



Validation and calibration of models to estimate photosynthetically active radiation considering different time scales and sky conditions

Marian de Blas^a, Ana García-Rodríguez^b, Ignacio García^{a,*}, José Luis Torres^a

^a *Institute of Smart Cities (ISC), Department of Engineering, Public University of Navarre, Campus Arrosadía, 31006 Pamplona, Spain*

^b *Research Group Solar and Wind Feasibility Technologies (SWIFT), Electromechanical Engineering Department, University of Burgos, 09006 Burgos, Spain*

Received 2 January 2022; received in revised form 13 May 2022; accepted 3 July 2022

Abstract

Photosynthetically Active Radiation (*PAR*) is a fundamental parameter for developing plant productivity models. Nevertheless, instrumentation for measuring *PAR* and to record it is scarce at conventional meteorological stations. Several procedures have therefore been proposed for *PAR* estimation. In this work, 21 previously published analytical models that correlate *PAR* with easily available meteorological parameters are collected. Although longer time scales were considered in the original publications, a minute range was applied in this work to calibrate the *PAR* models. In total, more than 10 million input records were gathered from the SURFRAD station network from a 10-year long time series with data frequencies recorded every 1 min. The models were calibrated both globally, using data from all stations and locally, with data from each station. After calibration, the models were validated for minute, hourly and daily data, obtaining low fitting errors at the different stations in all cases, both when using the globally calibrated models and with the models calibrated for each location. Although the *PAR* results in general improved for locally calibrated models, the use of local models is not justified, since the global models presented offered very satisfactory *PAR* results for the different climatic conditions where the meteorological stations are located. Thus, *PAR* estimation model should then be selected, solely considering the meteorological variables available at the specific location. When applying the globally calibrated models to input data classified according to sky conditions (from clear to overcast), the *PAR* models continued to perform satisfactorily, although the error statistics of some models for overcast skies worsened.

© 2022 COSPAR. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Keywords: Photosynthetically active radiation; Solar irradiance; Sky types; Model calibration

1. Introduction

Photosynthetically Active Radiation (*PAR*) incident on the vegetal canopy is one of the basic parameters for the characterization of plant growth behavior, as plants use energy from solar radiation, emitted within the 400 and

700 nm spectral range, to activate photosynthesis that transforms solar into chemical energy.

The intensity of *PAR* that plants process is a key parameter to construct productivity models and cultivation strategies aimed at optimizing the use of energy. A number of published references considered the *PAR* levels that crops process as an input to model the behavior of mixed plantations: coconut/corn (Dauzat and Eroy, 1997), maize/peanut (Awal et al., 2006), wheat/cotton (Zhang et al., 2008), maize/soybean (Liu et al., 2018). Research

* Corresponding author.

E-mail address: ignacio.garcia@unavarra.es (I. García).

Nomenclature

| | | | |
|-------------------------|---|-----------------------|--|
| <i>AIC</i> | Akaike In formation Criterion | <i>N</i> | Total number of <i>PAR</i> data |
| <i>BIC</i> | Bayesian Information Criterion | <i>P₀</i> | Extra-terrestrial Photosynthetically Active Radiation on a horizontal surface ($W \cdot m^{-2}$) |
| <i>MPE</i> | Mean Percentage Error (%) | <i>P_{sc}</i> | Solar Constant of Photosynthetically Active Irradiance (preset value $530.8 W \cdot m^{-2}$) |
| <i>PAR</i> | Photosynthetically Active Radiation, expressed either in irradiance units ($W \cdot m^{-2}$) or as photon flux density (PPFD) ($\mu mol \cdot m^{-2} \cdot s^{-1}$) | <i>RH</i> | Relative humidity (%) |
| <i>RMSE</i> | Root Mean Squared Error ($W \cdot m^{-2}$) | <i>R²</i> | Determination coefficient |
| <i>RMSE_r</i> | Relative Root Mean Squared Error (%) | <i>SG</i> | Standard global irradiance |
| <i>RSD</i> | Relative Standard Deviation (%) | <i>Si</i> | Sky Index (Igawa, 2014) |
| <i>BSRN</i> | Baseline Surface Radiation Network | <i>T</i> | Air temperature ($^{\circ}C$) |
| <i>NIR</i> | Near InfraRed irradiance ($W \cdot m^{-2}$) | <i>T_d</i> | Dew point temperature ($^{\circ}C$) |
| <i>QC</i> | Quality Control | <i>e</i> | Vapor pressure (hPa) |
| <i>Cle</i> | Cloudless index | <i>k_T</i> | Clearness index (G/G_0) |
| <i>E_i</i> | Calculated value of <i>PAR</i> ($W \cdot m^{-2}$) | <i>k_c</i> | Clear sky index |
| <i>E_{avg}</i> | Average of calculated values of <i>PAR</i> ($W \cdot m^{-2}$) | <i>k_d</i> | Diffuse fraction or cloud ratio (G_d/G) |
| <i>G</i> | Global solar horizontal irradiance ($W \cdot m^{-2}$) | <i>k_{ds}</i> | Standard cloud ratio |
| <i>G₀</i> | Extra-terrestrial horizontal irradiance ($W \cdot m^{-2}$) | <i>m</i> | Relative optical air mass |
| <i>G_d</i> | Diffuse solar horizontal irradiance ($W \cdot m^{-2}$) | <i>w</i> | Precipitable water (cm) |
| <i>G_{0n}</i> | Extra-terrestrial normal irradiance ($W \cdot m^{-2}$) | <i>α_s</i> | Solar altitude (rad) |
| <i>G_{bn}</i> | Direct solar normal irradiance ($W \cdot m^{-2}$) | Δ | Sky's brightness (Perez et al., 1990) |
| <i>G_{sc}</i> | Solar Constant (preset value $1361.1 W \cdot m^{-2}$) | ε | Sky's clearness (Perez et al., 1990) |
| <i>M_i</i> | Measured value of <i>PAR</i> ($W \cdot m^{-2}$) | θ_z | Solar zenith angle (rad) |
| <i>M_{avg}</i> | Average of measured values of <i>PAR</i> ($W \cdot m^{-2}$) | | |

in the field of plant physiology and ecology has included the value of the incident *PAR* as a key variable for modeling the photosynthetic behavior of plants in response to sunlight (Bhattacharya, 2019; Campillo et al., 2012; Jajoo et al., 2014; Ogburn and Edwards, 2010), for selecting photosynthetically efficient cultivars (Peng et al., 2000), for analyzing the metabolic behavior of aquatic species (O'Gorman et al., 2012) and, in some examples, plant growth and flowering (Bredmose and Costes, 2017).

PAR can be measured in energetic terms ($W \cdot m^{-2}$) or in photobiological units, *i.e.*, in terms of photon flux density ($\mu mol \cdot m^{-2} \cdot s^{-1}$). The Photosynthetic Photon Flux Density (*PPFD*) is the number of photons in the 400–700 nm waveband incident on unit surface area in unit time (Foyo-Moreno et al., 2017). McCree (1972) proposed a widely employed constant ratio of $4.57 \mu mol \cdot J^{-1}$ between the *PPFD* and the incident *PAR* in terms of energy. Actually, there is a monochromatic relationship between these two variables and, therefore, the integrated broadband photon flux cannot be directly obtained from the global irradiance in the 400–700 nm waveband (Ross and Sulev, 2000; Sun et al., 2017). Notwithstanding, Akitsu et al. (2015) analyzed the dependence of McCree's ratio on climatic factors and considered the constant value acceptable for most purposes.

Existing instruments for measuring *PAR* can be classified into two classes (Mottus et al., 2012): *PAR* quantum photovoltaic sensors that are sensitive to photoelectric

effects; and *PAR* energy sensors, which mainly include thermoelectric instruments. In addition, some field instruments of these technologies have been developed for measuring absorbed *PAR* in crops and pastures (Rahman et al., 2014) and for obtaining the daily light integral in greenhouses (Torres and Lopez, 2012). Nevertheless, despite the *PAR* value being a key variable in physiological models of plant growth, there are only a limited number of meteorological stations around the world that provide data with reliable measurements of this parameter for research (Foyo-Moreno et al., 2017). It is also difficult to maintain measurement accuracy and there is no standard for the quality control of *PAR* measurements (Mizoguchi et al., 2010; Mizoguchi et al., 2014).

