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YIELD PREDICTIONS FOR PHOTOVOLTAIC POWER PLANTS: EMPIRICAL VALIDATION, RECENT ADVANCES AND REMAINING UNCERTAINTIES

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ABSTRACT: Yield predictions are performed to predict the solar resource, the performance and the energy production over the expected life time of a Photovoltaic (PV) system. In this study we compare yield predictions and monitored data for 26 PV power plants. The monitoring data includes in-plane irradiance for comparison with the estimated solar resource and energy yield for comparison with predicted performance. The results show that, due to increased irradiance in recent years ("global brightening") the yield predictions systematically underestimate the energy yield of PV systems by about 5%. As common irradiance databases and averaging times were used for the yield predictions analyzed in this paper, it is concluded, that yield predictions for areas where the global brightening effect occurred in general underestimated the energy yield by the same magnitude. Using recent satellite derived irradiance time series avoids this underestimation. The observed Performance Ratio of the analyzed systems decreases by 0.5 %/year in average with a relatively high spread between individual systems. This decrease is a main factor for the combined uncertainty of yield predictions. It is attributed to non-reversible degradation of PV cells or modules and to reversible effects, like soiling. Based on the results of the validation the combined uncertainty of state of the art yield predictions using recent solar irradiance data is estimated to about 8%.
Keywords: PV systems, yield prediction, performance ratio, solar resource assessment, global dimming and brightening

1 INTRODUCTION

Since the beginning of the current millennium, commercially operated Photovoltaic (PV) systems have become a common source of energy supply. PV power plants with installed capacities of several hundred kilowatts to multiple megawatts became possible especially due to the introduction of fixed feed-in tariffs for roof-top and free-standing systems in Germany in 2004 [1], the year where world-wide annual PV installations exceeded one gigawatt for the first time [2]. In the following years a growing number of power plants were installed in Germany. In 2007 and 2008 a second country joined this development: Spain saw something like a "PV gold rush" in these years with massive installations of big PV power plants. Italy joined with first bigger installations in 2008. Since 2010 the number of big PV power plants increased in various countries in Europe and other regions all over the world.

Right from the beginning an assessment of the expected energy yield was an essential precondition for the financing of PV power plants. This is especially true for European countries with feed-in tariffs: due to fixed tariffs and guaranteed rights to feed in all energy produced, one of the main uncertainties for an investment in a PV power plant is the expected energy production within its life time or its investment time horizon. This assessment is performed within a yield prediction. In order to allow a better understanding of the following sections, we will first briefly describe the steps involved in such a prediction.

A yield prediction is "an estimate of the total energy production for a PV system at a specific site" [3]. The primary aim is to predict the annual energy production over the expected lifetime of the system. Usually it is performed at an early stage of a planned PV project. Yield predictions can be partitioned in three main parts i) an assessment of the solar resource, ii) modelling of the expected PV system energy output based on the estimated meteorological values and iii) an estimation of long-term changes in energy yield over the expected life time of the system under consideration.

For a solar resource assessment, the long-term average solar radiation from the past (the reference period) is used as an estimator for the availability of solar resources in the future (the prediction period). Since long-term ground measurements of solar radiation for a specific site are most often not available, satellite derived solar irradiance is commonly used for the reference period (sometimes in combination with interpolations of ground measurements).

PV system modelling can be defined as a set of models, methods and parameters to simulate the energy delivery of a PV system using the specifications of the system (PV modules, inverters, azimuth and elevation, wiring, etc.) and meteorological values (solar irradiance, ambient or module temperature, wind speed, etc.) for the location of the system. As usually no measurements are available for a yield prediction, model parameters cannot be extracted from system performance data. Laboratory measurements, data sheets or typical characteristics have to be used instead. This is in contrast to PV system modelling carried out in the context of system monitoring, to compare actual with simulated system performance in order to detect failures. For such purposes previously measured meteorological parameters and system performance can be used to calibrate simulation models. This difference is crucial when comparing modeling errors and uncertainties reported in publications that focus on PV system modelling (see e.g. [4–7]).

Long-term effects that influence the energy yield are either changes in system performance or changes in availability of the solar resource. Estimates of long-term changes in system performance are usually based on an assumption of expected degradation rates for the PV modules. On the other hand, changes in the solar resource are often neglected or considered to be negligible [8–10]. Recent publications show, however, that this factor does need to be considered [11].

