values which varies depending on the irradiation database used in the yield assessment. It is the combination of the median value (P50), which mainly depends on irradiation, and of the uncertainty (which depends on the overall quality of the data used in the yield assessment) that will determine the P90 value and thus the bankability of a project.

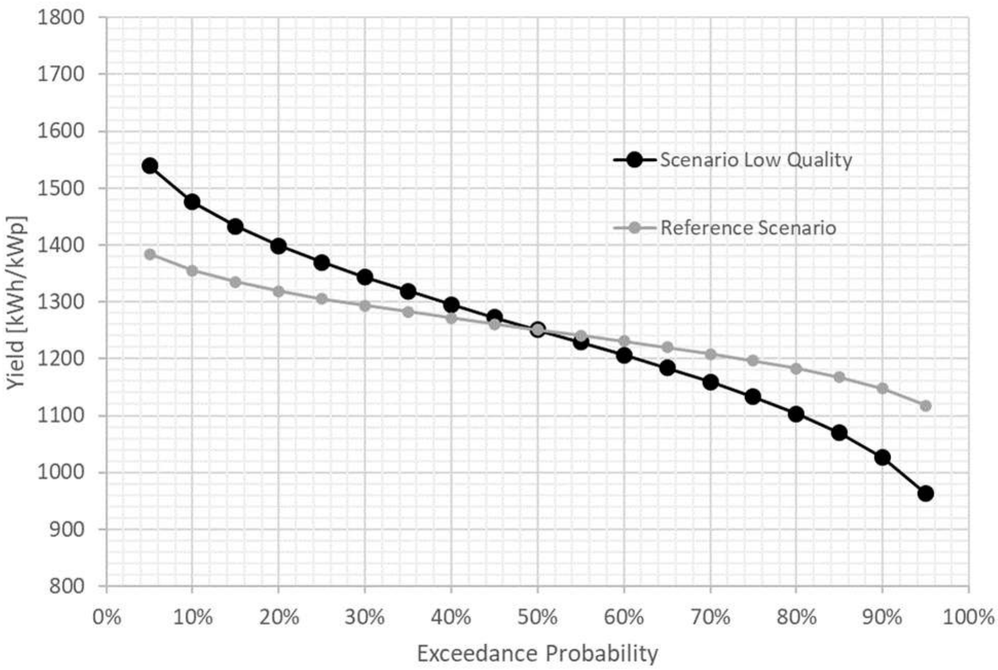


Figure 17: Yield assessment distribution for the values in Table 1 and by using the high-end range of uncertainties

2.4 Service life prediction

In LTYP, the lifetime is usually set based more on economic consideration rather than technical ones. For example, during the feed-in tariffs era, the common timeframe for LTYP was set to 20 years (as the length of the FITs incentive system). When technical considerations are included, they usually rely solely on the performance guarantee as given by the manufacturer. Although it is clear that YAs and LTYP are performed as input to business models, and are thus of importance for economic considerations, a stronger link with the technical boundaries is much needed.

Knowing the time period PV modules and systems will last, or the remaining useful lifetime (RUL) for operational systems, is of great importance for making good financial decisions as well as planning operation and maintenance activities on PV systems. This task is not straightforward as i) the portfolio of PV plants with lifetime longer than 20 years is rather limited and statistical analysis cannot thus be performed, ii) the technology is in continuous evolution and insights based on today's PV plants might not apply to future plants. To overcome this issue, mathematical models are utilized to determine the lifetime of PV modules and systems in shorter periods.

Physical models can be very helpful to understand the correlation of the predicted performance degradation to different climatic variables. They can also highlight the dominating degradation mechanisms based on local climatic conditions. The main challenges of such models are their associated uncertainties and generalisations. As described in 2.2.2, there is no standardised way to calculate and report module and system degradation and the calculated value depends on the combination of filtering, metric and methodology. The uncertainties in the evaluation of RUL and lifetime predictions can thus be rather high.

On the other hand, data-driven techniques that utilise monitored operational data related to system's performance can be used to forecast the future trend or the RUL. They are normally applied to complex systems, where developing a physical model could be more complex and expensive. Generally, in spite of the recognized potential of empirical data-driven techniques for time series forecast, limitations still exist for their application in long-term PV degradation evaluation. Different factors such as outliers in the dataset, seasonal variations, and many other reducing factors (e.g., soiling) should be separated from long-term non-reversible degradation. The lack of a systematic and flexible approach to select parameters of these techniques and their black box character limit the understanding and control of their performance.

Recently (2019), Kaaya et al [49] proposed a model based on a rigorous analysis of degradation data of several PV modules as well as systems of different technologies and installed in different locations. The proposed method aims to evaluate the irreversible long-term degradation of PV modules and systems. To achieve this, they proposed an iterative algorithm for degradation trends evaluation that allows to separate seasonal variations and other reversible performance reducing effects from irreversible degradation (see Figure 18). The shape of the curve is based on the evaluation of the degradation in the calibration zone where several models are fitted and the best is selected to calculate the degradation trend.

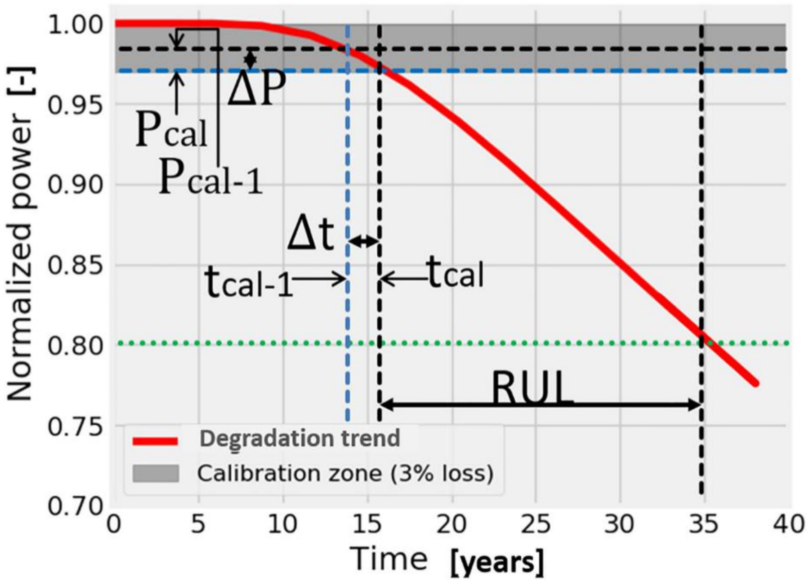


Figure 18: Illustration of the different degradation pattern parameters extracted during calibration and the remaining useful lifetime (RUL). Taken from [49]

An overview of approaches and possibilities to estimate service life, remaining useful lifetime and degradation rates using mathematical modelling is also described in the report "Service Life Prediction of PV Modules" of this task [50].

3 UNCERTAINTIES OF INITIAL YIELD ASSESSMENT AND SCENARIOS IN REAL CASE STUDIES

The aim of this chapter is to show how different expert yield assessors can provide results for the same site which vary in terms of P50 (related to the assumptions and models used in the calculation) and P90 (related to the uncertainties used in the calculation). The exercise was not aimed for defining the best yield assessor, rather for providing a framework for discussing and understanding why the results can differ widely with a subsequent impact on the PV system cashflow model.

Two sites were selected for the benchmarking yield assessment exercised:

- Bolzano, Italy. Characterized by shading due to the surrounding mountainous environment, possible snow loss and insolation variability depending on the used database.
- Alice Springs, Australia. Characterized by high insolation values, near object shading (trees), degradation and soiling.

3.1 Site selection and assumptions

The yield assessors were given a minimal amount of information, which also frequently occurs under commercial projects conditions, see Table 3 and Table 4 (PV module and inverter technology and electrical characteristics, shading diagram, coordinates). For all the other inputs, the yield assessors were asked to use their best assumptions.

Table 3: Input data given to each yield assessor

Parameter	Assumption
Location	Given Latitude/Longitude, tilt angle and azimuth
Irradiance and transposition	Each independent YA used their favourite database
Temperature	Each independent YA used their favourite database
Technology and mismatch	PV module technology given (module datasheet). Mismatch and power tolerance, each YA applied their own consideration For the Alice Springs site: flash list with measured power was provided
Inverter	Given (datasheet)
Shading	Bolzano: Given shading diagram Alice Spring: Photos provided of near objects
Soiling	Each independent YA applied their own considerations
Wind speed	Each independent YA used their favourite database
Long term insolation effects	Each independent YA used their own considerations
Degradation	Each independent YA applied their own considerations
Snow loss / snow fall	Each independent YA applied their own considerations
Availability	Each independent YA applied their own considerations

Table 4: Main features for the two selected sites for the YAs and LTYPs

Site	Number of years of operation	Data available	PV System
Bolzano (Italy)	Since August 2010	Meteo, plant info, production data, costs	4.2 kWp polycrystalline silicon
Alice Springs (Australia)	Varies by array. Evaluated arrays from 2008 and 2009	Meteo, plant info, production data, costs	A) 5.4 kWp array at DKASC, Alice Springs, Australia B) 5.25 kWp array at DKASC, Alice Springs, Australia C) 5.805 kWp array at DKASC, Alice Springs, Australia

3.2 Results from the independent yield assessments

Each Yield Assessor independently ran the analysis and the results were collected and compiled by Eurac Research. The results of the independent yield assessment are shown in Figure 19 for the Bolzano site and in Figure 21 for the Alice Springs site.

Five yield assessment and lifetime yield prediction of 1 polycrystalline technology were collected for the test site located in Bolzano (Figure 19), Italy, and 6 for the site located in Alice Springs (Figure 21), Australia (2 polycrystalline technologies and 1 monocrystalline technology).

For the Bolzano site, the P50 ranged between 1095 and 1406 kWh/kWp, P90 ranged between 997 and 1274 kWh/kWp. The average value for the initial YAs is 1278 kWh/kWp with a STD (σ) of 9.7 %. Taking into account the estimated Performance loss rates of the LTYP’s (only 3 provided out of 5), the average annual energy yield over the time period the system is in operation (2010 to 2019) would be 1253 kWh/kWp. The measured average yield in the period is 1275 kWh/kWp.

For the Alice Springs site, the P50 ranged between 1757 and 1985 kWh/kWp and the P90 between 1631 and 1819 kWh/kWp. The average value for the initial YAs is 1878 kWh/kWp with a STD (σ) of 3.9 %. The system has been in operation since 2009 with an initial yield of 2075 kWh/kWp and 1926 kWh/kWp as 10-year average.

Using the average of the initial YAs can thus not be the right strategy as the values would be too conservative in both cases compared to real operational data; see Figure 19 and Figure 21 where the average P50 value of the initial YAs (orange square) is close or even below the average value of the measured yield over the lifetime of the PV plant, thus including degradation/PLR. P90 values would be even more conservative.

The main reasons causing the deviations between the 5 YAs for the Bolzano site are due to i) the initial insolation value (the mountainous environment has an impact on the quality of the satellite data used by various data providers) and ii) by the far shading correction which becomes evident in the effective GTI (see Figure 20 and Table 5). The transposition model also has an impact with the increase from GHI to GTI varying from 18.8 % to 24.6 % (even if the yield assessors all claimed to have used the Perez model [51]). However, at least a part of the deviation between irradiance transposition can also be attributed to the different time series used (with different irradiance distribution and direct / diffuse ratios).

In addition to this, the insolation value depended also on the reference period used. A proper YAs should have considered a reference period before the installation of the plant. All the modelling steps after the conversion of irradiance into DC electricity gave similar derating factors for the 5 YAs. Site adaptation for similarly challenging mountainous regions might be of additional benefit as satellite data could be compared to a short time series of locally measured irradiance data (for example with a 3 to 6 months experimental campaign even if 12 months would be a suggested time range). This would allow the yield assessor to understand which satellite data is the best one for a particular site in terms of hourly/daily/monthly variability and in terms of P50 value.