More often than not, *PAR* is therefore indirectly estimated from other parameters. The physical relationship between *PAR* and global irradiance (*G*) depends on the absorption and dispersion caused by the atmospheric components such as aerosol, water vapor, ozone, and clouds (Janjai et al., 2015).

Some current *PAR* estimation models include inputs obtained from satellite data (Hao et al., 2020; Janjai et al., 2015; Vindel et al., 2018). Likewise, radiative transfer models use either satellite or terrestrial observations or both (Akitsu et al., 2015; Li et al., 2015; Tang et al., 2017; Wandji Nyamsi et al., 2015; Wandji Nyamsi et al., 2019).

In general, *PAR* results from physical models are very good, but the required input and the application of the

models can be difficult for first-time users. In contrast, semi-empirical models can correlate PAR or the PAR/G ratio with other parameters directly measured at weather stations or derived from weather station data (Aguilar et al., 2012; Alados et al., 1996; Foyo-Moreno et al., 2017; Ge et al., 2011; Hu et al., 2007; Janjai et al., 2015; Li et al., 2010; Mizoguchi et al., 2014; Wang et al., 1961; Yu et al., 2015; Vindel et al., 2018). Various models also use artificial neural network techniques with calculable parameters (Ferrera-Cobos et al., 2020; García-Rodríguez et al., 2021; Jacovides et al., 2015; Wang et al., 2016; Zempila et al., 2016).

The models cited above considered a time scale ranging from 10 min to monthly PAR values. Literature reviews revealed that the fitting quality of the different models varied as a function of meteorological, seasonal, and geographic characteristics of locations. The correlation between PAR and the meteorological parameters also differed, depending on the local conditions (García-Rodríguez et al., 2020; García-Rodríguez et al., 2021; Wang et al., 2016). An exhaustive review of empirical models for PAR estimation can be found in Nwokolo and Amadi (2018).

In the study by Li et al. (2010), the PAR/G ratio increased under high humidity or cloudy conditions, because water vapor content in the atmosphere increases the absorption of radiation in the NIR spectrum, whereas the absorption of radiation is unaffected in the PAR region. Yu et al. (2015) analyzed the influence of parameters on semi-empirical models using experimental PAR data from the Surface Radiation Budget Network (SURFRAD) for a daily temporal resolution. They observed a high correlation between daily PAR/G and the clearness index (k_T), *i.e.*, the global solar horizontal irradiance over the corresponding extra-terrestrial irradiance (G/G_0). This ratio denoted high values for low k_T and vice versa. Likewise, a negative correlation was obtained between the PAR/G ratio and the cosine of the solar zenith angle ($\cos \theta_z$) and dew point temperature (T_d) and a positive correlation between that ratio and both the diffuse fraction (k_d) and the sky's brightness (Δ) values. They also concluded, unlike other published research, that the dew point value, used to describe atmospheric humidity, had no significant influence on the PAR/G ratio.

A physical model was published (Sun et al., 2017) to estimate PAR from both global and direct radiation in the spectral region between 200 and 700 nm. This model was validated using data with a 1-min temporal resolution that included a part of the experimental PAR data used in the present research.

In general, the semi-empirical models reported in the literature yielded accurate results, by means of a simple mathematical expression, when applied under local conditions similar to those considered for calibration. In contrast, the transferability of models to other locations and their local adaptation still needs further discussion (García-Rodríguez et al., 2021).

When the calibration site and the location of interest have comparable atmospheric conditions, it is expected that the atmospheric conditions in both places will cause a similar attenuation of solar radiation in the PAR wavelength range. Therefore, the model for PAR determination should produce accurate results. Different coefficients in similar equations have been proposed, to take into account the sky conditions (Ferrera-Cobos et al., 2020; Jacovides et al., 2007; Wang et al., 1961; Yu et al., 2015).

In this work, 21 models for PAR estimation were calibrated and evaluated. For this purpose, a 10-year long series of 1-min resolution data was configured from data recorded at seven weather stations within the SURFRAD network, covering a wide range of climatic conditions in the USA. The main objective of this work is to present models that can be generally applied and that provide accurate PAR values using meteorological variables measured at ground stations and considering time intervals between one minute and one day. An objective that was achieved with a data set of more than 10 million PAR and meteorological measurements that are representative of a large variety of regional and weather conditions.

The expected errors in PAR estimation when the 21 models under analysis were applied, were firstly quantified for all sky conditions together and then considering the prevailing sky conditions. By doing so, users who need to know the PAR at a given location are provided with a set of easy-to-implement equations and they can select the most appropriate model, depending on the available meteorological input data. In order to analyze the effect of local climatic conditions on PAR estimation, models were also calibrated using data from each particular weather station and the obtained PAR values were compared with PAR resulting from applying the globally calibrated models at each location.

This paper is organized into five sections. The meteorological data and its classification in sky types are detailed in Section 2. In Section 3, the PAR models and the calibration procedure is described. The calibrated models for the minute-time scale and the statistical analysis of the results when the models were applied to three-time scales (minute, hourly, and daily) and to different sky types are presented in Section 4. Finally, the conclusions are detailed in Section 5.

2. Weather data

We used high quality datasets retrieved from the Surface Radiation Budget Network (SURFRAD) FTP Server based in the United States: PAR on the horizontal plane, global and diffuse solar irradiance on the horizontal plane, air temperature and relative humidity.

Global PAR was measured with an LI-COR Quantum sensor within the 400 to 700 nm broadband range. PAR values are given in $W \cdot m^{-2}$. The G values were obtained from a Spectrolab SR-75 pyranometer and diffuse irradi-

ance was measured on the horizontal plane with an Eppley 8–48 pyranometer. Both pyranometers measure data within the 280–3000 nm broadband range.

The seven stations belonging to the SURFRAD network are distributed throughout different climatic areas in the United States, as shown in Fig. 1. The Köppen-Geiger climate classification map shown in Fig. 1 was extracted from Beck et al. (2018). The ground properties of these stations were described in Wandji Nyamsi et al. (2019). Table 1 shows the geographical location and the basic climatic data from the seven weather stations.

All the SURFRAD stations never started to take measures at the same time. The earliest radiation measurements were taken in 1995 and the latest, in 2003. Notwithstanding, with the aim of comparing similar series of data for model calibration purposes, we considered a common time range of records between 1/1/2009 and 31/12/2018 at every station, with a temporal resolution of 1 min. Irradiance data collected at the stations within the network had previously passed the Baseline Surface Radiation Network (BSRN) quality control checks, as explained in Long and Dutton (2002). Unfortunately, criteria for Quality Control (QC) of *PAR* are neither covered in the BSRN procedures or in any assessment standards we have consulted in the bibliography available to us. Therefore, an in-house QC method described below was set in accordance with the physical limits of *PAR*. Global *PAR* on the horizontal plane cannot be higher than extraterrestrial *PAR* on the horizontal plane corresponding to the same time. Extrater-

restrial *PAR* on the horizontal plane (P_0) is calculated with the correction factor (f_c) applied to the *PAR* solar constant (P_{sc}) that takes into account the eccentricity of the Earth’s orbit and then multiplies the result by the cosine of the solar zenith angle, Eq. (1).

$$P_0 = f_c P_{sc} \cos \theta_z. \quad (1)$$

Gueymard (2018) obtained a value of $1361.1 \text{ W} \cdot \text{m}^{-2}$ for the solar constant (G_{sc}), but no standardized value for the irradiance in the *PAR* spectral range. Thus, the irradiance curve between 400 and 700 nm of the extraterrestrial spectrum proposed by Gueymard et al. (2002) was integrated, in order to estimate this constant, resulting in a value of $530.8 \text{ W} \cdot \text{m}^{-2}$. Gueymard’s extraterrestrial spectrum is proposed to determine the reference AM1.5 spectrum specified in standard IEC 60904–3:2019 (IEC, 2019). Data corresponding to solar elevation angles lower than 5° were discarded to avoid the cosine response problems of global irradiance and *PAR* measuring instruments. Table 2 shows the number of data initially available at each station and the number of records that passed the QC checks.

