

Satellite derived product benchmarking and empirical model development for estimating photosynthetically active radiation at high latitudes

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ABSTRACT

Photosynthetically Active Radiation (PAR) is a critical parameter for understanding plant growth and optimising agricultural productivity. Accurate estimation and measurement of PAR are essential for various applications, including the design of agrivoltaic systems, which enable dual use of land for solar energy conversion and crop cultivation. Despite its importance, routine measurements of PAR remain scarce globally, creating a significant gap in comprehensive tracking. This study addresses this gap by comparing PAR estimates derived from satellite sources such as CERES and SARAH-3 and the mesoscale model STRÅNG with weather station measurements. In addition, a multiple linear regression model was developed and calibrated for Sweden using data from the Integrated Carbon Observation System network. Seasonal and hourly variations in the PAR to Global Horizontal Irradiance (GHI) ratio were also analysed to understand their dynamic changes over time. The findings indicate that linear models using GHI as the primary predictor for PAR demonstrated high accuracy, with normalised Mean Absolute Error below 8% at all stations, with values such as 4% at Degerö and 3.2% at Norunda. Seasonal variability in the PAR to GHI ratio was observed, particularly during winter months at higher latitudes, where the ratio fluctuated between 0.39 and 0.42 at Degerö. In contrast, the summer period showed minimal variation, with the PAR/GHI ratio remaining stable across locations. Moreover, the spatial regression model, which combined data from different stations, successfully predicted PAR at new sites such as Norunda, achieving an R^2 of 0.98 to 0.99. Model residuals were within the typical uncertainty of PAR sensors ($\pm 5\%$), confirming remaining deviations are dominated by measurement error rather than modelling uncertainty. This demonstrates the model's applicability across Sweden, providing a robust and versatile tool for estimating PAR in areas lacking measurements. The linear model reduces the need for extensive PAR measurement campaigns.

1. Introduction

Photosynthetically Active Radiation (PAR) is fundamental for photosynthesis and plays a crucial role in agricultural productivity. It represents the portion of sunlight that plants use to convert light energy into biomass, making its accurate measurement and estimation vital for optimising crop growth in diverse agricultural contexts. Despite its importance, routine measurements of PAR are scarce, particularly in regions like Sweden, where solar dynamics are complex due to high-latitude conditions such as low solar angles and extended daylight variations. PAR is typically composed of two main components: direct and diffuse irradiance. Direct PAR reaches plants without scattering, providing intense, directional light that can create shadows and lead to uneven distribution across the plant canopy. In contrast, diffuse PAR

results from atmospheric scattering, offering more uniform illumination that benefits photosynthesis in shaded areas. The balance and interplay between these components are crucial for understanding plant growth dynamics, especially under varying environmental conditions. Accurate modelling of PAR, including its direct and diffuse fractions, is essential to predict canopy photosynthesis and refine agricultural practices. Spitters et al. (1986) highlighted the significance of separating these components, noting that traditional methods often underestimate the diffuse fraction, leading to inaccuracies in crop growth models. Traditional estimation in many crop models treated the sky as alternating fully clear vs fully overcast (an “on–off” cloud switch) and then derived direct/diffuse shares from that binary mix (Spitters et al., 1986). According to the study by Spitters et al. (1986), under clear skies, the diffuse component in the photosynthetically active wavebands can be

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about 40 % larger than in the total global irradiance spectrum due to the scattering effects of the atmosphere, which enhances the availability of PAR in shaded areas.

Ma Lu et al. (2022) benchmarked several models that decompose PAR into its direct and diffuse components to better understand PAR in Sweden, where measurements of diffuse PAR are less commonly recorded. Despite the importance of these components, routine measurements of global PAR remain uncommon. Here, the term routine refers to both the limited spatial coverage and temporal continuity of PAR observations, as such measurements are not part of standard meteorological station datasets. The Swedish Meteorological and Hydrological Institute (SMHI) operates multiple weather stations with irradiance measurements, but these typically do not include PAR data (SMHI, 2024a). While the Integrated Carbon Observation System (ICOS) has deployed sensors at several sites across Europe, including seven stations in Sweden (ICOS, 2024). Unfortunately, not all these stations measure PAR, which highlights a gap in the comprehensive tracking of this critical agricultural parameter.

To address this gap, PAR data can be obtained through satellite-derived products. For instance, the SARA-3 product provides high-resolution surface solar radiation datasets, with a spatial accuracy of $0.05^\circ \times 0.05^\circ$ and a temporal resolution of up to 30 min (Pfeifroth et al., 2023). SARA-3 derives PAR using the Heliosat algorithm in combination with the SPECMAGIC radiative transfer model, which calculates spectrally resolved irradiance from 200 to 4000 nm under clear-sky conditions considering aerosols, ozone, and water vapour. PAR (400–700 nm) is obtained by integrating the simulated spectral irradiance and scaling it to all-sky conditions via the satellite-derived cloud index. This approach allows SARA-3 to dynamically capture atmospheric and cloud-dependent variations in the PAR fraction, rather than assuming a constant ratio to total shortwave irradiance. Meanwhile, NASA's Clouds and the Earth's Radiant Energy System (CERES) offers a broader perspective with its coarser spatial resolution of $1^\circ \times 1^\circ$ and an hourly temporal resolution. CERES estimates surface PAR (400–700 nm) from broadband shortwave radiances by partitioning the SARB spectral bands (357.5–689.7 nm) using lookup tables derived from radiative-transfer simulations (Su et al., 2007). The algorithm accounts for aerosol and cloud optical properties retrieved from MODIS and uses the Fu–Liou radiative-transfer code to compute vertical fluxes, enabling separate retrievals of direct and diffuse PAR components validated against SURFRAD and ARM measurements. While CERES does not provide the fine granularity of SARA-3, its global coverage makes it invaluable for comprehensive climate studies and large-scale environmental monitoring (CERES, 2024). On a more localised scale, SMHI has developed STRÅNG, a mesoscale analysis system that combines data from a regional numerical weather prediction model, remote sensing data (radar and satellite) with ground-based meteorological observations (SMHI, 2024b). STRÅNG computes global, direct, and diffuse irradiance under clear-sky conditions using the libRadtran radiative transfer package (Emde et al., 2016) configured with the correlated-k parameterisation of Kato et al. (1999). This approach divides the solar spectrum into 32 bands and enables efficient yet spectrally resolved modelling of radiative fluxes. For PAR, STRÅNG integrates the simulated irradiance across Kato bands 7–16, which span the interval 408–704 nm. The model accounts for Rayleigh scattering, absorption by ozone, water vapour, uniformly mixed gases, and aerosols, as well as surface albedo and solar-zenith geometry. This semi-empirical coupling allows STRÅNG to represent both clear- and all-sky conditions at high spatial ($2.5 \text{ km} \times 2.5 \text{ km}$) and hourly temporal resolution (SMHI, 2001).

Despite the availability of advanced products like SARA-3, CERES, and STRÅNG for estimating PAR in Sweden, there is a significant gap in the validation of these estimates against ground truth measurements. Current data from satellite and mesoscale products provide crucial insights into PAR levels across various regions. However, the accuracy of these models remains largely unconfirmed due to the limited alignment with on-the-ground observations. This lack of comprehensive validation

is particularly problematic in high-latitude areas like Sweden, where solar irradiance dynamics are complex due to factors such as low solar angles and extended periods of daylight or darkness. The discrepancies between modelled estimates and actual measurements can lead to uncertainties in research and practical applications, potentially affecting future agrivoltaic (APV) projects.

Several studies have explored the estimation of PAR using different modelling techniques, revealing the significant impact of local atmospheric conditions on the accuracy of these models. Global Horizontal Irradiance (GHI), the total shortwave solar irradiance received per unit area on a horizontal surface, including both direct and diffuse components, serves as the fundamental input variable in most empirical PAR models. For instance, Jacovides et al. (2004) found that sky clearness, brightness, and path length significantly influenced the PAR fraction through direct measurements taken over nearly three years in Athalassa, Cyprus. Their findings highlighted that the PAR/GHI ratio fluctuates considerably with sky conditions, presenting higher ratios under overcast skies compared to clear ones. This necessitates precise model calibration to accommodate local atmospheric variations. Complementing this, Wang et al. (2007) in Beijing, China, and Alonso-Tristán et al. (2021) in Burgos, Spain, also developed empirical models based on similar atmospheric parameters. Both studies confirmed the seasonal patterns of PAR and GHI, peaking in summer and declining in winter, with Alonso-Tristán et al. (2021) employing methodologies including multilinear regression and Artificial Neural Networks (ANN). These models utilised a comprehensive set of meteorological parameters and demonstrated that factors such as the clearness index (k_T) and GHI were highly correlated with PAR, underscoring GHI as the most influential variable across different sky conditions.

Jacovides et al. (2003) studied PAR/GHI ratios in the Eastern Mediterranean, reporting seasonal variability and higher ratios under diffuse conditions due to cloud scattering effects. Similarly, Proutsos et al. (2022) analysed the composition of GHI into PAR at a high-altitude forest site in Greece, discovering annual PAR/GHI ratios with low variability. The influence of sky clearness was pronounced, enhancing the need for incorporating a broad spectrum of atmospheric parameters in PAR estimation models. Foyo-Moreno et al. (2017) demonstrated in Granada, Spain, that k_T and solar zenith angle (θ_z) accurately reproduce PAR, with coefficient of determination (R^2) = 0.994–0.997 across validation sites and normalised Mean Bias Error (nMBE) between -3.1% and -0.3% , underscoring the robustness of such formulations under diverse conditions. In addition, Ferrera-Cobos et al. (2020) assessed multiple models in varying climatic zones of Spain, finding that localised model adaptations significantly boost performance, particularly in oceanic climates. However, contrasting these findings, García et al. (2022) reported minimal gains from local calibration across different U. S. climatic conditions, as assessed using the SURFRAD network data. They evaluated numerous analytical models, all of which achieved high determination coefficients (R^2 above 0.99), yet the improvement from local calibration was not deemed sufficient to advocate for its broad application. This discrepancy emphasises the necessity of considering sky conditions and the potential limitations of transferring models across diverse environments.