Only a few publications on the combined uncertainties of yield predictions are available so far [8,12–14]. Most of them lack a comparison with measurement data from real PV systems.

In this paper an empirical validation of yield predictions against measured irradiance and measured energy yields of commercially operated PV systems is presented. For some of the systems, up to eight years of data are available. Differences and reasons for bias differences will be identified and analyzed. The findings from the validation and the analysis will be used for an uncertainty assessment of state of the art yield predictions. All uncertainties given in this paper are standard uncertainties (i.e. k=1 with a confidence interval of 68%).

2 VALIDATION OF YIELD PREDICTIONS WITH MEASUREMENTS

In this section yield predictions are validated with monitored data from commercially operated PV power plants. The comparison is done for irradiance in plane of array (GPOA), Performance Ratio (PR) and specific energy yield (Yield) of the systems.

2.1 Yield predictions and measured data

Yield predictions estimate the long-term yield of a system; therefore only systems that are measured for five or more calendar years are used for the comparison. Consequently, the yield predictions for those systems were prepared between the years 2004 and 2009. For most of the calculations the simulation program INSEL (http://insel.eu, last accessed 2014-06-30) was used; eight yield predictions were done with Fraunhofer ISE's in-house simulation software ZENIT. German test reference years or time series from the Satel-Light server (http://www.satel-light.com, last accessed 2014-06-30) were used as input time series of solar radiation and ambient temperature. At German sites the Satel-Light time series were scaled to reflect the long-term mean irradiance values derived from the German meteorological service (Deutscher Wetterdienst, DWD). The first predictions used long-term values from the period 1980 to 2000. Later predictions used even longer time periods ranging up to year 2006 (also starting in 1980). For all sites outside of Germany annual mean irradiance values from University of Oldenburg for the time period 1997 to 2006 were used.

Monitoring data of PV systems used for the comparison with yield predictions is obtained with common Fraunhofer ISE monitoring systems. For measurement of in-plane irradiance regularly calibrated silicon reference cells are used. The data is measured each second, averaged to five minute intervals and stored by an industrial data logger. Each night data is transferred to the institute and undergoes a set of plausibility and quality checks. Measurement uncertainties of the monitoring system are estimated to be 2% to 3% for irradiance measurement, about 1% for the AC energy yield and resulting in an uncertainty of approximately 3% for PR values [7].

Additional uncertainties for specific yield and PR may appear due to differences between nominal and actual installed power. Installed power cannot be determined without uncertainty: On the one hand, there is the measurement uncertainty on the power at Standard Test Conditions (STC) of single PV modules. To date, measurement uncertainties of as low as 0.8% for crystalline silicon PV modules can be achieved, whereas some 5–10 years ago, measurement uncertainties were in a range of 1.5% to 2.5% [15, uncertainties converted to standard uncertainties]. On the other hand, not all modules of a PV plant can be measured with low uncertainty as achieved in an advanced laboratory. Therefore, the sampling of modules introduces additional uncertainty [16]. In addition, initial stability aspects like light induced degradation (LID, power loss of 0% to 2% after 20 kWh/m^2 for crystalline silicon) need to be considered [17]. Taking into account an additional 2% uncertainty for installed STC power, the overall uncertainty for specific yield may reach more than 2%, leading to an uncertainty of 3.5% for PR.

Note, that for yield predictions irradiance data with similar physical properties as pyranometer measurements are used, whereas the monitoring systems use reference cells. Mainly due to different angular sensitivity, spectral effects and soiling, the readings of pyranometers and silicon sensors differ. To account for this difference, the irradiance and PR values from yield predictions were adjusted with predicted angular, soiling and spectral losses.

For a more detailed description of the monitoring system, the irradiance correction and its validation by comparison with pyranometer measurements please refer to [7] and [14].

2.2 Systems available for comparison

A first condition for inclusion of monitoring data into the comparison is data availability. For the comparison in this paper as a standard an annual data availability of 98% is required (i.e. not more than about one week out of a year may be missing). While this may be a relatively strict condition, typical data availability within our monitoring is around 99.5% so this criterion doesn't exclude any systems. To ensure a fair comparison, we excluded the whole year if only one measurement quantity was missing. E.g. a year with an irradiance sensor defect, that couldn't be repaired / exchanged within one week, is completely excluded. After applying this rule, plants with less than three years of remaining reliable data left are excluded.