Data were classified into five sky types according to the Sky Index (Si), Eq. (2), proposed by Igawa (2014) that can be seen in Table 3. This classification allowed us to analyze the influence of a given atmospheric condition, represented by the sky type, on the behavior of the models to be evaluated.

$$Si = \sqrt{(1 - k_c)^2 - (1 - Cle^{0.5})^2}, \quad (2)$$

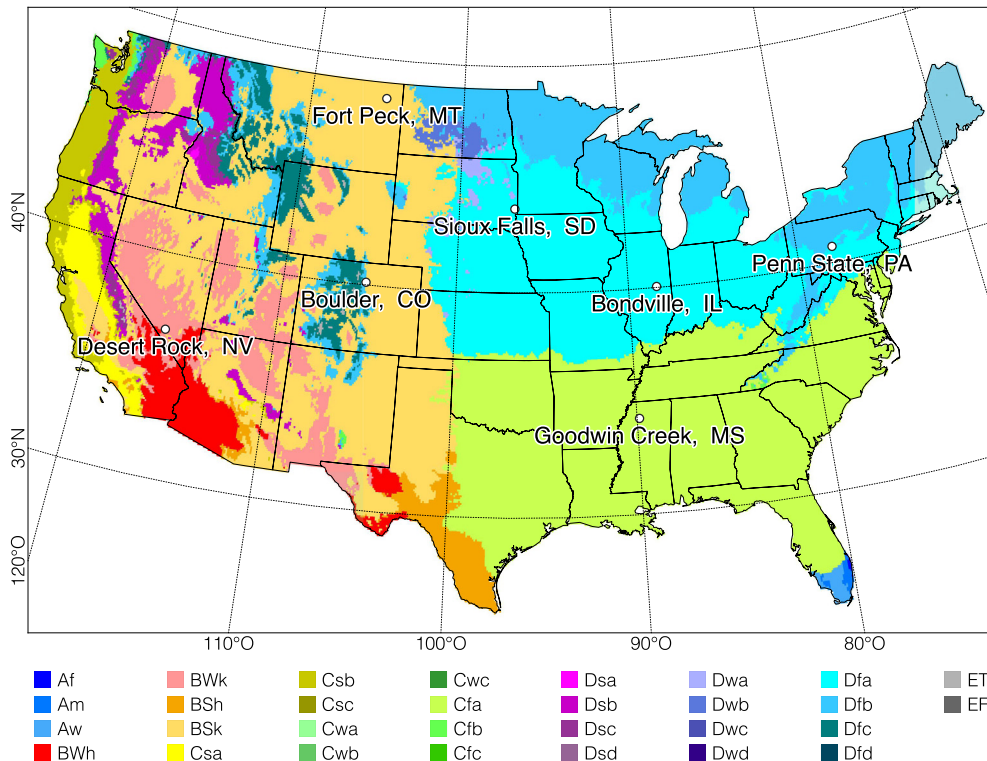


Fig. 1. Locations of the seven SURFRAD stations. Köppen-Geiger climate classification map extracted from Beck et al. (2018).

Table 1
Geographical location and basic climatic data from the seven SURFRAD weather stations.

| Station | Code | Latitude (°N) | Longitude (°W) | Elevation (m) | Average temperature (°C) | Average relative humidity (%) | Average G ($W \cdot m^{-2}$) | Average PAR ($W \cdot m^{-2}$) | Köppen-Geiger class (*) |
|---------------------------------|------|---------------|----------------|---------------|--------------------------|-------------------------------|----------------------------------|------------------------------------|-------------------------|
| Bondville, Illinois | BON | 40.0519 | 88.3731 | 230 | 11.53 | 72.65 | 170.46 | 73.82 | Dfa |
| Table Mtn., Boulder, Colorado | TBL | 40.1250 | 105.237 | 1689 | 12.25 | 46.92 | 193.71 | 84.29 | Bsk |
| Desert Rock, Nevada | DRA | 36.6237 | 116.019 | 1007 | 18.81 | 28.04 | 235.18 | 104.22 | Bwk |
| Fort Peck, Montana | FPK | 48.3078 | 105.102 | 634 | 5.84 | 67.24 | 161.89 | 72.66 | Bsk |
| Goodwin Creek, Mississippi | GWN | 34.2547 | 89.8729 | 98 | 16.73 | 71.89 | 182.14 | 79.07 | Cfa |
| Penn. State Univ., Pennsylvania | PSU | 40.7201 | 77.9309 | 376 | 10.52 | 70.01 | 152.83 | 65.73 | Dfa |
| Sioux Falls, South Dakota | SXF | 43.734 | 96.6233 | 473 | 7.96 | 73.13 | 166.50 | 74.40 | Dfa |

(*) Bwk (arid, desert, cold), Bsk (arid, steppe, cold), Cfa (temperate, no dry season, hot summer), Dfa (cold, no dry season, hot summer).

where k_c is the clear sky index, Eq. (3), and Cle is the cloudless index calculated by Eq. (7).

$$k_c = G/SG. \quad (3)$$

$$Cle = (1 - k_d)/(1 - k_{ds}), \quad (4)$$

where G is the global horizontal irradiance, SG the standard global irradiance, calculated by Eq. (5), k_d the diffuse fraction (G_d/G), referred to as cloud ratio by Igawa (2014), and k_{ds} the standard cloud ratio, Eq. (6).

$$SG = \frac{0.84G_{sc}}{m \exp(-0.054m)}. \quad (5)$$

$$k_{ds} = 0.08302 + 0.5358 \exp(-17.3\alpha_s) + 0.3818 \times \exp(-3.2899\alpha_s), \quad (6)$$

where m the relative optical air mass (Kasten and Young, 1989) and α_s is the solar altitude, expressed in radians.

Table 4 shows the number of available measurements at each station to calibrate and to validate PAR estimation models after having passed the QC. Calibration of a model implies using 50% of the data, alternatively chosen, for the model calibration and 50% to validate the resulting expressions.

SURFRAD stations register a large number of meteorological variables, but only those necessary for the application of the models described in Section 3 were considered in this paper: global PAR on the horizontal plane (PAR), global (G) and diffuse (G_d) horizontal irradiance, and air temperature (T) and relative humidity (RH). However, various models consider the atmospheric water vapor content by means of the dew point (T_d), the vapor pressure (e) or the precipitable water content (w). These parameters are not directly registered in the stations; hence they were estimated on the basis of T and RH . T_d and e were calculated according to Eqs. (7) and (8).

$$T_d = \frac{243.04 \left(\ln \left(\frac{RH}{100} \right) + \frac{17.625T}{T+243.04} \right)}{17.625 - \ln \left(\frac{RH}{100} \right) - \frac{17.625T}{T+243.04}}. \quad (7)$$

$$e = 6.11 \frac{RH}{100} \cdot 10^{\frac{7.5T}{T+237.3}}. \quad (8)$$

The precipitable water content (w) was obtained from Leckner (1978), according to Eq. (9).

$$w = \frac{0.00493e_s RH}{T + 273.15}. \quad (9)$$

w depends on the partial pressure of water vapor in saturated air (e_s), calculated by Eq. (10).

$$e_s = \exp \left(26.23 - \frac{5416}{T + 273.15} \right). \quad (10)$$

Some of the analyzed models also depend on one or both of the variables proposed by Perez et al. (1990) to parameterize the sky conditions, i.e., the sky's clearness and brightness. The sky's clearness (ϵ) can be calculated according to Eq. (11).

Table 2

Total number of records available at each SURFRAD network station and number of records that passed the QC checks.

| | Station | | | | | | |
|--|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| | BON | DRA | FPK | GWN | PSU | SXF | TBL |
| Available data ($\theta_z < 85^\circ$) | 1,501,535 | 1,769,842 | 2,130,006 | 1,627,176 | 1,634,785 | 1,440,148 | 1,602,364 |
| Data passing QC | 1,371,257 | 1,545,048 | 1,852,600 | 1,363,076 | 1,478,690 | 1,310,735 | 1,413,606 |
| Data passing QC (%) | 91.32 | 87.30 | 86.98 | 83.77 | 90.45 | 91.01 | 88.22 |

Table 3

Sky classification according to the Sky Index (S_i) proposed by Igawa (2014).

| Sky classification | Sky Index (S_i) |
|--|-----------------------|
| Clear Sky (Clear) | < 0.15 |
| Intermediate Clear Sky (I-Clear) | $0.15 \leq S_i < 0.3$ |
| Intermediate Sky (Intermediate) | $0.3 \leq S_i < 0.9$ |
| Intermediate Overcast Sky (I-Overcast) | $0.9 \leq S_i < 1.15$ |
| Overcast Sky (Overcast) | $S_i \geq 1.15$ |

$$\varepsilon = \frac{\frac{(G_d + G_{bn})}{G_d} + 1.041\theta_z^3}{1 + 1.041\theta_z^3}, \quad (11)$$

where G_{bn} is the direct normal irradiance and the solar zenith angle (θ_z) should be expressed in radians.

