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Robust Performance Loss Rate Calculation for Photovoltaic Systems in High Latitude Locations

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ABSTRACT

Photovoltaic (PV) production grows rapidly in the Nordics, but literature on calculating long-term PV performance losses remains limited in these conditions, leading to inaccurate yield estimations and economic losses. To fill this knowledge gap, this contribution (1) shows typical PV performance characteristics, (2) obtains performance loss rates (PLRs) from multiple systems, and (3) assesses the best practices of PLR calculation under these conditions. For these objectives, we compared various methods for all steps of PLR calculation, including data filters, performance metrics, aggregation intervals, and statistical models for five systems (with 2.5–6 years of data) across Finland, from 60° to 67° N. Dark winters and snow coverage caused gaps and anomalies to the performance time series during wintertime, resulting in unrealistic PLRs. Excluding these anomalies with performance threshold filter improved the results. As the different methods can drastically affect the PLR value, an ensemble method consisting of an assessment of average PLR with over 700 calculation approaches was validated to be essential in identifying robust PLRs. Using this ensemble method, the system PLR estimates ranged from −0.41%/year to −2.65%/year. The data and codes are made publicly available, contributing to open access of PV datasets and allowing wider application of the PLR methodology.

1 | Introduction

Photovoltaics (PV) has become an increasingly crucial energy source all over the world with its low prices and good market availability [1]. Installed and planned PV capacity has seen a significant increase, even in high latitude locations [2]. Currently in 2026, the national PV capacity of Finland is around 1.5 GWp [3]. However, there were over 26 GWp of utility-scale (over 1 MWp) PV capacity either under construction or permitting phase in June 2025 [4], and the national grid operator is considering possible increase up to 4000% by Year 2040 [5]. Given the mean national summer load of 8 GW (during July–August in 2025) [6], even partially realized PV capacity additions would have a major impact on the Finnish power markets. Household PV installations are expected to continue to significantly increase as well, thanks to the good scalability of PV.

Techno-economic assessment of different Nordic PV systems has become an important research topic [7, 8]. For these economic analyses, reliable estimates of performance loss rates (PLRs) from relevant existing systems are important for assessing the lifetime and estimating the long-term energy production of a PV system. Additionally, system PLR is an important metric indicating the system's state-of-health, especially when combined with fault detection and diagnosis [9]. Therefore, assessment of PLR is highly relevant for PV project developers and operation and maintenance of real systems to have more accurate yield estimations and minimize the economic losses, as well as academics to develop the PLR calculation methodology for all climatic regions and performing techno-economic assessments for PV systems. PLR indicates a linear loss in power output of a given PV system in the unit of %/year, and contains long-term performance effects, such

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as irreversible panel and system component degradation as well as reversible effects, such as soiling and snow coverage. However, removing reversible effects that vary from year to year, such as changing shadows from trees and snow cover, provides better assessment of the actual state-of-health of a system [10]. PLR refers to the performance of the whole system [11]; therefore, it is calculated from operational outdoor time-series data of the system. This work studies the PLR calculation in high latitude locations, where comprehensive analyses are yet lacking. However, research on these conditions is crucial, since the weather characteristics, such as high seasonality, low sun angles, and snow coverage, bring out challenges on long-term performance assessment not apparent on lower latitudes [12, 13].

Different PLR calculation approaches have been shown to affect the PLR results, which have made the assessment of the best practices for PLR calculation an important research topic. The related works have focused on the different parts of the PLR workflow, from data quality and preprocessing [14, 15], data filtering [16, 17], performance metrics [16], and statistical models for the PLR assessment [15, 18]. These works have led to efforts on unifying the PLR calculation methodology, one of the most foundational being the work by International Energy Agency's (IEA) PVPS Task 13 [19, 20], which benchmarked various PLR approaches in various climatic zones. One of the main conclusions was that there might not exist a single PLR calculation approach that would suit all cases, but an ensemble method combining multiple approaches could provide reliable PLR estimates. Additionally, it introduced a general four-step PLR framework, including input data cleaning and filtering, performance metric calculation and aggregation, time-series feature correction, and statistical modelling of PLR. Based on these efforts, Lindig et al. later compiled a work on the best practices of PLR calculation [21]. In addition to research articles, different libraries have been developed to unify the PLR calculation, such as RdTools [22]. Restricting the available methods by utilizing a dedicated library for PLR assessment has been shown to reduce the PLR variability [16].

However, most of the existing works, such as the contribution by the IEA PVPS Task 13 [19, 20], focus on low- and mid-latitude locations (Köppen–Geiger climate zones B [arid] and C [temperate], including their subcategories [23]), while comprehensive studies on PLR calculation in high latitude locations are still lacking. High latitude locations consist mostly of Dfb (humid continental), Dfc (subarctic), and ET (tundra) Köppen–Geiger climate zones [23], which are characterized by low sun elevation, snow coverage during winters, and high seasonal variability in irradiance, day length, and temperature. Especially, this strong seasonality can cause challenges for PLR assessment [12]. Many of the works on PV performance losses in high latitudes assess the performance losses near STC by comparing few datapoints over multiple years [24, 25]. However, this previously common practice to apply strict irradiance and temperature filters to select only data near STC has recently been concluded not to be a good practice, due to the large amount of data removal [21], but also because of possible bias of high irradiance conditions to PLR [12, 20]. Indeed, more insights regarding how operational conditions—especially irradiance—impact the PLR would be beneficial for the community.

There are a few works related to PLR calculations methods in high latitudes, but they tend to have a specific focus or they are limited to one system/area: Paudyal and Imenes [26] studied how different data aggregation intervals affect the long-term performance time series and showed that the seasonal variability of the time series was decreased by a spectral correction. Øgaard et al. [27] analyzed how data filters affect the performance metric variation in different parts of Norway. They concluded that tailored filters for reducing the performance variability increase the reliability of performance monitoring. Sveen et al. [13] compared different variants of year-on-year model (YOY) on daily aggregated performance index (PI) based on the PVWatts model of PV system in eastern Norway. In addition to fixed filters removing low and high power output values and PI outliers, values for plane-of-array (POA) threshold limit, angle-of-incidence (AOI), and clear-sky (CS) filters were set by PLR uncertainty minimization. However, it remained unreported how the selection of different values affects the PLR results.

We have previously compared how the different data filters and statistical models affect the PLR of one south-facing PV system [28], located in southern Finland, showing huge variability in PLRs between different methods. Furthermore, we extended our comparison in work [12], where we included various data filters, performance metrics, aggregation intervals, and statistical models, covering all steps of PLR calculation, to a small vertical bifacial PV system located in the same location in southern Finland. Although there are works on PLR assessment in high latitudes, the existing literature lacks comprehensive studies where various PLR methods from all PLR calculation steps would be analyzed in several high latitude locations.

In addition to identifying the most robust PLR methodologies, it is important to report PLR values and to systematically compile published results into literature reviews, to better understand PLR trends across PV technologies, climates, and outdoor exposure [29–32]. These reviews are especially interesting, since there has been reported a distinct increase in PLRs by a recent analysis by Chen et al. [31] published in 2025 compared with earlier works published a decade ago [29, 30]. Additionally, while previously it has been concluded that a typical PLR in snowy climate is below $-0.5\%/year$ (below meaning closer to zero) for crystalline silicon (c-Si) technology [30], the recent compendium analysis showed PLR values to be typically at least $-1\%/year$ in Finland and Norway [31], representing snowy climates. However, the amount of datapoints was very limited for these locations, and the work considered only one PLR value from Finland [12]. Tonita et al. [32] compiled PLR values from literature of cold and snowy climates, focusing on Dfb (humid continental), Dfc (subarctic), and ET (tundra) Köppen–Geiger climates [23]. They showed a median PLR of $-0.33\%/year$ and a mean PLR of $-0.45\%/year$ for these climates, which greatly deviates from the results by Chen et al. [31]. However, Tonita et al. also reported increases in performance losses with recent deployment compared with older systems [32]. The discrepancies in the reported PLR values in the cold and snowy conditions calls for more PLR studies, helping to provide better conclusion on the climatical effects on PLRs.

The aim of this work is to evaluate the best practices for PLR calculation in high latitudes. Therefore, this work investigates

several PLR calculation methods that are applied to multiple PV systems of different sizes in various locations in high latitudes—such a comprehensive analysis is lacking from the existing literature. The locations are across Finland, covering latitudes from 60° to 67° (Dfb and Dfc climate zones), and all of the studied datasets cover 3–6 years of data. We apply an extensive selection of methods for all steps of PLR calculation, including data filters, performance metrics, data aggregation, and statistical models, utilizing commonly used methods [19–21] and expanding the methodology from our previous work [12]. Table 1 compiles the contributions of relevant literature and this work. Our work will (1) validate the PV performance characteristics of high latitude conditions, (2) obtain PLR values from multiple systems, and (3) extend the best practices of PLR calculation to these high latitude locations. Furthermore, our work contributes to the global understanding of PV PLR under different climatic zones and

impact of filtering, specifically cutting of the low irradiances. We have made the codes publicly available in [34], therefore providing the PLR framework to be implemented in wider use cases.

2 | Methodology

In this work, we implemented a comprehensive analysis methodology with a large variety of data filters, performance metrics, data aggregation intervals, and statistical models to understand which of them provide the most robust PLR estimates. The methodology is similar to our previous work, which covered one vertical PV setup [12], but here, we analyze multiple systems across Finland. Compared to the previous study, we also included additional data filters, reflection corrections to POA irradiance, and modified cell temperature estimation, outlier filter, and PVUSA

TABLE 1 | Descriptions of relevant PLR literature and our work.

Work	Aim	Climate	Dataset size	Filtering	Modelling approach
IEA PVPS [19, 20]	Finding best PLR methods	Dfb, BSk, Cfa, BWk, BWh, Cfb, Csa, ET	23 systems, 2.5–10 years	Various combinations of threshold and outlier filters	Various metrics, aggregation intervals, and statistical models
Louwen et al. [33]	Obtaining PLR trends for different climates and technologies	Cfa, Cfb, Csa, Csb	2200 systems, 3–25 years	Removal of PR outliers	LR to STL trend from monthly PR
Paudyal and Imenes [26]	PLR analysis of 4 panels with 2 methods	Dfb	4 panels, 5 years	Only positive electrical values, G_{POA} within 25–1000 W/m ² , 1. $I_{\text{SC}}/G_{\text{POA}}$ within mean $\pm$ 2SD 2. $G_{\text{POA}} \geq 400$ W/m ² and AOI > 50°	1. $I_{\text{SC}}/G_{\text{POA}}$ near STC, 2. LR to temperature- and irradiance-corrected IV parameters
Sveen et al. [13]	PLR analysis of 1 system and developing a variant of YOY	Dfb	1 system, 5 years	G_{POA} , AOI, and CS threshold filters with uncertainty minimization, low and high power threshold, IQR outlier filter on PI	2 YOY variations on daily PI
Tonita et al. [32]	Compiling PLRs for cold and snowy climates and obtaining PLRs of three systems	Dfc	3 systems, 5–16 years	CS, $G_{\text{POA}} \geq 50$ W/m ² , clipping filter, energy yield $\geq 60\%$ of modelled	YOY on daily PI
Our previous work [12]	Finding best PLR methods for high latitude conditions	Dfb	1 panel, 4 years	Various combinations of threshold, outlier, and CS filters	Various metrics with LR and YOY
This work	Validate the ensemble method for PLR calculation and expand the analysis of our previous work to multiple systems	Dfb, Dfc	5 systems 2.5–6 years	Initial data quality and snow filter with various combinations of threshold, outlier, and CS filters	Various metrics with LR and YOY

Abbreviations: AOI = angle-of-incidence, CS = clear-sky, G_{POA} = plane-of-array irradiance, I_{SC} = short circuit current, IQR = interquartile range, IV = current-voltage, LR = linear regression, PI = performance index, PR = performance ratio, SD = standard deviation, YOY = year-on-year.

