RESEARCH ARTICLE

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State-of-Play and Emerging Challenges in Photovoltaic Energy Yield Simulations: A Multi-Case Multi-Model Benchmarking Study

Ioannis (John) A. Tsanakas, Ismaël Lokhat, Arnaud Jay, Clément Gregoire, Branislav Schnierer, Jozef Rusnak, Lukas Dvonc, Joséphine Berthelot, Chloé Monet, Kévin Garcia, Iván Lombardero, Jonathan Leloux, Babacar Sarr, Alfons Armbruster, and Jefferson Bor*

In the framework of the H2020 SERENDI-PV project, it is aspired to tackle challenges in photovoltaic (PV) modeling and yield simulations, that are emerging today, on four interrelated aspects: i) improved modeling of loss/degradation mechanisms, ii) improved modeling of bifacial PV, floating PV, and building integrated photovoltaics systems, iii) solar resource and uncertainties modeling, and iv) financial risks modeling. As groundwork for this effort, a comprehensive 8-month study is carried out, the results of which are presented in this article. The study has two parts and main objectives: i) a comprehensive survey addressed to multiple stakeholders, to identify and assess today's "best practices" and needs of the PV industry on PV energy yield simulations; ii) a multi-model multi-case benchmarking and evaluation study, i.e., of eight state-of-the-art tools/software for PV energy yield simulations of seven real-life PV systems addressing diverse "scenarios" (different climates, site characteristics, PV typologies, and technologies).

1. Rationale and Objectives

Current and future (projected) market shares of new (or emerging) photovoltaic (PV) technologies and system configurations present a significantly increasing trend. This is particularly the case for bifacial PV, floating PV, and integrated/applied (e.g., in buildings, greenhouses) PV systems. Eventually, such PV applications require tailored modeling/simulation approaches (and better understanding) to ensure highly accurate, realistic, and reliable assessments of their PV energy yield. In turn, realistic and accurate PV energy simulations are essential to lower the level of technical (and economic) risk as perceived by the financing institutions or investors, thus bringing further down the weighted cost of capital (WACC) and levelized cost of electricity (LCoE) of PV.

Today's commercial "black-box" solutions for PV energy yield simulations are widely used for modeling standard PV system designs; yet, they present considerable limitations and are rather insufficient to address design- and technology-specific parameters of PV modules and systems.[1,2] Moreover, certain environmental stressors, mismatches, or losses (e.g., due to soiling, shading, etc.) and the propagation of failure/degradation mechanisms over time are, in practice, neither precisely modeled nor adequately considered in standard PV energy yield

I.(J.) A. Tsanakas, A. Jay, C. Gregoire
Univ. Grenoble Alpes, CEA, Liten
73375 Le Bourget du Lac, France
E-mail: ioannis.tsanakas@cea.fr

I. Lokhat
Cythelia Energy
73290 La Motte-Servolex, France

B. Schnierer, J. Rusnak, L. Dvonc
Solargis s.r.o.
81109 Bratislava, Slovakia

J. Berthelot
Akuo
75008 Paris, France

The ORCID identification number(s) for the author(s) of this article can be found under https://doi.org/10.1002/solr.202200582.

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C. Monet, K. Garcia
Compagnie Nationale du Rhône (CNR)
69004 Lyon, France

I. Lombardero
Qualifying Photovoltaics (QPV)
28031 Madrid, Spain

J. Leloux, B. Sarr
LuciSun
1495 Villers-la-Ville, Belgium

A. Armbruster, J. Bor
Fraunhofer ISE
79110 Freiburg im Breisgau, Germany

simulations.[3,4] These constraints can limit not only the simulation tools' accuracy but also their resilience, e.g., data-driven PV power forecasting, underperformance diagnostics, or techno-economical assessments.[5] Recent advances in physics-based models for tailored multi-factor (electrical, optical, thermal) PV simulations are particularly promising to overcome the aforementioned limitations.[6,7]

In one of the early research efforts energy yield modeling tailored for PV applications, Reich et al.[8] introduced a simulation concept for PV yield predictions, leveraging 3D drawing, ray-tracing, and computer-aided design (CAD) software-based rendering features. In such concept, the solar irradiation data used as input were compared to irradiation data derived from rendered images, thus providing 3D irradiance simulations in 3D CAD sceneries. Although it is versatile for modeling different PV system designs, such a conventional modeling approach ignores key aspects of the PV performance in long-term real-field conditions, such as mismatch losses—which, in certain scenarios has a major contribution to modeling quality and accuracy.

More recently, with the emergence of bifacial PV technology and the deployment of bifacial PV systems, consequent research efforts have been focusing on developing physics-based "customized" models to simulate the PV energy yield, under bifacial PV-specific conditions (e.g., albedo dependence, rear-side illumination and mismatches, etc). On the latter, Chudinzow et al.[9] introduced a bifacial PV model, with which they investigated and quantified experimentally the influence of ground size, cast ground shadows as well as ground reflectivity on the energy yield of the bifacial PV system. Sensitivity analysis-based results of their model showed that the extension of ground area, which contributes to ground-reflected irradiation, resulted in a slight, asymptotical increase of the energy yield. With the same model, it was possible to show, through ground shadow-free simulations, that the presence of ground shadows can reduce the annual bifacial PV yield by almost 4%, while the influence (and contribution) of ground reflectivity on the energy yield was modeled and validated for five different ground surfaces (dry asphalt, grass, dry grassland, white gravel, and white membrane). Durković et al. in ref. [10] presented a model for a more accurate calculation of irradiation for large bifacial PV power plants, i.e., PV power plants characterized by significantly bigger lengths than heights of PV rows. The model is claimed convenient for hourly meteorological data, which enables calculations of typical daily and annual electricity production of PV power plants. Unlike other existing similar models, the model proposed in ref. [10] considered the fact that less diffuse irradiation incident onto the surface between PV rows which are in the shade of previous PV rows, than entire horizontal diffuse irradiation; thus view factors (VFs) are calculated by simple algebraic relations instead of solving of a double integral. The obtained results indicate that, using the proposed and existing irradiation model, deflection in the production of the typical configuration of a bifacial PV plant can be as high as 10% or more. Similarly, Ledesma et al. also developed in 2019 and presented in ref. [11] their VF-based 2D model for calculating the rear irradiance in large bifacial PV plants has been developed now, then integrated into SISIFO (a free simulation tool developed at IES-UPM) for static structures and also for horizontal single-axis trackers. In either modeling approaches aforementioned, uncertainties (errors) in corresponding energy yield estimation derive primarily from the intrinsic non-uniformities of rear-side irradiance. Finally, in an effort to focus on modeling bifacial PV systems with single-axis tracking, Pelaez et al.[12] evolved the Radiance bifacial PV model,[13] including additional modeling steps, i.e., for calculating the array tilt, ground clearance, and row-to-row spacing for each time step. Unlike the conventional fixed-tilt simulation workflow (annual average bifacial gain calculation based on a single annual sky source), for a tracked system, multiple scene geometries were considered (for each tracker tilt in 5° increments), along with the solar resource (cumulative hourly values) corresponding to each tracker tilt angle.