Table 5: Summary of values used in the independent YA for the Bolzano site

	TMY 2007-2016	TMY 2005	2000-2009	1994-2006	year 2011
	Partner 1	**Partner 2**	**Partner 3**	**Partner 4**	**Partner 5**
Nominal Power	4.2	4.2	4.2	4.2	4.2
Annual GHI (kWh/m2)	1461	1363	1454	1363	1510
Transposition model (%)	24.3%	20.8%	22.6%	18.8%	24.6%
Annual GTI (kWh/m2)	1816	1647	1783	1619	1882
Horizon Shading Loss (%)	-9.0%	-9.7%	-5.7%	-7.7%	-5.4%
PR Annual GTI (kWh/m²)	1653	1487	1681	1495	1781
Near-Shadings Loss (%)	0%	-5%	-1%	0%	
IAM Loss (%)	-2.2%	-2.4%	-2.1%	-2.3%	-2.5%
Soiling Loss (%)	-2%	-1.0%	-0.5%	-1.2%	
Effective Annual GTI (kWh/m2)	1584	1363	1621	1440	1737
Spectral Loss			-1.0%		
Low Irradiance Loss (%)	-2.1%	-0.9%	-1.2%	-0.8%	
Module Temperature Loss (%)	-5.9%	-4.1%	-5.4%	-4.7%	
Electrical Shading Loss (%)					
Module Quality Loss (%)	-2.5%	-1.0%		-3.0%	
First Year Degradation Loss/LID (%)	-1.0%	-3.0%		-2.5%	
Module Mismatch Loss (%)	-1.1%	-1.1%	-0.8%	-1.1%	
DC Cabling Loss (%)	-0.7%	-0.9%	-0.9%	-0.9%	
DC side Energy Yield (MWh)	5820	4855	6191	5305	6313
Specific Yield at DC side (kWh/kWp)	1386	1156	1474	1263	1503
Performance Ratio at DC side (%)	83.9%	77.7%	87.7%	84.5%	84.4%
Inverter Performance Loss (%)	-4.1%	-4.2%	-4.1%	-3.9%	
Energy Yield at Inverter Output (MWh)	5580	4650	5939	5096	6069
Specific Yield at Inverter Output (kWh/kWp)	1329	1107	1414	1213	1445

Performance Ratio at Inverter Output (%)	80.4%	74.5%	84.1%	81.2%	81.1%
AC Cabling Loss (%)		-0.4%	-0.6%		
Transformer Losses (%)					
Auxiliary Consumption Loss (%)					
Availability Loss (%)		-0.8%			
P50 Energy Yield (MWh)	5580	4596	5905	5096	6069
AC Specific Yield (kWh/kWp)	1329	1094	1406	1213	1445
Performance Ratio (%)	80.4%	73.6%	83.6%	81.2%	81.1%

The main reasons causing the deviations between YAs for the Alice Springs site are mainly due to erroneous assumptions in terms of soiling and initial degradation (see Figure 22 and Table 6). Special care must be taken in the calculation of the PR as the availability of the flash tests was included by the yield assessors under a positive value in the module quality contribution. In the calculation of the PR, this contribution increases the system yield but also the nominal power of the PV system.

Table 6: Summary of values used in the independent YA for the Alice Springs site

	TMY 1993-2018	**TMY Constr.**	**2009-2018**	**1996-2015**	**1996-2015**	
	Partner 1	**Partner 2**	**Partner 3**	**Partner 4**	**Partner 6**	**Partner 7**
Nominal Power	5.4	5.4	5.4	5.4	5.4	5.4
Annual GHI (kWh/m2)	2236	2195	2235	2203	2203	2236
Transposition model (%)	9.0%	8.7%	8.7%	8.3%	8.9%	8.9%
Annual GTI (kWh/m2)	2437	2387	2428	2386	2399	2436
Horizon Shading Loss (%)	0%	0%	-0.3%	0%	0%	0%
PR Annual GTI	2437	2387	2421	2386	2399	2436
Near-Shadings Loss (%)	-0.3%	-0.8%				-0.4%
IAM Loss (%)	-2.7%	-2.5%	-2.5%	-2.8%	-2.8%	-2.6%
Soiling Loss (%)	-3%	-0.2%	-4%	-1%	-3%	-1.5%
Effective Annual GTI (kWh/m2)	2291	2304	2267	2296	2261	
Low Irradiance Loss (%)	-0.2%	-0.2%	-0.6%	-0.1%	-0.1%	-0.1%
Module Temperature Loss (%)	-10.2%	-9.7%	-9.1%	-10.1%	-9.9%	-9.9%
Electrical Shading Loss (%)	-0.1%	-0.6%				
Module Quality Loss (%)	3.6%	3.6%		-2.0%	-2.5%	0.0%
First Year Degradation Loss / LID (%)	-1.0%			-3.0%	-2.0%	-2.0%
Module Mismatch Loss (%)	-1.1%	-0.6%	-0.8%	-1.1%	-1.1%	-1.1%
DC Cabling Loss (%)	-0.8%	-0.3%	-1.0%	-0.1%	-1.2%	-0.5%
DC side Energy Yield (MWh)	11170	11450	10762	10483	10150	10890
Specific Yield at DC side (kWh/kWp)	2069	2120	1993	1941	1880	2017
Performance Ratio at DC side (%)	84.9%	88.8%	82.3%	81.4%	78.3%	82.8%
Inverter Performance Loss (%)	-4.8%	-4.7%	-5.2%	-4.7%	-4.6%	-4.7%
Energy Yield at Inverter Output (MWh)	10640	10900	10206	9990	9680	10390
Specific Yield at Inverter Output (kWh/kWp)	1970	2019	1890	1850	1793	1924

Performance Ratio at Inverter Output (%)	80.9%	84.6%	78.1%	77.5%	74.7%	79.0%
AC Cabling Loss (%)	-1.3%	-1.4%		-1.2%		-1.2%
Transformer Losses (%)						
Auxiliary Consumption Loss (%)						
Availability Loss (%)					-2%	
P50 Energy Yield (MWh)	10470	10671	10087	9867	9487	10213
AC Specific Yield (kWh/kWp)	1939	1976	1868	1827	1757	1891
Performance Ratio (%)	79.6%	82.8%	77.2%	76.6%	73.2%	77.6%

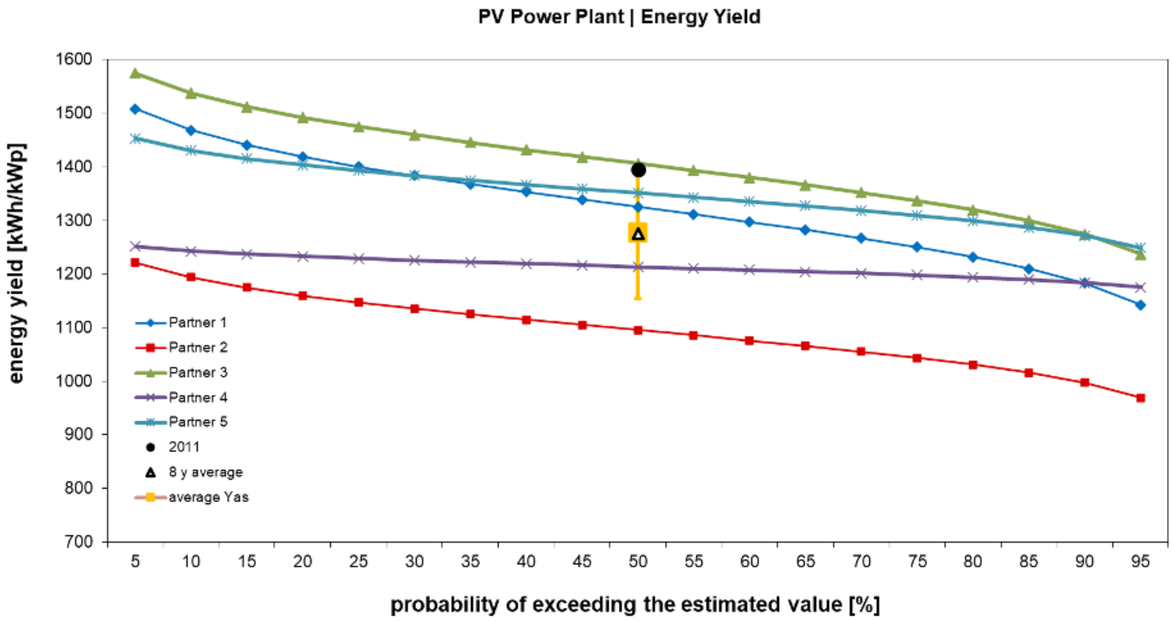


Figure 19: Results of the independent yield assessments for the Bolzano sites and the comparison with the first-year measured yield (black circle), the 8 years average of measured yield (triangle) and the average of the YAs (orange square with σ)

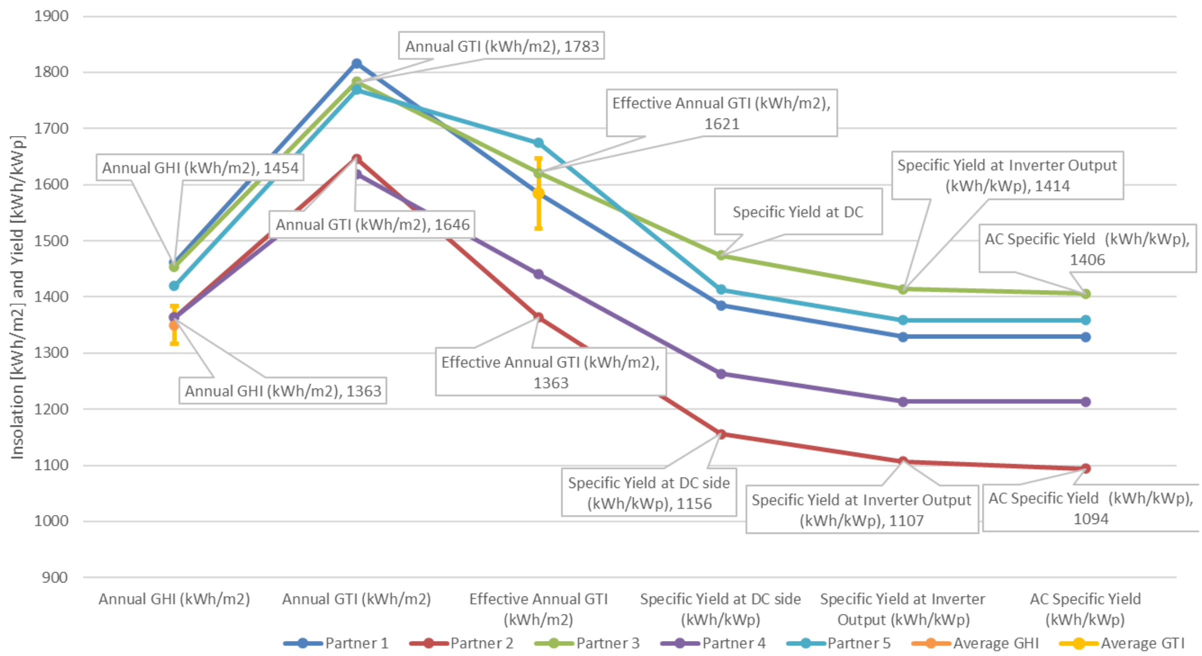


Figure 20: Detailed analysis of the contribution of each yield assessment modelling step from GHI to Alternating Current (AC) specific yield for the Bolzano site. The orange dots represent measured value over 2011-2019 with σ.

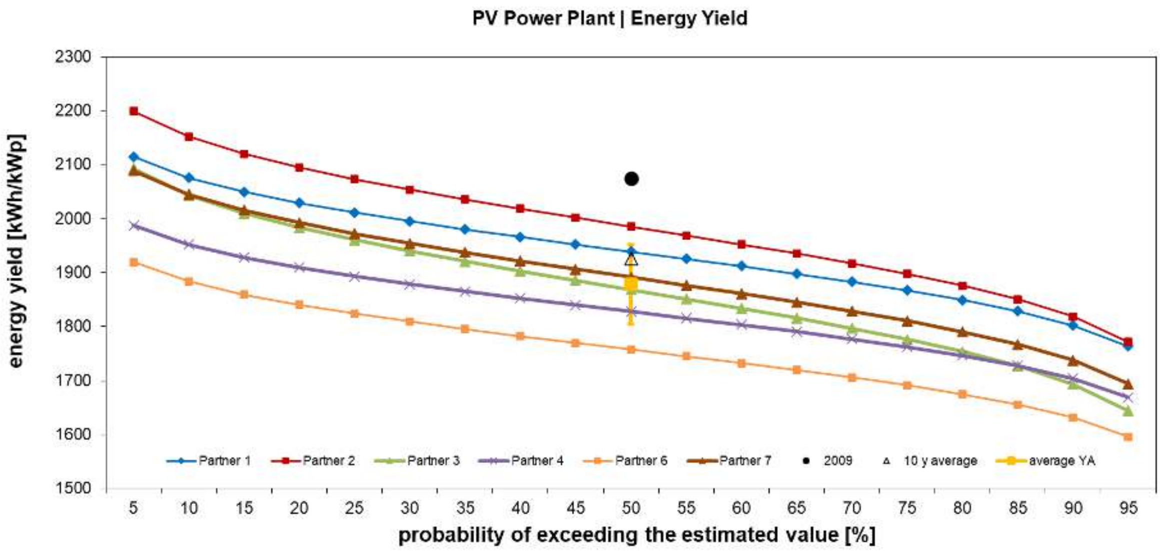


Figure 21: Results of the independent yield assessments (Initial energy yield) for the Alice Springs sites and the comparison with the first year yield (black circle), the 10 years average (triangle) and the average of the YAs (orange square with σ)