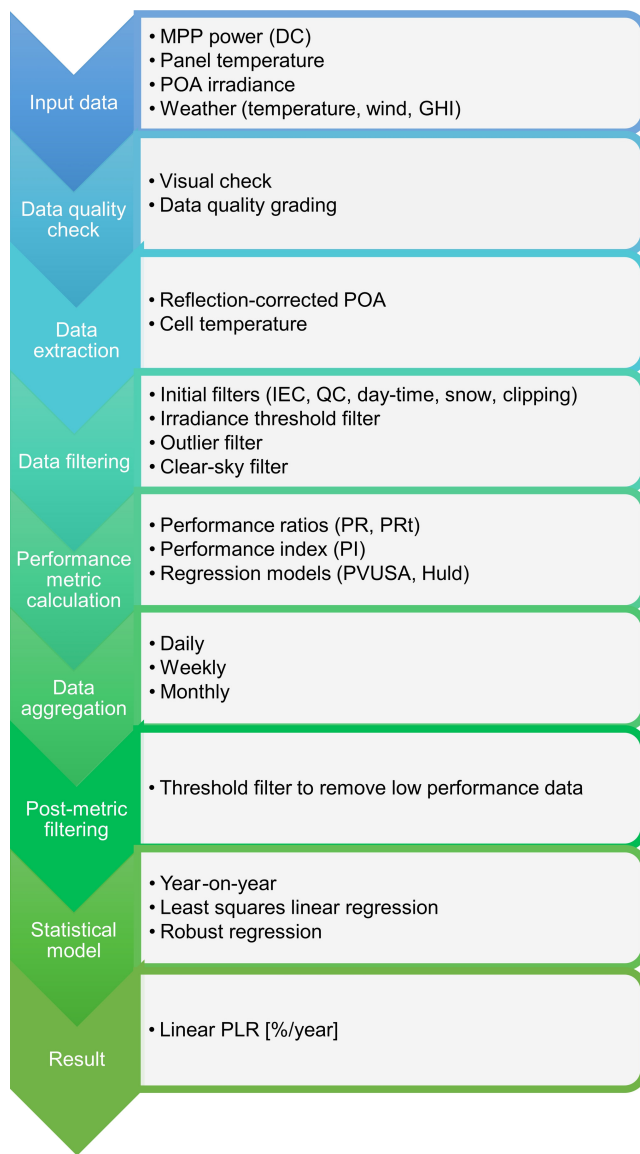


FIGURE 1 | PLR calculation framework and methods used in this work.

regression fitting. The workflow with the methods used is presented in Figure 1. The following sections describe the studied PV systems and the used PLR calculation methods. The codes for the PLR calculation are openly available in [34].

2.1 | Systems

We performed the analysis of five PV systems, representing four different locations in Finland, shown in Figure 2. The systems are named after the international airport abbreviations of the particular cities. SOT-20, SOT-90, KUO, and HEL systems are operated by the Finnish Meteorological Institute (FMI). The FMI systems are described in [35], and the data are openly available in [36]. TKU system is owned by the Turku University of Applied Sciences (TUAS), and the data are openly available in [37]. FMI's systems are recorded with 1-min resolution, whereas TKU's system has 5-min recording resolution, and the datasets are 2.5–6 years long. Thus, they provide long, well-suited datasets for

performance loss analysis. All data are accompanied by on-site weather measurements, including global horizontal irradiance (GHI), wind speed (WS), and air temperature (T_{air}). Most of the datasets also have POA irradiance and panel temperature (T_m) measurements, allowing accurate calculation of all performance metrics. For the analysis, we used direct current (DC) power to minimize the effects of inverter degradation. The key information for each system is presented in Table 2. The systems are further described below. For the azimuth angles of solar panels, 180° represents south, and the angle increases clockwise.

2.1.1 | Helsinki (HEL)

The Helsinki system is a south-east-facing (135°) 21-kWp flat-roof installation, consisting of 84 SolarWorld's SW 250 polycrystalline panels [39], 250 Wp each, with a tilt angle of 15° and six rows in two, slightly separated strings, with a row-to-row distance between 150 and 160 cm. Both strings are connected to the same ABB TRIO-20.0-TL-OUTD (20 kW) inverter [40]. The system is prone to self-shading under low sun elevation and snow piling due to the low clearance (see Figure 2).

2.1.2 | Turku (TKU)

The TKU system is a south-facing (180°) 4.5-kWp flat-roof installation, consisting of 18 Kingdom Solar KD-250 polycrystalline panels [41] with a tilt angle of 15° in three rows. Panels are connected to Fronius Symo Hybrid 4.0 inverter [42]. The system is prone to snow piling and moderately shaded by two trees located 15 m in south-west and the current-voltage room located around 2.5 m to the east, causing roughly 3.5% shading losses annually. The GHI pyranometer was cleaned regularly to prevent its soiling.

2.1.3 | Kuopio (KUO)

The KUO system is a south-west-facing (217°) 20.28-kWp flat-roof installation, consisting of 78 SOLARWATT's BLUE 60P polycrystalline panels [43] with a tilt angle of 15°, low clearance, and six rows in two sets: one with four and the other with two rows with a row-to-row distance of 170 cm (see Figure 2). Both sets are connected to one ABB TRIO-20.0-TL-OUTD inverter [40]. Similarly to HEL system, KUO system is prone to self-shading and snow piling due to low clearance.

2.1.4 | Sodankylä-20 (SOT-20)

The SOT-20 system has one east-southeast-facing (azimuth of 123°) 260-Wp SolarWorld SW 260 polycrystalline panel [44] with a tilt of 20°, and connected to an Aeconversion INV-350-60 micro-inverter [45]. The panel is installed 4 m from the ground with a high clearance, allowing snow to slide off the panel (see Figure 2).

2.1.5 | Sodankylä-90 (SOT-90)

The SOT-90 system has another 260-Wp SolarWorld SW 260 polycrystalline panel [44] installed at the same azimuth of 123°

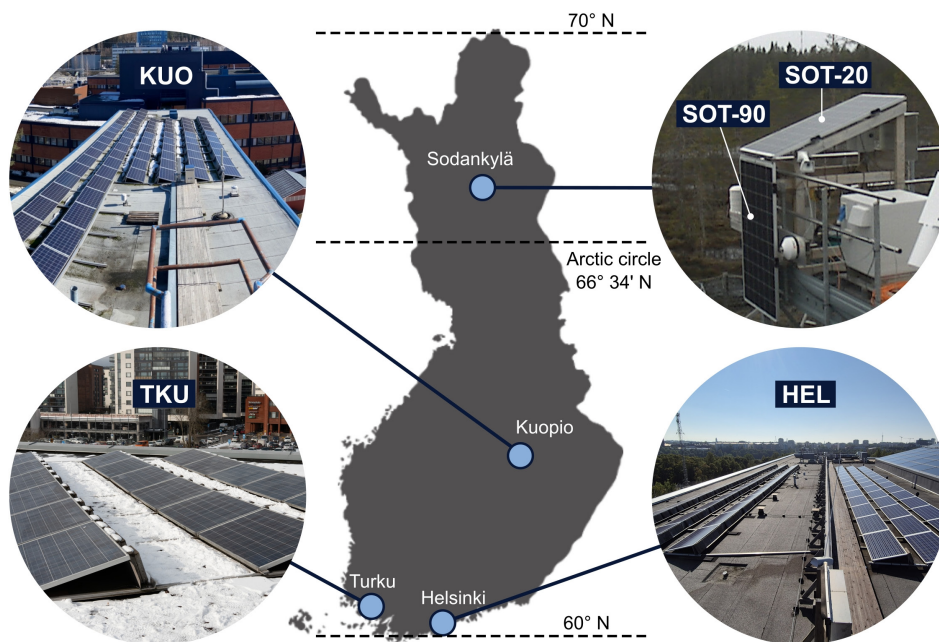


FIGURE 2 | Locations of the systems used in this work. Source of the map: Vecteezy.com. Photographs of Helsinki, Kuopio, and Sodankylä systems by Karhu/FMI, and Turku system by Anttalainen/UTU.

TABLE 2 | System information.

	HEL	TKU	KUO	SOT-20	SOT-90
KG climate	Dfb	Dfb	Dfc	Dfc	Dfc
KGPV climate	FL	FL	FL	EL	EL
Latitude (° N)	60.20	60.45	62.89	67.37	67.37
Longitude (° E)	24.96	22.30	27.63	26.65	26.65
Altitude (m)	30	28	85	180	180
Commission date	August 26, 2015	July 2017	February 2, 2017	February 2, 2017	September 22, 2016
Monitoring period	December 2015– December 2021	January 2018– September 2020	April 2017– November 2020	March 2018– November 2021	February 2018– November 2021
System rated power (Wp)	21,000	4500	20,280	260	260
γ (%/°C)	−0.41	−0.41	−0.38	−0.41	−0.41
Panel azimuth (°)	135	180	217	123	123
Panel tilt (°)	15	15	15	20	90
Shading	Minor	Moderate	Minor	Negligible	Negligible
Measurement resolution (min)	1	5	1	1	1
Measured weather parameters	T_{air} , T_{m} , WS GHI, DNI, DHI, G_{POA}	T_{air} , WS, GHI	T_{air} , T_{m} , WS GHI, DHI, G_{POA}	T_{air} , T_{m} , WS GHI, DNI, DHI	T_{air} , T_{m} , WS GHI, DNI, DHI, G_{POA}

Note: γ is the temperature coefficient of power. The scaling of the shading is based on five-level scale (1. Negligible, 2. Minor, 3. Moderate, 4. Considerable, 5. Severe), where “moderate shading” losses correspond to around 3.5%/year. Köppen–Geiger (KG) climates [23]: Dfb = humid continental and Dfc = subarctic; Köppen–Geiger photovoltaic (KGPV) climates [38]: FL = polar low irradiance, EL = cold low irradiance.

and with a tilt of 90° (vertical installation). It is also connected to an Aeconversion INV-350-60 microinverter [45]. This panel is installed to the same platform on 4 m from the ground as SOT-20.

2.2 | Data Quality Grading

The quality grading criteria presented in [20] were applied to all our datasets. When PLR is estimated from outdoor time-series performance data, the output data are based on inverter-based data acquisition, and weather data are based on various sensor readings and data loggers. Therefore, there can be many sources of errors, from data logging malfunctions to sensor drifting, which can produce poor quality data (see Section 2.4 for their elimination) and gaps in data. Among these, the power limitation of the inverter (i.e., inverter clipping) is one of the largest error factor in our data collection, and for that, we included a separate filtering step. Other significantly faulty datapoints are expected to be captured in other filtering steps (see Section 2.4). The grading quantifies the quality of the input data, which has a great impact on the PLR analysis [14]. The grading classification ranks the dataset in terms of the percentage of data outliers, missing data, and the longest gap from A to D. The quality grading is presented in Section 3 in Table 5.