In addition to the aforementioned efforts mostly in bifacial PV modeling, the need for understanding, modeling, and quantifying loss mechanisms (related to, e.g., degradation, soiling, and snow) and their impact on PV energy yield simulations accuracy, represents an active research field as well. In ref. [14], Fountoukis et al. investigated the dust-induced daily PV energy yield losses within an arid environment (Doha, Qatar) comparing actual versus simulated data derived from a 3D dust dispersion model. Among the key outcomes of this study, it has been found that there is a rather low correlation between the observed concentrations of PM for particles with diameters up to 10 μm (PM10), as inputs in the model, and the change in daily energy yield, while modeling results showed that the ambient PM concentration, even for particles larger than 10 μm, is a surprisingly weak predictor of daily PV energy yield loss. Recently, Smestad et al.,[15] developed an empirical modeling approach for PV soiling losses, yet rather on the basis of optical characterization, in terms of both spectral and particle size distribution. Polo et al.,[16] in contrast, focused on soiling loss modeling for rooftop PV applications in urban/suburban environment, evaluating two models (Kimber and HSU), determining that a cleaning threshold value in the range of 4–6 mm is adequate for accurate simulations/predictions and eventually pointing out the need of precise determination of deposition velocity. More recently, You et al.[17] developed a modeling framework to predict PV soiling losses both in PV energy yield and economic terms, in function of relative humidity, precipitation, and PV array's tilt angle. Øgaard et al.[18] introduced a modeling approach for PV energy yield losses due to snow, on the basis of the Marion model,[19] for determining the snow depth dependent clearing rate coefficient. The model approach was evaluated in seven roof-mounted PV plants prone to regular snow cover and losses, achieving a satisfactory fit between measured and modeled yield loss estimations. Besides, it has been observed that the thinner the snow cover, the higher the uncertainty introduced in the model-based loss estimations. In ref. [20], Hashemi et al. proposed prediction models for PV yield losses due to snow, for the region of Ontario (Canada), using and assessing different machine learning algorithms (i.e., regression trees, gradient boosted trees, random forest, feed-forward, and recurrent artificial neural networks, and support vector machines), solely based on meteorological data. Their validation, through comparison with actual PV yield data, showed that gradient-boosted trees obtained the minimum prediction error and thus the best-performing simulation of the PV energy yields under the impact of snow. In a rather different approach, to overcome the limitation in underlying statistics for snow losses estimations in PV, van Noord et al.[21] investigated the estimation of snow losses using a PV system's yield data together with freely available gridded weather datasets, enabling snow loss modeling for high numbers of PV systems and winter seasons using existing large datasets. Finally, with regard to the modeling of PV degradation mechanisms and their impact on energy yield losses estimations, a comprehensive review study from Lindig et al.[22] shed light on several analytical models for degradation mechanisms, notably for corrosion and PID, in three different climatic zones/stress profiles. As in the case of[23] as well, principal conclusions from most modeling efforts on PV service lifetime prediction and degradation modeling indicate that most simulations/models are still based on numerous assumptions and simplifications and validation is only possible through indoor (accelerated) aging tests; which, in turn, have intrinsic uncertainties in revealing and propagating most PV degradation mechanisms.

In overall, so far, most of the described modeling efforts are hardly compatible for integration into state-of-the-art commercial PV simulation tools. Moreover, most modeling approaches are computationally intensive, thus not suitable for calculating the lifetime performance of PV systems, especially utility-scale ones. Considering, for instance, the case of bifacial PV, as presented earlier, to avoid the increasing computational complexity and runtime, most of the existing physics-based models simplify the bifacial PV module's response to ambient conditions by modeling a single, "typical" module within the array and then extrapolate the results to a full-size array. As a result, the impact of mismatch effects caused by spatial variations of bifacial irradiance is not considered.

In the EU-funded project SERENDI-PV, we aspire—among other aimed innovations—to tackle exactly these emerging challenges in PV modeling and yield simulations, on 4 interrelated aspects: i) improved modeling of loss/degradation mechanisms, ii) improved modeling of bifacial PV, floating PV and building integrated photovoltaics (BIPV) systems, iii) solar resource and uncertainties modeling, and iv) financial risks modeling. As groundwork in this effort, we carried out a comprehensive 8-month study with a twofold objective: 1) Identification and assessment of today's "best practices" and needs of the PV industry on PV energy yield simulations 2) "Benchmarking" and evaluation of multiple commercial and state-of-the-art tools for PV modeling and energy yield simulations, for different cases—"scenarios" PV systems.

2. Approach—Methodology Aspects

2.1. Survey on Industry Best Practices and Needs

To identify and assess the PV industry's state-of-play (best practices and needs) in PV energy yield simulations, we carried out a detailed survey, addressed to multiple stakeholders/actors in the field. The survey was organized into seven sections: i) respondents profiling (anonymized), ii) meteorological data (base) being used, iii) modeling/simulation software being used, out of 35 options listed, iv) evaluation of PV losses (degradation, soiling, snow), v) modeling/simulation of new PV technologies (bifacial, floating and building-integrated PV), vi) uncertainties, and vii) economical assessment. The survey was distributed from the involved SERENDI-PV partners through multiple communication channels, including direct emailing, newsletters, professional social networks, and the project's website. **Figure 1** and **2** provides a snapshot of the stakeholders-respondents profile, in terms of business segment, country of origin, and portfolio (simulated PV systems size and technology).