Based on these quality criteria, 38 systems are available for comparison. In the next step of the selection procedure we identified systems, for which the original specifications used for the yield prediction (e.g. installed DC power, azimuth angle or tilt angle) differ from those of the built system. The following major deviations were identified:

- Installed power differs by more than 10%: 2 systems
- Azimuth angle differs by more than 10°: 4 systems
- Tilt angle differs by more than 5°: 2 systems

As a result, a further seven systems were excluded from comparison. The fact that seven out of 38 systems (18%) are not built as expected during the yield assessment study, clearly demonstrates the need for an integrated quality assurance for bankable PV investments [18].

From the remaining 31 systems, we excluded those in which system failures (particularly inverter failures) reduced the number of available operating years below three. This removes another five systems, at the end leaving a batch of 26 systems for comparison.

The remaining systems collectively provide 129 years of operating data. From these, we excluded single years with system failures (11 years, equivalent to 9%), resulting in a final data set of 118 years. For some systems eight years of data, at minimum (per definition) three years and in average 4.5 years per system are available. Three of the systems are sun-tracking systems, while the others have fixed tilt angles in a range of 15° to 30° in combination with azimuth angles ranging from south east (150°) to south west (230°). Two systems are located in Spain, all other systems in Germany. All systems are equipped with modules made of crystalline silicon cells.

2.3 Validation

For the validation annual relative differences between measured and predicted values (GPOA, PR and energy yield) are calculated. Furthermore the overall difference (referring to the entire measurement period) is calculated. The results of the validation are shown in Figure 1. The systems are sorted by their commissioning date (oldest systems on top).

Note that as the age of installations differ, the differences shown in Figure 1 refer to operating periods of unequal length (ranging from three to nine years, see section 2.2). Although the comparison is influenced by this fact (especially for GPOA and yield due to their high year-to-year variations), the figure nevertheless shows the current status of measurements compared to yield predictions.

Figure 1 shows that measured GPOA is higher than predicted for almost all systems. In fact, the measured irradiance for 20 out of 26 systems is more than 3% above the prediction (which is equal to the estimated uncertainty of the irradiance measurement). This leads to an overall mean difference of +4.9%. Systems #22, #24 and #26 show a negative difference or extraordinary small positive difference. Two of these systems (#22, #24) are the systems located in Spain with irradiance data from a different source and time period used in the yield prediction (see section 2.1). We will analyze the reasons for these differences in section 3.2. For now, it can be concluded, that GPOA is systematically underestimated by the yield predictions.

PR over all systems seems in line with the predictions. The mean difference of -0.8% is clearly within uncertainties of the PR measurements. However, for the first half of the systems (the older systems) PR seems to be slightly overestimated. Systems #4, #6, #8 and #11 show negative differences of more than 3.5% (estimated uncertainty of the PR measurements). The reason for this underestimation is mainly due to a decrease of PR over time. For the yield predictions no decrease in PR or an estimate of degradation effects was considered. So the difference of the measured to the predicted PR tends to become more negative from year to year. We will further analyze this in section 3.1.

As a consequence of higher irradiance and a slightly lower than predicted PR, measured energy yield of the systems is approximately 4% above predictions. Single years exceed the predicted long-term average energy production by up to 18% due to annual fluctuations in solar resource and underestimated irradiance.