2.3 | Irradiance and Cell Temperature Modelling

2.3.1 | Plane-of-Array Irradiance

For SOT-90, KUO, and HEL systems, G_{POA} was measured, whereas for TKU and SOT-20 systems, it was estimated based on other measured irradiance components. For SOT-20, G_{POA} was estimated from GHI, DNI, and DHI components, which were measured at a nearby (1 km) weather station. Using these components, the beam (B_{POA}), diffuse (D_{POA}), and ground-reflected (R_{POA}) irradiance components were estimated, where B_{POA} and R_{POA} were obtained using the following equations.

$$B_{\text{POA}} = |\text{DNI} \cdot \cos(\text{AOI})| \quad (1)$$

$$R_{\text{POA}} = \text{GHI} \cdot \alpha_{\text{albedo}} \cdot (1 - \cos(\beta_{\text{tilt}}))/2, \quad (2)$$

where AOI is the angle-of-incidence of the radiation, α_{albedo} is the albedo of the ground near the system, and β_{tilt} is the tilt of the panels. Albedo of $\alpha_{\text{albedo}} = 0.7$ was used if ground snow depth was greater than 0 on two consecutive days (ground snow readings are reported only once a day). For FMI systems, these snow measurements were included in the original datasets at [36], whereas for TKU system, the measurements were obtained from FMI's data service (Artukainen station) [46]. For snow-free days, albedo of $\alpha_{\text{albedo}} = 0.151$ was used, as it is the default value in FMI Open PV Forecast application [47]. D_{POA} was obtained with Perez model [48] using PVlib (version 0.11.2) [49].

For KUO system, DNI was estimated, and for TKU system, both DNI and DHI were estimated from GHI using the Erbs

decomposition model [50] using the `erbs` function within PVlib. After estimating DNI, a correction method introduced by Böök et al. [51] was applied to DNI for KUO and TKU systems, after which B_{POA} , D_{POA} , and R_{POA} were estimated as above described.

For TKU and SOT-20 systems, where G_{POA} was calculated from the components, reflection losses were taken into account by applying reflection corrections based on Martin and Ruiz model [52] to the POA components, denoted by subscript "rc":

$$B_{\text{POA,rc}} = (1 - \alpha_{\text{B}}) \cdot B_{\text{POA}} \quad (3)$$

$$D_{\text{POA,rc}} = (1 - \alpha_{\text{D}}) \cdot D_{\text{POA}} \quad (4)$$

$$R_{\text{POA,rc}} = (1 - \alpha_{\text{R}}) \cdot R_{\text{POA}}, \quad (5)$$

where

$$\alpha_{\text{B}}^{\text{upper}} = \exp\left(-\frac{\cos(\text{AOI})}{a_r}\right) - \exp\left(-\frac{1}{a_r}\right) \quad (6)$$

$$\alpha_{\text{B}}^{\text{lower}} = 1 - \exp\left(-\frac{1}{a_r}\right) \quad (7)$$

$$\alpha_{\text{B}} = \frac{\alpha_{\text{B}}^{\text{upper}}}{\alpha_{\text{B}}^{\text{lower}}} \quad (8)$$

$$\alpha_{\text{D}}^{\text{tilt}} = \sin(\beta_{\text{tilt}}) + \frac{\pi - \beta_{\text{tilt}} - \sin(\beta_{\text{tilt}})}{1 + \cos(\beta_{\text{tilt}})} \quad (9)$$

$$\alpha_{\text{D}} = \exp\left(-\frac{1}{a_r} \cdot (c_1 \cdot \alpha_{\text{D}}^{\text{tilt}} + c_2 \cdot (\alpha_{\text{D}}^{\text{tilt}})^2)\right) \quad (10)$$

$$\alpha_{\text{R}}^{\text{tilt}} = \sin(\beta_{\text{tilt}}) + \frac{\beta_{\text{tilt}} - \sin(\beta_{\text{tilt}})}{1 - \cos(\beta_{\text{tilt}})} \quad (11)$$

$$\alpha_{\text{R}} = \exp\left(-\frac{1}{a_r} \cdot (c_1 \cdot \alpha_{\text{R}}^{\text{tilt}} + c_2 \cdot (\alpha_{\text{R}}^{\text{tilt}})^2)\right) \quad (12)$$

$$a_r = 0.159 \quad (13)$$

$$c_1 = \frac{4}{3 \cdot \pi} \quad (14)$$

$$c_2 = -0.074. \quad (15)$$

Then, the reflection-corrected (i.e., absorbed) POA, G_{eff} , is obtained as the sum of the components:

$$G_{\text{eff}} = B_{\text{POA,rc}} + D_{\text{POA,rc}} + R_{\text{POA,rc}}. \quad (16)$$

In the case of HEL, KUO, and SOT-90 systems with G_{POA} measurements, the reflection losses were estimated using the losses obtained from modelled G_{POA} :

$$G_{\text{eff}}^{\text{meas}} = G_{\text{POA}}^{\text{meas}} \frac{G_{\text{eff}}^{\text{modelled}}}{G_{\text{POA}}^{\text{modelled}}}, \quad (17)$$

where $G_{\text{POA}}^{\text{modelled}}$ is the POA irradiance obtained by summing the modelled B_{POA} , D_{POA} , and R_{POA} , whereas $G_{\text{eff}}^{\text{modelled}}$ is obtained by applying the reflection corrections, presented above.

For HEL and KUO systems, FMI has calculated the root mean squared errors (RMSE) of transposition modelling using the Perez model [48] of POA from DNI, GHI, and DHI to be around 20–30 W/m^2 [51]. In the case of TKU and SOT-20 systems, the errors are likely higher due to missing DNI and DHI measurements for TKU and higher latitude of SOT-20. Missing DNI and DHI measurements requires decomposition modelling, adding another layer of modelling error [53], and high latitude locations with higher albedo due to snow can cause higher modelling errors as well [53, 54]. Relative RMSE for estimating G_{POA} from GHI of around 7%–12% can be expected for Dfb climate [53]. Although the modelling procedure introduces errors due to modelling inaccuracies and approximations (e.g., albedo), using ground-mounted irradiance data and applying the DNI correction [51] to model G_{POA} provides the best estimates when direct measurements are lacking.

2.3.2 | Cell Temperature

Cell temperatures were estimated with the Sandia model [55]:

$$T_{\text{cell}} = T_{\text{m}} + \frac{G_{\text{eff}}}{G_{\text{ref}}} \Delta T, \quad (18)$$

where ΔT is the temperature difference between the cell and rear side surface temperature under $G_{\text{ref}} = 1000 \text{ W}/\text{m}^2$. Value of $\Delta T = 1^\circ\text{C}$ was used, based on the work of Varjopuro et al. [56], where the difference between cell and rear side temperature for FMI's Helsinki system was simulated to be around 1°C under STC. In the case of SOT-20, SOT-90, KUO, and HEL systems, T_{m} was obtained with thermocouples, attached to the rear sides of the systems. TKU system did not have thermocouple readings; thus, the cell temperature was estimated using the following modification of the Sandia module temperature model [55]:

$$T_{\text{cell}} = G_{\text{eff}} \cdot \exp(a + b \cdot WS) + T_{\text{air}}, \quad (19)$$

where parameters $a = -3.43$ and $b = -0.125$ were used, corresponding to values found for silicon solar panels by Varjopuro et al. [56]. Typically, Equation (19) is used for obtaining the panel temperature, but Varjopuro et al. assessed the parameters for cell temperature directly. These parameters were obtained for HEL system, but since the setup is similar with the TKU system (rooftop installations with same tilt and three rows), the application of this model is justified.

2.4 | Filters

Initial filters. We applied the following initial data filters to the 1- and 5-min resolution datasets to exclude nighttime data, unrealistic and erroneous datapoints, and conditions difficult to model:

1. Daytime filter ($G_{\text{POA}} \geq 5 \text{ W}/\text{m}^2$)
2. IEC threshold filters [57]

3. Clipping filter (by excluding points above a threshold power limit below the clipping power)
4. Snow and quality filters introduced by Karhu et al. [35] to FMI datasets, referred here as QC filter.

The low value of $5 \text{ W}/\text{m}^2$ was selected to preserve other low irradiance datapoints. The IEC filter, introduced by the International Electrotechnical Commission in [57], excludes ambient conditions far from the typical operation conditions, presented in Table 3.

The clipping filter was applied to KUO and HEL systems by excluding data where the power was over 20 kW. This filter was applied, since the inverter was capping the power slightly over 20 kW (see Figure 5A,C). For TKU system, data with power below 100 W and G_{rc} over $100 \text{ W}/\text{m}^2$ were excluded to discard the low-power line (see Figure 5B). This low-power line can be caused by, e.g., stuck power readings and snow coverage.

QC filter excluded snow coverage and data quality issues based on manual classification from images and data for FMI systems, described in [35]. The following selections were used for filtering data obtained in [36]: “dataQC = 1” and “vis_SnoP = 0,” where “dataQC” and “vis_SnoP” are the column names. The filters are further described by Karhu et al. in [35]. Possible stuck/frozen readings were excluded by “dataQC” filter.

Premetric filters. After these initial filters, G_{POA} lower limit (POA LL), outlier, and CS filters were applied before performance metric calculation step to select data for the performance loss analysis. These filters are presented in Table 4. The purpose of these additional filters are to curate the dataset to include only the best behaving data or specific ambient conditions.

TABLE 3 | IEC filters.

Variable	Lower limit	Upper limit
G_{POA} (W/m^2)	−6	1500
T_{air} ($^\circ\text{C}$)	−20	50
WS (m/s)	0	32
P_{AC} (W)	$-0.01 \cdot P_0$	$1.02 \cdot P_0$

Abbreviations: G_{POA} = plane-of-array irradiance, P_{AC} = AC power after inverter, P_0 = rated DC power, T_{air} = air temperature, WS = wind speed.

TABLE 4 | Premetric data filters.

Filter description	Filter conditions
POA lower limit filter	5, 20, 50, 100, 200, 500, 800 (W/m^2)
Outlier filter	$\pm 2\text{SD}$ from the mean P/G_{eff} of rolling horizon
CS filter	$0.8 \leq \text{CSI} \leq 1.2$

Abbreviations: CSI = clear-sky index, G_{eff} = absorbed plane-of-array irradiance, P = power, SD = standard deviation.

Irradiance threshold filter is commonly applied to get rid of low and mid irradiance conditions, which introduce nonlinear behavior of efficiency [58, 59] and are far from STC. In the past, high irradiance threshold filters around 800 W/m^2 and above were applied to obtain data near STC, but nowadays, lower irradiance threshold is preferred to preserve larger amount of data [20]. In Figure S8, the remaining data percentages for each POA LL are shown for the studies systems, and it can be seen that having a medium LL of 200 W/m^2 already removes over half of daytime data, whereas a high LL of 800 W/m^2 removes around 95% of the daytime data. In this work, we apply a wide range of irradiance threshold filters to assess their effect on the results, since the selection of this irradiance lower limit has been shown to affect the PLR values [12, 17], and we want to further build insight on that matter.

Outlier filter is typically applied to performance metric data by using interquartile ranges (IQR) or standard deviation (SD) [20, 21]. In this work, we applied an outlier filter by excluding data outside $2 \times \text{SD}$ from the mean of P/G_{eff} using a rolling horizon to increasing G_{eff} data, with a window size of 800 datapoints. A window size of 800 was selected after evaluating the data removal percentage, RMSE between normalized power and irradiance, and coefficient of determinations (R_2) for window sizes of 100, 200, 400, 800, 1600, 3200, and 6400. The results are shown in Figure S6. While the window size had little effect on RMSE and R_2 , the data removal reached minimum values around 800 with majority of the systems. This filter differs from our previous work [12], where we performed the filtering using monthly bins instead of rolling horizon.

Cloudy conditions can impede the performance analysis, e.g., due to possible power-irradiance mismatch datapoints, if the irradiance sensor and panels have nonuniform cloud coverage: Clouds can cover irradiance sensor while panels receive direct sun, and vice versa. This effect can be increased by the different time constants of the PV system (reacts very quickly) and the solar radiation measurement (pyranometer reaction time is order of seconds). Thus, applying a CS filter is a common practice [20, 21]. We modelled CS GHI with Haurwitz model [60] within PVlib and excluded points where the ratio of measured GHI and modelled CS GHI, i.e., the clear-sky index (CSI), was outside 1 ± 0.2 .