2.2. Benchmarking and Evaluation Study of PV Modeling/Simulation Tools

2.2.1. The Simulation Tools

In this context, we benchmarked and evaluated eight PV simulation tools: Archelios PRO (Cythelia Energy), PVsyst, Evaluate

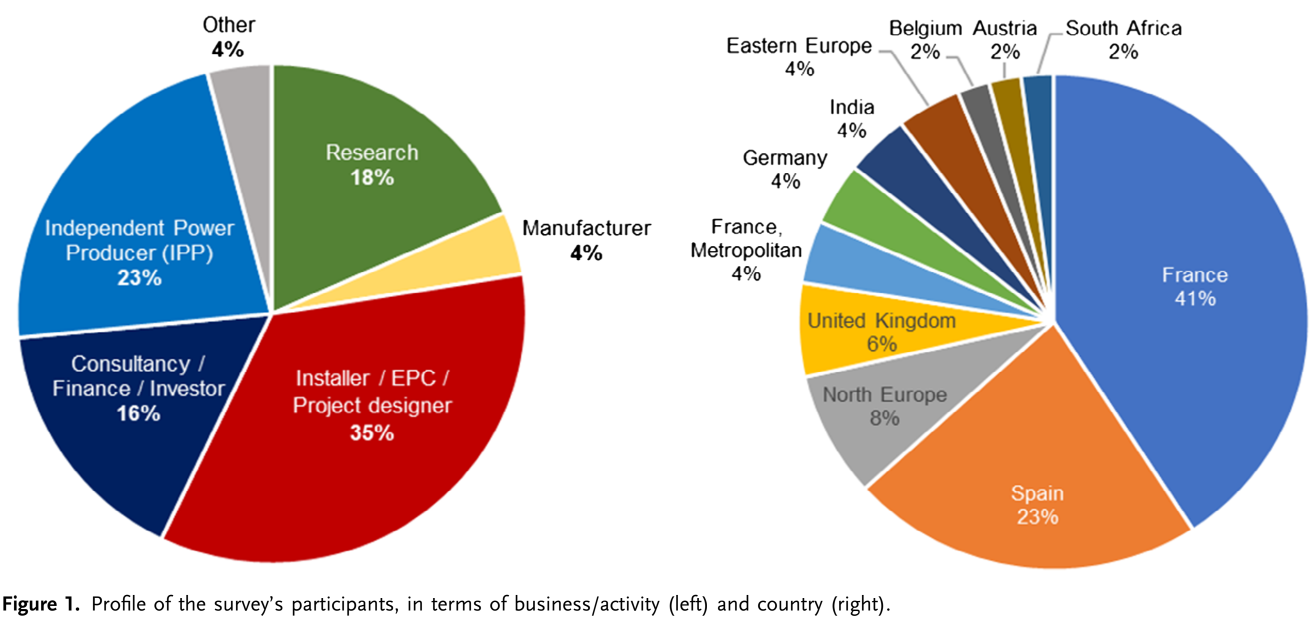


Figure 1. Profile of the survey's participants, in terms of business/activity (left) and country (right).

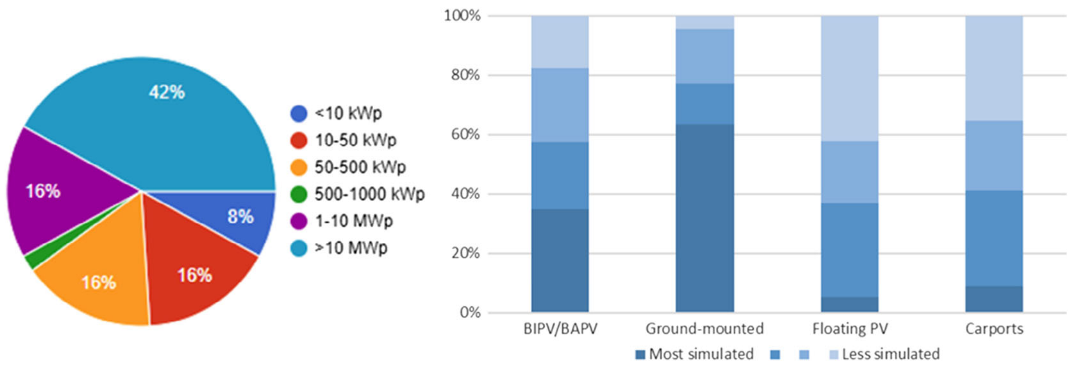


Figure 2. Profile of the survey's participants, in terms of installed power of simulated photovoltaics (PV) systems in their portfolio (left) and typology/technology of the PV systems they simulate (right).

(Solargis), TriFactors (CEA), Zenit (Fraunhofer), LUSim (LuciSun), SISIFO (IES-UPM)[11] and SAM (System Advisor Model–NREL). These tools comprise either widely used commercial solutions or (proprietary) in-house software tools (prototypes) of certain SERENDI-PV partners. To minimize uncertainties due to user bias, all partners-participants in the benchmarking study defined common parameters and hypotheses (assumptions) for their respective simulations. An overview of such assumptions for the different modeling steps and losses at the system, module, and/or site level, is given in **Table 1**. For confidentiality, software names have been anonymized throughout the presentation and discussion of the results (Section 3).

2.2.2. The Simulated PV Plants

In total, seven (anonymized) PV plants (**Table 2**) were simulated by all partners, in the context of this benchmarking study. The selection of the PV plants was elaborated jointly by the simulation tool owners or users (Cythelia, CEA, Solargis, Fraunhofer ISE, LuciSun, QPV) and the PV plant/data providers (Akuo, CNR, QPV), to allow: 1) evaluation on diverse PV system sizes, designs, technologies or site characteristics; 2) evaluation of climatic profiles and effect of seasonality, i.e., climate-/season-specific stressors; 3) availability of actual historic data (PV production and meteorological data) of at least one year.

Besides, the latter selection was done by the data providers with two criteria in mind: i) the (a priori) data availability and ii) the age of the plant, prioritizing the newest possible PV plants, to minimize the influence of degradation. Indicatively, the installed capacity of the simulated PV plants ranges from 250 kWp up to 21 MWp.

2.2.3. Solar Resource, Meteorological, and Site Data

High-resolution satellite data (including numerical model-based calculations), provided by the Solargis database and model approach,[24,25] have been used in all simulations of this study, for the solar resource, meteorological, and albedo parameters. This choice was made to ensure a common "reference" for all simulation partners for such parameters-inputs, while mitigating potential inconsistencies and/or uncertainties due to the lack of common information on certain sensors/instruments (type, calibration, maintenance logs, etc.) in some of the simulated PV plants.