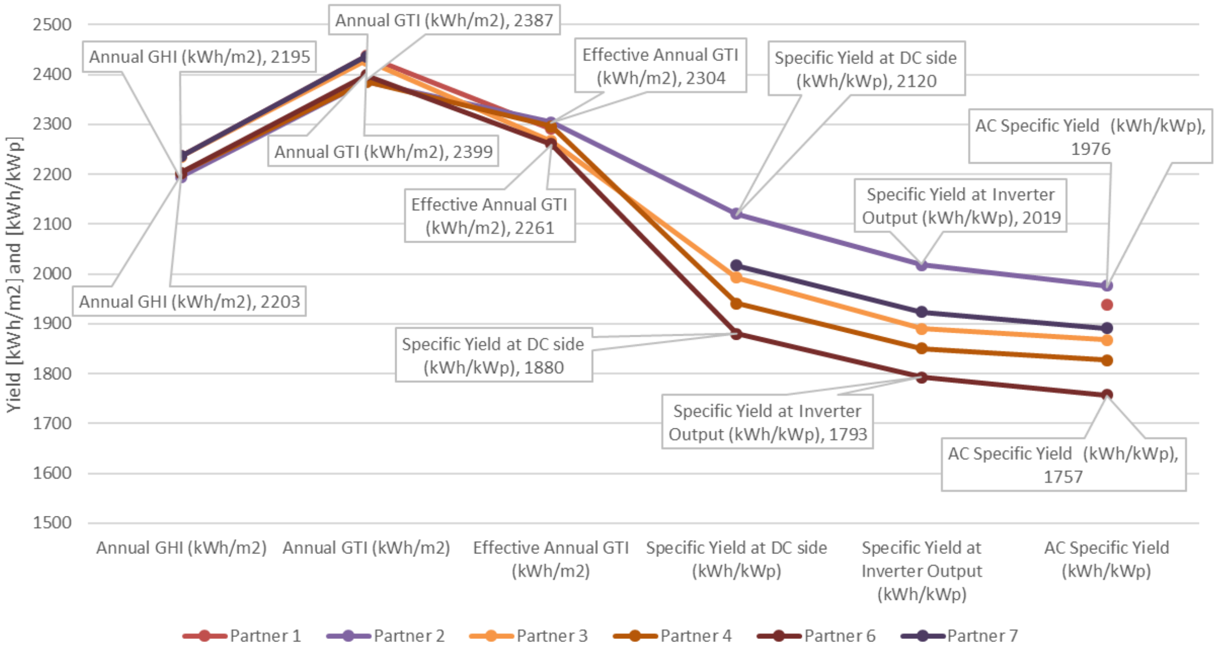


Figure 22: Detailed analysis of the contribution of each yield assessment modelling step from GHI to AC specific yield for the Alice Springs site

3.3 Technical comparison with real operational data

Figure 23 and Figure 24 show the LTYP results for partner 1 as an example of reliable LTYP. Figure 23 shows on the left the comparison with measured data during the period 2011 to 2019. On the right side, the measured data are presented as a cumulative rolling average over the period to better reflect the meaning of a LTYP (the cumulative rolling average is calculated as the average of all of the data up until the current datum point). An important feature of LTYP is that the uncertainty provided over the years decreases due to the decreasing interannual variability (dashed lines represent P10 and P90 values). For this specific case, partner 1 reported an uncertainty of 8.4 % for the initial year, and of 5.4 % at the end of the prediction period.

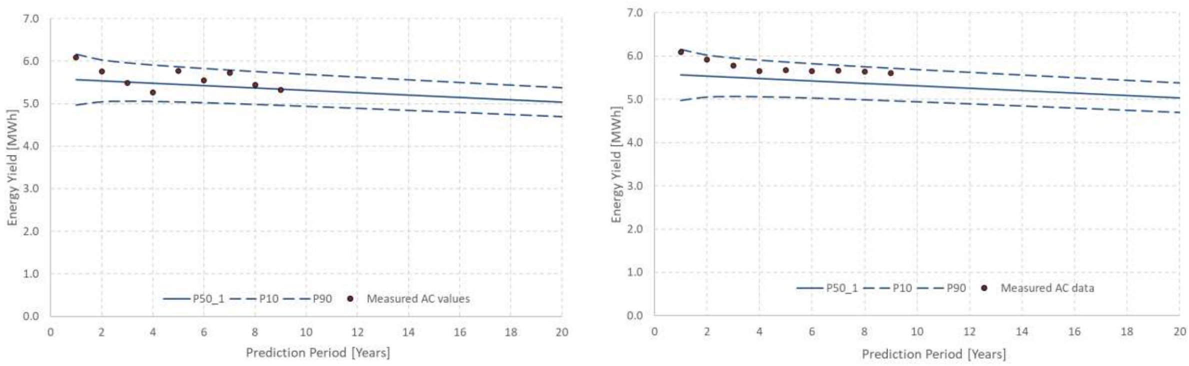


Figure 23: Comparison on yearly yield (left) and cumulative rolling average (right) of real production with the Lifetime Yield Prediction provided by Partner 1 for the Bolzano site

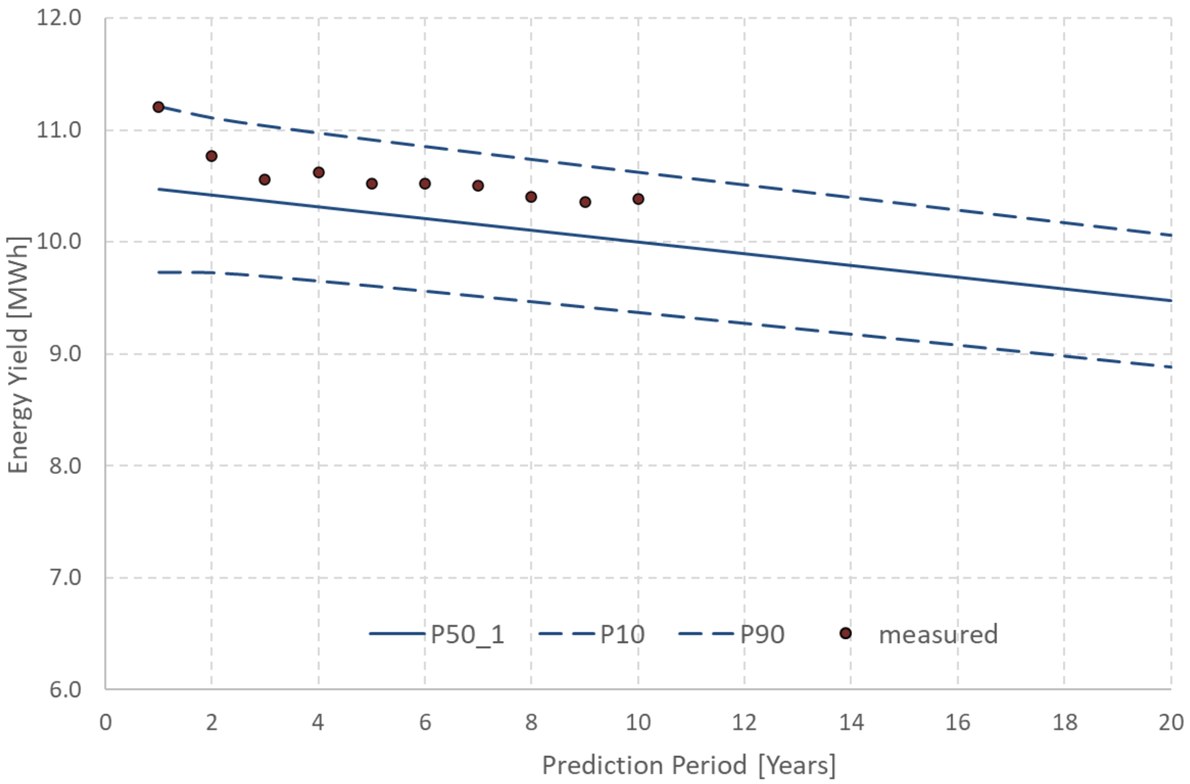


Figure 24: Comparison on cumulative rolling average of real production with the Life-time Yield Prediction provided by Partner 1 for the Alice Springs site

Yield assessments typically only provide values for the initial energy yield. It is good practice to provide values for other years or the average energy yield over the PV system's lifetime. See for example Figure 25 where the initial yield assessment is in good agreement with the first year measured data. The system performance loss rate was underestimated with a value of -0.25 %/y instead of -0.84 %/y and it can thus be seen that the P50 of the distribution for the average value over 20 years overestimates the current 8 years average value. The consequence of the PLR underestimation is that if the PLR of the system remains linear up to year 20, the measured operational value will be below the 20 years average P90 value provided by the assessors.

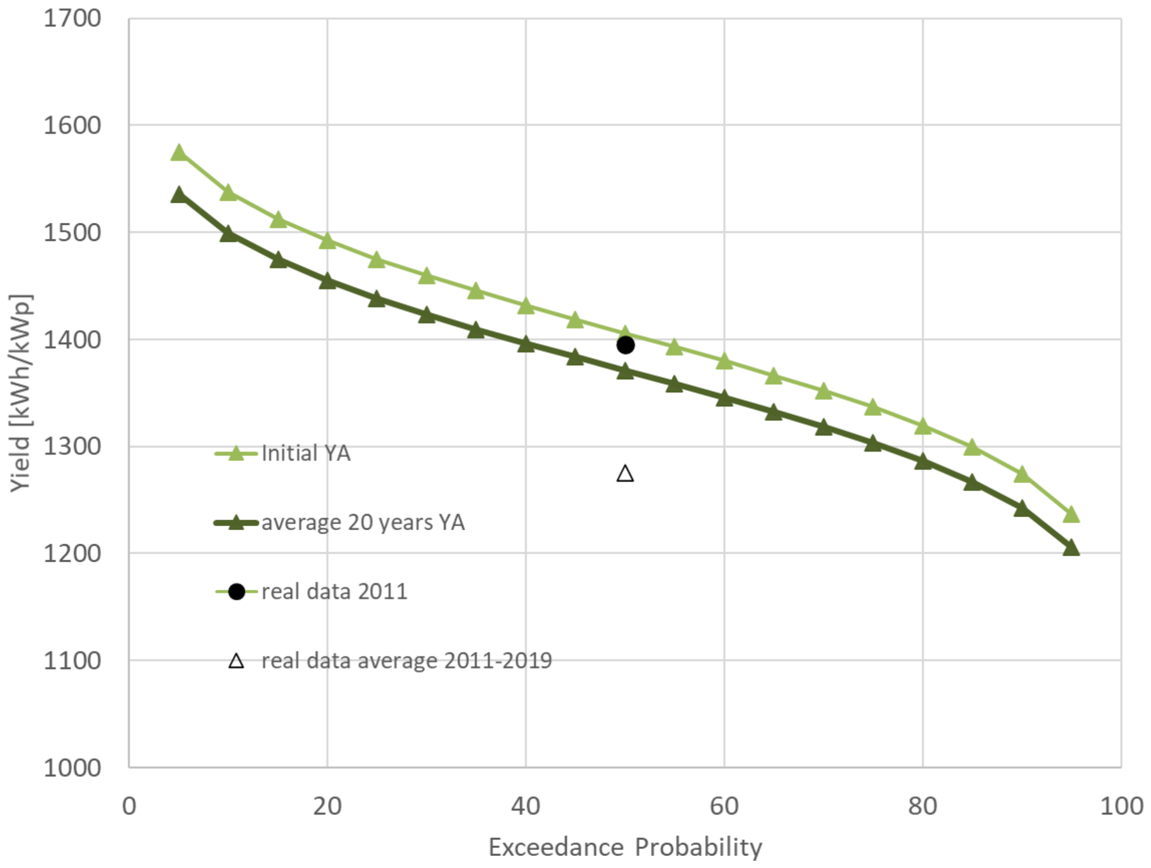


Figure 25: Initial and average yield distribution for partner 3 with 7.3 % uncertainty value

3.3.1 Detailed analysis of long-term yield predictions

Detailed analyses or reviews of long term yield predictions are rarely found in literature, due to a variety of reasons, ranging from the reputational or commercial impact that this information can have for asset owners, the design firms, EPC contractors and O&M providers, as well as a lack of interest by some parties to revisit old assumptions, or evolving technological progress. Nevertheless, when it can be done, a detailed LTYP review can clarify which assumptions made in the design process were correct or not, which can subsequently be adapted for future LTYPs. The unique benefit of evaluating the DKASC data is that most of the conditions for the arrays are identical: same location (and weather), same O&M procedures, and the same monitoring equipment is used. As such, system-specific effects, or modelling assumptions, can be more easily identified.

Figure 26 shows the yield and PR forecasts for the three DKASC arrays (refer to Table 4 for the inputs) by one partner. The top row has the absolute yield as measured displayed against multiple often-used Px values, while the bottom row shows the evolution of the measured and predicted PR. The plane-of-the-array (POA) irradiance (global tilted irradiance, GTI) to calculate the PR was calculated from the global horizontal irradiance (GHI), per the approach discussed in [51].