Postmetric threshold filter. We applied a threshold filter after calculating the aggregated (daily, weekly, or monthly) performance metric values (see next Section 2.5) to get rid of low-performance winter data points and other outliers that distort PLRs. For KUO, TKU, and HEL systems, we used a threshold value of 0.8, whereas for SOT-20 and SOT-90, a value of 0.65 was used. Lower value for SOT systems was used, since the power outputs for these systems are slightly lower throughout the years and seasons compared with the other systems (visible in Figure 6A). Strict thresholds were applied instead of IQRs or SDs, which are typical for this purpose [20], to limit the performance values to preserve only high-performance data, mostly occurring during summertime. Flagging the outliers based on the spread of the data, e.g., by using SD, can lead to poor filtering in our case, since dark winters with few datapoints and large gaps lead to high rates of low-performance datapoints, regardless of the performance metric. Figure 3 demonstrates how the

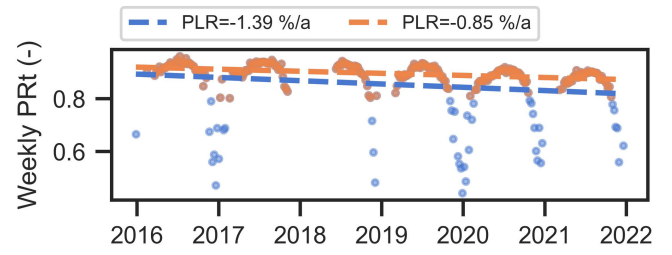


FIGURE 3 | Weekly temperature-corrected performance ratio (PRT) datapoints of Helsinki system with 0.8 threshold filter (orange) and without it (all points). Initial filtering with the outlier filter and irradiance threshold filter of 50 W/m^2 were applied here.

threshold filter can improve the PLR assessment by removing the wintertime anomalies.

2.5 | Performance Metrics

We analyzed five performance metrics, which are shortly presented below. Further descriptions are presented in [12]. After the calculation of performance metric time series, these performance time series with 1- and 5-min resolution were aggregated to daily, weekly, or monthly time series using G_{eff} -weighted mean.

Performance ratio is given by the following equation [61]:

$$PR = Y_f/Y_r = \sum_k (P_k \cdot \tau_k) / \sum_k \left(\frac{P_0 \cdot G_{\text{eff},k} \cdot \tau_k}{G_{\text{ref}}} \right), \quad (20)$$

where Y_f [kWh] is the final yield, Y_r [kWh] is the reference yield, P_k [kW] is the system's output power, τ_k [h] is the duration of the k^{th} recording interval within the reporting period, P_0 [kWp] is the rated power, $G_{\text{eff},k}$ [kW] is the POA irradiance at the k^{th} recording, and G_{ref} [kW] is the reference irradiance of 1000 W/m^2 .

Temperature-corrected performance ratio is given by the following formula [61]:

$$PRT = Y_f/Y_{r,t} = \sum_k (P_k \cdot \tau_k) / \sum_k \left(\frac{C_k \cdot P_0 \cdot G_{\text{eff},k} \cdot \tau_k}{G_{\text{ref}}} \right), \quad (21)$$

where $Y_{r,t}$ [kWh] is the temperature-corrected reference yield and the temperature correction C_k [-] is given by the equation

$$C_k = 1 + \gamma \cdot (T_{\text{cell},k} - T_{\text{ref}}), \quad (22)$$

where γ [$1/^\circ\text{C}$] is the temperature coefficient of power, $T_{\text{cell},k}$ [$^\circ\text{C}$] is the cell temperature in time interval k , and T_{ref} is the STC temperature of 25°C .

Power PI is a ratio of measured output to expected output, and for that, we used the PVWatts model [62], given by the following equation:

$$PI = \frac{P_{\text{measured}}}{P_{\text{expected}}} = \frac{P}{(P_0 \cdot G_{\text{eff}}/G_{\text{ref}} \cdot C_k)}. \quad (23)$$

PVUSA regression model is a regression-based power model given by the following equation [63]:

$$P(G_{\text{eff}}, T_{\text{air}}, WS) = G_{\text{eff}} \cdot (a' + b' \cdot G_{\text{eff}} + c' \cdot T_{\text{air}} + d' \cdot WS), \quad (24)$$

where $a' - d'$ are regression coefficients. Here, PVUSA is applied by fitting Equation (24) to the first year of data to obtain the regression coefficients. Then, these coefficients are used to predict the powers throughout the monitored periods, and performance losses can be evaluated by comparing the measured powers to these modelled (expected) powers, similarly than formulated in Equation (23). The regression fits are obtained using nonlinear least squares implemented with a `curve_fit` function within the SciPy library [64] (version 1.15.3).

Huld regression model is another regression-based power model, given by the following equation [58]:

$$P(G', T') = G' \cdot [P_0 + k_1 \cdot \ln(G') + k_2 \cdot \ln(G')^2 + \quad (25)$$

$$k_3 \cdot T' + k_4 \cdot T' \cdot \ln(G') + k_5 \cdot T' \cdot G'^2 + k_6 \cdot T'^2] \quad (26)$$

$$G' \equiv G_{\text{eff}} / G_{\text{ref}}$$

$$T' \equiv T_{\text{cell}} - T_{\text{ref}}, \quad (27)$$

where $k_1 - k_6$ are the regression coefficients. In this study, the Huld model is implemented identically to PVUSA model.

2.6 | Statistical Models

Three models were applied for estimating PLR from the time-series performance data, presented below. Further descriptions can be found in [12]. We excluded seasonal decomposition models from this analysis due to the large amount of missing winter data. Additionally, commonly applied seasonal trend decomposition using LOESS (STL) and YOY have been reported to give similar PLR trends [19].

Least squares linear regression (LSLR). PLR can be calculated using the slope and the vertical intercept of a regression fit, given by the following equation [20]:

$$\text{PLR}[\%/ \text{year}] = \frac{\beta_0}{\beta_1} \cdot t \cdot 100, \quad (28)$$

where β_0 is the slope, β_1 is the vertical intercept of the linear model on performance time-series data, and t is the number of datapoints per year (e.g., 12 for monthly data and 52 for weekly data). The corresponding uncertainty u_{PLR} is obtained as follows [65]:

$$u_{\text{PLR}} = 1.96 \cdot \sqrt{\left(\frac{1}{\beta_1}\right)^2 \cdot u_{\beta_0}^2 + \left(\frac{\beta_0}{\beta_1^2}\right)^2 \cdot u_{\beta_1}^2}, \quad (29)$$

where u_{β_0} is the standard error of the slope estimate and u_{β_1} the standard error of the intercept estimate, and 1.96 a factor to make $\pm u_{\text{PLR}}$ a 95% confidence interval.

Robust linear regression (RLR). Huber's M-estimation [66] was used as RLR, using the Statsmodels library [67]

(version 0.14.0) for Python. The uncertainty is calculated with Equation (29).

Year-on-year. YOY is a method developed by Hasselbrink et al. for PLR assessment [68]. Here, YOY is applied using the RdTools library [22] (version 2.1.3). The uncertainty is obtained bootstrapping the YOY PLR distribution. It is worthwhile to mention that there is a newer variation of YOY called multi-YOY, not included in RdTools library and thus left out of this study. In multi-YOY, each point is compared with points from all subsequent years, thus increasing the amount of values in the YOY distribution and therefore increasing the PLR accuracy and decreasing uncertainty [69, 70].

2.7 | System PLR Estimate With Ensemble Approach

In this work, we utilized the ensemble approach, in which multiple calculation combinations are considered to obtain a PLR distribution, and from that distribution, system PLR noted as $\overline{PLR}$ is estimated. In the PLR work by IEA PVPS Task 13 [19, 20], a voting method including around 20 different calculation approaches for estimating $\overline{PLR}$ [20] was introduced. Using that as a basis, we further developed an ensemble method in our previous work [12], which considers hundreds of individual PLRs, creating a PLR distribution. In this work, this distribution is obtained by combining all different methods from all PLR calculation steps, illustrated in Figure 4. On top of initial

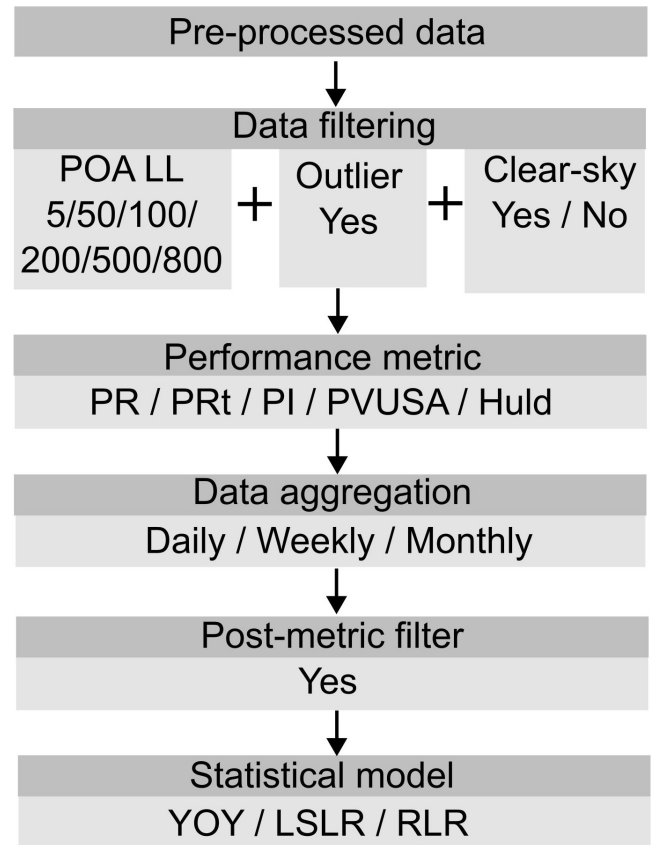


FIGURE 4 | Different methods in each step, which are used in the ensemble approach.

data filtering, outlier and postmetric threshold filters were applied to all calculation approaches included in the ensemble, because they eliminate data anomalies and not including them causes more inconsistent PLR distributions, shown later in Figure 7. CS filter and irradiance threshold filter has been shown to have systematic bias on PLR [12], and therefore averaging this biasing effect by including multiple values for them in the ensemble approach is crucial.

By combining all the methods shown in Figure 4, 2160 different PLRs are obtained theoretically. In practice, some combinations with YOY cannot be calculated due to gaps in data. In this analysis, we further selected only PLRs with both outlier filter and threshold filter, as discussed in Section 3.4. Then, PLR outliers of this distribution were excluded by filtering out PLRs outside $1.5 \times$ the IQR from the first and third quartiles. In this work, the $\overline{PLR}$ values are obtained as medians from these PLR distributions, since they are slightly skewed. The noisiness and amount of datapoints in the performance time series affect the uncertainty of the PLR value. To give less weight to PLRs with higher uncertainty, the medians are obtained by weighting the PLR values by $1/u_{PLR}$. As the uncertainties of the estimates, 95% CIs were obtained by bootstrapping the median, using SciPy library [64] (version 1.15.3) and `bootstrap` function therein with the default parameters.