Solar radiation is calculated by numerical models, which are parameterized by a set of inputs characterizing the cloud transmittance, state of the atmosphere, and terrain conditions. In the Solargis approach employed in this study, the solar irradiance is calculated in five steps: 1) Calculation of clear-sky irradiance, assuming all atmospheric effects except clouds, 2) Calculation of cloud properties from satellite data, 3) Integration of clear-sky irradiance and cloud effects and calculation of global horizontal irradiance (GHI), 4) Calculation of direct normal irradiance (DNI) from GHI and clear-sky irradiance, 5) Calculation of global tilted irradiance (GTI) from GHI and DNI.

Irradiation data (time series) were provided in the original 15 min time step and 250 m spatial resolution, while the meteorological data (time series) in hourly aggregation and 1 km spatial resolution. Ground albedo data, also provided through the Solargis database, is derived from the MODerate-resolution Imaging Spectroradiometer (MODIS), version 6 (MCD43A3).[26–28] Daily value represents the temporally weighted average of data from 16 days long window. The original MODIS data is available in 1 to 2 day frequency. The spatial resolution is 0.5 km and the temporal resolution is 1 day.

There is a fundamental difference between a satellite observation and an on-site (ground) measurement, i.e., the signal received by the satellite radiometer integrates an area (a footprint of visible and infrared channels represents an area of several km^2) while a ground station represents a pinpoint measurement. This results in a mismatch when comparing instantaneous values from these two observation instruments, mainly during intermittent cloudy weather and changing aerosol load. A solution to mismatch is to correlate satellite-derived data with ground measurements to understand the source of discrepancy and subsequently to reduce the uncertainty of the resulting historical time series. After correlation, site adaptation of the model is applied with the aim to remove general trends of disagreement between the measurements and the model data. This principle also mitigates the propagation of short-term issues in the ground measurements into the site adaptation results. Therefore, the site adaptation focuses on seasonal trends. At the monthly level, some disagreements between the measured and site-adapted

Table 1. Overview of the applied (common) assumptions applied for the different modeling steps/losses for all simulations.

Modeling steps/losses	Information from PV plant owner	Explanation/ Applied assumption
Transposition model		Perez model was chosen for all the plants (commonly available in all software).
Albedo	No	For each plant, monthly albedo values were determined from Solargis database.
Soling losses	No	Measurement of soiling is not available. Annual loss factor was estimated for each plant based on local microclimatic conditions.
Spectral correction		Not considered in simulations.
Module quality/ Tolerance	Yes	From module datasheet. Quarter of the difference between min and max values.
LID losses	No	2% default value for all plants (*p*-type silicon modules).
Module mismatch	For one PV plant only	If not already estimated by the plant owner, default values of 0.5% or 1% depending on the age of the plant.
Module ventilation	No	Default value except for roof-integrated (less ventilation) and floating (higher ventilation, to reflect the a priori lower ambient temperature) systems.
Annual degradation factor	No	Default value of 0.5%/year.
Bifacial: shed transparency	No	Conservative value: 0%.
Bifacial: non uniformity of rear irradiance		Default value: 10%.
Bifacial: shadow from structure	No	Default value: 15%. As the bifacial PV plant is a greenhouse installation, this value is high to consider the optical losses between the rows.
DC cables losses	For some PV plants	If not available, 1% at STC, which is the recommended value in the countries were the PV plants are located.
AC cables losses	For some PV plants	If not available, 1% at STC, which is the recommended value in the countries were the PV plants are located.
Transformer losses	For some PV plants	Not available. 0.1% for iron losses and 1% for resistive losses.
Auxiliaries	No	Not considered.
Unavailability	No	Not considered. Unavailability is corrected post-simulations based on actual production data.

Table 2. Overview of the simulated PV plants in this study.

	Type/technology	Climate profile
PV Plant 1	Monofacial, Fixed tilt	Warm temperature/ Mediterranean
PV Plant 2	Bifacial, Fixed tilt	Inter-tropical zone, tropical/oceanic
PV Plant 3	Monofacial, 1-axis tracker	Warm temperature/ Mediterranean
PV Plant 4	Monofacial, 1-axis tracker	Highly arid, warm (desert)
PV Plant 5	Monofacial, Roof-mounted	Warm temperature/ Mediterranean
PV Plant 6	Monofacial, BIPV	Warm temperature/ Mediterranean
PV Plant 7	Monofacial, Floating PV	Warm temperature/ Mediterranean/water reservoir microclimate

data may exist. To achieve reasonable results, high-quality ground measurements should be available for a period of about one year, so that all seasons are included. In case of a tight time schedule, a shorter period may be considered for on-site measurements. However, such data may not be capable to cover all deviations. In the optimal case, two years of data provide more robust results and allow decreasing uncertainty of resulting site-adapted data. In this context, prior to the comparison with satellite-based solar resource data, the ground-measured irradiance data underwent: 1) quality control (QC), through automatic QC tests (identification of missing values; correction of time shifts; evaluation of measurements against sun position; evaluation of the consistency of GHI, DNI, and diffused irradiance) and 2) visual quality control, aiming to identify and flag erroneous patterns (near and far shading; regular data error patterns; irregular patterns; comparison of measurements from different instruments, if available).

Finally, prior to the use of the data measured by the electricity meter (i.e., energy delivered to the distribution grid), the recordings (provided by Akuo Energy, CNR, QPV) were also quality controlled (QC) by Solargis. Automatic tests and manual visual control were performed to detect missing values, time shifts, extreme or unusual static values. The data readings, not passing one or more QC tests, were flagged and excluded from further analysis.

2.2.4. Key Performance Indicators (KPIs) in Benchmarking

The evaluation of the "performance" (simulated vs actual measured PV energy yield) of the different modeling/simulation tools for each case PV plant, was done on the basis of nine KPIs, i.e., relative difference, mean bias error (MBE), root mean square error (RMSE), normalized mean bias error (NMBE), normalized root mean square error (NRMSE), mean bias weighted error (MBWE), and root mean square weighted error (RMSWE).