In a broader review, Noreiga-Gardea et al. (2020) compiled an extensive analysis of empirical models for PAR estimation, focusing on spatiotemporal variations in the relationship between PAR and global solar irradiance. Their work highlighted the diversity of approaches, ranging from regression-based empirical models to those incorporating satellite-derived data and ANNs. They emphasised that while empirical models are widely utilised for their simplicity, their accuracy often depends on site-specific calibrations and input parameters such as k_T , θ_z , and aerosol optical depth. The review also pointed out the growing application of satellite products, such as MODIS, to provide continuous and spatially expansive PAR estimations. Complementing this, Tang et al. (2017) developed a remote sensing algorithm for PAR estimation that combined clear-sky radiative transfer models with MODIS satellite

products. Their validation against ground measurements from SURF-RAD and CMA radiation networks demonstrated strong agreement, with R^2 ranging from 0.92 to 0.98 across sites. These results highlight the capability of satellite-driven approaches to provide accurate and scalable PAR estimates at regional to global scales.

Together, these studies illustrate the complex dynamics of modelling PAR, where local atmospheric conditions, model specificity, and the chosen variables play pivotal roles in the accuracy and applicability of the results. Such insights are crucial for refining PAR estimation methods, particularly in adapting to the variability imposed by different geographical and climatic contexts.

In this study, we focus on modelling total (global) PAR rather than explicitly separating its direct and diffuse components. Diffuse PAR is a key driver of canopy photosynthesis because scattered irradiance penetrates deeper into vegetation and enhances light-use efficiency, especially under cloudy or partially shaded conditions. Classical formulations such as Spitters et al. (1986) estimate diffuse fractions using clearness-index relationships, while more recent high-latitude decomposition models, including those by Ma Lu et al. (2022, 2024), integrate additional meteorological and satellite-derived information. Here, we deliberately concentrate on total PAR as a first step, aiming to establish a simple and transferable empirical relationship with GHI under high-latitude conditions. The resulting total PAR estimates remain fully compatible with existing diffuse-fraction parameterisations, allowing users to apply subsequent decomposition where required for canopy, radiative-transfer or APV simulations.

This study advances the understanding of PAR estimation by addressing several methodological and practical gaps that remain unresolved under high-latitude conditions. Although empirical PAR/GHI relationships have been examined in many regions, their behaviour in environments characterised by low solar elevation, strong seasonal variation and high diffuse fractions is still insufficiently characterised. Prior work in Sweden explored the PAR/GHI ratio and benchmarked diffuse PAR decomposition models (Ma Lu et al., 2022), but an in-depth analysis or development of empirical models for estimating PAR from GHI has not yet been undertaken. In addition, commonly used gridded PAR products such as SARA-3, CERES and STRÅNG have not been comprehensively benchmarked against Swedish ground observations, leaving uncertainties regarding their performance under Nordic atmospheric and solar-geometry conditions.

2. Methodology

To address these objectives, we benchmarked PAR estimates from SARA-3, CERES and STRÅNG against ICOS ground observations and analysed the diurnal and seasonal variability of the PAR/GHI ratio. We then developed and calibrated empirical PAR estimation models using multiple linear regression, including both station-specific and spatial formulations. The spatial model integrates data from several locations to enable national-scale PAR estimates using GHI as the only required measured variable, while solar-geometry predictors were derived from astronomical calculations. These combined steps form a practical and transferable framework for estimating PAR across Sweden using existing irradiance infrastructure.

2.1. Study locations and data collection

The study was conducted at three locations in Sweden, each

Table 1
Integrated Carbon Observation System weather stations under consideration.

Locations	Latitude (°N)	Longitude (°E)	Altitude (m)
Hyltemossa	56.06	13.25	115
Norunda	60.05	17.29	46
Degerö	64.11	19.33	270

representing different climatic and geographical conditions (Table 1, Fig. 1). The primary data used in this study include PAR and GHI, both retrieved from the ICOS network through their publicly accessible database (ICOS, 2024). The three ICOS Sweden stations used in this study span a clear north–south climatic gradient representative of Sweden’s major ecosystem zones. Hyltemossa, in southern Sweden, is located within a temperate and humid mixed coniferous forest characterised by mild winters, mean annual temperatures around 7 °C, and mean annual precipitation near 830 mm. Norunda, in central Sweden, represents the boreal forest zone, dominated by Norway spruce and Scots pine on sandy-loamy soils, with a mean annual temperature about 7 °C and precipitation around 570 mm. Degerö, in northern Sweden, lies within a sub-arctic peatland (minerogenic mire) landscape, where mean annual temperature is approximately 1 °C and precipitation about 520 mm. All three sites are situated on flat or gently undulating terrain with open horizons, ensuring negligible slope-related effects on solar geometry and measured irradiance. Consequently, differences in PAR–GHI relationships among sites primarily reflect latitudinal and atmospheric gradients rather than topographic influence.

At each site, measurements of GHI were performed using Kipp & Zonen CMP21 pyranometers, which are classified as ISO 9060:1990 secondary standard instruments. These sensors are known for their high accuracy and stability, with typical uncertainties around $\pm 2\%$ under outdoor conditions and a directional error of less than $\pm 10^\circ$ W/m² (Kipp and Zonen, 2025). The CMP21 sensors were deployed at all sites, Norunda (serial number 120,922), Degerö (serial number 120,869) and Hyltemossa (serial number 140,118). For PAR measurements, quantum sensors were employed using a LI-COR LI-190R. The LI-190R is widely used in ecological studies and provides PAR measurements with an uncertainty of approximately $\pm 5\%$ (LI-COR, 2025). Consequently, part

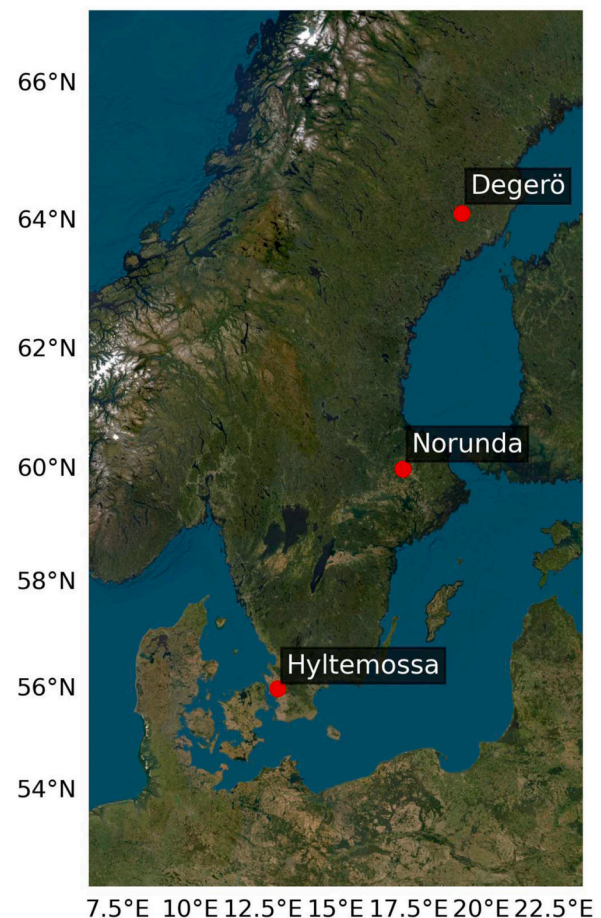


Fig. 1. Weather stations under consideration located in Sweden.

of the observed residuals may arise from sensor-specific offsets or gradual calibration drift rather than genuine model error. This limitation should be taken into account when interpreting the performance metrics. ICOS measurements were originally recorded at 30 min intervals and were averaged to hourly values to be consistent with the resolution of the gridded products.

Three high-latitude gridded products STRÅNG, CERES, and SARA-3 PAR estimates were benchmarked using the ICOS stations as ground truth. Data filtering was performed to ensure that only complete and physically meaningful records were included in the analysis. Specifically, all nighttime data points (i.e., when the solar elevation angle was below zero) were excluded to retain only daylight periods relevant for solar irradiation analysis. Furthermore, any remaining records containing missing or invalid values in any variable (e.g., PAR, GHI, or computed solar geometry parameters) were removed. This two-step filtering ensured that the datasets from Hyltemossa, Norunda, and Degerö were internally consistent, contained only valid daylight observations, and were suitable for subsequent comparison and modelling. The data were retrieved from 1 January 2021 to 27 November 2023.