3 | Results and Discussion

3.1 | Quality Grading and Effects of Data Filters

Data quality results are presented in Table 5. The missing percentage and longest gap are shown both for raw data and data after the initial filtering. Nighttimes were excluded in all cases. It can be seen that missing data percentage with the initial filtered data reaches high rates, ranging from 18% to 54%, resulting in gradings from B to D. However, most of the missing data comes from the initial filtering, which removes bad-quality data and snow coverage. Additionally, the longest data gaps are long, providing low grades of C and D for all the datasets. The amount of outliers, assessed by the outlier filter presented in Section 2.4 on initial filtered data, is below 10% for all the systems, providing grade A. Due to the winters in these conditions, removing snowy conditions will result in large amount of missing data.

Therefore, high missing data rates and gaps are inevitable in these conditions.

To visually assess the performance of the initial filters and the outlier filter, power-irradiance graphs for each system are presented in Figure 5. Since the power is strongly correlated with irradiance, visualizing the power as a function of irradiance can be used to detect power-irradiance mismatches, caused by shadows [71], for example. Figure 5 shows that the systems have different spreads of the P/G_{eff} points. Especially, SOT-20 (Figure 5D) has a large amount of outlying P/G_{eff} values. One reason for the large spread for this system is the lack of POA irradiance measurements, in which case the POA needs to be modelled using GHI, DNI, and DHI. This modelling can introduce inaccuracies to G_{eff} values due to errors in the irradiance transposition modelling [53]. Another possible reason is the greater distance between the PV site and the solar radiation measurements in Sodankylä compared with other sites, which means that more scattering of power-irradiance points can be expected under partly cloudy conditions than in other sites. Moreover, the greater amount of snow in Sodankylä compared with the southern locations may also add to this.

The figure shows that the prefilters (initial filters) reduce the amount of daytime datapoints from 2% up to 16% in all systems. The majority of the filtered data comes from the QC filter, which excludes data with unexpected behavior and snow coverage. Especially, excluding the snowy points from the data removes a large part of the data. For TKU system, there was no similar QC filtering available; therefore, snow-covered data are included after prefilters.

Overall, from Figure 5, it can be seen that the prefiltering excludes some of the data anomalies, especially low production points under high irradiance. However, there still remains high amount of scattered data (in orange) after this initial filtering. These P/G_{eff} mismatch points can be caused by various reasons, such as shading of panels or the irradiance sensors. To obtain well-behaving sets of datapoints for the PLR analysis, the outlier filter was applied to reduce the number of these mismatched P/G_{eff} datapoints. Figure 5 indicates that the outlier filter excludes the most crude outliers and includes data near the linear line of the P/G_{eff} points (green points). With SOT-20, there is a “hook” under high irradiance conditions after applying the

TABLE 5 | Quality grades for all systems based on criteria from [20].

	Missing data (%)		Longest gap (days)		Outliers (%)	Dataset length (years)	Grade (Missing, gap, outlier, P/F)
	Raw	Initial filters	Raw	Initial filters			
HEL	18	28	217	217	6	6	CDAP
TKU	14	23	43	43	5	2.5	BCAP
KUO	17	35	126	163	4	3.5	CDAP
SOT-20	6	18	98	138	4	3.5	BDAP
SOT-90	13	54	40	67	4	3.5	DCAP

Note: Grades are from A to D for missing data, longest gap, and outliers, where A refers to best grade. The dataset length is graded as a pass (P) if the length is over 2 years, and as a fail (F) otherwise. Nighttimes were excluded using PVlib's `sun_rise_set_transit_spa` function (G_{POA} cannot be used for this purpose here due to missing data). Missing data are calculated from daytime data.

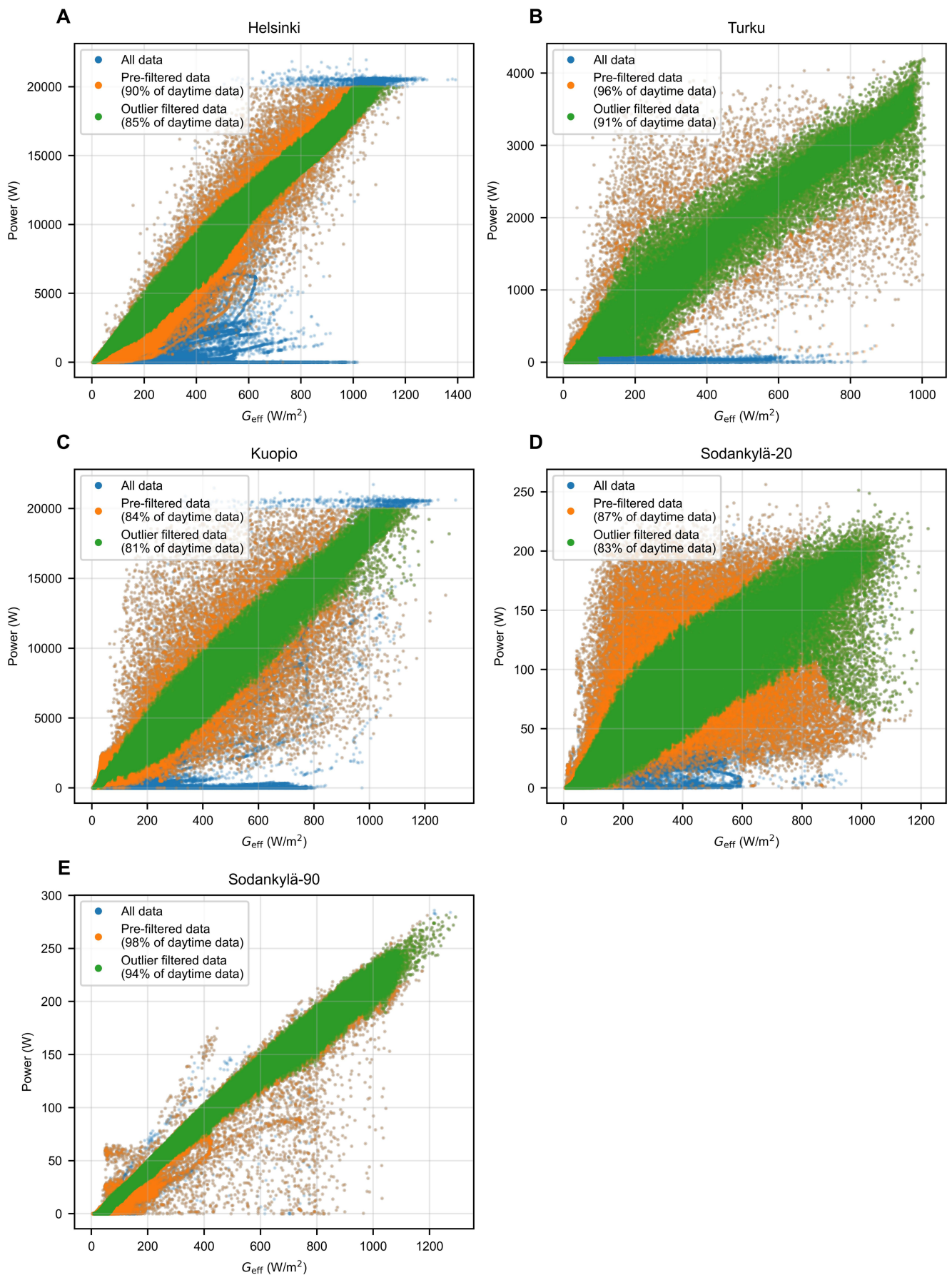


FIGURE 5 | Power as a function of reflection-corrected plane-of-array irradiance (G_{eff}) with different filter conditions for (A) Helsinki, (B) Turku, (C) Kuopio, (D) Sodankylä-20, and (E) Sodankylä-90 systems.

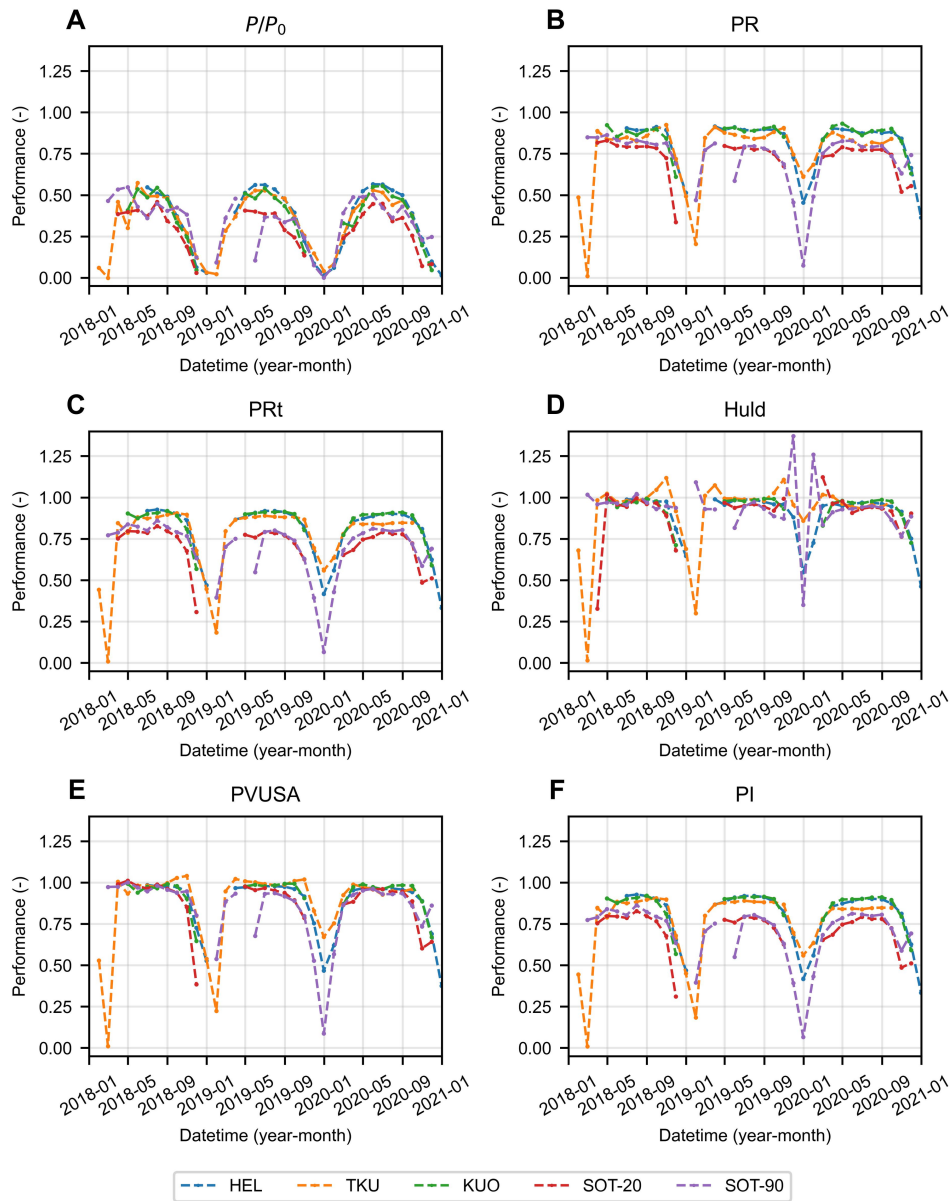


FIGURE 6 | Monthly time series of different performance metrics: (A) power, (B) performance ratio, (C) temperature-corrected performance ratio, (D) Huld regression model, (E) PVUSA regression model, and (F) performance index. As filtering conditions, the initial filters with the outlier filter were applied. Years 2018–2020 are shown.

outlier filter, which is due to the rolling horizon and smaller data density under high irradiance. The data density is not visible from Figure 5, since the colors saturate due to low transparency of the points. Instead, to visualize the data density of this hook, we show the data density graphs in Figure S7 for points over 200 W/m^2 . These graphs show that most of the data are focused on the diagonal line, and the data density decreases when irradiance increases. Additionally, the hook is not visible in Figure S7D, due to low data density. Since the relative amount of data points within this high irradiance is small, the impacts of this hook are deemed to be negligible. In all systems, the application of the outlier filter preserves the majority of the initial filtered datapoints, at highest discarding only 5%-points of data, implying that the size of dataset should not be compromised by excluding the scattered P/G_{eff} outliers.