Looking at the absolute annual yields in the context of the P10 to P90 band, it appears that the modelled uncertainty bounds were taken too small, with the measured yield hitting or exceeding the P10 to P90 boundaries. The year 2016 stands out for all three systems as a year in which the measured yield was significantly lower than the surrounding years. From Figure 27, it can be seen that the year 2016 saw a combination of lower insolation and higher annual average temperature, yet no significant O&M-related yield-loss events are noted on the DKASC events page [52].

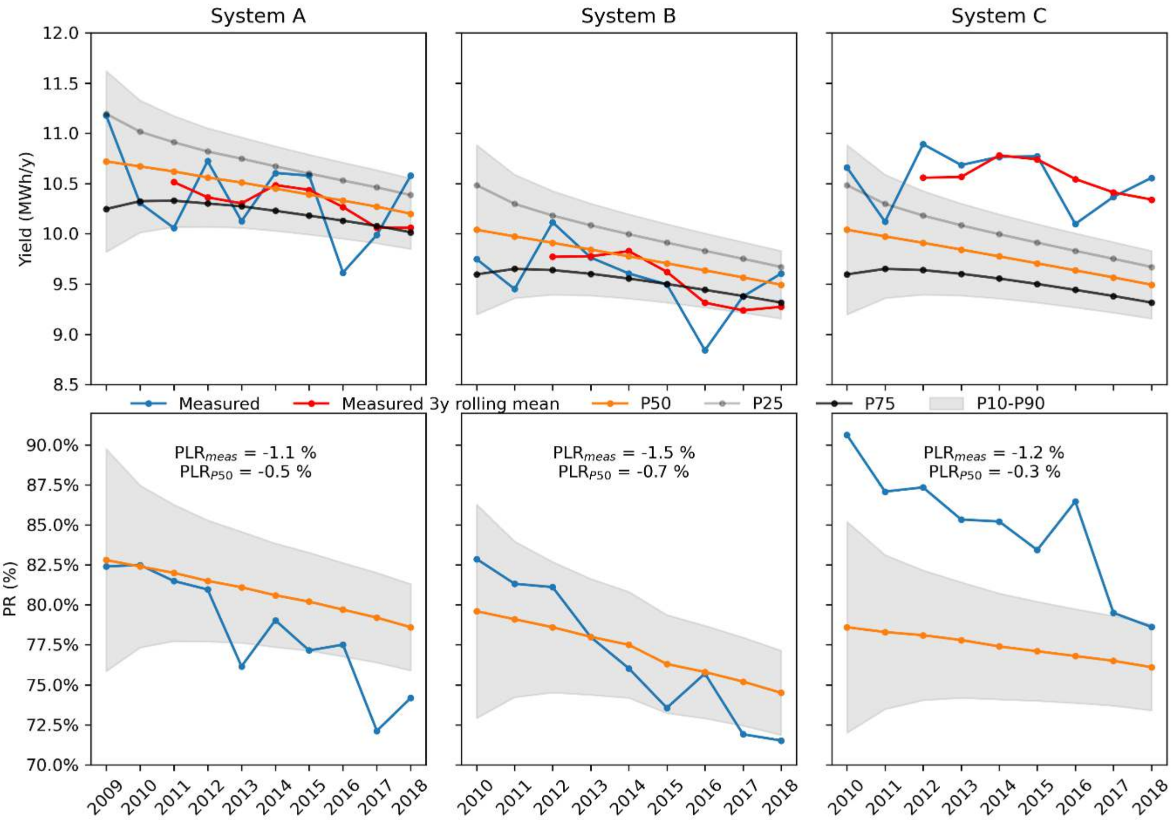


Figure 26: Forecasted and measured yield analysis for the three DKASC Systems. PLR values calculated as simple linear regression.

From an asset owner's perspective, the absolute yields and corresponding PR values for the three systems paint a mixed picture.

- System A's three-year rolling average yield by 2018 is slightly above the P75 expectation, yet the PLR (PLRmeas in Figure 26) appears to be much worse than modelled (PLR_{P50}), at -1.1 %/year instead of -0.5 %/year, with the PR starting as modelled and then remaining below the P50 line.
- System B has the PR which much more of time lies within the P10 to P90 boundaries, yet the measured PLR is the worst of the three systems, at -1.5 %/year. The three-year rolling average yield ends up below the P75 expectation by the year 2018.
- System C sees a yield that is significantly above what was modelled which would be seen positively by the owner, yet the measured PLR (-1.8 %/year) sees the PR dropping much more strongly than expected, which would be concerning in the longer term.
- All three systems are impacted by the measured insolation, particularly for low-energy years, yet other effects (on top of the already identified aggressive degradation) also

appear to play a role. In practice, this analysis would likely spur even more detailed investigation of the root causes of system under-performance.

Considering how the designer, owner's engineer, EPC and O&M provider would evaluate (or be evaluated) for the first two years of the system's performance, few issues would be flagged, as the PR and absolute yield would be at or above the modelled values, or explained by the insolation (see the change in annual insolation in Figure 27 and the change in annual yields).

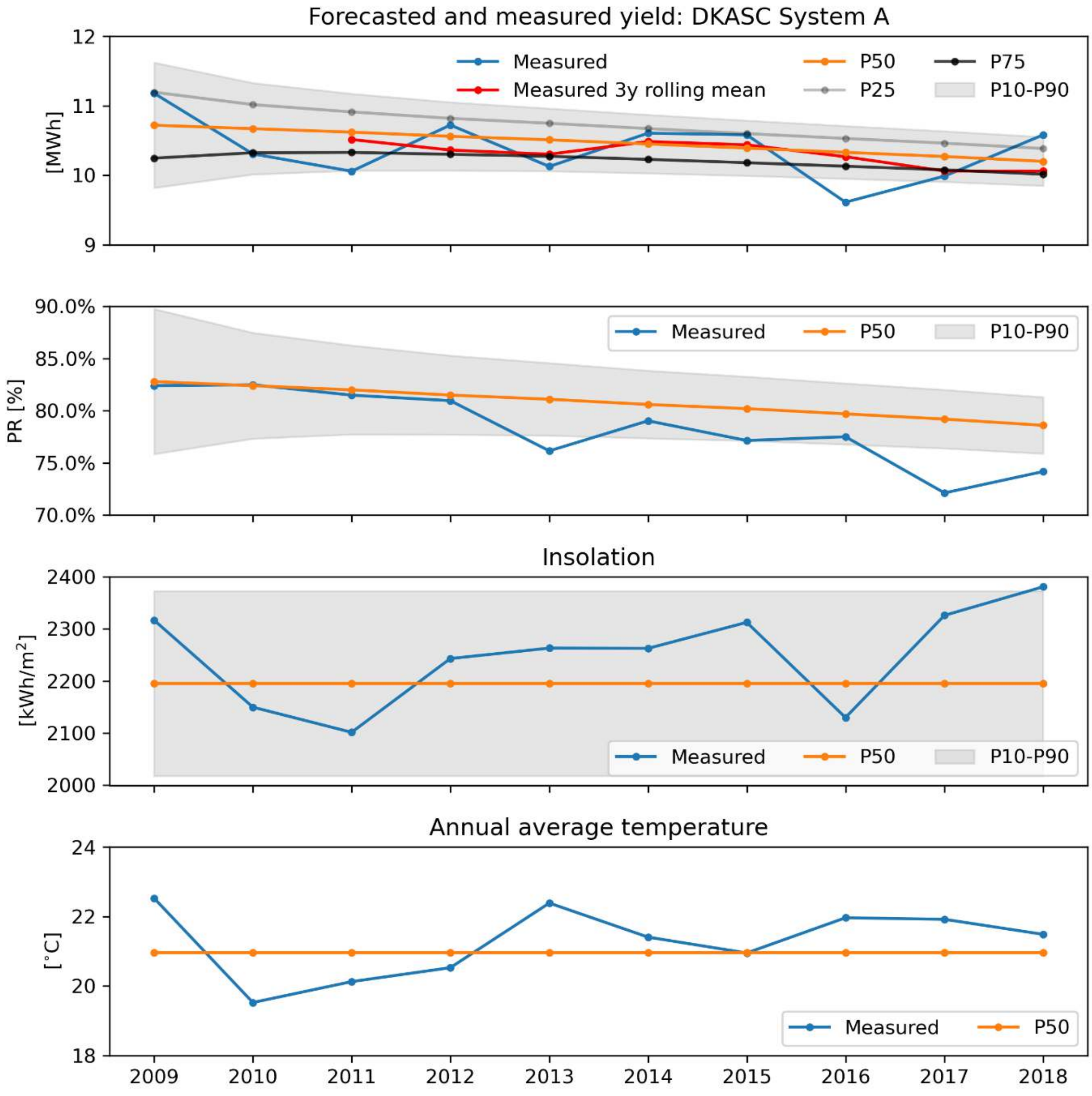


Figure 27: In-depth look at the LTYP of DKASC System A over time and possible contributors to the yield and/or PR deviating from the expected range.

Taking the above analysis as a learning or evaluation experience (e.g. for new team members tasked with yield predictions, or an engineering firm taking on work in a new geographic area), a few key points arise:

- The modelled uncertainty bounds were calculated as too low, with the “constant” (i.e. time-invariant) uncertainties too low, and potentially also the insolation inter-annual variability.
- It appears that the annual performance loss rate in Arid desert hot (BWh Köppen-Geiger climate zone) is much higher than expected, with all three systems discussed seeing a PLR of -1.1 %/year or worse, instead of the (historical) industry-standard assumption of -0.5 %/year.
- The significant over-performance by System C compared to predicted values suggests that thermal losses were over-estimated (for example by using not validated temperature coefficients and/or Nominal Module Operating Temperature, NMOT), and likely also suggests better light capture by these modules.
- Focusing on single, or highly aggregated, KPIs can lead to assessment biases:
    - Modelling errors or assumptions can be masked (e.g. an over-estimation in GHI compensated by under-estimation in the module temperature).
    - From a yield (and with it, revenue) perspective, a P90 yield year does not necessarily mean a poorly performing or designed system, provided other metrics can support this hypothesis.

3.4 The impact of assumptions in the yield assessment

For the Bolzano site we have expanded the analysis to show the impact of some assumptions to the yield assessment. To do so we have defined 16 different insolation values by varying the source, the period and the use of site adaptation. This analysis is important as the results from the independent yield assessors showed a variability of 4.5 % in GHI and 7.8 % in GTI including far shading losses.

3.4.1 Different data sources and time range for global horizontal insolation

The long-term yield assessment requires long time-series (e.g., 15-30 years) of representative solar insolation values at a specific location. To generate such long time-series, two procedures are commonly practiced.

One option is to run a measurement campaign prior the yield assessment (e.g., at least 10 months of irradiance data), and apply site-adaptation techniques using long-term satellite-based data (see 3.4.4). The second option, when no in-situ measurements are available, requires the usage of highly accurate satellite-based or reanalysis-based irradiance data, or a combination of them to reduce uncertainties. In this section, two data sources are compared to in-situ measurements: irradiance data from a reanalysis-based model (ERA5, [53]) and from a satellite-based model (3E, [54]–[56]). In summary, 16 different irradiance datasets have been tested. Thereby, seven are based on ERA5 data (five taken from PVGIS and two directly from the Copernicus Data Store [57]), six on 3E satellite data and three datasets are ground measurements. Apart from different data sources, different time ranges and the usage of site-adaptation techniques have been used.

Once the solar irradiance time-series are generated from satellite or re-analysis data, the Typical Meteorological Year (TMY) needs to be calculated. A TMY dataset represent the weather (insolation, temperature, wind speed, etc.) of the specific location at each time of the year (e.g., hourly resolution), and it is generated by finding the most representative months of the long time series through a weighting method. For example, for the datasets k) to p), the most representative weather data for January in Bolzano was observed in 2016, the most representative February was observed in 2017, and so on for each month.

While using different data sources, considering different time ranges for each, and applying site-adaptation techniques, the same procedure yields different results for the TMY dataset and subsequently for the long-term energy yield assessment.

Table 7 shows the results in terms of insolation on the horizontal plane and on the plane of array using different insolation sources and time range. The table also shows the impact of the transposition model, far shading and temperature losses. It also includes the yearly variability calculated as the ratio between the standard deviation of the GHI annual insolation values and the average GHI over the period.

The value for the GTI that should be used in the PR calculation includes far shading losses, GTI_{eff} includes far shading, soiling and IAM losses. If we look at GTI without using side adaptation using ERA5 data, the values range from 1541 kWh/m^2 (2005 to 2016) to 1714 kWh/m^2 (2006 to 2015). Average measured data for the period 2011 to 2019 show a value of 1585 kWh/m^2 with a variability of 4.2 %. The impact of site adaptation can be seen by an increase in the GTI values (ERA5 2005-2016, ERA5 2005-2016 SA) from 1541 to 1607 kWh/m^2 and in the decrease from 1644 to 1586 kWh/m^2 for 3E 2004-2020 TMY P50. Site adaptation effectively removes the bias of the satellite data.