2.2. Solar irradiance calculations

For each station, the solar elevation and azimuth angles were calculated using orbital elements and trigonometry (Schlyter, 2024). The extraterrestrial irradiance (E_{exth}) was computed using the solar constant ($E_{\text{sc}} = 1361.2 \text{ W m}^{-2}$) and considering the day of the year (doy) to account for the Earth's elliptical orbit. The formula used is as follows (Duffie and Beckman, 2013):

$$E_{\text{exth}} = E_{\text{sc}} \cdot E_0, \quad (1)$$

$$E_0 = 1.00011 + 0.034221 \cdot \cos(B) + 0.00128 \cdot \sin(B) + 0.000719 \cdot \cos(2B) + 0.000077 \cdot \sin(2B), \quad (2)$$

where

$$B = \frac{2\pi \cdot \text{doy}}{365} \quad (3)$$

2.3. Data analysis and model evaluation

The study aims to compare the PAR estimates from different meso-scale and satellite models and to develop predictive models. The first approach used a linear model with PAR as the dependent variable and E_{exth} , θ_z , and GHI as independent variables. The linear model can be expressed as follows:

$$\text{PAR} = \beta_0 + \beta_1 \cdot \text{GHI} + \beta_2 \cdot \theta_z + \beta_3 \cdot E_{\text{exth}} + \epsilon, \quad (4)$$

where β_0 is the intercept of the model, β_1 , β_2 , and β_3 are the coefficients corresponding to the independent variables E_{exth} , θ_z , and GHI, respectively. ϵ represents the error term, capturing the variability in PAR that is not explained by the linear relationship with the independent variables. This term is omitted from the site-specific fitted equations presented later, as it does not correspond to a model coefficient but simply accounts for random deviations between measured and predicted PAR. The selection of predictors in the multiple linear regression model, E_{exth} , θ_z , and GHI, is grounded in both physical reasoning and empirical evidence. GHI directly represents the total shortwave energy reaching the surface and is therefore the dominant determinant of PAR (Alonso-Tristán et al., 2021; Jacovides et al., 2003). E_{exth} captures the annual variation in Earth–Sun geometry, while θ_z accounts for instantaneous path-length effects and scattering processes that influence the spectral composition of solar irradiation. These variables have consistently been identified as influential predictors in both empirical and physically based PAR models (Noriega Gardea et al., 2020). The use of these parameters ensures that accurate PAR estimates can be derived solely from standard irradiance measurements, without requiring

additional meteorological inputs. This simplicity makes the model highly transferable and operationally practical, as it can be readily applied wherever GHI data exist. In contrast to data-intensive or site-specific machine-learning models, the linear formulation offers full transparency and physical interpretability while retaining accuracy comparable to more complex approaches.

The second approach utilised a simple PAR/GHI ratio model, where the yearly ratio of PAR to GHI was calculated at each station and compared with the linear model's predictions. To maintain sufficient data for both training and testing, and given that the number of valid data points varies by location, the datasets were split roughly in half chronologically: the first 50 % of the time series was used for training, and the remaining 50 % for testing. This approach results in approximately 1 to 1.5 years of training data and the remainder for testing, ensuring that the model is evaluated on temporally independent data without overlap. To extend the applicability of the linear model across different locations in Sweden, a spatial regression model was developed by combining data from Degerö and Hyltemossa by using all retrieved data between 1 January 2021 to 30 September 2023 to predict PAR during the same period in Norunda, assessing the feasibility of a spatial regression model applicable across different locations. This approach aimed to assess whether a model trained on data from certain sites could accurately predict PAR at new, untested locations, thereby demonstrating its potential for broader application. Model performance was evaluated using accuracy metrics such as normalised Mean Absolute Error (nMAE), nMBE, and R^2 . These metrics provide insights into the predictive accuracy and reliability of the models.

To assess the relative contribution of each predictor in the linear PAR estimation model, a feature importance analysis was performed on the training dataset, consisting of combined observations from Degerö and Hyltemossa. The analysis was based on the absolute values of the standardised regression coefficients (β) obtained by refitting the multiple linear model to z-scored variables, where both predictors (GHI, θ_z , and E_{exth}) and the response variable (PAR) were normalised to zero mean and unit variance. This approach removes the influence of differing variable scales and units, allowing direct comparison of the predictors' relative weights in explaining variations in PAR. The normalised coefficients were then expressed as percentages of the total absolute coefficient sum, providing a quantitative measure of each variable's relative importance in the fitted model. The procedure was applied solely to the training data, ensuring that the results reflect the intrinsic structure of the model without influence from the independent test site (Norunda). The resulting feature importance values thus indicate the proportional explanatory power of each predictor under the empirical conditions represented in the training data, rather than an independent validation metric.

To evaluate the robustness and generalisability of the proposed regression approach, an additional benchmarking exercise was conducted against established empirical PAR-GHI relationships from the literature. Specifically, four of the best-performing global models reported by García et al. (2022) were implemented for comparison, using a similar set of input variables to ensure consistency in evaluation. Each formulation was first re-fitted to the Degerö and Hyltemossa datasets and then validated at the independent Norunda site. The published global coefficients from García et al. (2022) were also applied directly to quantify their transferability under Nordic conditions. A detailed description and discussion of this benchmarking are provided in Appendix A.

By implementing this methodology, the study aims to determine the accuracy of different gridded products and predictive models for estimating PAR at various locations in Sweden and to explore the potential for spatial regression models across different high-latitude regions.

3. Results and discussions

3.1. Evaluation of gridded products

An in-depth investigation of the ratio between PAR and GHI reveals that monthly variations across different geographical locations and times of the year are not substantial. Fig. 2 shows larger variation during the winter months for all locations, with the strongest variability at Degerö. This pattern can be interpreted through basic solar geometry and atmospheric optics. At high latitudes, the sun angles remains low above the horizon during winter, increasing the optical path length and the proportion of scattered light. The enhanced scattering raises the relative contribution of diffuse irradiance, which tends to increase the

PAR fraction and amplify its variability over time. Consequently, the seasonal differences observed among the Swedish stations are an expected outcome of latitude-dependent solar elevation and atmospheric conditions rather than measurement uncertainty. Similar relationships between solar angle, aerosol optical depth, and diffuse irradiance have been described in earlier irradiance studies (Jacovides et al., 2004; Spitters et al., 1986), supporting this interpretation. Nonetheless, for agricultural productivity, the winter period is less critical compared to the summer period, during which the PAR to GHI ratio shows minimal variation across different locations and months. However, small but systematic differences are evident between the gridded products in the PAR/GHI ratios derived from their respective PAR and GHI values. All datasets were compared at identical hourly timestamps, ensuring equal

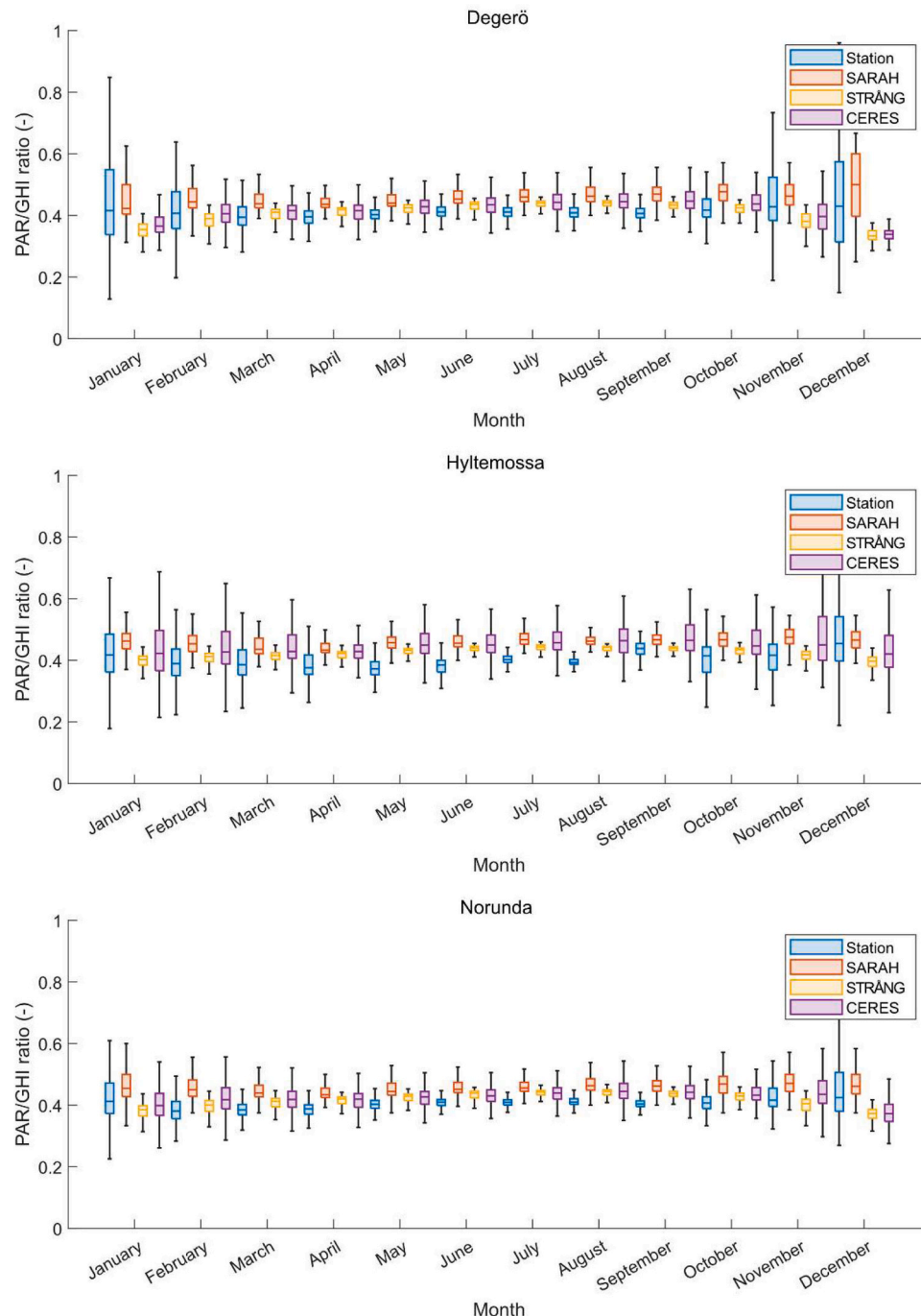


Fig. 2. Monthly variation in PAR/GHI ratio at Degerö, Hyltemossa, and Norunda weather stations.

sample sizes and consistent temporal resolution between models and ground measurements. Therefore, the observed deviations are not caused by unequal sampling or averaging intervals but rather reflect intrinsic differences in spatial resolution and radiative-transfer parameterisations. CERES, for example, operates at a coarse $1^\circ \times 1^\circ$ grid and partitions broadband radiances into PAR using lookup tables, which can smooth local cloud and aerosol variability. In contrast, SARA-3 and STRÅNG have finer spatial detail (0.05° and 2.5 km, respectively) and employ region-specific cloud transmittance schemes, allowing them to capture short-term variations more effectively. These algorithmic and spatial differences explain the residual spread. These differences underscore the importance of careful selection and validation of gridded products when used for PAR estimation, as the accuracy of these estimates can vary significantly depending on the product and the specific conditions at each location.