The sky's brightness (Δ) is given by Eq. (12).

$$\Delta = \frac{mG_d}{G_{0n}}, \quad (12)$$

where G_{0n} is the extra-terrestrial normal irradiance.

3. Methodology

Table 5 shows the mathematical expressions corresponding to the 21 models considered in this work for estimating PAR and their corresponding source. Models M1 to M10 for the PAR/G fraction were previously calibrated

by Yu et al. (2015), considering daily values obtained from the SURFRAD network over the period between 2009 and 2010 and for all sites and all sky conditions together. The resulting R^2 values ranged from 0.4599 (M5) to 0.5475 (M10), which are low values for this parameter, and RMSE values (in $\text{MJ} \cdot \text{m}^{-2}$) from 0.02131 (M9) to 0.02326 (M7). It should be noted that Yu et al. (2015) attributed models M5 to M10 to various authors, but on consulting the referenced publications, it was found that the models and the citations could not be cross-referenced. In this work, we have therefore attributed the models whose original reference is uncertain to Yu et al. (2015).

We downloaded 10,335,012 data items (Table 3) from all stations that had passed the QC to conduct the calibration process described in this work and to fit the results of models M1 to M21. All the models were fitted for PAR (in $\text{W} \cdot \text{m}^{-2}$) and not for the PAR/G fraction, in order to achieve homogeneity. However, models M1 to M13 and M19 were originally published considering PAR/G as the dependent variable. A 1-min time base was used to adjust the models, because the PAR values obtained with this frequency were thought to provide users with useful input data for later studies that might require in-depth analysis. The behavior of the models obtained from the adjustment considering an hourly basis was also evaluated, since data from the input parameters required in the models is often available at this frequency. Furthermore, 1-day input data

Table 4

Total data and data classified according to the sky type that have passed the quality control and the solar minimum elevation parameter for each station. Time series includes data from 2009 to 2018.

| Station | All sky | Clear | I-Clear | Intermediate | I-Overcast | Overcast |
|---------|------------|-----------|-----------|--------------|------------|----------|
| BON | 1,371,257 | 636,401 | 259,743 | 352,698 | 105,381 | 17,034 |
| % | 100 | 46.41 | 18.94 | 25.72 | 7.68 | 1.24 |
| DRA | 1,852,600 | 1,399,386 | 185,258 | 214,100 | 49,715 | 4,141 |
| % | 100 | 75.54 | 10 | 11.56 | 2.68 | 0.22 |
| FPK | 1,363,076 | 682,583 | 232,362 | 323,409 | 108,049 | 16,673 |
| % | 100 | 50.08 | 17.05 | 23.73 | 7.93 | 1.22 |
| GWN | 1,478,690 | 700,298 | 265,390 | 340,367 | 138,794 | 33,841 |
| % | 100 | 47.36 | 17.95 | 23.02 | 9.39 | 2.29 |
| PSU | 1,310,735 | 490,228 | 216,272 | 348,225 | 200,990 | 55,020 |
| % | 100 | 37.4 | 16.5 | 26.57 | 15.33 | 4.2 |
| SXF | 1,413,606 | 701,128 | 229,540 | 327,663 | 130,533 | 24,742 |
| % | 100 | 49.6 | 16.24 | 23.18 | 9.23 | 1.75 |
| TBL | 1,545,048 | 883,883 | 182,998 | 314,297 | 138,336 | 25,534 |
| % | 100 | 57.21 | 11.84 | 20.34 | 8.95 | 1.65 |
| Total | 10,335,012 | 5,493,907 | 1,571,563 | 2,220,759 | 871,798 | 176,985 |
| % | 100 | 53.16 | 15.21 | 21.49 | 8.44 | 1.71 |

Table 5
Models evaluated for PAR estimation.

| Model | Expression | Variables | Reference |
|-------|--|--|-----------------------------|
| M1 | $PAR = G(a_1 \ln \varepsilon + b_1 \ln \Delta + c_1 T_d + d_1 \cos^2 \theta_z + f_1)$ | $G, \varepsilon, \Delta, T_d, \cos \theta_z$ | Alados et al. (1996) |
| M2 | $PAR = G(a_2 \ln \varepsilon + b_2 \ln \Delta + c_2 \cos^2 \theta_z + d_2)$ | $G, k_d, \Delta, \cos \theta_z$ | Alados et al. (1996) |
| M3 | $PAR = G(a_3 \ln k_T + b_3 T_d + c_3 \cos \theta_z + d_3)$ | $G, k_T, T_d, \cos \theta_z$ | Alados et al. (1996) |
| M4 | $PAR = G(a_4 \ln k_T + b_4 \cos \theta_z + c_4)$ | $G, k_T, \cos \theta_z$ | Alados et al. (1996) |
| M5 | $PAR = G(a_5 \ln k_T + b_5)$ | G, k_T | Wandji Nyamsi et al. (2019) |
| M6 | $PAR = G[a_6 (\ln k_T)^2 + b_6 \ln k_T + c_6]$ | G, k_T | Yu et al. (2015) |
| M7 | $PAR = G(a_7 \ln k_d + b_7 \ln \Delta + c_7)$ | G, Δ, k_d | Yu et al. (2015) |
| M8 | $PAR = G[a_8 (\ln k_T)^2 + b_8 \ln k_T + c_8 T_d + d_8]$ | G, k_T, T_d | Yu et al. (2015) |
| M9 | $PAR = G[a_9 (\ln k_T)^2 + b_9 \ln k_T + c_9 \cos \theta_z + d_9]$ | $G, k_T, \cos \theta_z$ | Yu et al. (2015) |
| M10 | $PAR = G[a_{10} (\ln k_T)^2 + b_{10} \ln k_T + c_{10} T_d + d_{10} \cos \theta_z + f_{10}]$ | $G, k_T, T_d, \cos \theta_z$ | Yu et al. (2015) |
| M11 | $PAR = G(a_{11} \ln \varepsilon + b_{11} \ln \Delta + c_{11} \ln w + d_{11} \cos \theta_z + f_{11})$ | $G, \varepsilon, \Delta, w, \cos \theta_z$ | Hu et al. (2007) |
| M12 | $PAR = G(a_{12} \ln \varepsilon + b_{12} \ln \Delta + c_{12} \cos \theta_z + d_{12})$ | $G, \varepsilon, \Delta, \cos \theta_z$ | Hu et al. (2007) |
| M13 | $PAR = G(a_{13} \ln k_T + b_{13} w + c_{13} \cos \theta_z + d_{13})$ | $G, k_T, w, \cos \theta_z$ | Hu et al. (2007) |
| M14 | $PAR = (a_{14} k_T + b_{14} k_T^2 + c_{14} k_T^3 + d_{14}) (\cos \theta_z)^{14}$ | $k_T, \cos \theta_z$ | Wang et al. (1961) |
| M15 | $PAR = a_{15} k_T \cos \theta_z$ | $k_T, \cos \theta_z$ | Foyo-Moreno et al. (2017) |
| M16 | $PAR = a_{16} G + b_{16}$ | G | Aguiar et al. (2012) |
| M17 | $PAR = a_{17} G + b_{17} k_T + c_{17}$ | G, k_T | Aguiar et al. (2012) |
| M18 | $PAR = a_{18} G + b_{18} k_T + c_{18} \Delta e + d_{18}$ | G, k_T, Δ, e | Aguiar et al. (2012) |
| M19 | $PAR = G(a_{19} \ln k_T + b_{19} \ln m + c_{19} e + d_{19})$ | G, k_T, m, e | Mizoguchi et al. (2014) |
| M20 | $PAR = a_{20} G + b_{20} G \cos \theta_z + c_{20} G k_T + d_{20}$ | $G, k_T, \cos \theta_z$ | Ge et al. (2011) |
| M21 | $PAR = a_{21} k_T \cos \theta_z + b_{21}$ | $k_T, \cos \theta_z$ | Variation of M15 |

were also considered for testing the models, since the results may be of interest for comparison with other previous studies where daily PAR values were obtained.