3.2 | Performance Time Series

To get an understanding how the applied performance metrics perform in the different systems, the performance time series for all systems are presented in Figure 6. Years 2018–2021 are visualized since all datasets cover this period. More detailed plots over the entire monitoring periods for each systems are presented in the Supporting Information Section S2. Figure 6 highlights that all the metrics introduce strong seasonal patterns with all the systems. Although all metrics consider irradiance, low irradiance values and operation conditions far from STC during wintertime can be the source for the low-performance values. Here, the majority of the winter-time data are removed due to the snow coverage, resulting in gaps in the time-series data.

Out of the studied metrics, none of them provides distinctly robust time series against the seasonality. Compared with our previous analysis with a vertical bifacial panel [12], the seasonal behavior is stronger with the analyzed systems here. One reason for this difference can be the amount of missing data during wintertimes; when there is less data, the outliers can have greater weight on the aggregated performance values. In the previous work, we could assume that no snow is piled on the panel due to its vertical positioning and no snow filtering was needed, resulting higher amount of wintertime data. Additionally, although the outlier filter visually excludes the crudest P/G_{eff} mismatch points (Figure 5), the output power still has a large variance under a given irradiance (e.g., the power can be between 100 and 1500 W under irradiance of 200 W/m² in TKU system shown in Figure 5B), leading to possible time-series outliers. In our earlier study [12], the Huld model (there referred as “6k model”) provided very stable performance time series with minimal seasonal behavior. However, here, the Huld model introduces anomalies during the wintertimes, similarly than other metrics. The most distinct outlier with Huld model occurs with SOT-20 system during winter 2019–2020, where there is a positive performance value above 1.3. These outliers are caused by the low amount of winter data, in which case the regression fit (Equation 25) remains poor for winters.

The temperature correction in PRt (Figure 6C) and PI (Figure 6F) increases the summertime performance values slightly from PR (Figure 6B), as expected. Similarly, the performance points are slightly decreased during wintertimes when temperature correction is applied, since then, the cell temperature is generally under the reference temperature of 25°C. Because of these factors, the temperature correction in these conditions slightly increases the seasonal behavior of the time series. This phenomenon is characteristics for these snowy conditions. Generally, in lower latitudes with no snow coverage and less seasonal weather patterns, PR peaks during wintertime due to higher efficiency, in which case the temperature correction reduces the seasonal pattern [20].

The normalized power, PR, PRt, and PI result in distinctly lower performance values for SOT-20 and SOT-90 systems, compared with other systems. This indicates that the output of the panels are lower than expected, since the powers are from the DC side. However, this underperformance might also be caused by issues with the microinverters, as there have been reported low inverter efficiencies [35]. However, with Huld and PVUSA, the performance is more similar that of other systems. This similarity originates from the fitting of these models, which teaches the models site-specific characteristics, such as output production that is lower than expected.

3.3 | Validating Ensemble Method

Generally, PV installations are made so that the time series and the nameplate power are available, as is the case also here. Such availability of data leads to a challenge in validating PLR results. Even having initial and recent flash tests, which are done in STC, fail to capture the PLR, which is related to system performance across the whole operational conditions. Indeed, robust validation of system PLR would require testing

of the entire system in both initial and final stages under different weather conditions, which is practically unfeasible. To validate PLR calculation methodology, utilization of synthetic datasets [20, 69] and replication study approach, where PLR distribution mean is used to benchmark individual calculation approaches [20], have been used. In this work, we use synthetic data to validate the effectiveness of the ensemble method and replication study approach to compare different PLR calculation methods.

To validate the effectiveness of the ensemble method, we applied it to four simulated datasets, two of which have known energy PLRs of −4.89%/year (PLR under the full operation conditions) and STC PLR of −4.41%/year (PLR under STC). Two of the datasets have PLRs of 0%/year. The datasets are available at [72], introduced in IEA PVPS Task 13 [19]. We benchmarked the ensemble method by comparing the results with an example RdTools calculation pipeline shown in [73], which utilizes YOY on daily PI with POA between 200 and 1200 W/m² and post-aggregation outlier filter based on moving horizon. The results are shown in Table 6.

Regarding Datasets 1 and 2, $\overline{PLR}$ s with the ensemble approach are between the STC and energy PLR of the simulated system. RdTools produces similar PLR with Dataset 2, but the PLR of Dataset 1 is outside the range between STC and energy PLRs. The estimates of these two datasets with the ensemble approach are closer to each other compared with RdTools results, indicating that the ensemble approach is more consistent. For the Dataset 3, both the ensemble method and RdTools method provide the correct result of 0%/year within the confidence intervals, but the value of the ensemble method is one order of magnitude closer to the real value with significantly smaller CI compared with RdTools results. This demonstrates the accuracy of the ensemble method over a common RdTools calculation approach. For Dataset 4, both the ensemble and RdTool approaches provide the correct PLR of 0%/year to the accuracy of hundredth of a percent.

3.4 | Estimating Real PLR With Ensemble Method

To estimate the system PLR ($\overline{PLR}$), PLR distributions obtained with different filter-metric-aggregation-model combinations, as presented in Section 2.7, for each system are shown in Figure 7. Four distributions are shown, resulting from the different combinations of outlier and threshold filters. Because the aim of these two filters are to reduce the number of scattered data in the performance time series, we assessed how these filters affect the PLR distributions. The distributions are normalized to have an area of 1. The dashed lines represent the $\overline{PLR}$ estimates, obtained as the medians of the distributions. Similar PLR distributions for the four simulated datasets are presented in Figure S18.

Without the threshold filter (blue), the distributions are highly skewed and spread, although there are distinct peaks. Since the typical PLR values for silicon panels are reported to be around −0.33%/year to −0.9%/year [30, 32], PLR values far beyond this range as well as positive PLR values need to be carefully examined, since they might be caused by the interplay of

TABLE 6 | $\overline{PLR}$ estimates, and PLRs calculated with RdTools ($PLR_{RdTools}$) for each simulated datasets, representing the medians of the PLR distributions.

System	$\overline{PLR}$	$PLR_{RdTools}$	STC PLR	Energy PLR
Simulated 1	-4.62 ± 0.04	-5.1 ± 0.3	-4.41	-4.89
Simulated 2	-4.73 ± 0.02	-4.70 ± 0.05	-4.41	-4.89
Simulated 3	0.03 ± 0.07	-0.3 ± 0.3	0	0
Simulated 4	0.00 ± 0.01	$0 \pm 5 \cdot 10^{-9}$	0	0

Note: The uncertainties are obtained as 95% confidence intervals of the PLR medians. STC and Energy PLRs refer to known system PLRs. PLRs are given in a unit of %/year.

different methods and not by actual performance losses. As can be seen from Figure S19, these outlying values are mostly caused by LSLR on noisy performance time-series data. Regarding the TKU system (Figure 7B), there is a long tail of positive PLR values, up to 10%/year, even after the most extreme PLR values were removed from the distribution. These positive values are resulting from the performance time-series shape of the system: As can be seen from Figure 6 (and even better from Figure S10), the monitoring period of the system starts from January and ends in Autumn, which leads to a time-series pattern that has low values in the start and high values at the end of the period. Additionally, the wintertime performance during Years 2019–2020 is higher with all of the performance metrics, compared with the winters of the first 2 years, resulting in asymmetric time-series. When LSLR is fitted to this data, the slope will be positive, which leads to positive PLRs. This effect highlights the importance of careful data treatment and selecting suitable methods to prevent bias from factors which are not caused by actual performance losses. Having these unrealistic and not representative PLR values skewing the distributions will lead to inaccurate $\overline{PLR}$ estimates.

The distributions with an outlier filter but no threshold filter (green) also result in skewed distribution with long tails and even less distinct peaks compared with no threshold distributions. The number of datapoints are approximately halved from the “No threshold” distribution, which included all points, whether outlier filter was applied or not.

With the threshold filter (orange and red), the distributions have less deviation and more distinct peaks. This result indicates that implementing the low-performance threshold filter that excludes the scattered wintertime data can increase the robustness of the $\overline{PLR}$ estimate. Additionally, the uncertainties of individual PLRs are significantly reduced when the threshold filter is applied, shown in the Supporting Information Section S7.

As the final system $\overline{PLR}$ estimates, we selected the PLR distribution medians with outlier and threshold filter, because they had the least deviation, and the estimates were closest to the peaks of the distributions, on average. For all systems, the distributions consisted of over 700 PLR values. These estimated $\overline{PLRs}$ are shown in Table 7. For HEL and KUO systems, the $\overline{PLR}$ values are well above -1% /year, indicating typical values for c-Si technology. However, TKU and SOT-90 systems show

significantly higher performance losses. Especially, the absolute value of -2.65% /year for TKU is very high but is in line with our previous study, where we analyzed the PLR of this same system [28]. It should be noted that soiling losses are included in these PLR estimates.

To evaluate the power degradation and soiling losses, TUAS performed indoor flash test for six panels from the TKU system before and after cleaning the panels in December 2021 (see Supporting Information Section S9). The average power losses from the rated power before cleaning were 13.6%, leading to PLR of -3.0% /year after the 4.5 years of operation, which is lower than our estimate. However, this value is average panel PLR from a subset of six out of 18 panels, whereas $\overline{PLR}$ represent the system PLR. Additionally, the reference starting point has a great impact. The flash test PLR is obtained by comparing the losses to the rated power at STC, and the panels can be already degraded right after the installation, e.g., due to microcracks. The average power losses from the rated power after cleaning were 3.3%, leading to a degradation rate of -0.7% /year. This degradation rate falls into the typical range of c-Si PLR between -0.33% /year and -0.9% /year [30, 32]. While these soiling measurements did not include all the panels of the system, all the six panels showed high soiling losses. To visually validate high soiling conditions of the site, TUAS took photographs of some of the TKU panels on April 2026, shown in the Supporting Information Section S9. The panels show visual soiling (e.g., bird droppings in Figures S32 and S33, and visible dust accumulation in all of the figures). The site is on a rooftop near a busy road and sand fields, which make the site prone to dust accumulation. Based on the flash tests and the visual inspection, it can be concluded that the main reason for the low PLR of TKU system is high soiling losses.

For SOT-90 system, the absolute value of -1.35% /year is also high. Interestingly, $\overline{PLR}$ of SOT-20 is distinctly higher than that of SOT-90, although the SOT systems are located in the same place and have the same panel type. Soiling could be one cause for the low PLR and difference between the two systems. Other reasons for the low value of SOT-90 can be the noisy time-series data, shown in Figure S13, that can hinder the PLR assessment. It should also be noted that the SOT systems comprise just one panel each, and panel-to-panel variation may impact results.