To gain deeper insights into the PAR/GHI ratio, Table 2 presents the annual and cumulative values across the three locations. The data reveals that the year-to-year variation is minimal, with the most notable fluctuation occurring in Hyltemossa, where the variation reaches approximately 14 %. Additionally, a trend is evident in the PAR/GHI ratio across different stations: as latitude increases, the PAR/GHI ratio also tends to increase. This suggests a relationship between latitude and the PAR/GHI ratio, although the variation is relatively small and may not be highly significant.

Understanding the hourly and seasonal variations in the PAR to GHI ratio is also of interest. In Fig. 3, the PAR to GHI ratio is compared across three locations by examining hourly variations during the spring equinox, summer solstice, autumn equinox, and winter solstice. The hourly variation is generally low, although there are occasional fluctuations for a single hour. Notably, the ratio at Degerö station is generally higher (above 0.4) compared to Hyltemossa station (below 0.4), indicating differences between latitudes. The gridded products showed a higher PAR to GHI ratio at Hyltemossa compared to weather station measurements, while remaining almost identical at other locations. The observations aligns with previous research on the PAR/GHI ratio. For example, Grimenes and Thue-Hansen (2019) reported a yearly mean PAR/GHI ratio of 0.48 at the Norwegian University of Life Sciences, with minimal variation throughout the year. This value is notably higher than the ratios we observed, which could be attributed to differences in solar elevation angles, atmospheric conditions, and the specific methodologies used for data collection and analysis. However, a consistent finding with our study is the low annual variation in the PAR/GHI ratio. Atmospheric water vapour introduces an additional, though relatively minor, source of regional variability in the PAR/GHI relationship. High leaf area index or humid environments with elevated evapotranspiration can increase near-surface moisture and aerosol content, enhancing scattering and thereby slightly increasing the diffuse fraction of PAR (Proutsos et al., 2022). However, such effects are implicitly represented in the model through the observed GHI, which already responds to variations in atmospheric transmission. Consequently, water-vapour feedback does not create systematic bias but rather contributes to the natural variability of the fitted coefficients among sites.

Furthermore, the seasonal variation we observed showed more pronounced fluctuations during the winter months, which is consistent with findings by Ge et al. (2011) and Li et al. (2010). These studies noted that higher latitude locations tend to exhibit more significant seasonal changes in the PAR/GHI ratio. They emphasised the impact of cloud

cover and solar angle on this ratio, which could explain the higher variability observed at Degerö station, a pattern that was also evident in our results.

There are limitations to gridded products at high-latitude locations. In Sweden, SARA-3, STRÅNG, and CERES are the only products providing available PAR estimates. Assessing the accuracy of these products at various locations in Sweden is also important. As shown in Fig. 4, the discrepancies among the three gridded PAR products are substantial and site-dependent, with R^2 ranging from 0.78 to 0.94. SARA-3 consistently outperformed the other datasets, achieving the lowest nMAE values (17–19 %) and the highest R^2 (0.91–0.94) across all stations. CERES ranked second, with nMAE between 21 % and 24 % and R^2 from 0.86 to 0.88, whereas STRÅNG exhibited the weakest performance (nMAE = 29–31 %, R^2 = 0.78–0.80). STRÅNG also showed a systematic underestimation of PAR at Degerö (nMBE = −4.7 %) and greater inter-site variability, suggesting a poorer representation of irradiance under northern latitudes. In contrast, CERES and SARA-3 displayed consistent positive biases (nMBE = 3.7–10.1 %). All products and in-situ data were compared at identical hourly timestamps (equal sample sizes), so the observed dispersion in Fig. 4 does not stem from temporal misalignment. Instead, the scatter reflects uncertainties already present in the underlying broadband GHI retrievals from which PAR is derived, meaning that PAR accuracy cannot substantially exceed that of its parent GHI estimates (Su et al., 2007). The loop-like (“hysteresis”) pattern, where similar measured PAR values correspond to different satellite estimates, can be attributed to diurnal solar-geometry effects: at low solar elevations (morning, evening, and winter), small errors in cloud optical depth, aerosol loading, or surface albedo propagate non-linearly through the radiative-transfer calculations, widening scatter and shifting slopes away from unity (Grosvenor and Wood, 2014; Lu and Ma, 2023). These effects become particularly pronounced at high latitudes, where extended periods of low Sun angles amplify angular-dependence errors in cloud retrievals, a limitation recognised in both satellite-based irradiance and cloud-property products (Grosvenor and Wood, 2014). To further illustrate how these angular- and cloud-dependent effects manifest at the diurnal scale, Appendix B presents hysteresis plots for a clear-sky and a cloudy day at Hyltemossa, showing how asymmetries in PAR estimation differ across products. The regression slopes and intercepts in Fig. 4 show that STRÅNG and SARA-3 remain close to unity, whereas CERES tends to slightly underestimate PAR, consistent with its coarser spatial resolution and broadband-to-PAR scaling approach. Because both measured and gridded PAR contain observational uncertainty, the slopes and intercepts shown in Fig. 4 were estimated using reduced major axis (geometric mean) regression, which provides an unbiased comparison when errors are present in both variables. Overall, these results confirm that the differences among satellite products are systematic and physically explainable, and that the accuracy of PAR estimates is effectively bounded by the known high-latitude limitations of satellite irradiance retrievals rather than by sampling or terrain effects. In addition to these angular-dependent retrieval challenges, winter-specific surface and atmospheric conditions further affect the performance of the gridded-products. Their residuals increase during winter, particularly during periods with very low solar elevations. This behaviour is expected because sensor cosine response, local horizon effects and the strong surface reflectance associated with snow cover. Future work may reduce this bias by including information on snow cover, surface albedo and correction factors for low solar elevation. Such conditions represent an inherent challenge for optical irradiation modelling at high latitudes and should be explicitly incorporated in future extensions of the framework.

The variation in the PAR to GHI ratio indicates that the visible spectrum does not vary significantly, although there are seasonal trends, especially at higher latitudes. This suggests that PAR can be estimated effectively by understanding the proportion of visible light within the solar spectrum, which shows low hourly variation. Consequently, there

Table 2

Annual and cumulative PAR/GHI ratios at Degerö, Hyltemossa, and Norunda weather stations.

	2021	2022	2023	Total
Degerö	0.4205	0.4179	0.3901	0.4095
Hyltemossa	0.3979	0.3899	0.4431	0.4103
Norunda	0.4107	0.4087	0.4004	0.4066