In order to evaluate the dependence of the models on the local conditions of each station, two analyses were performed. First, the behavior of each of the 21 globally fitted models –considering all the stations of the SURFRAD network– was evaluated for each of the stations. Secondly, a local calibration of the models was carried out using data from each site. In this way, it was possible to compare the performance of the locally fitted models with the global ones. It should be remembered that, in all cases, the distribution of data for calibration and validation was carried out according to the criterion described in Section 2, *i.e.*, half of the dataset for calibration and the other half for validation.

The following statistics, described by Eqs. (13)–(17), were used for the validation of the models:

- Determination coefficient:

$$R^2 = \frac{\sum_{i=1}^N (E_i - E_{avg})(M_i - M_{avg})}{\left\{ \left[\sum_{i=1}^N (E_i - E_{avg})^2 \right] \left[\sum_{i=1}^N (M_i - M_{avg})^2 \right] \right\}^{0.5}} \quad (13)$$

- Root Mean Squared Error:

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^N (E_i - M_i)^2 \right]^{0.5} \quad (14)$$

- Relative Root Mean Squared Error:

$$RMSEr(\%) = \frac{100}{M_{avg}} \left[\frac{1}{N} \sum_{i=1}^N (E_i - M_i)^2 \right]^{0.5} \quad (15)$$

- Relative Standard Deviation:

$$RSD(\%) = \left[\frac{1}{N} \sum_{i=1}^N \left(\frac{E_i - M_i}{M_i} \right)^2 \right]^{0.5} 100. \quad (16)$$

- Mean Percentage Error:

$$MPE(\%) = \frac{1}{N} \left(\sum_{i=1}^N \frac{E_i - M_i}{M_i} \right) 100, \quad (17)$$

where E_i is the calculated value, E_{avg} is the mean of the calculated values, M_i is the measured value, M_{avg} is the mean of the measured values and N is the total number of data items.

The Akaike Information Criterion (*AIC*) and the Bayesian Information Criterion (*BIC*), calculated by Wolfram Mathematica® software, were used to measure the relative quality of the models under analysis, in order to select the model that was sufficiently good and simple, *i.e.*, the most parsimonious model. The underlying idea was to find a balance between the goodness of fit of a model and its complexity.

4. Results and discussion

4.1. Globally calibrated models evaluated both globally and locally for each SURFRAD station

Table 6 shows the results of the coefficients for models M1 to M21 globally calibrated, *i.e.*, considering all sites and sky types together.

Due to space reasons, given the length of the results to be shown, the estimation errors obtained by the models

Table 6

Globally calibrated models for PAR using 1-min input data from all stations and obtained determination coefficients (R^2).

| Model | Calibrated expression | R^2 |
|-------|---|--------|
| M1 | $PAR = G(-0.0206671 \cos^2 \theta_z - 0.028342 \ln \Delta - 0.0270876 \ln \varepsilon + 0.000152279T_d + 0.425525)$ | 0.9987 |
| M2 | $PAR = G(-0.0182345 \cos^2 \theta_z - 0.0286075 \ln \Delta - 0.0280839 \ln \varepsilon + 0.425987)$ | 0.9987 |
| M3 | $PAR = G(-0.028706 \cos \theta_z - 0.0278875 \ln k_T + 0.000129279T_d + 0.437906)$ | 0.9988 |
| M4 | $PAR = G(-0.0258378 \cos \theta_z - 0.0295837 \ln k_T + 0.435928)$ | 0.9988 |
| M5 | $PAR = G(0.415212 - 0.0350336 \ln k_T)$ | 0.9987 |
| M6 | $PAR = G(-0.0340535 (\ln k_T)^2 - 0.0757318 \ln k_T + 0.406944)$ | 0.9987 |
| M7 | $PAR = G(0.0336608 \ln k_d - 0.0349165 \ln \Delta + 0.413051)$ | 0.9986 |
| M8 | $PAR = G(-0.0349876 (\ln k_T)^2 - 0.0774526 \ln k_T - 0.0000716119T_d + 0.406896)$ | 0.9987 |
| M9 | $PAR = G(-0.02303 \cos \theta_z - 0.0197733 (\ln k_T)^2 - 0.0538075 \ln k_T + 0.428876)$ | 0.9988 |
| M10 | $PAR = G(-0.0255814 \cos \theta_z - 0.0169287 (\ln k_T)^2 - 0.0490527 \ln k_T + 0.0000967929T_d + 0.431371)$ | 0.9988 |
| M11 | $PAR = G(-0.0297581 \cos \theta_z - 0.0284931 \ln \Delta - 0.0271005 \ln \varepsilon + 0.0022675 \ln w + 0.435327)$ | 0.9988 |
| M12 | $PAR = G(-0.0264467 \cos \theta_z - 0.0287232 \ln \Delta - 0.028097 \ln \varepsilon + 0.434845)$ | 0.9987 |
| M13 | $PAR = G(-0.0279869 \cos \theta_z - 0.0281807 \ln k_T + 0.000938004w + 0.436261)$ | 0.9988 |
| M14 | $PAR = (\cos \theta_z)^{0.928878} (-167.836k_T^3 + 202.545k_T^2 + 481.162k_T + 16.7594)$ | 0.9987 |
| M15 | $PAR = 574.278k_T \cos \theta_z$ | 0.998 |
| M16 | $PAR = 0.413286G + 8.38447$ | 0.9939 |
| M17 | $PAR = 0.414235G - 1.94159k_T + 9.13333$ | 0.9939 |
| M18 | $PAR = 0.0885944e + 0.41312G - 0.0993371k_T + 7.6279$ | 0.994 |
| M19 | $PAR = G(0.000155103e - 0.0277219 \ln k_T + 0.0176706 \ln m + 0.409838)$ | 0.9988 |
| M20 | $PAR = 0.474298G - 0.0196574G \cos \theta_z - 0.0483035Gk_T + 1.403$ | 0.9943 |
| M21 | $PAR = 550.309k_T \cos \theta_z + 11.5173$ | 0.9929 |

are included in [Appendix A. Table A.1](#) shows the statistical results derived from the fit of the experimental data with the theoretical models at minute frequency. Experimental data were evaluated for all sites together and by station, in order to analyze the local effect. All the models yielded very satisfactory fitted results, with values of R^2 over 0.99. When 1-min frequency was considered for input data, $RMSE$ values ranged from $8.416 \text{ W} \cdot \text{m}^{-2}$ in M10 to $10.93 \text{ W} \cdot \text{m}^{-2}$ in M15 for all sites together. At the stations BON, PSU and TBL with Dfa climate (cold, no dry season, hot summer), $RMSE$ values ranged between $7.451 \text{ W} \cdot \text{m}^{-2}$ (M10) and $11.742 \text{ W} \cdot \text{m}^{-2}$ (M15). At GWN station with Cfa climate (temperate, no dry season, hot summer), the range of $RMSE$ variation was narrower, between $9.034 \text{ W} \cdot \text{m}^{-2}$ (M10) and $10.307 \text{ W} \cdot \text{m}^{-2}$ (M15). Two stations (FPK and TBL) are located in Bsk (arid, steppe, cold) climate sites. In this case, $RMSE$ values varied between $6.875 \text{ W} \cdot \text{m}^{-2}$ (M10) and $10.842 \text{ W} \cdot \text{m}^{-2}$ (M15). At the DRA station located in Bwk climate (arid, desert, cold), $RMSE$ ranged from $8.061 \text{ W} \cdot \text{m}^{-2}$ (M4) to $11.846 \text{ W} \cdot \text{m}^{-2}$ (M15).