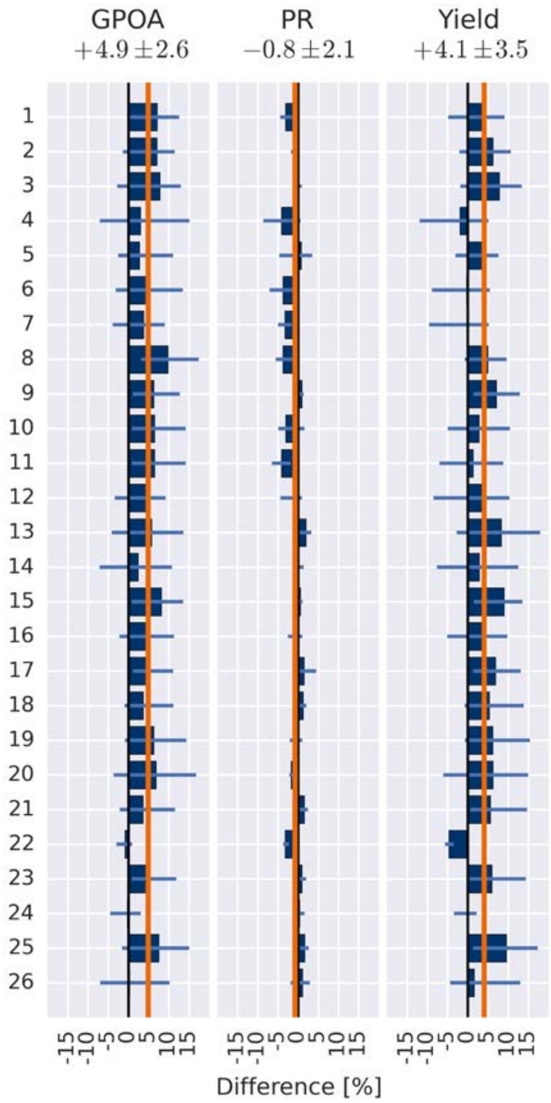

Figure 1: Measured values compared to predictions. Blue bars show differences over the entire measurement period. Lines in light blue indicate interannual variability; the vertical line in orange indicates the mean difference. The mean and the standard deviation for GPOA, PR and yield are specified on the subplot titles.

3 INVESTIGATION OF BIAS DIFFERENCES

The results from the previous section naturally lead to the question *why* the predicted energy yield is systematically underestimated. Within this section we will identify the reasons for the observed systematic differences and try to identify approaches to reduce them in future yield assessments.

3.1 Long-term system stability

As stated in section 2.3 the long-term decrease in PR influences the differences shown in Figure 1.

To analyze this influence we computed change rates for all systems under consideration. Note, that we avoid the term “degradation” here to differentiate between changes in performance caused by potentially reversible effects (e.g. soiling) and non-reversible degradation of PV modules or cells. A separation of these effects is not possible from the data available for this paper. Details of the method and the filtering procedure we used are given in [19]. Figure 2 shows the histogram of the annual change rates for PR.

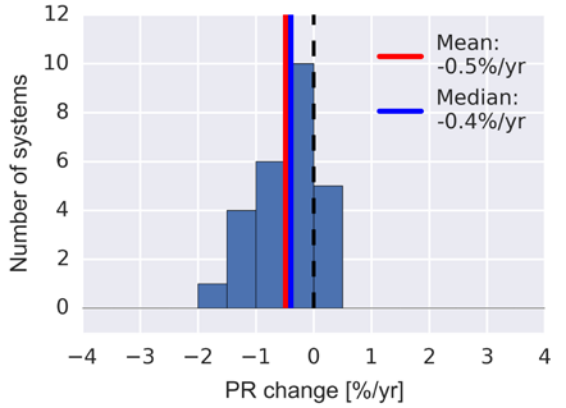

Figure 2: Histogram of annual PR changes for the systems under consideration.

Mean and median indicate a negative trend of about –0.5 %/year. Five systems show a slightly positive change rate (of up to +0.2 %/year). The mean for all systems is not influenced (up to the first digit) if for these systems zero change rate would be assumed. Another five systems show a decrease of more than –1 %/year, which means that typical power guaranties of PV module manufacturers (80% of rated power after 20 years) do not hold. There are no relevant differences between mono- (5 systems) and poly-crystalline systems (21 systems): the mean, the median and the range are similar, however, in our sample the mono-crystalline systems are older in average. An overview on the development of change rates depending on operating time is given in Figure 3.

Figure 3: Changes in PR depending on operation years.

The results are basically in accordance with data available in the literature: Jordan and Kurz [20] recently published a comprehensive review on long-term performance of PV modules and systems. They identify a median change rate of about –0.5 %/year for polycrystalline systems (for installations after 2000) and a change rate of about –0.2 %/year for monocrystalline systems. Change rates for PV modules of the same technology are similar.

The magnitude of the changes rates found for the systems under consideration here are also similar, with the exception, that no differences between mono- and polycrystalline systems were found. The fact that there is no difference between both technologies may indicate that other effects like soiling dominate change rates; however the sample size is small.

As a sound separation in reversible and non-reversible effects is not possible here, we use the calculated change rates to check their influence on the comparison of measured and predicted PR and energy yield. To do so, the predicted annual energy yield and PR is reduced by the individual change rates of the systems. Note, that this is not a realistic case for a yield prediction, as the change rates will be unknown beforehand, however it (nearly) removes changes over time from the comparison. The results are shown in Figure 4.