Table 7: Impact of different irradiance sources and timeframe on various parameters for the Bolzano site

#	Dataset	GHI [kWh/m²]	GTI [kWh/m²]	GTI For PR [kWh/m²]	GTI_{eff} [kWh/m²]	Trans-posi-tion [%]	Far shading [%]	Temp. losses [%]	Yearly Varia-bility [%]
a)	PVGIS ERA5 2005-2014 TMY	1408	1704	1618	1569	21.0	-6.06	-6.29	2.68
b)	PVGIS ERA5 2006-2015 TMY	1503	1861	1769	1714	23.8	-6.11	-6.86	2.65
c)	PVGIS ERA5 2007-2016 TMY	1434	1775	1682	1627	23.8	-6.52	-6.23	2.52
d)	PVGIS ERA5 2005-2016 TMY	1312	1620	1541	1493	23.5	-5.98	-2.14	2.52
e)	PVGIS ERA5 2005-2016 TMY SA	1362	1686	1607	1558	23.8	-5.80	-2.48	2.52
f)	ERA5 1990-2020 TMY	1379	1723	1600	1538	25.0	-8.95	-2.20	2.52*
g)	ERA5 1990-2020 TMY SA	1397	1740	1631	1574	24.6	-7.79	-2.56	2.52*
h)	Measured 2012	1283	1551	1478	1436	20.9	-5.65	-6.11	
i)	Measured 2015	1360	1656	1575	1528	21.8	-5.99	-6.41	
j)	Measured 2016	1332	1601	1525	1481	20.3	-5.76	-6.21	
k)	3E 2004-2020 TMY P50	1436	1752	1644	1588	22.1	-7.60	-3.56	2.83**
l)	3E 2004-2020 TMY P75	1371	1649	1544	1493	20.3	-7.64	-2.88	
m)	3E 2004-2020 TMY P90	1310	1558	1458	1411	19.0	-7.63	-2.59	
n)	3E 2004-2020 TMY P50 SA	1384	1681	1586	1536	21.5	-6.84	-3.49	2.83**
o)	3E 2004-2020 TMY P75 SA	1321	1582	1493	1447	19.8	-6.72	-3.10	
p)	3E 2004-2020 TMY P90 SA	1263	1495	1410	1367	18.4	-6.75	-2.56	

*2020 removed, ** 2004 & 2020 removed

A similar analysis is not so important for the Alice Springs site as the difference in GHI shown by the seven independent yield assessments is very limited and so is the contribution of the transposition model. In fact, the variability in values is only 0.9% in GHI and 1% in GTI (Table 8).

Table 8: GHI and GTI values for Alice Springs showing limited dependence on the chosen period

	TMY 1993-2018	TMY Constructed	2009-2018	1996-2015	1996-2015	
	Partner 1	Partner 2	Partner 3	Partner 4	Partner 6	Partner 7
Annual GHI (kWh/m2)	2236	2195	2235	2203	2203	2236
Transposition model (%)	9.0%	8.7%	8.7%	8.3%	8.9%	8.9%
Annual GTI (kWh/m2)	2437	2387	2428	2386	2399	2436

3.4.2 The calculation of PR

Table 9: Calculation of PR depending on the chosen reference global tilted insolation

#	Dataset	$Yield_{array}$ [kWh/kWp]	$Yield_{final}$ [kWh/kWp]	PR_{AC} [%] no losses	PR_{AC} [%] $= Yield_f / Yield_{ref}(GTI_{eff})$	PR_{AC} [%] Far shading
a)	PVGIS ERA5 2005-2014 TMY	1381	1326	77.78	84.49	81.92
b)	PVGIS ERA5 2006-2015 TMY	1501	1442	77.48	84.14	81.53
c)	PVGIS ERA5 2007-2016 TMY	1433	1377	77.54	84.60	81.84
d)	PVGIS ERA5 2005-2016 TMY	1376	1322	81.58	88.48	85.72
e)	PVGIS ERA5 2005-2016 TMY SA	1431	1375	81.52	88.23	85.55
f)	ERA5 1990-2020 TMY	1416	1361	78.96	88.46	85.01
g)	ERA5 1990-2020 TMY SA	1445	1389	79.79	88.23	85.11
h)	Measured 2012	1267	1215	78.32	84.57	82.19
i)	Measured 2015	1343	1289	77.79	84.31	81.81
j)	Measured 2016	1300	1247	77.83	84.15	81.73
k)	3E 2004-2020 TMY P50	1425	1368	78.07	86.14	83.21
l)	3E 2004-2020 TMY P75	1362	1307	79.25	87.52	84.61
m)	3E 2004-2020 TMY P90	1290	1238	79.41	87.70	84.85
n)	3E 2004-2020 TMY P50 SA	1395	1340	79.69	87.19	84.43
o)	3E 2004-2020 TMY P75 SA	1318	1265	79.94	87.40	84.70
p)	3E 2004-2020 TMY P90 SA	1251	1200	80.26	87.77	85.10

Table 9 shows the impact on PR of the selected reference plane-of-array irradiance. Some software used in Yield Assessment calculates the effective irradiance without including far shading losses, leading to a low value of PR. The reference plane-of-array irradiance should be comparable to what can be measured by a pyranometer or a reference cell. A pyranometer should only be affected by far shading and not by row and object shading and by soiling as it should provide the maximum amount of insolation that can reach a PV system. In Table 9 we show the calculation of PR without (PR_{AC} no losses) or with (PR_{AC} far shading) the inclusion of far shading in the effective irradiance. PR_{AC} calculated using the GTI_{eff} will have the highest values as they also include IAM and soiling losses on top of far shading losses in the reference POA values thus underestimating the reference insolation values.

3.4.3 The impact of far shading

Far shading can have an important impact in yield assessment as shown for the Bolzano case. The five independent yield assessors, using the same shading diagram, have reported 5 different values of losses due to far horizon shading ranging from -5.4% to -9.7% (see Table 7 and Table 10). These deviations highlight the importance to have reliable insolation sources not only in terms of annual values but also with the ability to capture the typical hourly profile of irradiance.

Table 10: impact of far shading for the Bolzano site as reported by the independent yield assessors

	TMY 2007-2016 **Partner 1**	TMY 2005 **Partner 2**	2000-2009 **Partner 3**	1994-2006 **Partner 4**	year 2011 **Partner 5**
Horizon Shading Loss (%)	-9.0%	-9.7%	-5.7%	-7.7%	-5.4%

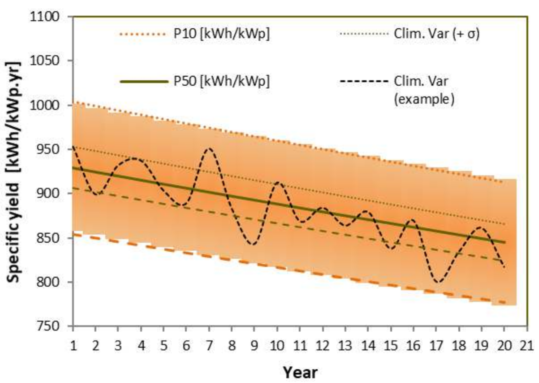
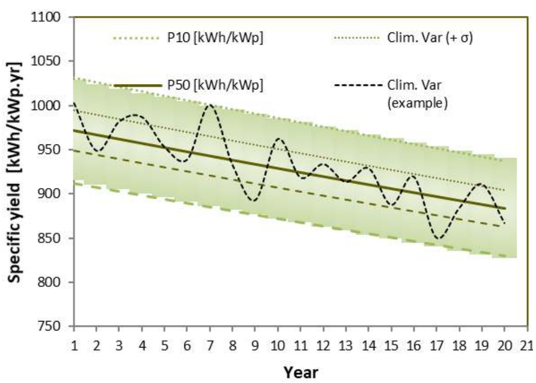
3.4.4 The impact of site-adaptation techniques

As introduced in Chapter 2.2.1, the application of a site adaptation methodology can significantly reduce the uncertainty in the long-term solar resource. The reduction of uncertainty will depend on different factors such as the bias of the satellite data and its behaviour over time, the quality of the on-site measurements used for the site adaptation, the period of concurrent data between satellite and the on-site measurements, and the site-adaptation methodology used.

A comparison of two input data sources with different uncertainties (one with the site adaptation methodology applied and the other one without) is presented in Table 11 for illustrative purposes. A simplification is made using a normal distribution assumption to allow an easier comparison of the effect of the uncertainty reduction on the solar resource quantification and its impact on long-term indicators such as e.g. P90. In the example, an initial uncertainty of ±5% is considered for the uncorrected long-term satellite-based data source, while an uncertainty of ±3% is considered for the data source after the application of the site adaptation technique using one year of on-site measurements taken by an ISO 9060:2018 Class A pyranometer.

The effect of the propagation of this uncertainty into the final expected yield (kWh/kWp) for both, a P50 and a P90 scenario, is shown in Table 11.

Table 11: impact of site adaptation on the long-term yield estimation

	Uncorrected satellite-based irradiation	**After site adaption application**
		
GTI unc. (σ_{irr})	±5.0%	±3.0%
Clim. Variability (σ_{clim})	±2.5%	±2.5%
PV modelling unc. (σ_{mod})	±2.0%	±2.0%

Total uncertainty (σ_{total})	±6.3%	±4.8%
GTI P50:	1100 kWh/m^2	1150 kWh/m^2
Specific yield–yr1 (P50):	930 kWh/kWp	972 kWh/kWp
Specific yield–yr1 (P90):	855 kWh/kWp	913 kWh/kWp
P90/P50 (lifetime yield):	7.4%	5.2%

3.4.5 Personal experience

As discussed in the sections above and in what follows, a calculated LTYP is influenced by a variety of factors:

- Selection of the appropriate GHI database(s) and time period (individual expertise and/or organisational resources);
- Modelling of far and near shading of PV arrays (individual expertise, ease of use and type of software);
- Modelling assumptions on module temperature (thermal convection coefficients: individual expertise and/or organisational assumptions);
- Module and system degradation, and system mismatch losses (individual expertise and/or organisational assumptions);
- Modelling assumptions: taking PV modelling software outputs at face value (i.e. single run), or applying Monte-Carlo simulations (individual expertise, organisational preferences, available time or budget);
- Type of modelling software used (individual expertise and/or organisational resources / preferences);
- Company/institutional preferences (e.g. “we always assume 0.5 % module degradation” versus “our assumptions vary according to the project and bankable warranties”)

As discussed in [58], significant single-year prediction deviations were observed when comparing modelled versus measured systems. The impact of personal experience was observable, with deviations in modelled yields ranging from -16 % to +17 %. Repeating this exercise over multiple years as discussed in this report (which thus also incorporates degradation, O&M procedures and actions, and inter-annual insolation variability), shows the challenge for those who make the yield predictions, as well as those who then decide to finance PV systems or not.

4 UNCERTAINTIES IN YIELD ASSESSMENTS: FROM MODELLED TO REAL LCOE OF PV PROJECTS

Various definitions of LCOE can be found in the literature. In general terms it is defined as the average generation cost, i.e., including all the costs involved in supplying PV electricity at the point of connection to the grid.

The PV LCOE includes all the costs and profit margins of the whole value chain including manufacturing, installation, project development, O&M, inverter replacement, etc. A parameter that will become even more important in the future LCOE calculations is the system residual value, also called salvage value. In other words, the residual value corresponds to the possible earnings coming from the disposal of the power plant at the end of its life. It is like a revenue, which has the effect of reducing the overall costs of the plant because of the possible recycling and sales of the reused materials thus decreasing the LCOE. PV LCOE also includes the cost of financing but excludes the profit margin of electricity sales and thus represents the generation cost, not the electricity sales price which can vary depending on the market situation.

The PV LCOE, expressed in €/kWh in real money, can be defined by equation (1) as implemented in [59]:

$$(1)\ LCOE = \frac{CAPEX + \frac{InvRepl}{(1+WACC_{nom})^{N/2}} + \frac{ResValue}{(1+WACC_{nom})^{N}} + \sum_{t=1}^{N} \frac{OPEX(t)}{(1+WACC_{nom})^{t}}}{\sum_{t=1}^{N} \frac{Yield_0 \cdot (1-PLR)^{t}}{(1+WACC_{real})^{t}}} \left[\frac{€}{kWh}\right]$$

where

N is economic lifetime of the system

t is year number ranging from 1 to N

CAPEX is total capital expenditure of the system, made at $t = 0$ in €/kWp

OPEX(t) is operation and maintenance expenditure in year t in €/kWp

InvRepl is the cost of inverter replacement, made at $t = N/2$ in €/kWp

ResValue is the residual value of the system at $t = N$ in €/kWp, can be either positive or negative

$Yield_0$ is initial annual yield in year 0 in kWh/kWp and is equivalent to the P50 yield

PLR is the annual performance loss rate

$WACC_{nom}$ is nominal weighted average cost of capital per annum

$WACC_{real}$ is real weighted average cost of capital per annum

The relationship between $WACC_{nom}$ and $WACC_{real}$ is expressed with the formula below:

$$(2)\ WACC_{real} = \frac{1+WACC_{nom}}{1+Infl} - 1$$

where *Infl* is the annual inflation rate.