[Figs. 2–4](#) show the $RMSEr$ values obtained when globally fitted models M1 to M21 were applied to all sites together and to individual stations, considering time frequencies for input data of 1 min, 1 h, and 1 day. When the globally calibrated models listed in [Table 6](#) were applied on hourly or daily input data, the good quality of the fitted results was maintained; no single model stood out due to its better or worse performance. Only the behavior of the M15 and M21 models was somewhat worse, as was the case in the previous minute-time scale calibration. The obtained $RMSEr$ values were somewhat smaller for all models and all time scales at the stations located in arid climate sites (FPK, TBL, DRA) than at those located in more

humid sites (SXF, BON, PSU). As can be seen, relative deviations were low, although in some of the models some of the statistics were somewhat higher. Based on these results of the models under study, it cannot be said that there are one or more models that stand out for their good or bad quality. AIC and BIC values were also used to assess model fit for all sites together but the results obtained were inconclusive.

4.2. Locally calibrated models for each SURFRAD station

Models M1 to M21 were also calibrated from 1-min frequency data at each of the seven stations of the SURFRAD network, representative of different climatic conditions. The locally calibrated models for each station are shown in [Tables B.1 to B.7](#) in [Appendix B](#). This way it was possible to analyze if models fitted for specific local conditions improve the estimates of PAR . [Table A.2](#) in [Appendix A](#) shows the statistical errors obtained after validation of the fitted models for each station from 1-min data.

[Figs. 5–7](#) show the obtained $RMSEr$ values at the different stations when the models, calibrated for each location, were applied to experimental data at 1-min, 1-h and 1-day frequency. In general, the $RMSEr$ values obtained decreased at all stations and for all models when the models were calibrated with data corresponding to the locality. However, the improvement of this statistical parameter was not significant when comparing the $RMSEr$ values obtained by the models calibrated for all stations together ([Figs. 2–4](#)) with that corresponding to the calibration by locality ([Figs. 5–7](#)). Thus, for 1-min data, the model with the lowest $RMSEr$ at each station in the global calibration

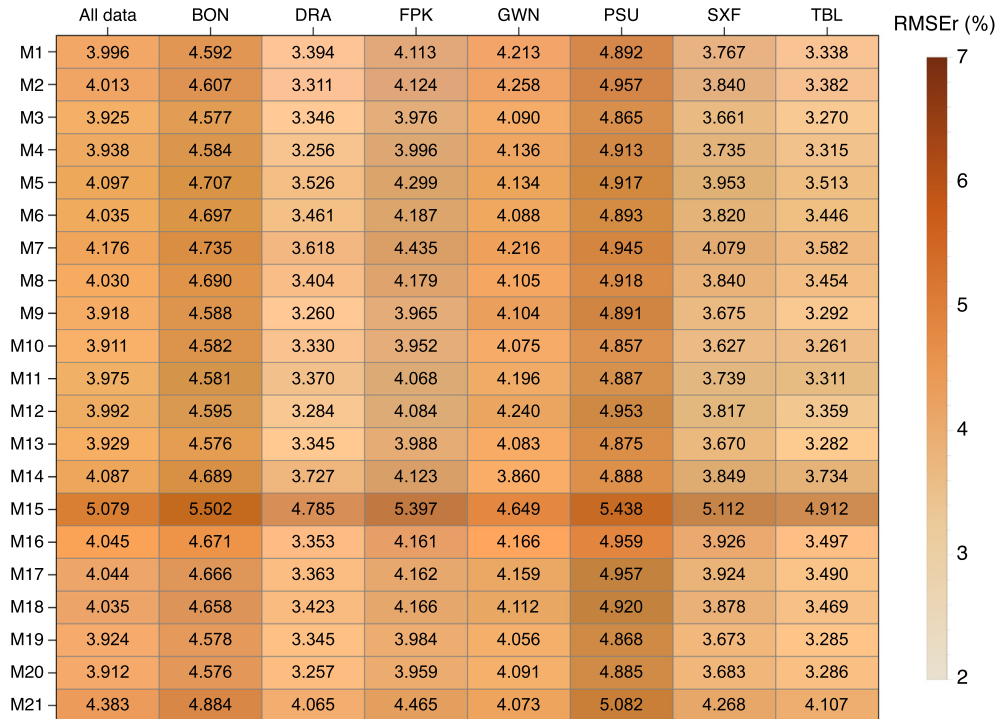


Fig. 2. *RMSEr* values (%) obtained for each model after validation, using 1-min data, of the models fitted globally from 1-min data. The errors obtained globally –considering all sites– and at each SURFRAD station are shown.

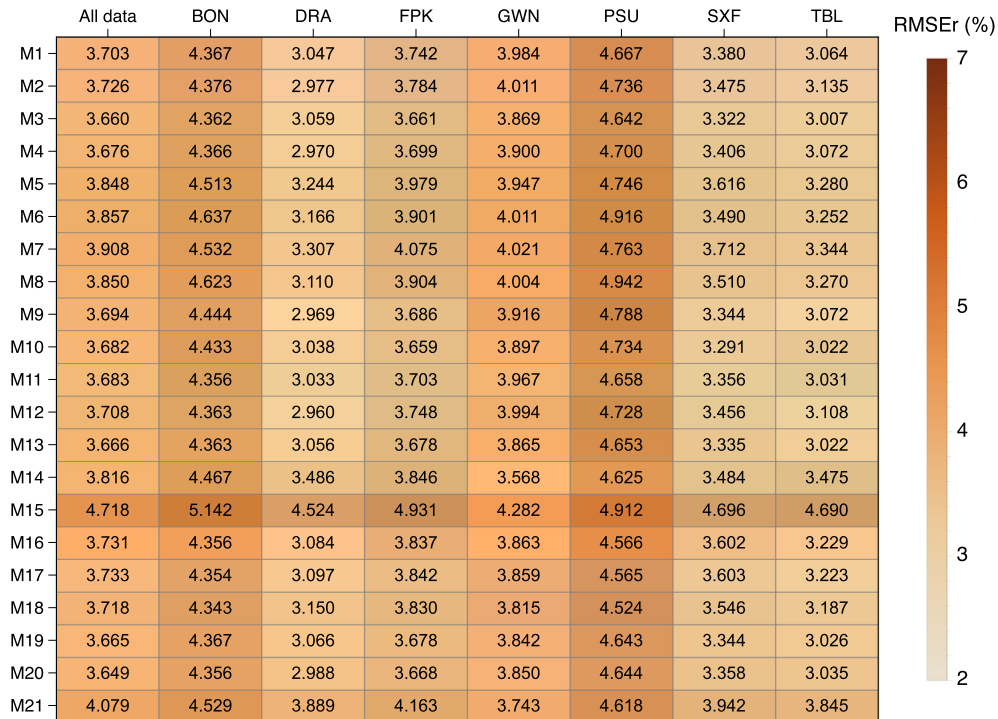


Fig. 3. *RMSEr* values (%) obtained for each model after validation, using 1-h data, of the models fitted globally from 1-min data. The errors obtained globally –considering all sites– and at each SURFRAD station are shown.

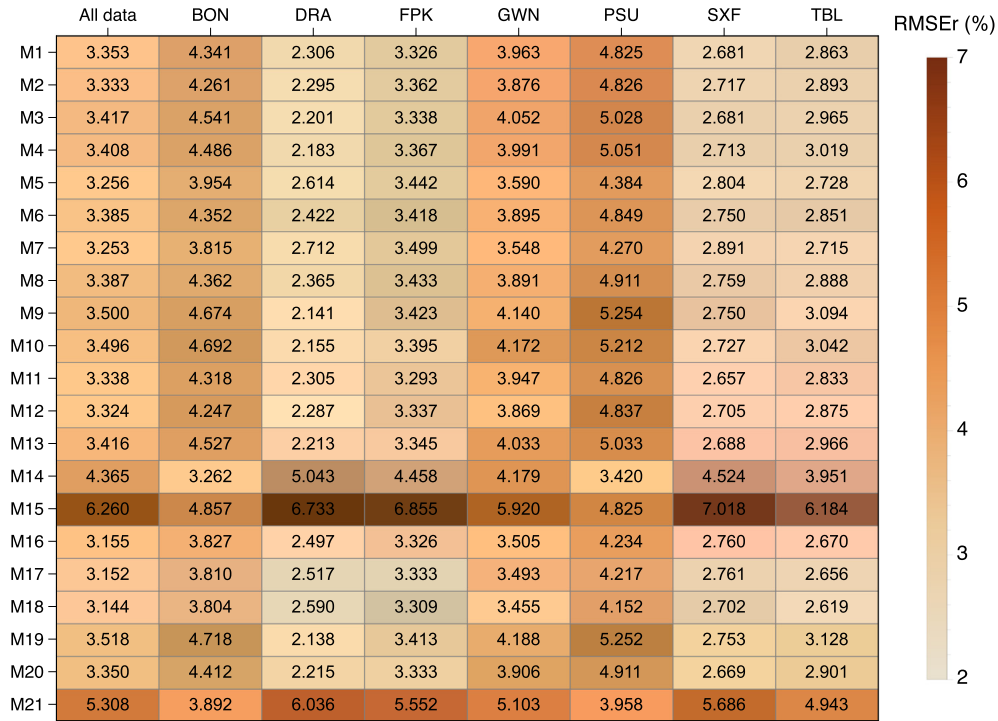


Fig. 4. *RMSEr* values (%) obtained for each model after validation, using 1-day data, of the models fitted globally from 1-min data. The errors obtained globally –considering all sites– and at each SURFRAD station are shown.