Compared to Figure 1 this removes the negative overall PR difference and reduces the shift especially for the older systems. The remaining scatter can be attributed to a combination of measurement uncertainties (monitoring data, nominal to real STC power) and discrepancies in system modelling within the yield predictions. However only for one system (#23) the difference exceeds the assumed measurement uncertainty of 3.5%.

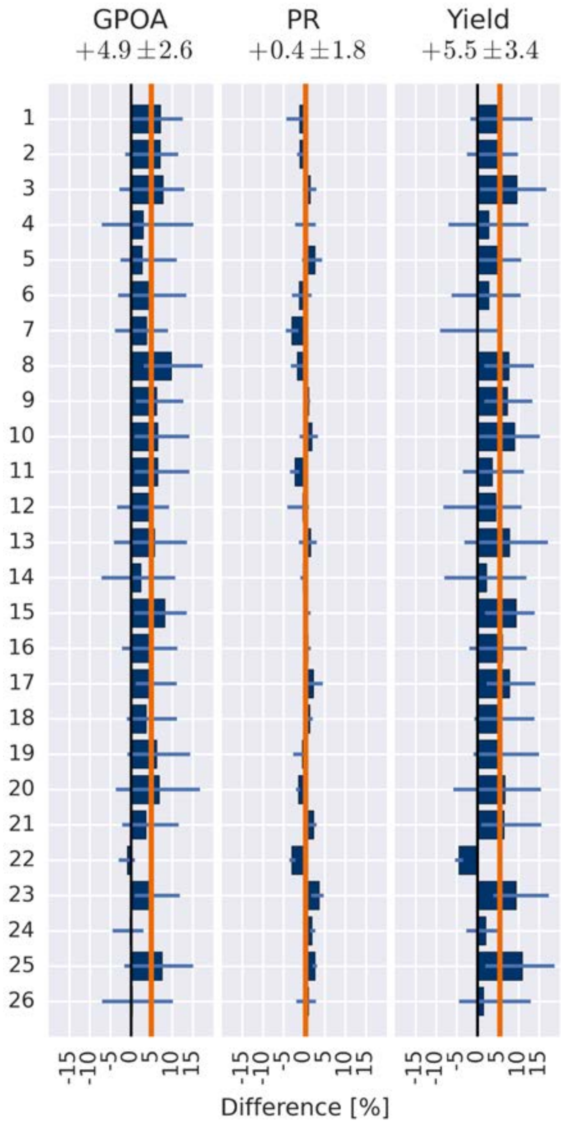

Figure 4: Comparison of measurements against predictions using the calculated rate of change for the PR

Note that the difference between measured and predicted energy yield also has changed: the mean difference of the measurements from the predictions is now above 5%. As changes in PR are now included in predicted values, this number is a measure for the real underestimation of the energy yield resulting from the underestimation of the solar resource.

3.2 Solar resource

As stated in section 2.1, for the original yield predictions, long-term average values of up to 26 years from the past were used to estimate solar irradiance on the horizontal plane. However, solar irradiance is not necessarily stable on such time scales and has in fact been shown to follow long-term trends spanning multiple decades [21]. While from the 1950s up to the 1980s a decline was observed, since the mid-1980s a gradual increase in solar radiation was observed at many sites around the world. This phenomenon is known as “global dimming and brightening”. A more detailed discussion of these trends and their causes can be found in [22–24].

In [11] the influence of these long-term trends on solar resource assessments is analyzed. From measurements at 8 stations of the DWD an average brightening trend of 3.3 %/decade is found for the years 1984–2010. Not only global horizontal irradiance (GHI), but also direct and diffuse irradiance measurements and modelled in-plane irradiance are analyzed. To reduce the forecasting error in the presence of long-term trends, [11] recommends using irradiance data from the 10 most recent years as a basis for solar resource assessments. This 10-year average was shown to result in about 5% higher predictions compared to predictions based on a 30-year average.

The yield predictions for the systems in the present study were all based on longer period averages (20 to 26 years), and the measurements clearly show that the predictions were systematically too low. The question, whether the predictions would have been systematically better if only 10 years of irradiance history had been used therefore presents itself.

To test this method, irradiance time series provided by Geomodel Solar [25] are used to recalculate the yield predictions with the 10 most recent years preceding the commissioning of the system. For a validation of these time series the reader is referred to [26].