In the calculation of the LCOE, the typical definition considers the degradation at PV module level as a result of irreversible degradation modes. However, performance losses evolve over time not only for PV modules but also for the Balance of System components. The value of $Yield_0$ is defined by the P50 yield and comes from the yield assessment and should include already an estimation of typical system unavailability, soiling, shading and other effects contributing towards performance reduction. As explained in Section 2.2.2, the calculation of the evolution of performance losses over time is referred to as Performance Loss Rate. The values of PLR calculated and reported in the literature will depend on the filtering and methodology used. If the aim is to assess the PLR due to components degradation, appropriate filtering will ensure that unavailability (and other effects causing downtime at large scale) is not included in the calculation. In the LCOE calculation it is thus important to make sure that not only module degradation is included, at the same time double counting of effects must be avoided (e.g. unavailability or soiling included in both $Yield_0$ and PLR taken from the literature).

Discounting the expenditures with $WACC_{nom}$ and electricity generation with $WACC_{real}$ ensures that the net present value (NPV) for the investment with $WACC_{nom}$ is zero when valuing the generated electricity for the real LCOE. An alternative method is to assume that the inflation rate is zero in the equation and to use real WACC for discounting both the expenditures and the generation. Both methods give the same value for LCOE.

The parameter with the largest impact on the LCOE is the cost of capital. Risk reduction in PV projects will lead to easy access to capital and thus to lower WACC or to projects with similar WACC. Technical parameters will thus become more important for the comparison of PV projects; the variation of technical parameters becomes essential in the benchmarking of LCOE. It is in this context that the competitiveness of PV in the future will be (i) closely linked to the uncertainty and variability of the input parameter determining the initial yield value and (ii) cost effectiveness and improvements of parameters related to the downstream sector of the PV value chain will have an impact. The assumptions are considered during the EPC phase but with an impact to the operational phase and O&M in terms of required lifetime, performance loss rate, performance ratio, availability, and operational costs. Quality along the whole value chain will thus become essential in order to match the expectations generated in the Yield Assessment.

Parameters like lifetime, degradation or Performance Loss Rate, Performance Ratio and Operational Expenditures can have an overall impact on the LCOE which can be as high as 100% (doubling of LCOE), see Figure 28.

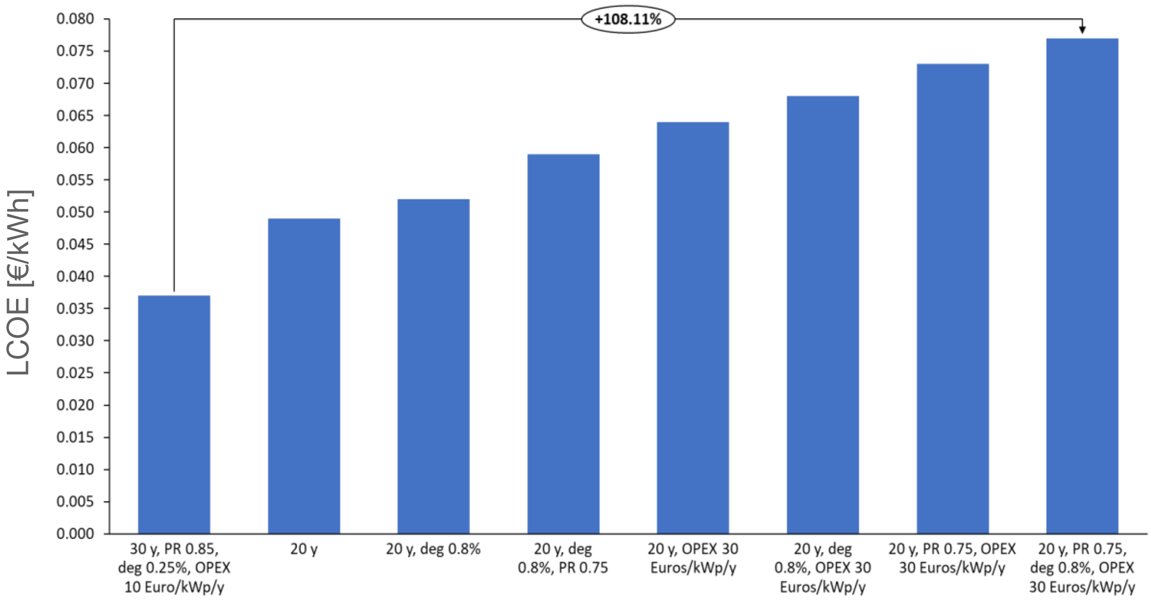


Figure 28: impact of technical parameters during the operational phase on the LCOE

4.1 Calculation of LCOE for the selected PV projects and cash flow models

The output of yield assessments can have a large impact on the LCOE and on the cash flow of business models. Various examples are reported in this section: net-billing scheme and PPA model in utility scale.

4.1.1 Net-billing scheme

The results of the Bolzano Yield Assessment as reported in Section 3 were used to assess the impact in terms of LCOE and cash flow for the case of a net-billing scheme (as for example implemented in Italy) for a residential system with a self-consumption of 30 % using the following scenarios:

Scenario 1) P50 = 1095 kWh/m^2, 1a) PLR = 0.25 %/y, 1b) PLR = 0.5 %/y

Scenario 2) P50 = 1406 kWh/m^2, 2a) PLR = 0.25 %/y, 2b) PLR = 0.5 %/y

The net-billing scheme is based on the Italian case where the owner of a PV plant obtains a valorisation of the grid injected PV generation of around 0.12 €/kWh (composed by the energy market price and a partial reimbursement of the grid costs) for the share that is needed to cover the electricity demand. The surplus, if any, is valorised to a much lower rate. For this specific exercise we have assumed that the energy generated is equal to the electricity demand, thus with no surplus.

The LCOE was calculated for a time horizon of 20 and 30 years. The following parameters were used in the calculation:

Table 12: Input used for the net-billing scheme

Nominal power		**Cost of storage**	
4.2	kW	0.00	Euros/kWh
Utilisation rate		**Storage nom capacity**	
1095 or 1406	kWh/kWp	0	kWh
CAPEX (including VAT)		**Performance Loss Rate**	
1500	Euro/kWp	-0.25% or -0.5%	%/y
OPEX		**Real discount rate**	
30	Euro/kWp	0.99%	%
Retail cost of electricity		**Nominal discount rate**	
0.2	Euro/kWh	2%	%
Net billing contribution		**Inflation rate**	
0.12	Euro/kWh	1%	%
Self-consumption	kWh		
30%	1771.56		

Yielding the following values for the LCOE:

Table 13: Results in terms of LCOE for the selected scenarios for the net-billing business model

€/kWh	Scenario 1a	Scenario 1b	Scenario 2a	Scenario 2b
LCOE 20 years	0.102	0.099	0.079	0.077
LCOE 30 years	0.080	0.078	0.063	0.060

The impact on the cash flow model is shown in Figure 29 highlighting the major impact of the input value for the irradiance with the Payback Time delayed by 3 years when the lowest value of insolation is considered. As expected, the impact of different assumptions in terms of performance loss rate is limited compared to the impact of the use of different insolation databases.

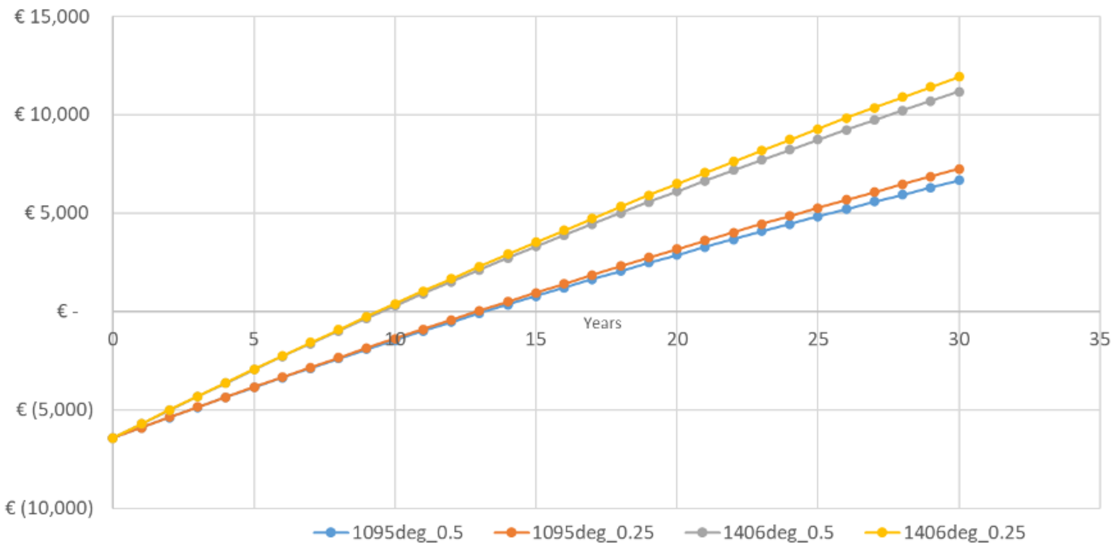


Figure 29: cash flow model of a 4.2 kWp installation in Bolzano Italy with net-billing scheme for the different scenarios

4.1.2 Power purchasing agreement and market price

The results of the Bolzano Yield Assessment as reported in Section 3 were also used to assess the impact in terms of LCOE and cash flow for the case of a 10-year power purchasing agreement using the following scenarios:

Scenario 1) P50 = 1095 kWh/m^2, 1a) PLR = 0.25 %/y, 1b) PLR = 0.5 %/y

Scenario 2) P50 = 1406 kWh/m^2, 2a) PLR = 0.25 %/y, 2b) PLR = 0.5 %/y

After the initial period of 10 years (with the PPA only covering a fraction of the total production, 75 % in this specific case), the electricity is sold at market price. The main point of the PPA is to establish a floor on the price to reduce risk exposure even if the floor is lower than the merchant. Then the remaining 25 % of the production is free to be sold on more volatile price markets. By trading only 75 % of the overall production one can also be sure that the PPA volume target is met. Even if the irradiation for one year is low, one should still be able to meet the 75 % of P50 value volume criteria in the contract.

The following input data were used for the calculations:

Table 14: Input data for the PPA business model

Financial model **1. Project specific data**	**Unit**	**Input value**	**Explanation**
Inauguration year	[-]	2021	Start of commercial operation
Project lifetime	[year]	30	End of commercial operation
Inflation rate	[%]	1.0%	A single inflation rate may be applied to several items - or differentiated among items (landlease vs. power price)
2. Energy yield assessment			
Specific energy yield (Yf)	[kWh/kWp]	1095 or 1406	Input to the financial model. P50 value must include all losses and must reflect the measured energy at the meter
3. Capital expenditures			
1. CAPEX - grid connection & substation	[EUR/kWp]	50	Must include all costs related to transformation, transport, regulation and metering of electricity at the grid connection point
2. CAPEX - hard (excl grid connection)	[EUR/kWp]	400	Must include all costs to engineer, procure and construct the project.
3. CAPEX - soft	[EUR/kWp]	50	Must include all costs to obtain construction and grid connection rights and permits and non-recourse project finance
CAPEX in total	[EUR/kWp]	500	Total specific CapEx required to realise the project
4. Power sales & revenue generation			
PV system (module) degradation	[%/year]	0.5 % or 0.25%	Factor used in the cash-flow model to reflect a constant yearly degradation of the project performance
Technical unavailability	[%]	0.5%	Factor used in the cash-flow model to reflect an expected yearly downtime of the project

A1. Market price - reference price	[EUR/MWh]	40	Market price refence. Used for calculating the non-PPA covered part of the revenue
A1. Market price - ref. price inflation	[%]	1.0%	Escalation rate expected for the merchant market price
D. Private Power Agreement	[EUR/MWh]	35	Power Purchase Agreement to reflect pay-as-produced conditions (after profile cost etc.)
D. PPA - number of years to be applied	[#]	10	PPA duration
D. PPA volume fraction of total energy sales	[%]	75%	Fraction of overall energy sales to be covered by the PPA.
G. Balancing cost	[EUR/MWh]	0	If not included under other sales contracts
5. Operational expenses			
A0. Land lease - fee per area	[EUR/ha]	1000	To be applied for the total area leased
A7. Land lease - escalation rate	[%]	1.0%	Inflation rate may be the same or different from other financial items
B2. O&M - fixed fee pr installed power	[EUR/kWp]	10	All O&M items incl. monitoring, power consumption, security, insurance, inverter replacement & asset management
6. Transaction concept			
Loan #1 - Depth ratio	[%]	0.0%	Senior non-recourse project finance fraction of total project cost
Loan #1 - Interest	[%]	0.0%	Interest to be paid to lender
Loan #1 - Maturity	[year]	20	Duration of load
Debt Service Reserve Account (DSRA)	[%]	50%	Specifies the funds that must always be available to service the loan even in periods with low irradiation/income
Depreciation period for linear share of project cost	[no of years]	25	Tax related assumption.
Tax rate	[%]	22%	Tax related assumption.