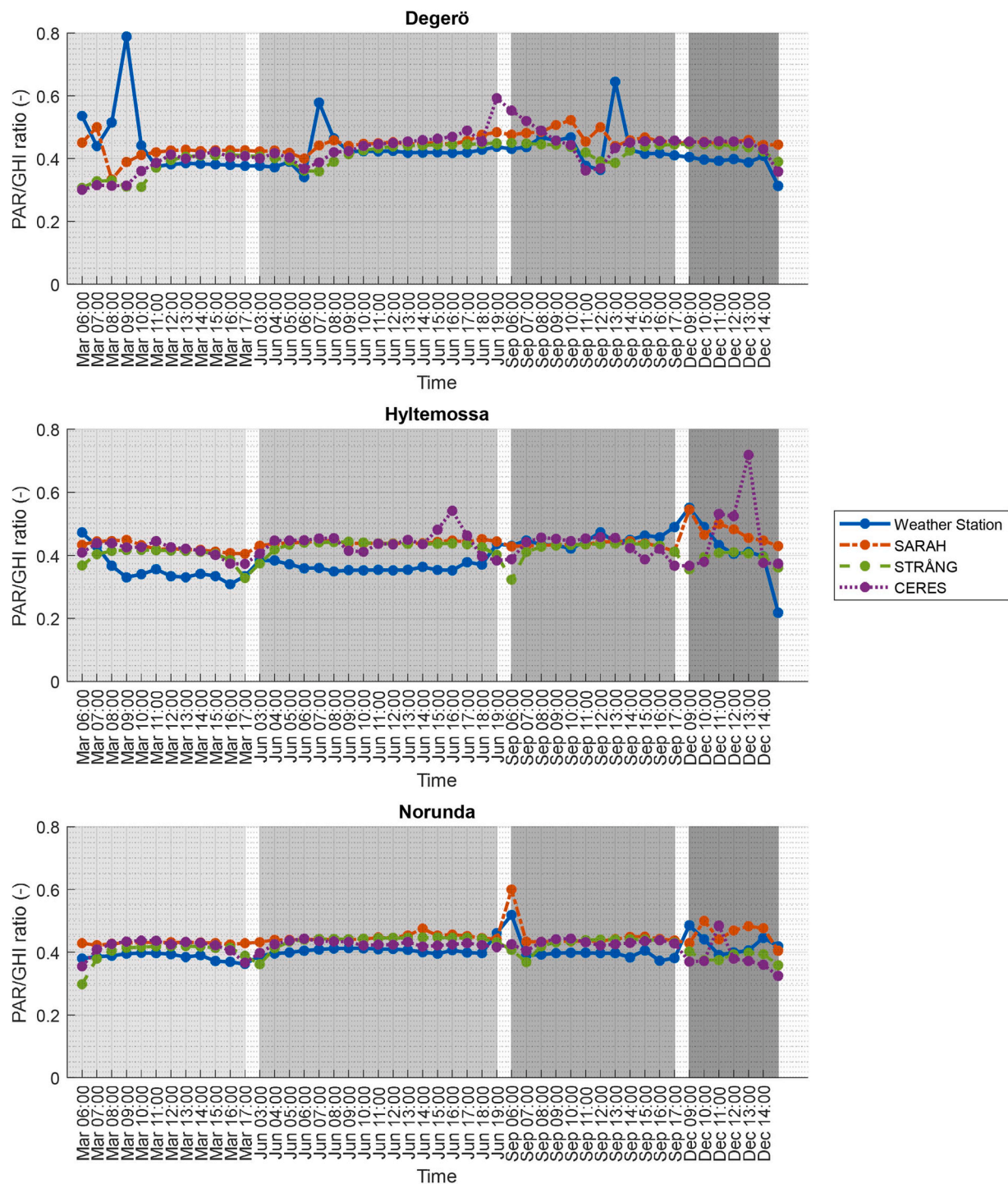


Fig. 3. Hourly variation in PAR/GHI ratio, comparing gridded products with ground-based measurements from weather stations at Degerö, Hyltemossa, and Norunda.

is no need for complex modelling to estimate PAR.

3.2. Performance of station-specific linear models

In Fig. 5, the accuracy of a linear model is compared to a simple PAR to GHI ratio at various locations. The PAR/GHI ratios used for each station were the cumulative PAR/GHI ratio presented in Table 2. The fitted linear regression models used for estimating the PAR at each site can be found in Table 3. The station-specific regressions reflect local irradiance conditions and the correlation structure among predictors at

each site. In Hyltemossa (southernmost site, higher solar elevations and shorter atmospheric path lengths), the model captures a slightly different angular sensitivity: the θ_z term (β_2) absorbs less variation (more negative but smaller magnitude) because a larger share of the PAR variability is already explained by GHI at those higher sun angles, while the intercept (β_0) compensates for baseline differences in the local irradiance–PAR relationship. In contrast, at higher-latitude sites the longer optical path and larger diffuse fraction give θ_z more explanatory leverage, altering the balance between β_0 and β_2 . This is also a consequence of site-specific collinearity among GHI, θ_z and E_{ext} . When

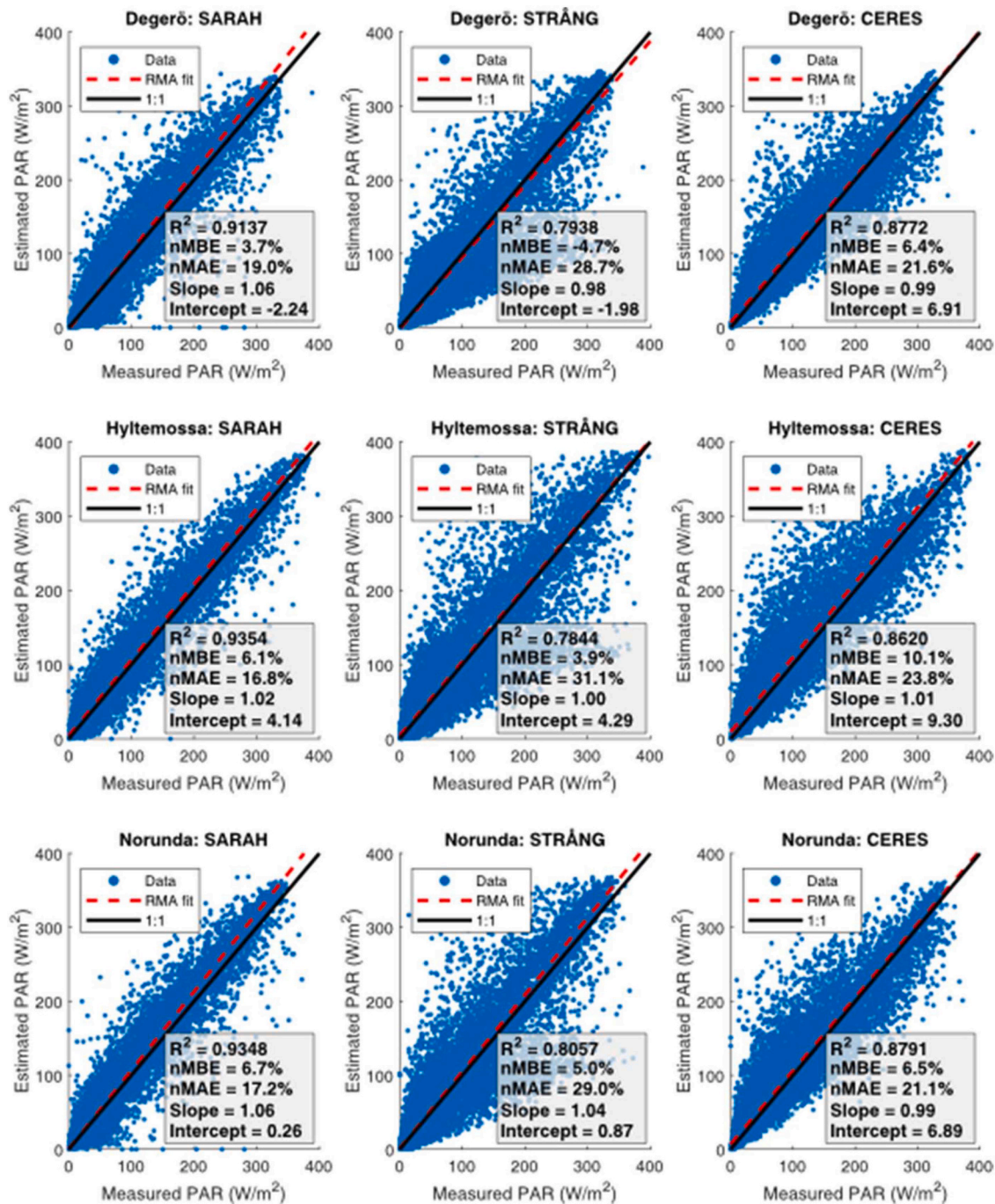


Fig. 4. Comparison of PAR estimations in Sweden by SARAH-3, STRÅNG, and CERES gridded products with measured data at ICOS stations.

predictors are correlated to different degrees across sites, the fitted weights redistribute without changing the model's predictive skill. The key point is that β_3 (on GHI) remains of similar order across sites, indicating a stable primary dependence on GHI, while β_0 and β_2 act as site-level adjustments for geometry and atmosphere (not model instability).

This demonstrates that both linear models and simple PAR/GHI ratios requiring only GHI measurements can effectively estimate PAR. In contrast, the PAR to GHI ratio method shows a slightly reduced accuracy compared to the linear models. Nonetheless, the simple PAR to GHI ratio method remains more accurate than gridded products in central and southern Sweden and can be a viable estimation method. While the present analysis focuses on total PAR, our empirical framework can serve as the foundation for further PAR decomposition into direct and diffuse components. Once total PAR is estimated from GHI with high

accuracy, relationships such as those proposed by Spitters et al. (1986) or Ma Lu et al. (2022, 2024) can be applied to obtain diffuse PAR for multilayer canopy or APV shading studies. Thus, the proposed model complements, rather than replaces, diffuse-irradiation models and offers a reliable input for such downstream applications. However, despite this compatibility, the model still carries an important structural limitation concerning its treatment of irradiation components. The present model estimates total PAR and does not partition irradiation into direct and diffuse components. Diffuse PAR is known to dominate under cloudy conditions and is highly relevant for canopy photosynthesis and three dimensional radiative transfer studies. Future development should incorporate diffuse fraction estimates derived from clearness index, cloud optical properties or sky based imaging in order to improve applicability in detailed canopy or APV shading analyses. Addressing