For the recalculation the PV module and inverter parameters from the original yield predictions are used. Note that at least in part different models had to be used for the recalculation. For the original yield predictions calculated with the simulation program INSEL the two-diode-model was applied for the simulation of PV module behavior and at least for the first predictions a polynomial interpolation to simulate inverter efficiencies. So new parameters had to be derived for the models used for the recalculation (see [27] for the module model and [28] for the inverter model). Furthermore for the simulation of shading losses, not all necessary parameters could be derived from the old predictions and the losses predicted in the original predictions were used as fixed loss factors in the recalculation.

For conversion to GPOA we applied two different models: the Perez [29] and the Hay model [30]. On one hand these models show a good agreement with measurements at different locations (especially at south oriented planes with tilt angles ≤45° which are typical for PV systems) and on the other hand the Perez model usually predicts higher irradiance than the Hay model [31–37]. This makes a combination of these models valuable to estimate the range of possible irradiances and their uncertainties.

The individual change rates for the PR as derived in section 3.1 are not adequate for a yield prediction, as these change rates are not known in advance. Therefore the average change rate of –0.5%/year as computed in section 3.1 is assumed for all systems.

The results of the recalculation are shown in Figure 5 using the Hay model and in Figure 6 using the Perez model.

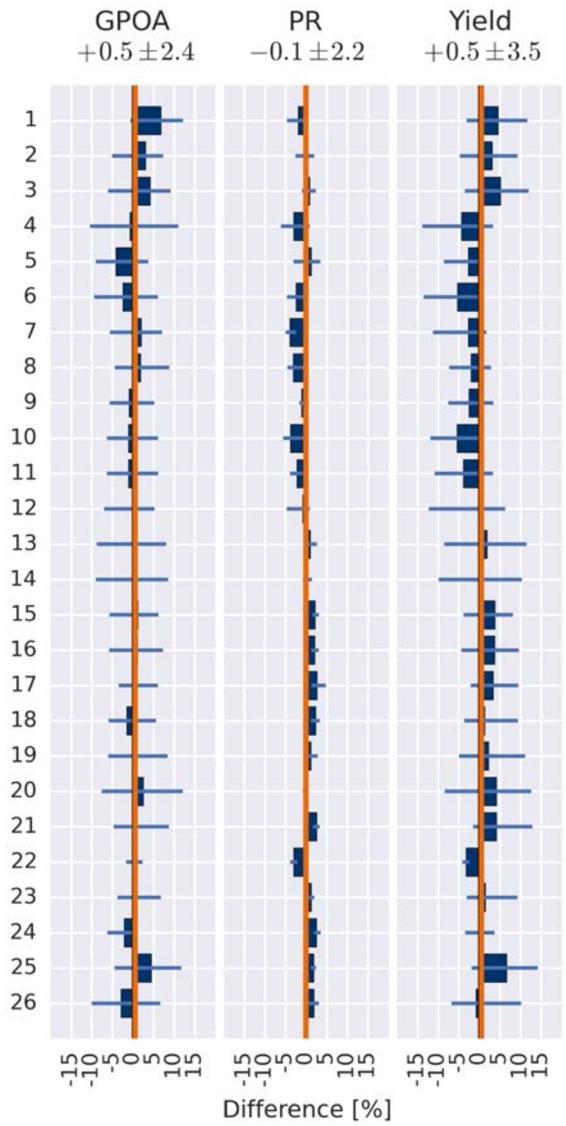

Figure 5: Results when using the Hay model and assuming a change rate of –0.5 %/year.