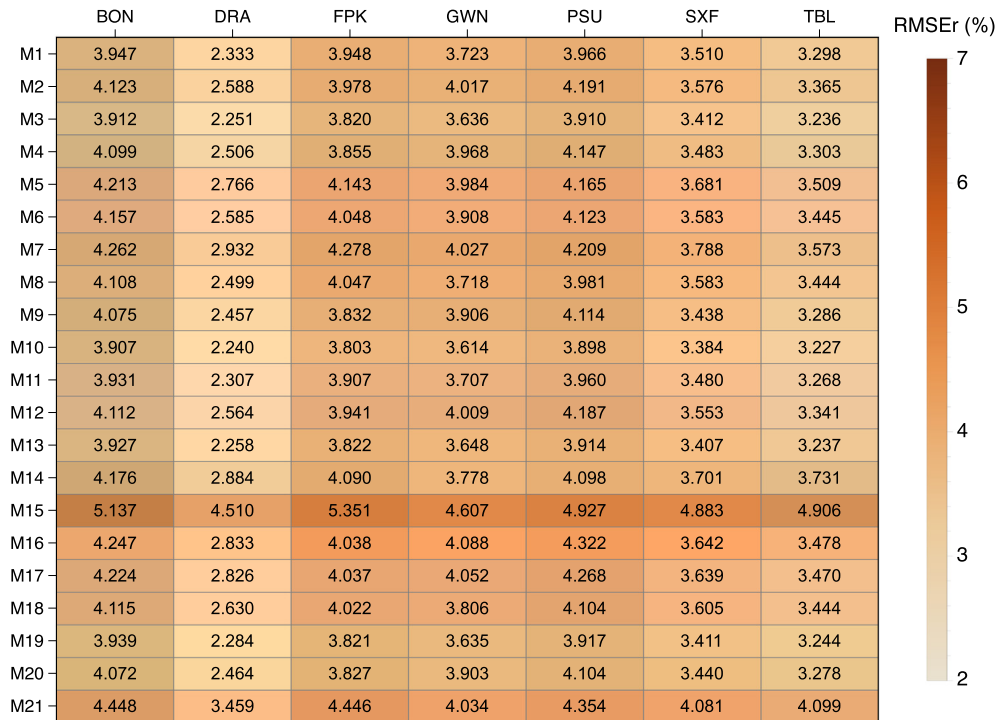


Fig. 5. *RMSEr* values (%) obtained for each model and at each SURFRAD station after validation, using 1-min data, of the models fitted locally from 1-min data.

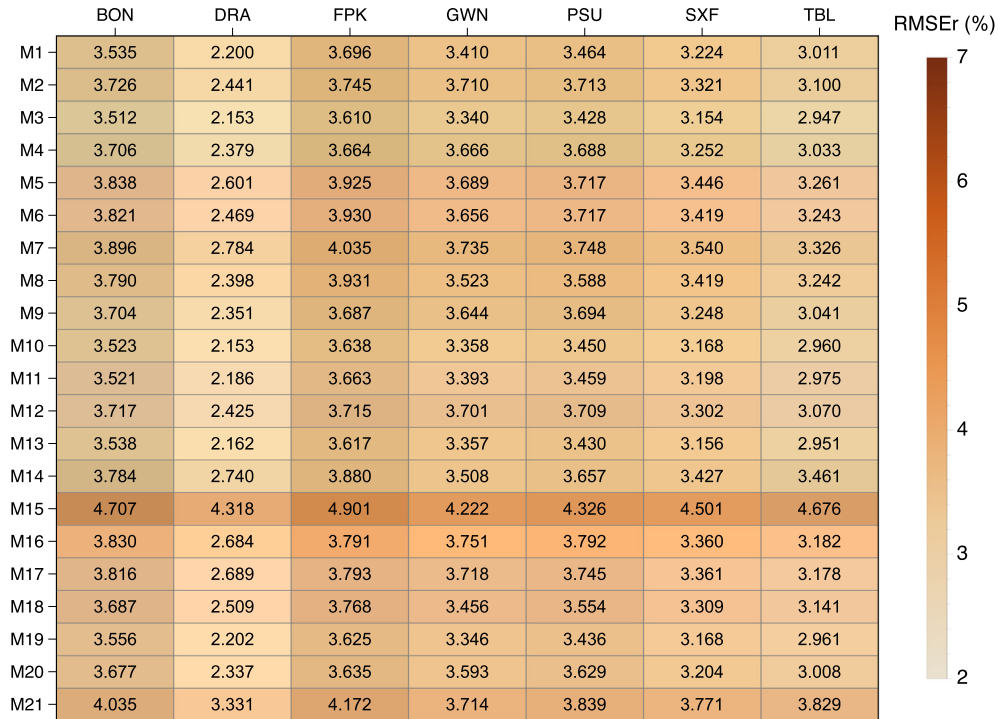


Fig. 6. *RMSEr* values (%) obtained for each model and at each SURFRAD station after validation, using 1-h data, of the models fitted locally from 1-min data.

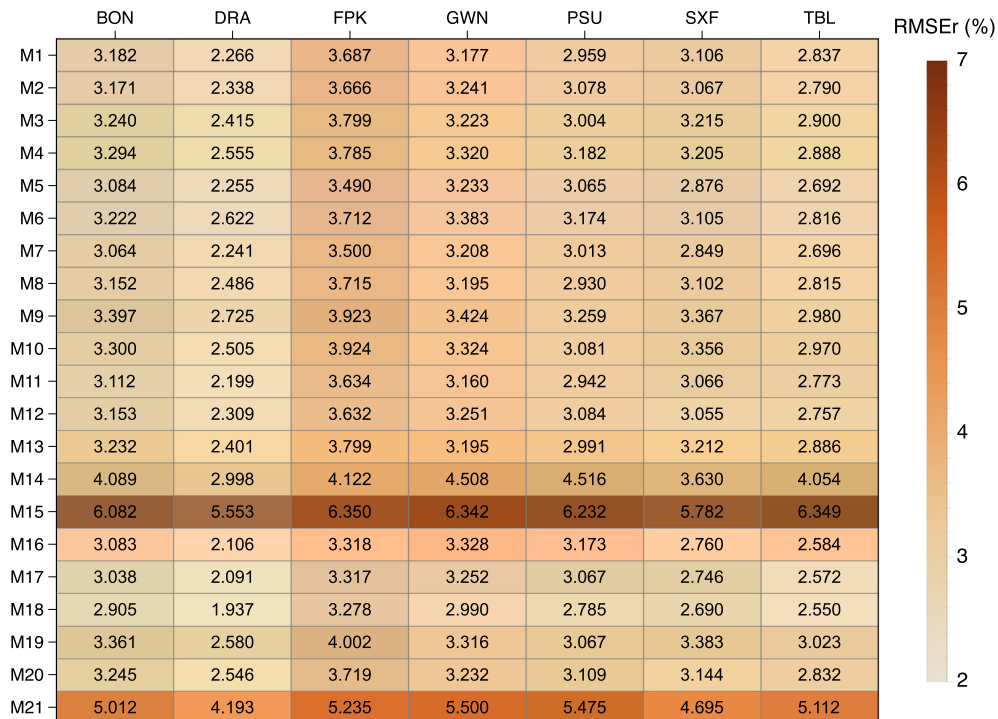


Fig. 7. *RMSEr* values (%) obtained for each model and at each SURFRAD station after validation, using 1-day data, of the models fitted locally from 1-min data.