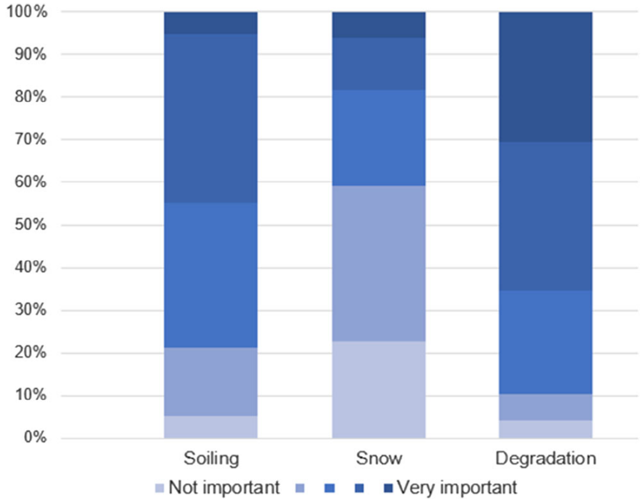


Figure 3. Perceived importance of different loss mechanisms in PV systems' simulations, according to the respondents.

3. Results and Discussion

3.1. Industry Needs and Best Practices—Survey Results

Figure 3–7 presents indicative (key) findings of the conducted survey. On the simulation of common PV loss mechanisms, responses indicated degradation and soiling as of higher importance (Figure 3). For the latter, for instance, it is worth observing that only 33% of today's simulation tools perform well for soiling-prone PV systems, with the majority of them giving overestimated (50%) or underestimated (17%) energy yield assessments (Figure 4, left). It should be clarified that as "overestimating" or "underestimating" simulations we consider those that present deviations from the actual PV yield beyond +2% or −2%, respectively (and less than ±5%). Eventually, simulations deviating from actual PV yield data within the ±2% are considered as "performing well." Besides, in the vast majority (74%) of PV projects, the soiling is still determined empirically through expert estimates or statistically through databases, rather than through actual data-driven modeling approaches (14%) (Figure 4, right).

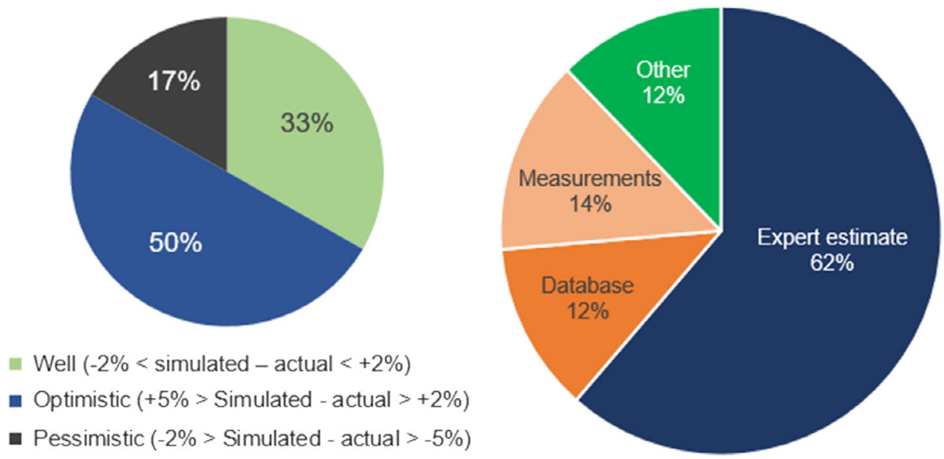


Figure 4. Evaluation of energy yield simulations in PV systems prone to soiling losses (left) and determination of soiling losses in PV energy yield simulations today (right).

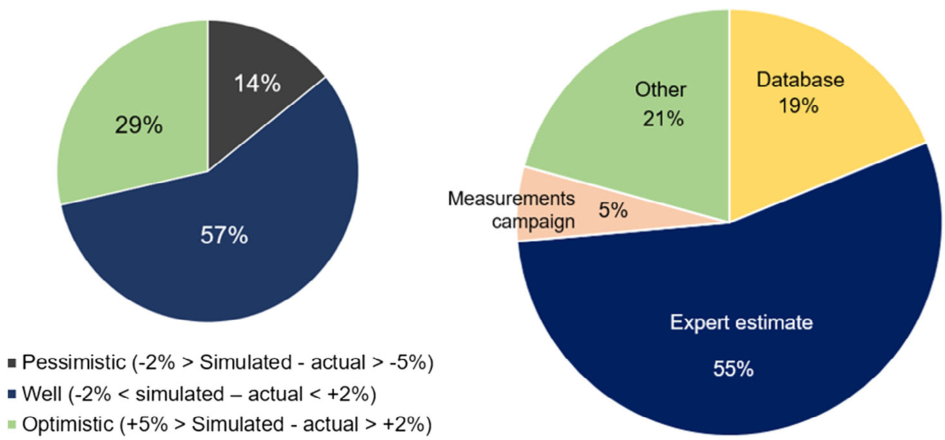


Figure 5. Evaluation of energy yield simulations in PV systems prone to snow losses (left) and determination of soiling losses in PV energy yield simulations today (right).

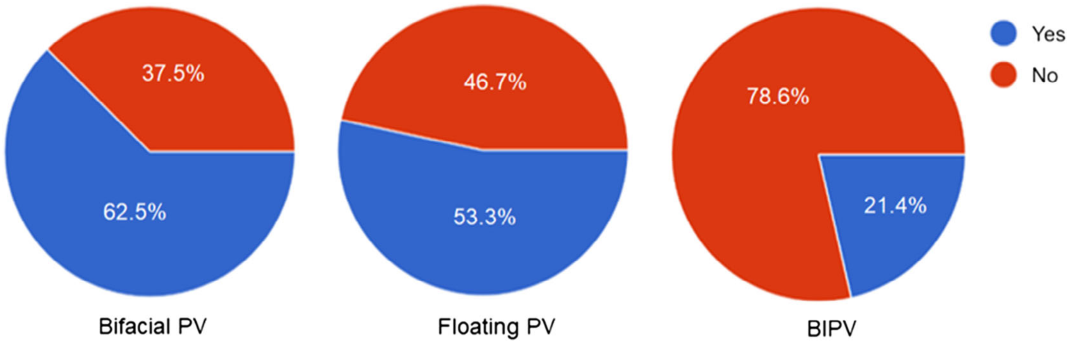


Figure 6. Specific needs (yes/no) in simulations of new PV technologies, as indicated by the survey's respondents.