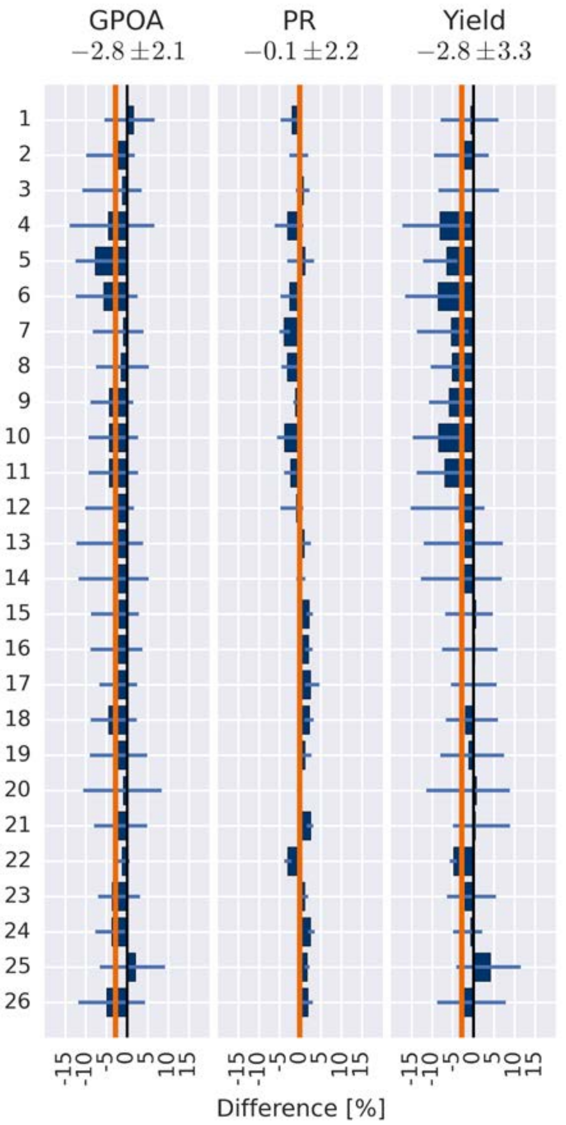

Figure 6: Results when using the Perez model and assuming a change rate of –0.5 %/year.

The most obvious finding from these results is the strong influence of the transposition model on the overall results: while measured GPOA and yield are slightly higher compared to the prediction when the Hay model is used, the higher irradiance gains from GHI to GPOA predicted by the Perez model lead to negative deviations. The predictions of the Hay model are very close to most GPOA measurements. Only for the first three systems, which are the tracking systems, the Perez model seems to predict lower differences. Note that this comparison does not allow for a ranking of transposition models as many sources of uncertainties are involved (see section 4).

The observed uncertainties for PR are low with a mean difference around zero and standard deviations of about 2%. For system #7 and #10 the differences are above the estimated measurement uncertainty. These differences however, can at least in part be attributed to deviations from the assumed change rate of –0.5%/year. For the older systems the differences again seem to be more pronounced than for the newer systems. This can be attributed to the fact that differences caused by deviations from the assumed change rate increase over time.

As a result the differences in energy yield are mainly influenced by the differences in GPOA and from deviations to the change rate assumed.

Overall it can be concluded, that the use of more recent irradiance data reduces bias differences of measured to predicted irradiance and energy yield, however relatively high uncertainties remain.

4 RESULTS AND DISCUSSION

The validation results and recalculated predictions from the previous sections can be used to estimate uncertainties for future yield predictions. However, for a complete uncertainty analysis, different sources of uncertainty have to be considered. Not all of these sources could be validated separately with measured data within this paper, as e.g. measurements of GHI are not available or a separation between reversible and non-reversible effects on long-term changes in performance is not possible. For this reason additional information from the literature is used to estimate uncertainties for each separate source. The aim is to derive uncertainties for a typical system in a moderate climate. Uncertainties for individual systems will differ from this estimate, depending on location and characteristics of the system. In a later step these theoretical uncertainties are compared with the results of the comparison of recalculated predictions.

For the GPOA comparison, the observed differences are not introduced by the transposition alone, but by a combination of effects:

1) Deviations of satellite derived GHI and “true” GHI in the reference period,
2) Deviations introduced by the transposition model (and the composition of direct and diffuse irradiance within the time series),
3) Deviations from the conversion of predicted (Pyranometer based) irradiance to equivalent silicon sensor based irradiance measurements and
4) Deviations between the irradiance in the reference period and the measurement period.

As no pyranometer measurements of GHI and GPOA are available, a further separation of the uncertainty contributions is not possible.

The deviations from 3) are usually part of the system modelling and their uncertainties are considered at this modelling step. The fact, that uncertainties of calculation of the effective irradiance (the irradiance after angular, soiling and spectral losses) are included in the GPOA comparison is a reason for the very low differences of the PR comparison in section 3.2.

Deviations for 4) are included as a long-term uncertainty from trends in irradiance. Note that in [11] the uncertainty of GPOA from long-term changes in solar resource is estimated to 4% to 5% for sites in Germany. However dimming and brightening trends do show regional differences in their magnitude. An overview for the brightening trends is given in Table 1. The highest brightening trends were observed for Germany, with slightly lower trends for Spain and Europe in general. As the aim of the uncertainty assessment performed within this paper is to estimate a typical uncertainty for a moderate climate, the uncertainty estimation is lower than stated in [11] for Germany.