The output of the two simulations is the following:

Table 15: Results for the PPA business model

Earnings		**1095 / -0.5%**	**1406 / -0.25%**	
Free cashflow (EBIDTA) IRR by CAPEX	[%]	4.7%	7.9%	IRR from free cashflow (EBIDTA) based on CapEx (not project cost)
Unleveraged IRR after tax and depreciation by CAPEX	[%]	3.9%	6.6%	IRR from free cashflow - unleveraged case
LCOE in total	[EUR/MWh]	36.9	27.9	Levelised Cost of Electricity

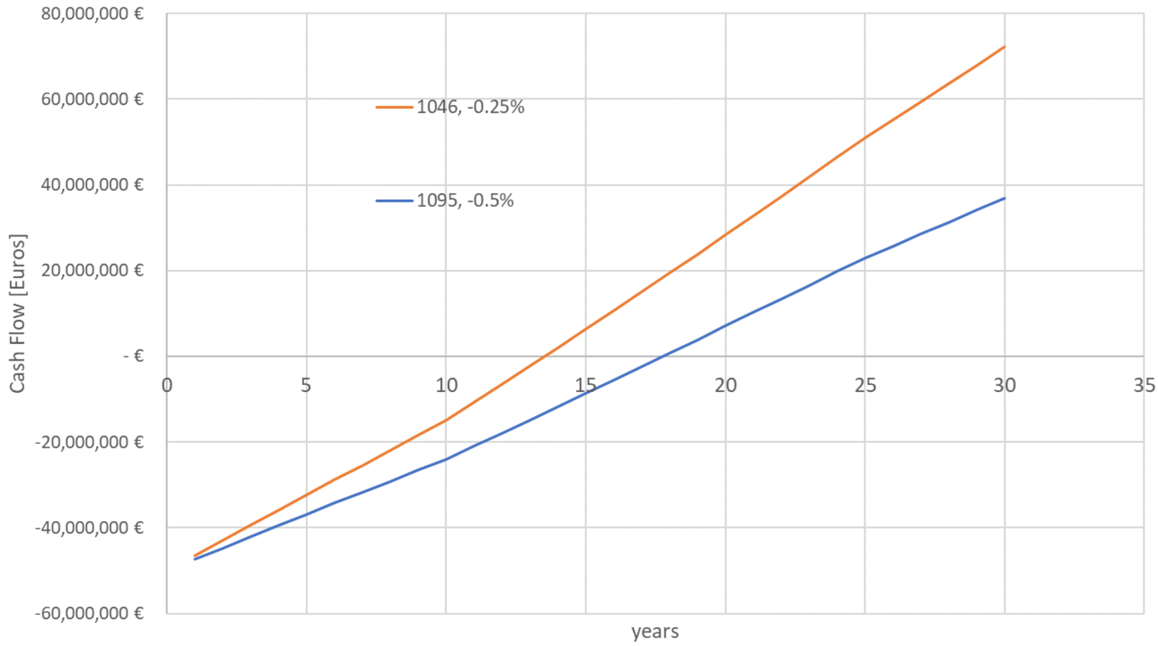


Figure 30: Cash flow for the 10-year PPA business model

4.2 Influence of uncertainties on financial models

The uncertainty information provided by state-of-the-art energy yield predictions for PV systems is not able to reflect deviations from predicted energy yields due to interannual variation of the solar resource and long-term effects such as degradation or long-term irradiance trends. In [60] a Monte Carlo approach is used to model these uncertainties. The result of the Monte Carlo based yield prediction (a sample of 10,000 possible 20 year annual yield time series) is used to determine the after tax-return in the form of cumulative internal rate of return (IRR) for Tax Equity Investor and Sponsor using one example, that of "All Equity Partnership Flip" taken from NREL's SAM model.

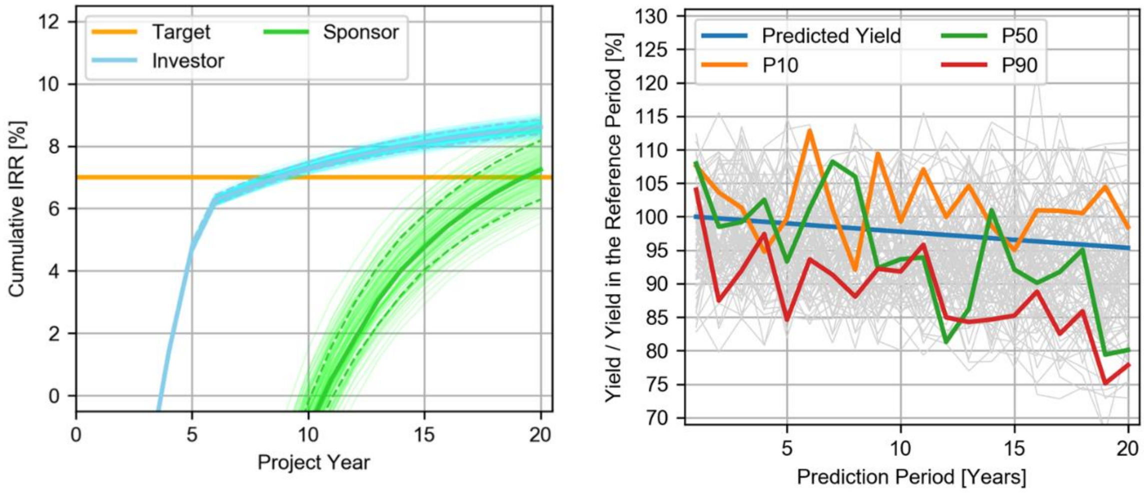


Figure 31: Long-term uncertainties and interannual variation and its influence on financial models. Left: example of a Monte Carlo based yield prediction, Right: Possible development of IRR's over time for Investor and Sponsor in an "All equity partnership flip model" (typically used in the US to finance PV plants).

As a result, due to the usage of a Monte Carlo approach a more complete understanding of the uncertainties associated with financial outcomes for an operating company is possible. Also, the understanding how these uncertainties are driven by the uncertainties associated with yield uncertainty should enable better management of risk. As an example, for the Tax Equity Flip model, it may be possible to optimize deal parameters to the benefit of both parties.

4.3 Comparison of modelled LCOE with real LCOE

The analysis is called "a posteriori" because it allows for the real monetary value, which is a parameter assumed in each year, from the year of planning/installation until now. This means that the annual costs, power production and economic indexes are updated each year. Assumptions have to be made only for the remaining years. This kind of procedure allows the PV plant owner to define the real LCOE value, i.e. the real cost of producing electricity for each year of service taking into account the variability of the economic indexes in time and the effective production due to the changes of the climatic conditions and to compare the values with the initial estimation from the yield assessment. The calculation methods aim to check the accuracy with which the LCOE can be predicted in the medium-term. For the "a posteriori" analysis, the real and measured data were provided by the plant owner and by Eurac Research for the PV Plant in Bolzano. Costs and power production are updated year by year until 2019 when available. The input data used for the "a posteriori" analysis are listed below. Unless otherwise specified, the costs input data are taken from the documentation of the photovoltaic plant, whereas the technical inputs were taken from Eurac Research.

4.3.1 Modelled LCOE

A. Cost Input

The studied 4.2 kWp system is part of a larger multi-technological facility. The assignment of the right cost is not a trivial task. The aim of this section is not the evaluation of LCOE in absolute values, rather the assessment in relative terms of the impact of assumptions to the final value. Table 16 shows the values used for the LCOE calculation. For the O&M cost we use 1% of CAPEX (45 €/kWp/y).

Table 16: Estimated cost of the 4.2 kWp system in Bolzano, 2010 prices

Investment cost component 2010		Cost [€]
Photovoltaic plant		
1	Mounting structures	2000
2	Modules	11000
3	Wiring	2000
4	Inverters	1600
5	Monitoring system	170
6	Data transmission system	130
7	Other (pc, software, etc.)	
Total photovoltaic plant		16900
Personnel cost		100
External services		1700
General costs		200
TOTAL INVESTMENT		18900
TOTAL INVESTMENT [€/kWp]		4500

B. Technical inputs

The technical input for the calculation of the LCOE are taken from the YAs presented in Section 3.2 and summarised in Table 17. Lifetime is assumed as 20 years.

Table 17: Technical input from the independent YA for the Bolzano site

	PR	P50 Yield	P90 Yield	Degradation/PLR
Partner 1	80.4%	1329	1183	0.5%
Partner 2	73.6%	1094	997	0.5%
Partner 3	83.6%	1406	1274	0.25%
Partner 4	81.2%	1213	1184	
Partner 5	81.1%	1445	1270	0.5%

C. Economic inputs

Discount rate/WACC: 5.11% real and 7.41% nominal from historical data of Italy.

Annual inflation rate: 2.3%

Using equation (1), the given cost and economic inputs, a lifetime of 20 years, we obtain for the various independent yield assessors the following values of LCOE differentiating in $Yield_0$ for the P50 and P90 values.

Table 18: Values of LCOE estimated for the 4.2 kWp system in Bolzano installed in 2010 using the results from the independent yield assessments

	$LCOE_{50}$ €/kWh 2010	$LCOE_{90}$ €/kWh 2010
Partner 1	0.338	0.379
Partner 2	0.410	0.450
Partner 3	0.314	0.346
Partner 5	0.310	0.353

The range of LCOE by varying only technical inputs goes from a minimum of 0.310 to a maximum of 0.450 €/kWh. The Feed-in-Tariffs in Italy in 2010 were in the range of 0.346-0.384 €/kWh depending on the PV plant size.

4.3.2 Real LCOE and comparison

A. Cost inputs

For the calculation of the real LCOE, the CAPEX data was kept the same as for the estimated LCOE.

For the OPEX data we have access to historical data which allows us to calculate the real impact of OPEX in the period 2011-2019. The year 2016 shows a low value due to the change in O&M operator. For the remaining years we use the average value of 27 €/kWp/y.

Table 19: OPEX for the Bolzano site

Year	Specific OPEX costs [€/kWp/y]
2011	57
2012	46
2013	46
2014	20
2015	16.5
2016	1.7
2017	17.9
2018	8.1
2019	31.4
Average	27.2

B. Technical inputs

The measured production is given in Table 20.

Table 20: Production for the period 2011-2019 for the 4.2 kWp system in Bolzano, Italy

Year	$Energy_{AC}$ [MWh]	Yield [kWh/kWp]
2011	6.092	1450
2012	5.753	1370
2013	5.489	1307
2014	5.270	1255
2015	5.773	1375
2016	5.542	1320
2017	5.719	1362
2018	5.440	1295
2019	5.327	1268

The PLR value is -0.84%/y and it is applied for the remaining period.

C. Economic inputs

The WACC and inflation values are the same as for the previous evaluation.

The resulting value for the LCOE with a lifetime of 20 years is of 0.274 €/kWh, which is lower than the lowest value resulting from the most favourable yield assessment, 0.310 €/kWh, and well below the feed-in-tariffs secured for the PV plant.

A lifetime of 25 years would further decrease the LCOE to a value of 0.248 €/kWh.

4.3.3 Actual LCOE values

To show the strong decrease in LCOE due to the decrease in CAPEX, OPEX, and increase in lifetime, we have selected the following input parameters referred to year 2020. We report two cases, one for residential and one for utility scale PV with the CAPEX and OPEX taken from [59], 1100 €/kW, 22 €/kW/y and 430 €/kW, 8.5 €/kW/y, respectively.