In their compendium analysis of PLRs in cold and snowy climates consisting of 27 systems, Tonita et al. [32] showed a

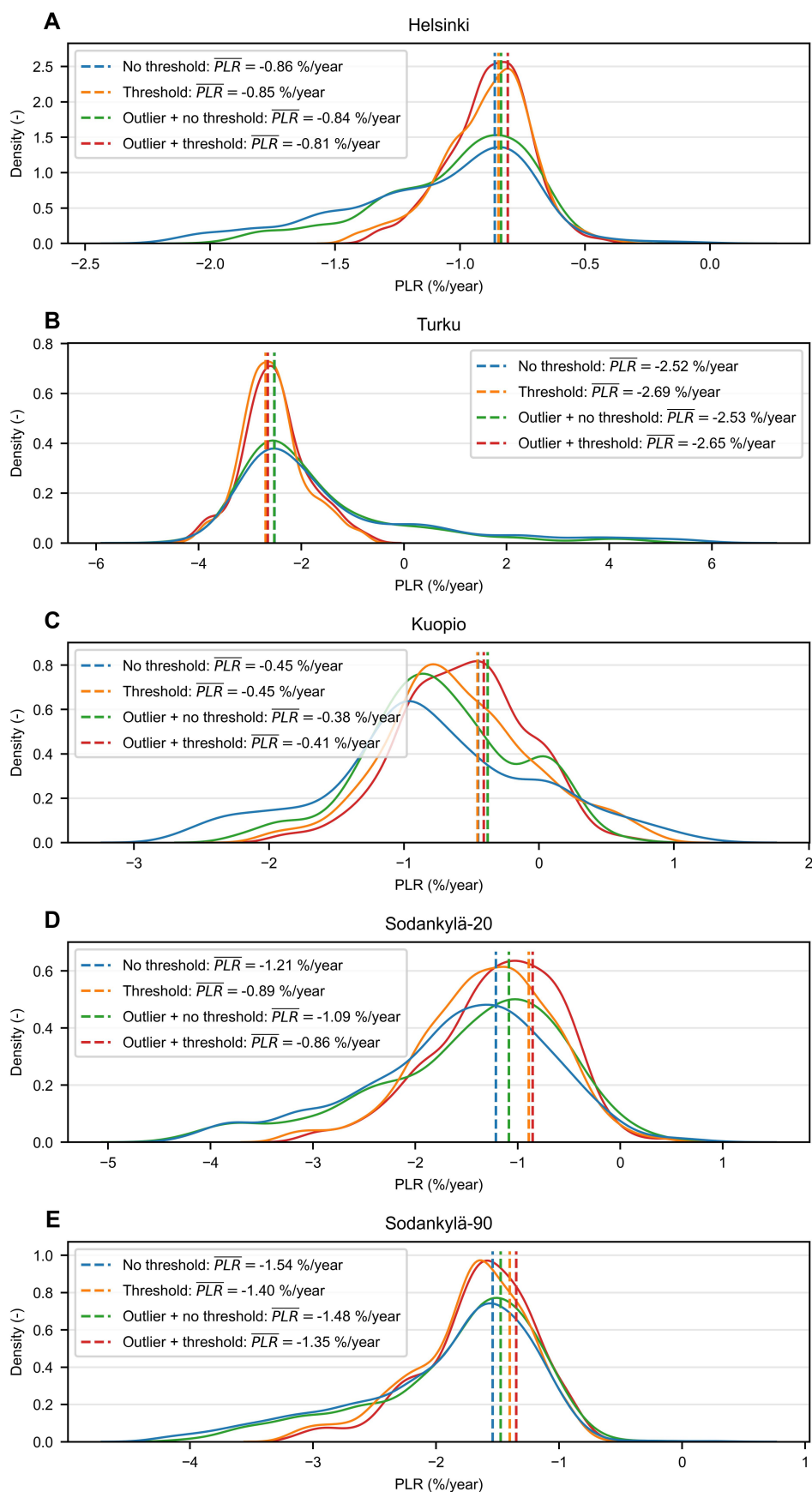


FIGURE 7 | Performance loss rate (PLR) distributions for (A) Helsinki, (B) Turku, (C) Kuopio, (D) Sodankylä-20, and (E) Sodankylä-90 systems under different filtering conditions. The lines represent the same distributions as the bars, and work as guide to eye.

PLR distribution with a median of $-0.33\%/year$ and a long tail up to $-1.6\%/year$, showing large variability between systems. Considering that the majority of the performance losses of TKU system are due to soiling, all reported PLRs in our work are within this range.

3.5 | Impact of Individual Methods on PLR

To understand how the different methods across different PLR calculation steps affect the PLR values, Figure 8 shows the effect

TABLE 7 | $\overline{PLR}$ estimates for each system, representing the medians of the PLR distributions.

System	$\overline{PLR}$ (%/year)
HEL	-0.81 ± 0.02
TKU	-2.65 ± 0.05
KUO	-0.41 ± 0.06
SOT-20	-0.86 ± 0.06
SOT-90	-1.35 ± 0.03

Note: The uncertainties are obtained as bootstrap 95% confidence intervals of the PLR medians.

of POA LL (Figure 8A), statistical model (Figure 8B), performance metric (Figure 8C), and filtering (Figure 8D) on the PLR distributions. The threshold filter was applied in all cases, and for Figure 8A–C, outlier filter was applied. In the figure, the points represent the PLR distribution median and the error bars 95% confidence intervals (CIs). Additional results showing the PLR distributions with various combinations and with and without the threshold filter are shown in the Supporting Information Section S6.

Regarding the POA LL filter in Figure 8A, PLR values systematically increase (get closer to zero), when POA LL increases, and PLRs under the highest LL of 800 W/m^2 are distinctly above the estimated $\overline{PLR}$ s. This pattern is not apparent with TKU system, which shows higher PLRs also with low POA LL $\leq 100 \text{ W/m}^2$. Although the POA LL of 800 W/m^2 removes around 95% of the daytime data (Figure S8), the PLR uncertainties with this high POA LL still remains on similar level and even smaller in many cases compared with other LLs, seen from Figure S25. Because the uncertainties with POA LL of 800 W/m^2 are not higher than with the rest of POA LLs, this pattern of increased performance losses under increased irradiance is credible. KUO system has the greatest difference between the PLRs of the lowest and highest POA LLs: The median PLR under POA LL of 5 W/m^2 is $-0.60\%/year$, whereas under POA LL of 800 W/m^2 , it is $-0.11\%/year$. This behavior is in line with other studies [12, 20]

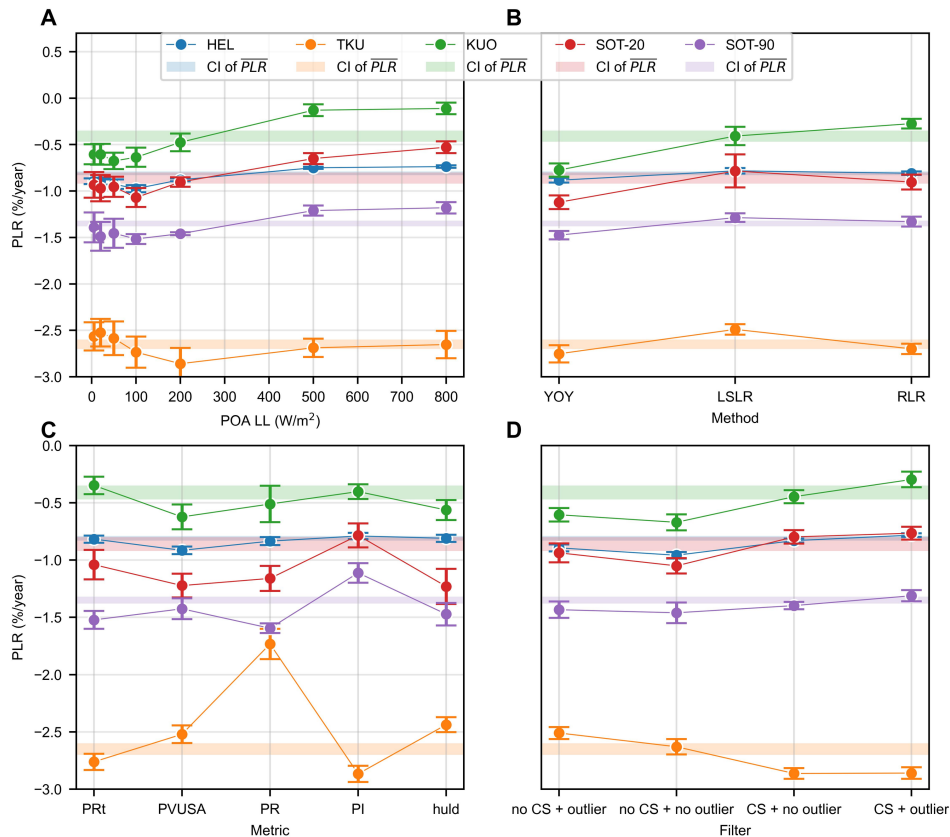


FIGURE 8 | The mean and 95% confidence intervals (CI) of PLR distributions for different methods: (A) irradiance threshold filter (POA LL), (B) statistical model, (C) performance metric, and (D) filter combination. For example, the PLR associated with a POA LL of 500 W/m^2 is obtained from PLR distribution consisting of PLR approaches, which has this specific POA LL. LSLR: least squares linear regression, RLR: robust linear regression, YOY: year-on-year, huld: Huld regression model, PI: performance index, PRT: temperature-corrected performance ratio, PR: performance ratio, PVUSA: PVUSA regression model, CS: clear-sky.

and implies higher performance degradation under lower light conditions, which could be due to the decrease in shunt resistance [20]. Decreased shunt resistance lowers the power production due to increased leakage currents [74, 75]. Additionally, it has been shown that shunt resistance exponentially decreases when irradiance increases [74]. Therefore, decreased shunt resistance due to degradation has larger effect under low irradiance conditions.

The 95% CIs are generally the narrowest with medium to high POA LLs from 200 to 800 W/m², indicating that lower POA LLs can provide more inconsistent results. However, lower POA LL can better represent system energy PLR, which is evident from simulated Datasets 1 and 2, shown in Figure S22A–D. With POA LLs from 5 to 100 W/m², the medians of the distributions are closer to the energy PLR of −4.89%/year, although the deviations of the distributions are larger compared with higher POA LLs. Especially, YOY, when threshold filter is applied, results in distributions with medians really close to the energy PLR (Figure S22B,D).

Figure 8B shows that depending on the system, the choice of statistical method can greatly affect the PLR values. Especially, YOY generally provides lower PLRs compared with the two regression methods, and this pattern is most distinct with TKU and KUO systems. When the threshold filter is not applied, Figure S19 shows that especially LSLR can cause large deviations in PLRs due to the scattered winter data. With YOY, the results are generally much closer to $\overline{PLR}$ and less spread. This result indicates that YOY outperforms linear regression and is consistent with previous works [12, 19, 20].

In Figure 8C, the comparison of different performance metrics shows that there is no distinct general pattern on which

metrics perform the best or worst in all cases. PRT is the only metric that produces PLR distribution with the 95% CI overlapping with the 95% CI of $\overline{PLR}$ for nearly all systems (the CIs of SOT-90 systems are almost overlapping). Figure S19 shows similar patterns between the metrics when the threshold filter is not applied.

Figure 8D presents how the different CS and outlier filter combinations affect the PLR results. Again, the effects of the filter combinations vary from system to system, and general patterns are not apparent. For example, having neither CS nor outlier filter produces a PLR distribution closest to $\overline{PLR}$ with TKU system, whereas with SOT systems, this combination leads to PLRs furthest from the $\overline{PLR}$. Especially with SOT systems, CS filter improves the results by bringing the PLRs closer $\overline{PLR}$. This is because the CS filter excludes some of the low-performance data, caused by cloud coverage, for example. Figure S21 shows that the CS filter generally shifts the PLR distributions closer to $\overline{PLR}$ under low POA LL of 100 W/m² or below, compared without the CS filter. The outlier filter slightly increases PLR values (shifts them towards 0) compared with the values without the outlier filter.

From all of these comparisons in Figure 8, it can be seen that different selections of methods can significantly shift the PLR distribution. This highlights the importance of comparing different PLR calculation methods, to avoid possible biases. These effects of different methods on the PLRs decrease when the monitoring period increases and the performance time series has a consistent pattern from year to year, as is the case with HEL system (see Figure S9).