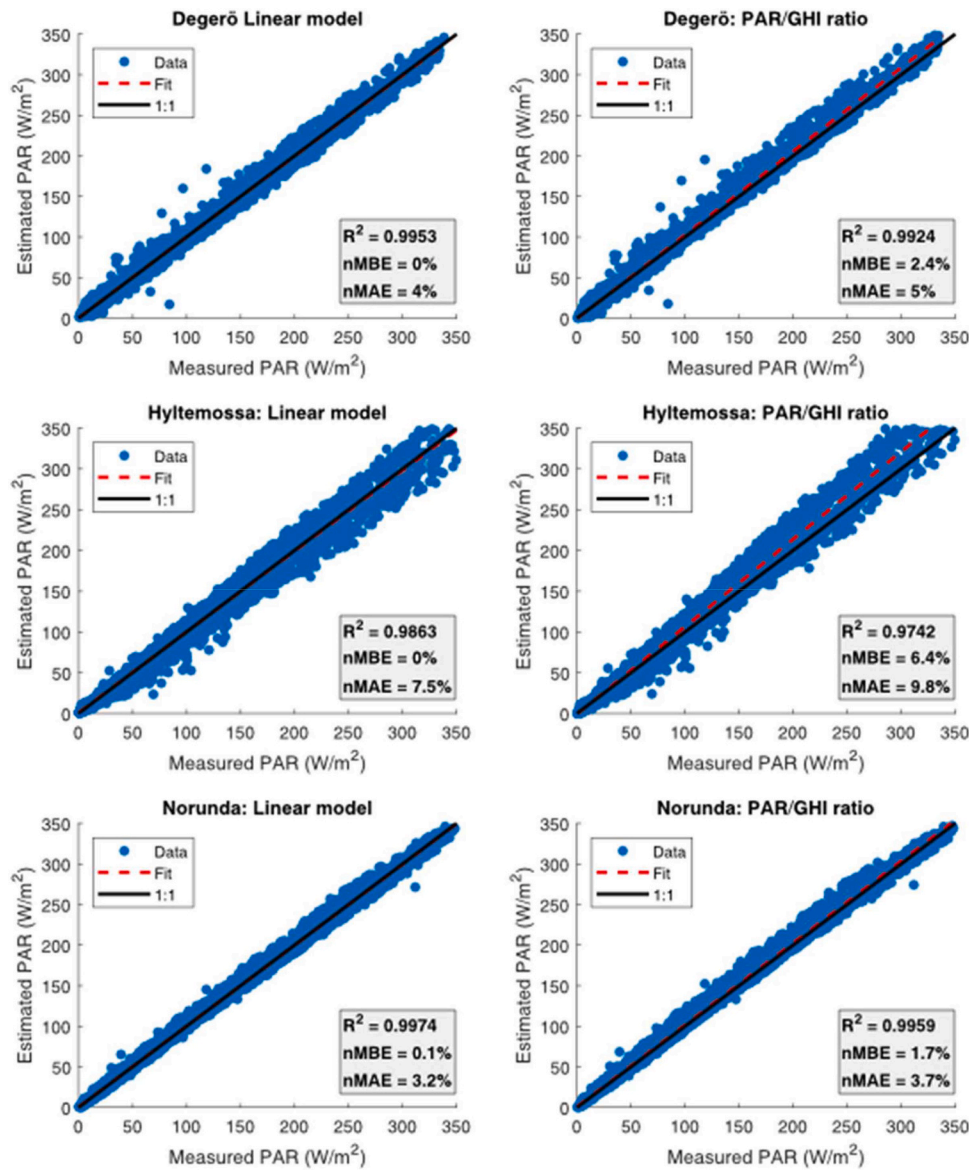


Fig. 5. Comparison of PAR estimations in Sweden using two approaches: Linear regression models (left) and cumulative PAR/GHI ratio models (right) at Degerö, Hyltemossa, and Norunda. The left panels show the performance of the station-specific linear models in predicting PAR, while the right panels illustrate the results of using the cumulative PAR/GHI ratio for each location.

Table 3

Coefficients of multiple linear regression models for estimating PAR at Degerö, Hyltemossa, and Norunda.

	Multiple Linear Regression Model
Degerö	$PAR = 196.6260 + GHI \cdot 0.3838 - \theta_z \cdot 2.1685 - E_{ext} \cdot 0.0935$
Hyltemossa	$PAR = 18.0887 + GHI \cdot 0.3718 - \theta_z \cdot 0.1966 - E_{ext} \cdot 0.0029$
Norunda	$PAR = 190.4453 + GHI \cdot 0.3900 - \theta_z \cdot 2.1098 - E_{ext} \cdot 0.0923$

this limitation would allow future versions of the model to support a broader class of applications, particularly those requiring 3D radiative-transfer realism.

The linear model can be used for site adaptation, although sufficient data may not always be available for model fitting. In the case of estimating PAR using GHI from weather stations, our results indicate that linear regression models can achieve high accuracy with minimal additional parameters, making it an excellent choice for this specific application. The strong performance of these linear models suggests that the incremental benefits of introducing more complex methods, such as

machine-learning, may be marginal, especially when the gains in accuracy are small relative to the increased complexity and computational demands.

However, when it comes to improving the estimates of PAR from gridded products, such as those derived from satellite or mesoscale models, the situation differs. Gridded products often encounter challenges due to biases and inaccuracies resulting from the complex environmental conditions they attempt to model, particularly in high-latitude regions like Sweden. In these cases, the limitations of linear models become apparent, as they may struggle to capture the non-linear relationships and interactions between multiple variables that are crucial for accurate site adaptation. As highlighted in the study by Zainali et al. (2024), machine-learning techniques can significantly enhance the accuracy of gridded irradiance estimates by addressing these biases and improving model performance through site adaptation. The flexibility of machine-learning models, such as support vector regression and ensemble methods, allows them to adjust to the specific conditions of different sites, making them particularly useful for improving the reliability of PAR estimates from gridded products. While

linear models offer a practical solution for direct estimation from GHI, machine-learning provides a more powerful tool for refining gridded data, ensuring higher accuracy and better support for applications like APV system design and solar energy planning.

3.3. Development of a spatial regression linear model

Given the variability in environmental conditions across Sweden, relying solely on site-specific models could limit the applicability of the findings. To overcome this, it becomes essential to develop a spatial regression model that can be efficiently applied across different locations within Sweden, rather than being tailored to a single site. This approach allows for a more versatile and broadly applicable tool, capable of providing reliable PAR estimates in regions where measurements data are not available. By adding the space dimension to the model, we can extend the benefits of accurate PAR estimation to a wider geographic area. Fig. 6 shows that the spatial regression model, can still estimate PAR with reasonable accuracy even at untrained locations like Norunda. Although the error metrics are slightly higher, this is expected when a model cover a larger geographic area rather than being tailored to a specific site. The fact that we observe high accuracy in Norunda, where the model was not explicitly trained, indicates that the spatial regression model is indeed successful in estimating PAR across various locations in Sweden, demonstrating its robustness and broader applicability.

To further evaluate the model's robustness, a benchmarking analysis was performed against the globally calibrated logarithmic PAR-GHI models of García et al. (2022) (Appendix A). These formulations, which represent the most accurate global empirical relationships available and require no additional inputs beyond GHI and solar geometry, served as a relevant reference for assessing transferability. While the global equations reproduced PAR with good accuracy after local recalibration ($R^2 > 0.98$), their direct application using the original coefficients resulted in noticeably higher errors under Nordic conditions. These results confirm that the regionally calibrated Swedish model provides more reliable and bias-free PAR estimates than globally fitted alternatives, while maintaining the same simplicity and data requirements, using only routinely measured GHI and computed solar geometry parameters.

The near-constant relationship between PAR and GHI observed across the stations underpins the strong performance of the linear model. Both hourly and monthly analyses show that the PAR/GHI ratio remains remarkably stable, with only minor site-to-site and seasonal variations. This stability confirms that most of the variability in PAR can be described by a single proportional relationship with GHI, with minor geometric corrections for θ_z and E_{ext} . Consequently, a linear regression is not only statistically justified but also physically representative of the irradiance processes involved. The resulting model reproduces measured PAR with an $R^2 = 0.9854\text{--}0.9941$ and $\text{nMAE} = 4.0\text{--}7.8\%$,

demonstrating that nearly all explainable variance is captured by this simple formulation. This performance can be largely attributed to the high quality and co-located nature of the ICOS data, where both PAR and GHI originate from well-calibrated sensors measuring the same radiative field. Independent validation using a separate station outside the ICOS network (Appendix C) further confirms that this relationship holds under different local conditions, supporting the robustness and general applicability of the approach across diverse radiative regimes.

Despite this strong performance, several factors that could influence the PAR–GHI relationship were not explicitly represented in the present modelling framework. One such factor is cloud regime. The model does not differentiate among cloud types such as stratiform and convective clouds, which is important because cloud type modulates the diffuse fraction and can introduce regime-specific variations in the PAR/GHI ratio. Future developments should integrate cloud-regime information from satellite products or sky-imaging systems to reduce potential biases, particularly in regions where persistent stratus cloud decks are common. In addition, the extent to which the model generalises beyond the environmental conditions represented in our dataset requires careful consideration. The model was trained and validated at sites located between 56 and 64°N in relatively flat and low-elevation terrain. Spatial transferability beyond these conditions has not yet been evaluated. Mountainous boreal regions, as well as lower-latitude ecosystems, may exhibit different interactions among topography, horizon shading and solar geometry. Future work should therefore test the model across a wider latitudinal range and in more complex terrains to define its broader domain of applicability.

Fig. 7 presents the standardised regression coefficients derived from the combined Degerö + Hyltemossa training data, illustrating the

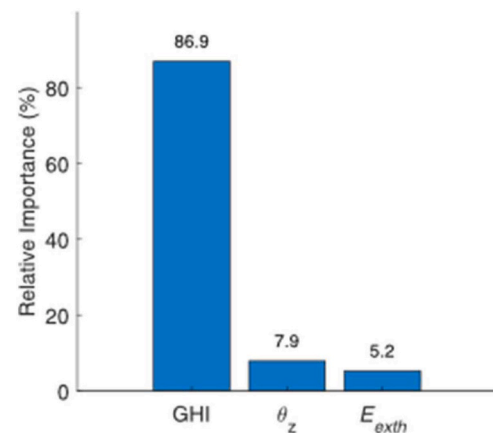


Fig. 7. Relative importance of predictors in the PAR model based on standardised coefficients from the Degerö + Hyltemossa training data.