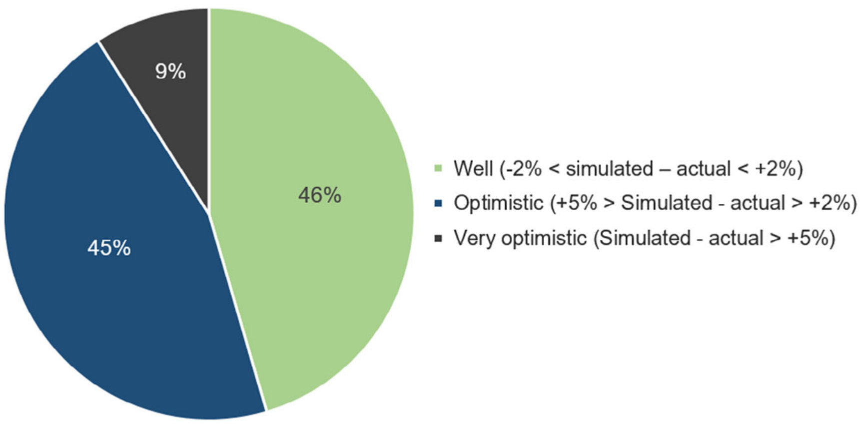


Figure 7. Assessment of energy yield simulations for bifacial PV today, according to the respondents' return of experience.

In contrast, for snow loss modeling, more than half (57%) of today's simulation tools provide results well in line with the actual yield and losses, while 29% and 14% of the respondents indicate overestimated or underestimated, respectively, energy yield assessments of PV systems with snow losses (Figure 5, left). In the latter case, again, for the majority of PV projects, snow losses are still determined empirically through expert estimates, other observations, or statistically through databases, rather than through actual measurement data-driven modeling (5%) (Figure 5, right).

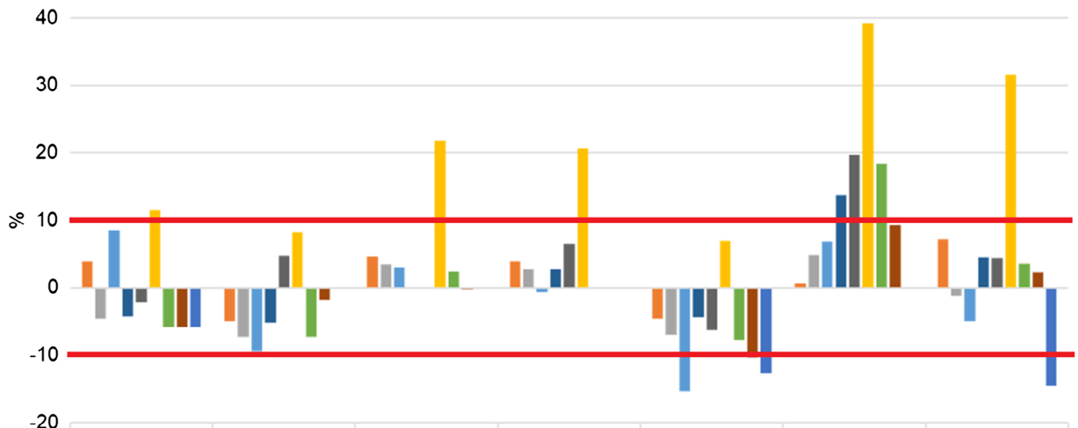
In terms of new/emerging PV technologies, as shown in Figure 6, the majority of the respondents indicate the importance of specific needs in yield simulations of bifacial PV (62.5%) and floating PV (53.3%). Such needs to be addressed in PV simulations/modeling include for instance: i) 3D shadows and reflections, back tracking, variable albedo, better validation and gain estimates, for bifacial PV and ii) the impact of water temperature and waves, for floating PV. For the particular case of bifacial PV systems, a PV systems' typology of increasing interest and market share, it is worth observing that, still, only nearly half (46%) of today's tools simulate well bifacial PV energy yields, while a considerable 54% delivers overestimated or highly overestimated assessments (Figure 7).

As a general remark, we should of course point out that the observed results and conclusions of this survey are prone to a certain degree of subjectivity, since some responses can be affected significantly by the profile of the participants and country/region- and site-specific experiences or needs. In particular, the perceived importance of different PV system loss mechanisms is dependent on the participants' profile: for instance, lower importance of snow is expected as only around 10% of participants are from countries having significant snow cover events.

3.2. PV Modeling/Simulation Benchmarking Results

A direct comparison between the actual yield of the studied PV plants and their yield simulated from the different simulation tools/software (S1 to S8) is presented in **Figure 8**.

S1.1 and S1.2 refer to software S1 which was used by two different partners ("users"), yet with uniform simulation parameters and assumptions. The different results in the latter case, indicate that the human factor remains important in the simulation process, comprising a considerable source of uncertainty. All simulation tools are used to simulate a "universal" type of PV systems (i.e., both monofacial and bifacial ones), except for the case of S5 which is rather optimized for simulating bifacial PV systems, and the output of this software is at the moment limited to DC power simulations and comparisons. Note also that the commercial version of software/tool S2 is based on calculations performed on average days for each month. Therefore, the hourly and daily KPIs are not calculated for S2; that is, "S2*"



	Plant 1	Plant 3	Plant 4	Plant 4 - adapted	Plant 5	Plant 6	Plant 7
S1.1	3,8	-5,0	4,6	3,9	-4,6	0,6	7,2
S1.2	-4,6	-7,3	3,4	2,7	-7,1	4,9	-1,2
S2*	8,5	-9,4	3,1	-0,7	-15,3	6,9	-5,0
S3	-4,3	-5,2		2,7	-4,4	13,7	4,5
S4	-2,1	4,7		6,5	-6,3	19,7	4,3
S5	11,5	8,2	21,8	20,7	7,0	39,1	31,6
S6	-5,9	-7,3	2,3		-7,7	18,3	3,5
S7	-5,9	-1,8	-0,2		-10,4	9,3	2,3
S8	-5,8				-12,7		-14,5

S1.1 S1.2 S2* S3 S4 S5 S6 S7 S8

Figure 8. Relative difference in actual versus simulated PV yields, in terms of hourly normalized mean bias weighted error (%). Deviations beyond a ± 10% range are typically considered insufficient.

indicates the pre-alpha version of S2 that has been used to compute hourly and daily values. Finally, it must be noted that PV plant 2 has not (yet) been taken into consideration in the benchmarking (that is why no results are shown in Figure 8), as only 9 months of monitoring data have been available so far in this project. A full 2-year simulation and comparison with the rest six PV plants will be presented and assessed in future work, as the project progresses.