Table 21: LCOE results based on the Bolzano system, Italy

Scenario	LCOE €/kWh
Modelled LCOE 2010	0.310-0.450
Real LCOE 2010	0.274
Modelled LCOE 2020 residential	0.068-0.099
Modelled LCOE 2020 utility scale	0.027-0.039

Modelled LCOE 2010: cost input defined above in 4.3.1, technical input from YAs, economic input defined in 4.3.1, lifetime 20 years

Real LCOE 2010: cost input defined above in 4.3.2, technical input from measured values, economic input defined in 4.3.2, lifetime 20 years

Modelled LCOE 2020 residential: cost input defined in 4.3.3, technical input from YAs, economic input defined in 4.3.1, lifetime 25 years

Modelled LCOE 2020 utility scale: cost input defined in 4.3.3, technical input from YAs, economic input defined in 4.3.1, lifetime 25 years

5 BEST PRACTICE AND GUIDELINES

Possible issue:	Best practice
Estimation of correct site insolation	Check various sources of satellite data Ask satellite data provider for validated data with ground measurements Apply site adaptation
Long-term trend	Check the trend over different time-periods (.e.g 2011-2020, 2001-2010)
Transposition of GHI to GTI	Check in the literature which is the best combination of decomposition and transposition models for the specific climate Check for consistency in the % contribution by using various irradiance sources
Parameterization of components (PV Modules, Inverters)	Check reliability of provided files, ask manufacturer for qualified data (e.g. independent PAN Files)
Shading	In case of far shading check the sensitivity of the yield on different hourly profiles
Soiling	In case of measurements, evaluate non-uniformity over the selected site
Temperature effects	Check various sources of satellite data Ask satellite data provider for validated data with ground measurements
Performance Loss Rates	Make sure that one includes not only module degradation and that also unavailability and reversible failures are considered
Calculation of uncertainty	Use semi-empirical calculation methods if long-term data is available and distribution deviates from normal (gaussian)
O&M costs in business models	Based the assumptions on real cost data and not on a % of CAPEX

6 CONCLUSIONS

In this report we have moved forward from the uncertainty framework in yield assessment to two real implementations of it and perform an assessment of the impact that uncertainties can have on lifetime yield predictions, on the LCOE and on the cash-flow.

One of the most relevant question that we have tried to answer is the following:

How reliable are YA's?

This is an apparently simple question; however, the answer is not equally simple. Typically, investors require one YA. In some cases, more YAs might be requested if results are unclear. The various YAs can be averaged to assign a purchase value to a given project. In any case the question remains unanswered: why do different assessors obtain different answers? Is one YA more reliable than others?

Investors know that past performance is no guarantee for future results. This maxim also applies to long-term yield assessments and the LCOE that can be determined from these, also within the context of a changing climate. Yield assessment is an essential step in a PV project, as it helps to determines whether a system will be funded or not. However, the YA is not only about the software used, it is mainly about the user. YAs may not be as reliable as expected, and in this report, we have demonstrated how seven highly skilled specialists did not arrive at the same result, having been provided the same detailed inputs. As seen from the YA exercises for Bolzano and Alice Springs, differences in these stem primarily from personal experience and assumptions by the modeler, of which

(v) the irradiance database selection and site adaptation (especially for mountainous terrain),
(vi) degradation/PLR assumption,
(vii) total modelling uncertainty values (as seen in the P50 and P90 ranges) and
(viii) soiling and far/near shading had the largest impact on the determined result.

The direct flow-on consequence from this is that LCOE values will also exhibit a variance, on top of the additional modelling assumptions that can be employed for LCOE calculations. Determining P50 and P90 values for LCOE results and highlighting the assumptions/modelling chain will be important. From an industry perspective, it would be beneficial if more "live" post-mortem analyses (i.e. comparison of the LTYP and measured data, at e.g. every 5 years of system life) would be made and published. These can then be used as crucial feedback and inputs for YA modelers, financiers, and insurers.

To conclude, we believe that together with the previous report [2], we have provided all the needed information to understand if one YA is more reliable than another and which input and output data must be provided by the assessor to reach this conclusion.

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ANNEX 1 BASIC INFORMATION IN A YIELD ASSESSMENT

PV system features: Coordinates, geometrical installation of the PV system (tilt angle, orientation, trackers' main features, etc.) should be provided

Components: datasheet of components (modules, inverters, etc.) used in the YA should be provided

PV system configuration: number of components, working conditions (environmental and technical) should be provided

Far Shading: if relevant, the shading diagram used in the YA should be provided

Object Shading: If relevant, the 3D model used for the object shading calculation should be provided

Meteo data: data source should be clearly indicated with the time range used for the calculation. Uncertainty should be provided in terms of mean value compared to "real value" and interannual variability.

Degradation: value used in module degradation should be given and properly referenced.

Calculation steps and models:

- software used
- The model used for the transposition model from GHI to GTI.
- Impact of far and near shading (including row shading)
- Losses due to soiling (and snow losses)
- Deviations from STC conditions
- Module losses due to mismatch
- Cable losses
- Inverter losses
- Auxiliary system consumption
- Transformer losses

The values provided for the PR should clearly state which effective irradiance is used for the calculation. The report should include a table with all the gains/losses step by step, uncertainty for each modelling step.

The YA should provide a value as initial Yield Assessment and one average value of yield over the lifetime of the PV system. A LTYP will include a deeper analysis in terms of yield decrease over the lifetime of the PV system with related uncertainties (and P10-P90 band).

ANNEX 2 FINANCIAL MODEL

Whereas an LCOE calculation can be performed in a simple version with only few input parameters, the financial model used by banks and investors contain more details on the financing, depreciation and taxation of the project and also focus on other Key Performance Indices like the project free cashflow Internal Rate of Return (IRR), Net Present Value (NPV) or enterprise value for an institutional investor with a given target IRR. In the example below, a set of items that may be included in such a financial model are listed.

1. Project specific data		**Comment**
Project variant	DK	Most models and calculations come in different versions that needs to be uniquely identified
Inauguration year	2021	Start of commercial operation
Project lifetime	30 y	End of commercial operation
Inflation rate	1.0%	A single inflation rate may be applied to several items - or differentiated among items (land lease vs. power price)
2. Site specific data		
Site name	DK	Identification of site or project
Area (lease)	100	Total leased area in ha
Construction area	90	Net area available for installation of the PV generator (substructure with panels including distance between rows)
Horizontal Global Irradiation (GHI)	1,000	Resource estimate in kWh/m2 per year
3. PV technology concept		
3.1 PV module		Details not required for the financial model. May be included in the investment pitch-deck.
PV module nominal dc power	450	DC power per panel in Wp - useful to compare with total installed power
3.2 Inverter		Details not required for the financial model. May be included in the investment pitch-deck.
Inverter AC nominal power	250	Nominal power in kW of relevance for general electrical design, maximum apparant power in kVA of relevance for grid operator.
3.3 Substructure		Details not required for the financial model. May be included in the investment pitch-deck.
Substructure	FT	Substructure for Fixed Tilt (FT) or Horizontal Single Axis Tracker (HSAT) with modules in Portrait (P) or Landscape (L)
3.4 Electrical configuration (inverter sizing)		Details not required for the financial model. May be included in the investment pitch-deck.
Number of strings per inverter	24	Sizing according to target dc/ac ratio
No of modules per string	26	Sizing according to design voltage for the full string (<1500 V @-10 °C)

Power ratio dc to ac	1.12	Key Performance Indicator (KPI) for inverter loading in kWp/kW
3.5 Electrical configuration (project sizing)		Details not required for the financial model. May be included in the investment pitch-deck.
No of inverters in project	227	Calculated to match the available construction area or available grid capacity or based on a construction layout
Modules in total	141648	KPI reflecting the overall size of the project
Total park DC power	63,742	KPI reflecting the energy-generating potential of the project in kWp
AC nominal power for full park (@inverter)	56,750	KPI reflecting the export capacity that must be made available by the utility in kW
Pitch axis-to-axis	10 m	Design input to be used for shading angle calculation and planning documentation/visualisation for the municipality
Ground Coverage Ratio (GCR)	35.5%	KPI reflecting the utilisation of the area (packing density)
4. Energy yield assessment		
Transposition Factor (TF)	1.2	The expected gain in irradiation received in Plane-Of-Array relative to the GHi resource estimate
Performance Ratio (Yf/Yr)	90%	KPI reflecting the expected overall performance of the project
Energy generation (1st year)	68.8	Input to the financial model. P50 value must include all losses and must reflect the measured energy at the meter in GWh
Specific energy yield (Yf)	1,080	KPI reflecting the expected ability of the hardware to deliver energy based on technology and engineering decisions in kWh/kWp
5. Capital expenditures		
1. CAPEX - grid connection & substation	50	Must include all costs in €/kWp related to transformation, transport, regulation and metering of electricity at the grid connection point
2. CAPEX - hard (excl grid connection)	400	Must include all costs in €/kWp to engineer, procure and construct the project.
3. CAPEX - soft	75	Must include all costs in €/kWp to obtain construction and grid connection rights and permits and non-recourse project finance
CAPEX in total	525	Total specific CapEx in €/kWp required to realise the project
Total CAPEX (fixed and variable)	33.46	Total CapEx in million Euro required to realise the project
6. Power sales & revenue generation		
PV system (module) degradation	0.5%	Factor used in the cash-flow model to reflect a constant yearly degradation of the project performance
Technical unavailability	0.5%	Factor used in the cash-flow model to reflect an expected yearly downtime of the project
Market price - reference price	40	Market price refence in EUR/MWh. Used for calculating the non-PPA covered part of the revenue

Market price - ref. price inflation	1.0%	Escalation rate expected for the merchant market price
Private Power Agreement	40	Power Purchase Agreement in EUR/MWh to reflect pay-as-produced conditions (after profile cost etc.)
PPA - number of years to be applied	10	PPA duration
PPA volume fraction of total energy sales	50%	Fraction of overall energy sales to be covered by the PPA.
Balancing cost	0	If not included under other sales contracts
7. Operational expenses		
Land lease - fee per area	1000	To be applied for the total area leased in in EUR/ha
Land lease - escalation rate	1.0%	Inflation rate may be the same or different from other financial items
O&M - fixed fee pr installed power	10	All O&M items incl. monitoring, power consumption, security, insurance, inverter replacement & asset management in EUR/kWp
8. Transaction concept		
Total project costs	33.72	Beside CapEx this item in million EURO includes costs for internal activities, due-diligence and construction finance
Loan #1 - Depth ratio	0.0%	Senior non-resource project finance fraction of total project cost
Loan #1 - Interest	0.0%	Interest to be payed to lender
Loan #1 - Maturity	20	Duration of loan
Debt Service Reserve Account (DSRA)	50%	Specifies the funds that must always be available to service the loan even in periods with low irradiation/income
Linear depreciation period	25	Tax related assumption
Tax rate	22%	Tax related assumption

9. Revenues	
Energy delivered to POC	Amount of energy sold in MWh
Market price to be obtained	Price expectation by year in €/MWh
Private Power Agreement	PPA expectation by year in €/MWh
Revenue from power sales	Income expectation by year in million €
10. Operational expenses	
Annual operational expenses	O&M expense expectations by year in tEUR
11. Financial performance	
Free cashflow (EBIDTA)	Free cashflow expectations by year in million EUR
Free cashflow (EBIDTA) IRR by CAPEX = **4.5%**	IRR from free cashflow (EBIDTA) based on CapEx (not project cost)

Depreciation	Yearly depreciation of the asset value in million EUR
Tax payable	Yearly tax to be paid
Free cash flow after depr. and tax (unleveraged)	Free cashflow expectations by year after depreciation and tax in M€
Unleveraged IRR after depr. and tax **=3.7%**	IRR from free cashflow - unleveraged case

9. Revenues	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**	**2031**	**2032**	**2033…**	**2036**	**2037**
Energy delivered to POC	68,497	68,154	67,813	67,474	67,137	66,801	66,467	66,135	65,804	65,475	65,148	64,822	64,498	63,535	63,218
Market price to be obtained	40.0	40.4	40.8	41.2	41.6	42.0	42.5	42.9	43.3	43.7	44.2	44.6	45.1	46.4	46.9
Private Power Agreement	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	0.0	0.0	0.0	0.0	0.0
Revenue from power sales	2.740	2.740	2.740	2.740	2.740	2.740	2.740	2.741	2.741	2.742	2.879	2.893	2.907	2.951	2.965
10. Operational expenses															
Annual operational expenses	737.4	743.8	750.2	756.7	763.3	769.9	776.6	783.4	790.2	797.1	804.1	811.1	818.3	840.0	847.4
11. Financial performance															
Free cashflow (EBIDTA)	2.002	1.996	1.990	1.983	1.977	1.970	1.964	1.957	1.951	1.945	2.074	2.082	2.089	2.110	2.118
Free cashflow (EBIDTA) IRR by CAPEX = **4.5%**															
Depreciation	1.339	1.339	1.339	1.339	1.339	1.339	1.339	1.339	1.339	1.339	1.339	1.339	1.339	1.339	1.339
Tax payable	0.146	0.145	0.143	0.142	0.140	0.139	0.138	0.136	0.135	0.133	0.162	0.163	0.165	0.170	0.171
Free cash flow after depr. and tax (unleveraged)	1.856	1.851	1.846	1.841	1.836	1.831	1.826	1.821	1.816	1.811	1.913	1.918	1.924	1.941	1.946

Unleveraged IRR after depr. and tax **=3.7%**

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