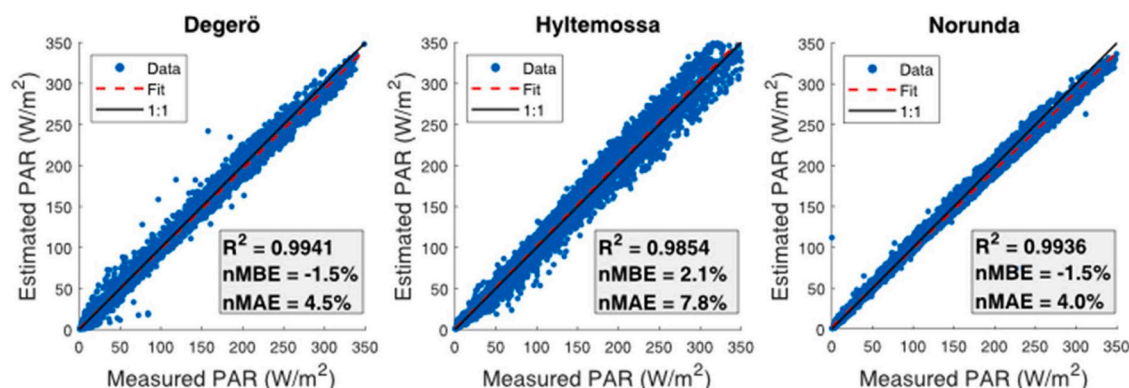


Fig. 6. Evaluation of the spatial regression model developed for Sweden.

relative weight of each predictor in the linear model. The results show that GHI dominates the relationship, accounting for approximately 86.9 % of the total model influence. The θ_z contributes around 7.9 %, while E_{exth} represents only 5.2 %. This distribution confirms that nearly all explainable variance in PAR can be captured by the direct relationship with GHI, while the additional predictors mainly provide geometric and seasonal corrections. The secondary role of θ_z reflects its function in adjusting for variations in solar elevation, which influence the angular distribution of incoming irradiance and the ratio of direct to diffuse components. The minor contribution of E_{exth} indicates that changes in Earth-Sun distance exert only a small modulation on ground-level PAR under the conditions represented by the dataset. These findings are physically consistent with expectations for high-latitude environments, where diurnal and synoptic variations in total irradiance dominate PAR dynamics, while geometric and orbital effects remain secondary. The relative weights also reinforce the suitability of a simple linear formulation, since the inclusion of complex non-linear or machine-learning terms would provide negligible improvement relative to the near-constant proportionality between PAR and GHI observed across sites.

Machine-learning approaches can, in theory, capture additional non-linearities. However, when the underlying relationship between PAR and GHI is as stable as observed here, added complexity yields negligible improvement. Machine-learning still requires representative input data to learn from and lacks the mechanistic transparency of empirical regressions (Foyo-Moreno et al., 2017; García et al., 2022). The residual differences between measured and estimated PAR are small and lie within the stated uncertainties of the instruments used for reference measurements. The CMP21 pyranometers used for GHI have a typical accuracy of ± 2 % ($\pm 10 \text{ W m}^{-2}$), while the PAR sensor (LI-COR LI-190R) have uncertainties of approximately ± 5 % for total PAR. Similarly, the instruments used in the independent validation (Delta-T BF5 and SPN1) report comparable accuracies of ± 5 % for PAR and GHI, respectively. When the model bias and nMAE fall within these uncertainty ranges, any additional optimisation would effectively target random sensor noise or calibration offsets rather than improving the underlying physical representation. In other words, further refinement beyond this point would attempt to fit variations arising from measurement uncertainty, which constitutes a form of overfitting rather than genuine model improvement. The presented model can therefore be considered to have reached the practical accuracy limit imposed by the precision of the observational data. Within a modelling chain, such as when PAR estimates feed into process-based crop models, this accuracy already far exceeds the uncertainty propagated through subsequent stages. Global crop-model intercomparisons show correlations of $R^2 = 0.4134\text{--}0.7885$ for major crops, meaning that any residual PAR error is inconsequential to overall yield simulations (Müller et al., 2017).

The empirical PAR model developed in this study enables accurate site-level estimates of PAR using only routinely available irradiance data. Because the PAR/GHI ratio was found to be highly stable across sites and timescales, reliable PAR values can be derived directly from standard GHI observations without the need for additional inputs or complex calibration. In APV applications, such site-level PAR information provides the necessary input for modelling the light transmitted beneath PV panels and the corresponding crop photosynthetic response. The linear formulation is straightforward to implement: GHI is the only required measured variable, while the remaining predictors, θ_z and E_{exth} , are readily computed from the site's geographic coordinates and time. This combination of simplicity, physical consistency, and transparency makes the model highly practical for large-scale applications and ensures seamless coupling with crop and canopy models, without the risk of overfitting or loss of interpretability associated with more complex algorithms. The equation for the spatial regression model is:

$$\text{PAR} = 48.3847 + \text{GHI} \cdot 0.3779 - \theta_z \cdot 0.5324 - E_{\text{exth}} \cdot 0.0173 \quad (5)$$

4. Conclusion

This study focused on improving the estimation of PAR in Sweden, a region previously underrepresented in PAR modelling research. By systematically comparing PAR estimates derived from various satellite sources, such as SARA-3 and CERES, and the mesoscale model STRÅNG against ground-based weather station measurements, we identified significant discrepancies in these models, particularly in high-latitude regions like Sweden. These findings underscored the need for more accurate, region-specific modelling approaches.

To address this need, we developed and calibrated multiple linear regression models specifically tailored to Sweden. These models utilised GHI as the primary predictor, along with θ_z and E_{exth} . The results demonstrated that these linear models achieved high accuracy, with nMAE consistently below 8 % across all weather stations. This high level of accuracy confirms the effectiveness of using GHI as a predictor for PAR, providing a practical and cost-effective method for estimating PAR in Sweden.

While GHI-based estimation remains the preferred and most accurate approach, the intercomparison also revealed that among the gridded datasets, the SARA-3 product exhibited the closest agreement with ground observations, outperforming both STRÅNG and CERES across all stations. This suggests that SARA-3 can serve as a reliable surrogate for GHI-derived inputs in regions or periods where direct irradiance measurements are unavailable, thereby extending the applicability of PAR estimation to data-scarce locations.

In addition to model development, the study explored the seasonal and hourly variability of the PAR/GHI ratio across different locations in Sweden. Significant seasonal variability was observed, particularly during winter at higher latitudes like Degerö. However, during the summer period, which is critical for agricultural applications, the PAR/GHI ratio exhibited minimal variation across locations. This consistency during the summer suggests that a simplified modelling approach, like the linear models developed in this study, can be effectively employed without compromising accuracy.

To further enhance the applicability of our approach, we developed a spatial regression model by combining data from multiple stations, including Hyltemossa and Degerö. This spatial regression model was successfully validated at Norunda, an untrained location, achieving a high R^2 between 0.98 and 0.99. The success of this spatial regression model highlights the potential for a unified model that can be applied across various geographical regions in Sweden, even in areas lacking PAR measurements.

The findings from this study have important implications for the design and optimisation of APV systems in Sweden. The high accuracy of the linear models during the critical summer period supports their use in optimising both crop yield and solar energy conversion.

CRedit authorship contribution statement

Sebastian Zainali: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Silvia Ma Lu:** Writing – review & editing. **Tomas Landelius:** Writing – review & editing. **Pietro Elia Campana:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: the company European Energy is financing half of Sebastian Zainali's Ph.D. salary.

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Likewise, the authors acknowledge ICOS Sweden for provisioning of Degerö, Hyltemossa and Norunda stations data. ICOS Sweden is funded by the Swedish Research Council as a national research infrastructure.

Appendix A

To assess the robustness and transferability of the Swedish spatial regression model, a benchmarking analysis was carried out against the most accurate global empirical relationships between PAR and GHI reported by García et al. (2022). These models were selected because, like the present study, they rely exclusively on routinely available irradiance and geometric parameters, i.e., GHI, θ_z , E_{ext} , and the k_T , without requiring any additional meteorological inputs. Four logarithmic formulations were implemented. Each expresses PAR as a function of GHI and the natural logarithm of the k_T , which is calculated as follows:

$$k_T = \frac{GHI}{E_{\text{ext}}} \quad (\text{A1})$$

In addition, θ_z and day of the year (doy) are used in certain model formulations depending on their original specification. Table A1 presents the four logarithmic PAR-GHI model formulations from García et al. (2022) together with their globally fitted regression coefficients. These models were originally calibrated using a large, multi-site dataset spanning diverse climates and therefore represent state-of-the-art empirical relationships for estimating PAR from GHI using only routinely available irradiance and geometric variables. In this study, the globally fitted versions were first evaluated directly to test their transferability to Nordic conditions. Subsequently, the same model structures were retrained using the Swedish ICOS data (Degerö + Hyltemossa) and validated at Norunda, following the identical training and validation procedure applied to the spatial regression model described in the main manuscript. This approach enables a direct comparison between globally derived coefficients and regionally calibrated ones developed specifically for Sweden.

Table A1

Global logarithmic PAR-GHI model formulations and coefficients from García et al. (2022) used for benchmarking the Swedish spatial regression model.