Overall, all simulation tools seem to overestimate the yields as unavailability periods are considered in the simulation and comparison. It should be noted that, in principle, significant deviations between simulated and actual PV energy yields, i.e., beyond a ± 10% range (as illustrated with the two red horizontal lines in Figure 8), are typically considered insufficient. This is particularly the case for the case of S5, in most PV plants, as well as for the case of PV plant 5 in most simulation tools. The PV plants which indicate the lowest performing simulations overall, thus worse KPIs (i.e., the highest MBWE and RMSWE) are the PV plants 5, 6, and 7, which are either BIPV/rooftop PV or floating PV technologies. Indicatively, the scatter plots presented in **Figure 9**, illustrate a qualitative comparison of hourly simulated versus hourly measured PV production data, for all simulations performed by the different tools/software for PV plant 5. These preliminary observations align with SERENDI-PV partners' view and ambition regarding the need for improved simulations/modeling of such new and emerging PV typologies. The aimed innovations will be assessed and validated toward the end of this project, by repeating this benchmarking study with the improved modeling.

4. Summary/Conclusions and Future Work

In the context of the H2020 SERENDI-PV project, we aim at upgrading and improving the accuracy of PV modeling and energy yield simulations, to better address the impact of certain loss mechanisms (e.g., soiling, snow) on one hand and emerging new PV technologies (e.g., bifacial PV, floating PV) on the other hand. To better understand and quantify today's industry needs, as well as the current performance and "barriers" for state-of-the-art modeling tools, we carried out and presented a comprehensive 8-month study with a twofold objective: i) identification and assessment of today's "best practices" and needs of the PV industry on PV energy yield simulations, ii) "benchmarking" and evaluation of multiple commercial and state-of-the-art tools for PV modeling and energy yield simulations, for different cases-"scenarios" PV systems.

Key findings from the comprehensive stakeholders' survey (Sections 2.1 and 3.1) reflect the particularly high importance (and need for) more tailored and accurate models for energy yield simulations of bifacial PV and PV systems with soiling losses and degradation. Besides, increasing attention is given recently also for better understanding and simulating the energy yield of floating PV systems and cases of PV systems with snow losses.

Through the (preliminary) benchmarking study we presented, we may conclude that the different commercial or in-house built modeling tools of SERENDI-PV partners present clear limitations, in terms of accuracy in energy yield assessment. In particular, all tools at their current development stage, appear to overestimate the energy yields of the simulated PV plants,

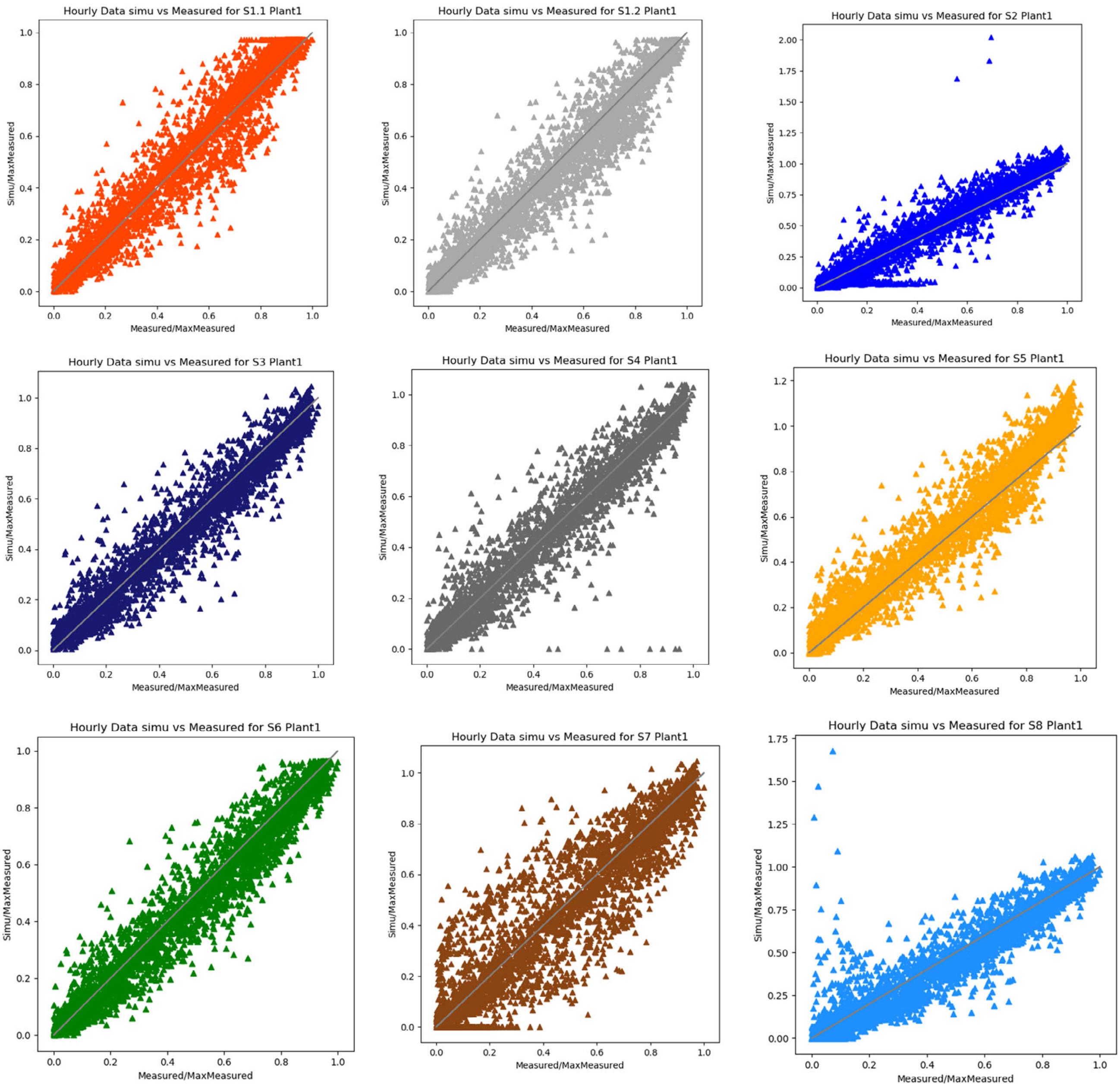


Figure 9. A qualitative analysis/comparison of simulated versus measured hourly PV production data: Indicative scatter plots for the case PV plant 5, for the different benchmarked simulation tools/software.

especially in the case of BIPV/rooftop PV or floating PV technologies where the worse KPIs (i.e., the highest MBWE and RMSWE) are calculated.