Figure 8 shows the general effects of the performance metrics, statistical models, and filters on the PLR results, but the analysis of their synergies remain limited. In Figure 9, individual PLR

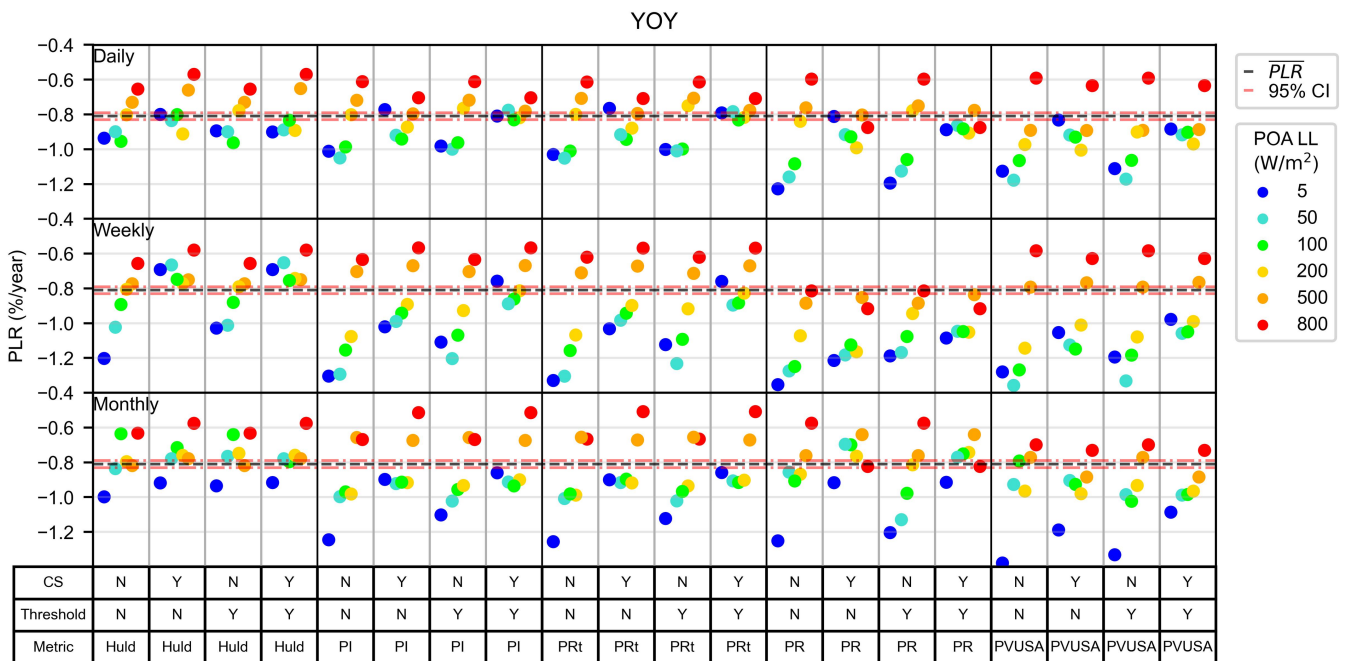


FIGURE 9 | PLRs obtained for Helsinki system with the year-on-year (YOY) method and different filter-aggregation-metric combinations. The black lines correspond to the PLR estimate, and the red lines are guides to the eye. POA LL: irradiance lower limit, CS: clear-sky filter, Huld: Huld regression model, PI: performance index, PRT: temperature-corrected performance ratio, PR: performance ratio, PVUSA: PVUSA regression model, N: no, Y: yes.

values of different possible metric-filter-aggregation-model combinations are shown for HEL system and YOY instead of PLR distributions, to better understand which combinations provide the most accurate and consistent estimates. For other statistical models and systems, similar graphs are presented in the [Supporting Information](#) Section S8. Figure 9 shows how much even minor differences in the methods can affect the result. For example, selecting between POA LL of 200 and 800 W/m² can change the PLR around −0.6%-point/year (daily PVUSA). With other systems shown in the [Supporting Information](#), the differences between the methods can be even greater. Especially, the results of KUO system with LSLR (Figure S29B) are so scattered, that only minority of the PLR values are within the visualized range of −0.0%/year to −1.0%/year.

Compared with our previous work [12], where YOY produced significantly more robust results compared with the linear regression models, here, the differences between the models are less distinct with all systems. With KUO system (Figure S29), YOY provides PLRs closer to $\overline{PLR}$ than LSLR or RLR, whereas with TKU (Figure S28), RLR outperforms YOY. Additionally, none of the daily, weekly, or monthly aggregation intervals distinctly outperforms the others by producing PLRs closer to the estimate.

Generally, mid to high POA LLs from 200 W/m² onwards provide quite consistently PLRs close to the $\overline{PLR}$, regardless of the metrics and other filters. However, as indicated by Figure 8A, the high POA LL of 800 W/m² can cause bias by providing low PLRs, and therefore is not recommended to be applied if only one calculation approach should be selected. When low POA LLs below 100 W/m² are applied, CS filter improves the results, as is shown in Figure S21. Unexpectedly, applying the threshold filter does not improve the individual PLR values shown in Figure 9 significantly. The threshold filter only excludes the crudest outlying PLR values but does not affect results which are already close to $\overline{PLR}$.

It should be noted that the datasets were heavily filtered, especially due to the QC filter, leading to long gaps and high missing data rates. These gaps and missing data could lead to higher sensitivity of the different methods towards the calculated PLR, especially when the length of the dataset is relatively short, such as 3 years. Therefore, the comparison of different calculation methods is even more important with short datasets, compared to long datasets, where the biases of individual methods become less distinct.

4 | Recommendations of Best Practices for PLR Calculation in Cold and Snowy Climates

The first and most important factor in identifying reliable PLR values is utilizing an ensemble method. This work validated the superiority of the ensemble method over using a commonly used YOY method with RdTools using simulated PV time-series data. Additionally, we have made the codes available in [34], allowing an easy implementation of the proposed ensemble method. An ensemble method is recommended since this and previous PLR studies [12,19,20] show that even slight differences in an individual PLR calculation approach can greatly vary the obtained PLR. Furthermore, the best calculation approach varies from system to system. In our previous analysis [12], daily or weekly aggregated

PI and PRT together with YOY were concluded to provide the most robust PLR results, but in this work, none of the metrics, aggregation intervals, or statistical models stood out similarly. Therefore, applying multiple calculation approaches, investigating their differences, and estimating the system PLR with an ensemble method is required to perform a reliable PLR analysis. In fact, comparing various calculation approaches and utilizing an ensemble method should be done regardless of the climatic conditions.

The second recommendation, specifically related to snowy conditions, is using an appropriate threshold filter to remove low-performance datapoints. Based on the results of this work, the performance data in these cold and snowy climates have distinct drops and gaps during wintertimes, due to low irradiance and snow coverage. These wintertime anomalies can be impossible to model. Since they impede accurate PLR assessment, the most robust estimates can be obtained by removing them. In this work, we used a fixed threshold filter for this purpose, since commonly applied rolling horizon methods or filters based on IQRs or SDs provide unreliable filtering in these conditions, due to the bias of the low-performance winter data. These gaps caused by snow coverage can be minimized by preventing prolonged snow coverage, for example, by installing panels in steeper tilt and higher clearance to allow snow to fall off and regularly cleaning the panels and irradiance sensors, if safely possible.

Thirdly, assessing and removing power-irradiance mismatch points caused by, e.g., shadows and snow coverage, is recommended, since the conditions causing these mismatches can be difficult to model. The amount of these mismatch points can be reduced again by keeping the panels and irradiance sensors free from snow, as well as equipping the system with POA irradiance measurement device to avoid POA modelling errors, and maintaining and calibrating the device to reach good accuracy.

Lastly, medium POA LLs of 200 and 500 W/m² provided the most robust results and is therefore recommended. CS filter is recommended if low POA LL of 100 W/m² or below is used. High POA LL of 800 W/m² was found to cause bias by introducing distinctly higher PLRs; thus, its application should be avoided. This bias in PLR under high irradiance causes a contradiction with the common approach of assessing PLR with flash tests under STC: Since the typical operational conditions, especially in high latitude locations, are far from STC, flash testing might not reflect the real-life PLR of the system. Therefore, we recommend that analyzing and reporting the effect of irradiance to PLR value should be an essential part of PLR analysis, if possible.

5 | Conclusions

This work analyzed the long-term performance and PLR of five PV systems across Finland, latitudes ranging from 60° to 67° N. The objectives were to (1) analyze typical PV performance characteristics, (2) obtain PLR values from multiple systems, and (3) extend the best practices of PLR calculation to more extreme conditions with high seasonality. This work progresses PLR assessment in high latitude conditions, where comparative analyses on PLR methodology remain unexplored to this extent. Additionally, the work extends the field of PLR calculation by validating the effectiveness of an ensemble method for

PLR assessment over individual calculation approaches. The data and codes used in this work are made publicly available, therefore contributing to open PV data sharing and allowing the ensemble PLR framework to be implemented in wider use cases.

Regarding the first objective, our analysis showed that due to dark winters and snow coverage, the performance time series presented anomalies during wintertime even after excluding snow-covered and poor quality data. Filtering out these bad-quality and snowy conditions will inherently lead to large amount of data removal and gaps during winters.

For the second objective, we estimated the system $\overline{PLRs}$ with an ensemble method by calculating PLRs with over 700 different filter-metric-aggregation-model combinations and selecting the medians of these distributions to represent the system PLR. $\overline{PLRs}$ varied between $-0.41\%/year$ and $-2.65\%/year$ for the different systems, and most of the values fit within the typical range between $-0.33\%/year$ and $-0.9\%/year$. $\overline{PLR}$ of $-2.65\%/year$ was connected to high soiling losses based on flash test results after washing a number of these panels.

For the third objective, the best practices for the robust PLR calculations in high latitudes are as follows: (1) using an ensemble method rather than one filter-metric-aggregation-model combination, since the best combinations varied from system to system, and there were no distinctly best individual methods; (2) applying a fixed threshold filter to eliminate impacts of wintertime anomalies, especially linear regression models provided very unrealistic values, if wintertime anomalies were included in the data; (3) visually analyzing power-irradiance points, and applying a P/G_{POA} outlier filter, adjusted to delete power-irradiance mismatch anomalies related to each dataset; and (4) applying a medium irradiance lower limits between 200 and 500 W/m². When irradiance lower limit of 100 W/m² or lower was used, then the application of clear-sky filter improved the results. However, applying a high lower limit of 800 W/m² was found to provide distinctly higher PLRs compared with the estimates, and therefore should be avoided. This systematic relation between irradiance and PLR raises the question whether PLR obtained with flash tests under STC lead to too optimistic results, and how well they represent PLR under real operational conditions. Analyzing and reporting the effect of irradiance to PLR should therefore be an essential part of PLR analysis, when possible.

Author Contributions

Lauri Karttunen: conceptualization, methodology, software, formal analysis, data curation, writing – original draft, writing – review and editing, visualization. **Väinö Anttalainen:** methodology, software, writing – review and editing. **Sami Jouttijärvi:** conceptualization, writing – review and editing, supervision. **Juha A. Karhu:** resources, data curation, writing – review and editing. **Hugo Huerta:** resources, data curation. **Samuli Ranta:** resources, funding acquisition. **Anders V. Lindfors:** resources, writing – review and editing. **Kati Miettunen:** conceptualization, writing – review and editing, supervision, funding acquisition.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

TUAS's data (TKU) are available in [37], and FMI's data (SOT, KUO, and HEL) are available in [36]. The codes used for the work are available in Github [34].

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. Supporting_Information.pdf.