Model	β_0	β_1	β_2	β_3	Equation
A1	0.4379	0.0013	- 0.0279	- 0.0287	$PAR = GHI(\beta_3 \cos(\theta_z) + \beta_2 \ln(k_T) + \beta_1 \text{doy} + \beta_0)$
A2	0.4359	- 0.0296	- 0.0258	-	$PAR = GHI(\beta_2 \cos(\theta_z) + \beta_1 \ln(k_T) + \beta_0)$
A3	0.4069	- 0.0757	- 0.0341	-	$PAR = GHI(\beta_2 (\ln(k_T))^2 + \beta_1 \ln(k_T) + \beta_0)$
A4	0.4289	- 0.0538	- 0.0198	- 0.0230	$PAR = GHI(\beta_3 \cos(\theta_z) + \beta_2 (\ln(k_T))^2 + \beta_1 \ln(k_T) + \beta_0)$

Table A2 presents the performance of the models after re-fitting their coefficients using the Swedish ICOS data from Degerö and Hyltemossa, while Table A3 shows the performance obtained when applying the original globally fitted parameters from García et al. (2022) without recalibration.

This comparison provides a direct assessment of how well globally derived empirical relationships transfer to Nordic radiative conditions and how much accuracy can be gained through regional recalibration. Across all formulations, the locally re-fitted models achieved consistently high accuracy, with R^2 values exceeding 0.98 and nMAE typically below 8 %. This demonstrates that the general structure of the logarithmic models proposed by García et al. (2022) remains valid under Swedish sky conditions when the coefficients are adjusted to local data. The inclusion of the logarithmic clearness-index term ($\ln k_T$) effectively captures the non-linear relationship between PAR and GHI, while geometric terms such as $\cos(\theta_z)$ provide minor but consistent improvements in bias correction.

Table A2

Locally re-fitted logarithmic models (Swedish calibration).

Model	Site	R^2	nMAE [%]	nMBE [%]
A1	Degerö	0.9943	4.4	-1.5
	Hyltemossa	0.9855	7.8	2.1
	Norunda	0.9937	3.9	-1.5
A2	Degerö	0.9943	4.4	-1.5
	Hyltemossa	0.9855	7.8	2.1
	Norunda	0.9937	3.9	-1.5
A3	Degerö	0.9940	4.5	-1.4
	Hyltemossa	0.9856	7.9	2.0
	Norunda	0.9933	4.1	-1.4
A4	Degerö	0.9943	4.4	-1.5
	Hyltemossa	0.9855	7.8	2.1
	Norunda	0.9938	4.0	-1.4

In contrast, the direct application of the global coefficients led to noticeably higher errors, particularly at Hyltemossa, where diffuse radiation fractions are greater and atmospheric transmission differs from the global training sites. This result indicates that while the global formulations are physically sound and broadly applicable, their coefficients are not fully representative of high-latitude optical and atmospheric conditions. Regionally

refitting the coefficients substantially improves accuracy and reduces systematic bias, demonstrating the importance of local calibration when high precision is required.

Table A3

Models using original coefficients by [García et al. \(2022\)](#).

Model	Site	R ²	nMAE [%]	nMBE [%]
A1	Degerö	0.9460	16.0	15.6
	Hyltemossa	0.9142	20.1	19.5
	Norunda	0.9515	15.7	15.5
A2	Degerö	0.9763	10.4	9.9
	Hyltemossa	0.9529	14.6	13.6
	Norunda	0.9790	10.0	9.7
A3	Degerö	0.9808	9.1	7.9
	Hyltemossa	0.9582	13.3	11.3
	Norunda	0.9822	8.7	8.0
A4	Degerö	0.9770	10.1	9.3
	Hyltemossa	0.9543	14.2	12.7
	Norunda	0.9794	9.6	9.2

Overall, the benchmarking confirms that the Swedish spatial regression model developed in this study outperforms both the globally fitted and locally refitted logarithmic models, despite relying on the same minimal set of inputs (GHI and solar-geometry-derived parameters). Its near-constant proportionality between PAR and GHI yields the most accurate and transferable results across sites, providing a simpler yet more robust framework for estimating PAR in Nordic environments.

Appendix B

To demonstrate how product-specific errors vary across the day, [Fig. B1](#) compares the PAR–PAR relationships for a clear-sky day (24 June 2022) and a cloudy day (22 June 2022) at Hyltemossa. Under clear-sky conditions, all products follow a nearly linear trajectory with minimal diurnal divergence, and differences are dominated by systematic bias (STRÅNG exhibiting the highest and SARA-3 the lowest). In contrast, the cloudy day reveals pronounced loop- or “hysteresis”-like behaviour, where morning and afternoon points deviate for the same measured PAR. STRÅNG shows the largest excursions during transient cloud breaks, CERES displays moderate asymmetry, and SARA-3 remains comparatively stable. These plots support the interpretation in the main text that diurnal asymmetry in cloud optical properties and solar geometry, not temporal misalignment, drives the observed dispersion and slope variability in [Fig. 4](#).

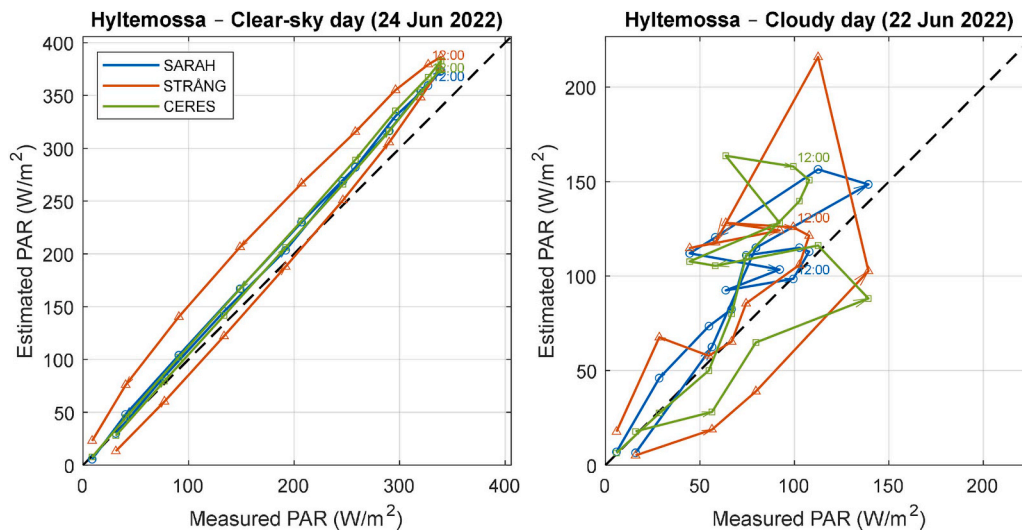


Fig. B1. Diurnal hysteresis of satellite-derived PAR estimates at Hyltemossa for a clear-sky day (left; 24 June 2022) and a cloudy day (right; 22 June 2022).

Each curve shows hourly estimated PAR from SARAH-3, STRÅNG and CERES plotted against measured PAR. Markers and connecting lines trace the diurnal progression, and the dashed line indicates the 1:1 reference. Under clear-sky conditions, products follow a single monotonic path with minimal hysteresis, whereas the cloudy day exhibits pronounced morning–afternoon divergence, especially for STRÅNG and CERES, illustrating the cloud- and solar-angle dependent behaviour.

Appendix C

To further validate the robustness of the spatial regression model, an additional validation was conducted using an independent dataset collected at the experimental APV facility at Kärrobo Prästgård (59.5593 °N, 16.7600 °E), near Västerås, Sweden. The dataset spans two complete years (2023–2024) and is not part of the ICOS network used for model training.

At this site, PAR was measured with a Delta-T Devices BF5 Sunshine Sensor, while GHI was recorded with a Delta-T SPN1 Pyranometer. The BF5

provides simultaneous measurements of total and diffuse PAR using a multi-sensor array with cosine correction, according to the manufacturer's specifications, the BF5 has a typical accuracy of $\pm 5\%$ for total PAR and $\pm 10\%$ for diffuse PAR under outdoor conditions, with spectral response from 400 to 700 nm (Delta-T Devices Ltd., 2016). The SPN1 has an accuracy of approximately $\pm 5\%$ for GHI and $\pm 8\%$ for diffuse irradiance, corresponding to an uncertainty of about $\pm 10\text{ W m}^{-2}$ for hourly averages (Delta-T Devices Ltd., 2016). The spatial regression model, previously calibrated using ICOS data (Degerö + Hyltemossa as training and Norunda for testing), was applied directly to this new dataset without any site-specific recalibration. The comparison between measured and modelled PAR is presented in Fig. C1, showing an $R^2 = 0.9947$, $\text{nMBE} = -1.3\%$, and $\text{nMAE} = 5.5\%$, confirming that the model performs with equally high accuracy at this independent location.

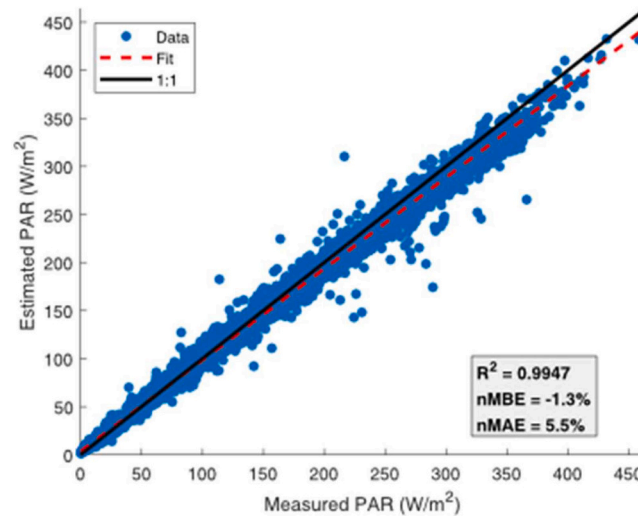


Fig. C1. Validation of the spatial regression model using data from the experimental APV facility at Kärro Prästgård (2023–2024).

Data availability

The reference to the data source is given in the manuscript. It can be retrieved from ICOS.

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