Table 1: Brightening trends for different regions of the world (time period: 1980s to 2000s). Mean values of various sources given in [21].

Region	brightening trend (%/decade)
Global	2.5
Europe	2.6
North America	3.0
Asia	2.1
Germany	3.4
Iberian Peninsula	2.4

The assessment of long-term performance stability showed a negative trend of about –0.5 %/year. Especially for outdoor measured PV systems a differentiation between non-reversible degradation of PV modules and possibly reversible effects like dust and soiling is not possible for the systems under consideration and very difficult to achieve in general. Soiling losses may be very high especially in arid regions [38], however, soiling also has an influence in moderate climates as found in Germany. For negative change rates of more than 1% the contribution of reversible effects is likely higher. So a cleaning concept may be an appropriate way to avoid such high decreases. For this reason the uncertainty of the long-term change rate is assumed to be about 0.5%/year (i.e. the expected change rate will be in a range of 0% to –1%). Over an expected system life time of 20 years this adds up to the estimated uncertainty for the life time energy yield.

A summary of estimated uncertainties and their contribution to the overall combined uncertainty is given in Table ***2***. Note that the combined uncertainties are calculated as the square root of the sum of squared individual uncertainties. More advanced statistical modelling techniques were used to combine uncertainties in [8] and [12]. However as long as variable uncertainties (with changing daily, seasonal and annual magnitudes) are not combined for individual modelling time steps such techniques are also imperfect. Nevertheless, a comparison of both approaches in [8] delivered similar results.

For the initial solar resource assessment the estimated combined uncertainty is about 4%. The comparison of recalculated GPOA with measurements reveals remaining differences of about 5%. The gap may be mainly attributed to the conversion of pyranometer to sensor irradiance. For the same reason, the theoretical uncertainties for initial PR modelling are slightly higher than the observed differences from the recalculation.

Differences between measured and predicted energy yield are only slightly higher than for GPOA. They are lower than theoretical estimations with about 8%. However, this is in line with expectations, as the energy yield compared within this paper does not cover the whole life time of the PV system, but only 4.5 years in average. As a result the observed differences are expected to increase with time.

For a final validation and uncertainty assessment 20 to 25 years of measurement data would be required.

The uncertainties estimated within this paper are valid for the life time energy yield. Individual years may show much higher deviations from predicted energy yields due to interannual variations in solar resource.

All in all it can be stated, that estimated uncertainties correspond with the findings from comparison of measurements and recalculated yield predictions. The use of longer and / or older reference periods (as done in the original yield predictions) will increase the uncertainty and add biases to the predictions.

Table 2: Estimated uncertainties and uncertainty contributions for a yield prediction of a typical crystalline silicon PV system in a moderate (middle European) climate. Depending on the technology, the uncertainties for PR modelling and long-term stability may be higher for thin-film modules.

	Estimation		Contribution		Sources and further reading
(Initial) Solar resource					
GHI	3%				[25, 26]
Transposition to GPOA	3%				[31-37]
		4.2%	58%		
(Initial) PR modelling					
System modelling	3%				[4-7]
Nominal power	2%				[15-17]
		3.6%	42%		
Yield before long-term effects		5.6%	100%	48%	
Long-term effects					
Performance changes		5%	74%		[20]
Solar resource trends		3%	26%		[11]
		5.8%	100%	52%	
Life time energy yield		8.1%		100%	[8]

5 CONCLUSION

Yield predictions that include older irradiance data for solar resource assessments underestimate the energy yield of PV systems systematically by about 5% in regions were brightening trends can be observed. The use of recent satellite derived irradiance time series can avoid this underestimation.

The combined uncertainty for life time energy yield is estimated to about 8%. Solar resource assessment and long-term changes in system performance contribute the most to this uncertainty.

A better understanding of regional soiling effects [39] and factors influencing PV module degradation [40] could help to separate reversible and non-reversible components of long-term system performance stability, making it possible to further reduce prediction uncertainty. Detailed on-site analyses, the development of site- and system-specific cleaning and maintenance concepts with the owners of the systems and additional measurements of meteorological and environmental parameters for the systems under consideration would be desirable.

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