Both two concluding remarks aforementioned indicate the need for further evolving and extending the modelling capabilities of state-of-the-art PV energy yield simulation tools (commercial or in-development prototypes). This direction is exactly where two ongoing development tasks in SERENDI-PV are aiming to address. The tasks are expected to be concluded within the next 12 months, with two global objectives: i) improved accuracy, beyond the state of the art, for energy yield simulations of bifacial PV, floating PV, and BIPV systems, including industry-relevant loss mechanisms (soiling, snow, degradation) and ii) integration of the developed upgraded models into commercial or prototype tools toward commercialization. In that context, we aim to repeat and extend such benchmarking study in the near future, where more advanced modeling approaches and more extended data periods will be evaluated.

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Keywords

market survey, photovoltaics, PV energy yield simulations, PV modeling, PV systems

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[1] I. T. Horvath, P. Manganiello, H. Goverde, D. Anagnostos, B. Aldalali, E. Voroshazi, F. Catthoor, J. Poortmans, in *36th European Photovoltaic Solar Energy Conf. Exhibition (EU-PVSEC)*, Marseille, France **2018**.
[2] J. S. Stein, B. Farnung, Report IEA-PVPS T13-06:2017, **2017**, ISBN 978-3-906042-50-3.
[3] E. Lorenzo, *Sol. Energy* **2021**, *218*, 587.
[4] I. Horváth, H. Goverde, P. Manganiello, J. Govaerts, L. Tous, B. Aldalali, E. Vöröshází, J. Szlufcik, F. Catthoor, J. Poortmans, *Sol. Energy* **2018**, *173*, 728.
[5] D. Moser, S. Lindig, M. Richter, J. Ascencio-Vásquez, I. Horvath, B. Müller, M. Green, J. Vedde, M. Herz, B. Herteleer, Report IEA-PVPS T13-18:2020, **2020**, ISBN 978-3-907281-06-2.
[6] P. Manganiello, M. Baka, H. Goverde, T. Borgers, J. Govaerts, A. van der Heide, E. Voroshazi, F. Catthoor, in *44th IEEE Photovoltaic Specialist Conf. (PVSC)*, IEEE, Piscataway, NJ **2017**, pp. 3343–3347.
[7] A. Gholami, M. Ameri, M. Zandi, R. G. Ghoachani, *Sustainable Energy Technol. Assess.* **2022**, *49*, 101711.
[8] N. H. Reich, W.G.J.H.M. Van Sark, W. C. Turkenburg, W. C. Sinke, *Sol. Energy* **2010**, *84*, 1526.
[9] D. Chudinzow, J. Haas, G. Díaz-Ferrán, S. Moreno-Leiva, L. Eltrop, *Sol. Energy* **2019**, *183*, 812.
[10] V. Durković, Ž. Durković, *Sol. Energy* **2019**, *191*, 272.
[11] J. R. Ledesma, R. H. Almeida, F. Martinez-Moreno, C. Rossa, J. Martín-Rueda, L. Narvarte, E. Lorenzo, *Sol. Energy* **2019**, *206*, 522.
[12] S. A. Pelaez, C. Deline, P. Greenberg, J. S. Stein, R. K. Kostuk, *IEEE J. Photovoltaics* **2019**, *9*, 715.
[13] G. J. Ward, in *Proc. 21st Annual Conf. Computer Graphics and Interactive Techniques*, Orlando (FL), USA **1994**, pp. 459–472.
[14] C. Fountoukis, B. Figgis, L. Ackermann, M. A. Ayoub, *Sol. Energy* **2018**, *164*, 94.
[15] G. P. Smestad, T. A. Germer, H. Alrashidi, E. F. Fernández, S. Dey, H. Brahma, N. Sarmah, A. Ghosh, N. Sellami, I. A. I. Hassan, M. Desouky, A. Kasry, B. Pesala, S. Sundaram, F. Almonacid, K. S. Reddy, T. K. Mallick, L. Micheli, *Sci. Rep.* **2020**, *10*, 58.
[16] J. Polo, N. Martín-Chivelet, C. Sanz-Saiz, J. Alonso-Montesinos, G. Lopez, M. Alonso-Abella, F. J. Battles, A. Marzo, N. Hanrieder, *Renewable Energy* **2021**, *178*, 420.
[17] S. You, Y. J. Lim, Y. Dai, C.-H. Wang, *Appl. Energy* **2018**, *228*, 1136.
[18] M. B. Øgaard, H. N. Riise, J. H. Selj, in *Proc. IEEE 48th Photovoltaic Specialists Conf. (PVSC)* **2021**, https://doi.org/10.1109/PVSC43889.2021.9518886.
[19] B. Marion, R. Schaefer, H. Caine, G. Sanchez, *Sol. Energy* **2013**, *97*, 112.
[20] B. Hashemi, A.-M. Cretu, S. Taheri, *IEEE J. Photovoltaics* **2020**, *10*, 1044.
[21] M. van Noord, T. Landelius, S. Andersson, *Energies* **2021**, *14*, 1574.
[22] S. Lindig, I. Kaaya, K.-A. Weiss, D. Moser, M. Topic, *IEEE J. Photovoltaics* **2018**, *8*, 1773.
[23] I. Kaaya, M. Koehl, A. P. Mehilli, S. de Cardona Mariano, K.-A. Weiss, *IEEE J. Photovoltaics* **2019**, *9*, 1105.
[24] R. Perez, T. Cebecauer, M. Šúri, in *Solar Energy Forecasting and Resource Assessment* (Ed: J. Kleissl), Academic press, Cambridge (MA), USA **2014**.
[25] T. Cebecauer, M. Šúri, R. Perez, in *ASES National Solar Conf.*, USA **2010**.
[26] NASA MODIS, https://modis.gsfc.nasa.gov/data/ (accessed: January 2022).
[27] AppEEARS Team, *Application for Extracting and Exploring Analysis Ready Samples (AppEEARS). Ver. 2.24*, NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, USA **2019**, https://lpdaacsvc.cr.usgs.gov/appeears/ (accessed: January 2022).
[28] C. Schaaf, Z. Wang, *MCD43A3 MODIS/Terra+Aqua BRDF/Albedo Daily L3 Global - 500m V006*, NASA EOSDIS Land Processes DAAC, Sioux Falls (SD), USA **2015**, https://doi.org/10.5067/MODIS/MCD43A3.006.