improved its value from 0.15% to 1%. In the case of the models with the greatest error, the improvement was a maximum of 0.5%. The same behavior was observed for

1-h values. At this frequency, the models that had lower *RMSEr* values for the global calibration, improved this statistic up to 0.94% for local calibration and those with

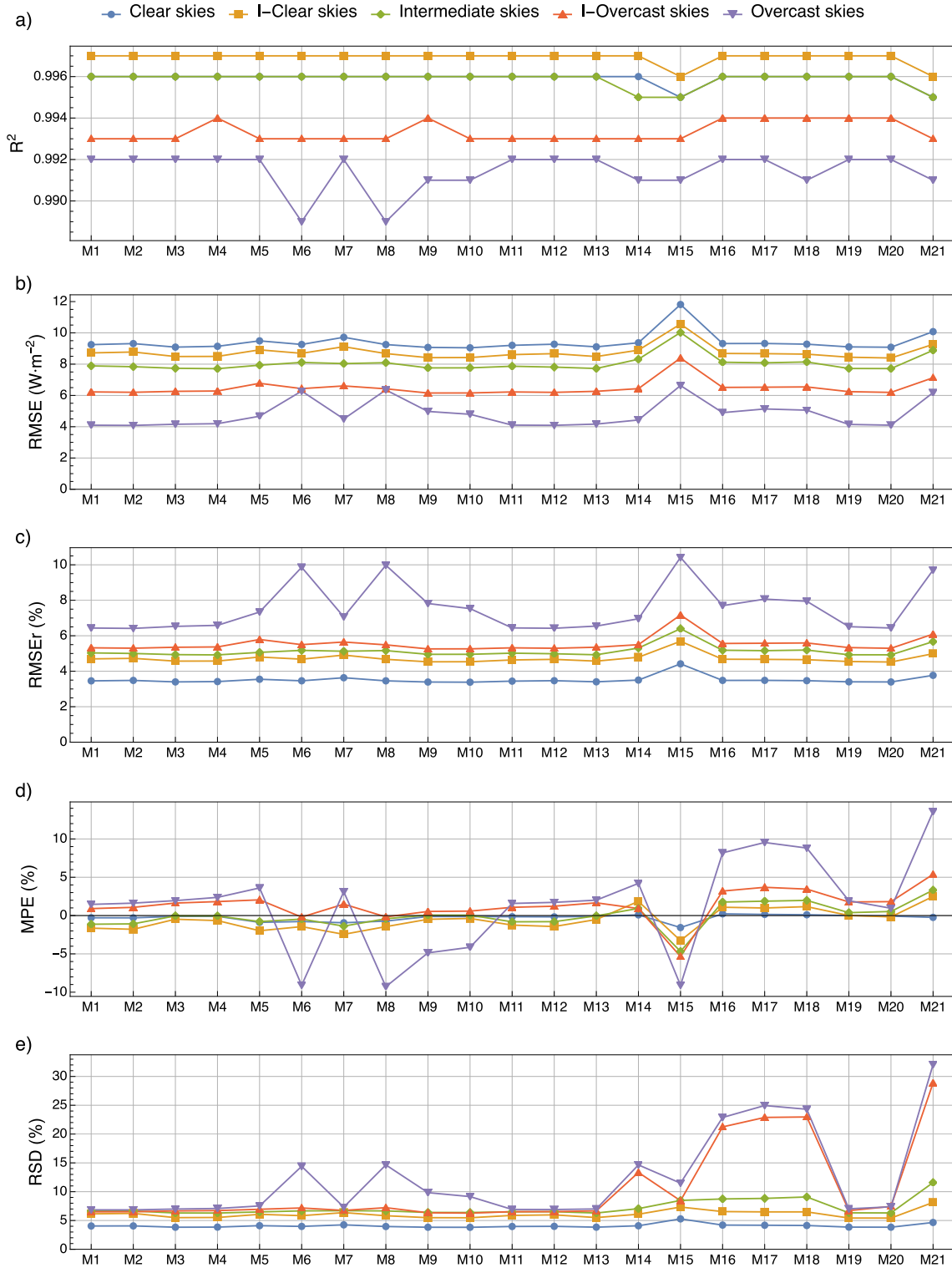


Fig. 8. Statistical errors for the five sky types and 1-min input data.

worse values up to 0.59%. For daily data the low values of $RMSEr$ were maintained or slightly improved for local calibration, although the behavior of $RMSEr$ was more anomalous and, in some stations like SFU, it even worsened when the models were calibrated with local data.

Regarding the other statistical errors under consideration, MPE is the one that improved the most when the local calibration of the models was performed. Thus, when globally calibrated models were applied, MPE reached values from 1% to 2% in most cases and even above 4% for some models and stations. In contrast, for local calibration

MPE reached maximum values of 0.5% in most cases and it seldom exceeded 1%.

Considering the results obtained, it can be stated that, although local calibration in general improved the quality of the estimated *PAR* values, the use of globally calibrated models provided sufficiently good results at all the analyzed locations.

4.3. Globally calibrated models evaluated by sky type

Fig. 8 shows the fit results of the *PAR* models when the measured data (Table 3) are classified into the five sky types proposed by Igawa (2014). In clear skies, which account for 53.1% of categories, the fitting errors remained small, with slightly improved percentage errors compared to those obtained when analyzing all skies together. The same was observed for intermediate clear skies (15.2% of the situations), in that the M15 and M21 model results had again somewhat worse fitting values, which was also observed for intermediate skies (21.5% of the cases). Intermediate overcast skies represent 8.5% of the total and overcast skies 1.7%. In these last two types of skies, worse *RSD*(%) and *MPE*(%) values can be seen, as well as a wider range of dispersion in the errors obtained for the different models. In clear to intermediate skies, most models tended to underestimate *PAR* values whereas in intermediate-overcast and overcast skies, the tendency was reverted and *PAR* was overestimated by most models. All models yielded higher R^2 values than 0.99 for the five sky types.

5. Conclusions

The use of a large time series including data on *PAR*, and both global and diffuse irradiance, as well as other meteorological variables, such as temperature and relative humidity, measured in the SURFRAD network of the USA at 1-min frequency, provided high quality data covering a wide range of climatic conditions. This dataset was used to calibrate 21 models previously published in the literature, to obtain *PAR* from climatic parameters that are easily measurable at weather stations.

When the globally calibrated models were applied to 1-min data, very satisfactory fitting results were achieved in all cases, with coefficients of determination above 0.99 and *RMSEr* ranging from 3.9% to 5%. When the same models were applied to hourly data, the quality of the *PAR* results obtained was maintained and the *RMSEr* values varied between 3.6% and 4.7%. In the case of daily *PAR* values, the *RMSEr* values varied between 3.33% and 6.26%. Taking account of the statistical indices, therefore, none of the reviewed models stood out from among the others.

When the *PAR* models were locally calibrated with the measured data at each station, the fit rating statistics improved slightly for most models and stations, although it was not a significant improvement that justifies the use

of locally calibrated models. The selection of the globally calibrated model for the estimation of *PAR* should then be done exclusively considering the meteorological variables available in the specific location.

Although the proposed models can potentially be applied to longer time ranges than one day, it was considered that the practical results of using *PAR* values of higher temporal resolution might worsen the quality.

Finally, *PAR* radiation is expected to behave similarly at different locations when a certain sky type is present, so the models' performance for the different sky conditions could be extrapolated to any location. When sky types are taken into account, after classifying skies into five categories ranging from clear to overcast, it was observed that in the overcast skies the error statistics giving relative values worsened in the models where global irradiance was not considered or had been integrated in the linear equation (M15 to M18 and M21). Therefore, in the case of overcast skies, the use of models other than those listed above is recommended.

Funding

The authors gratefully acknowledge the financial support provided by the Spanish Ministry of Science & Innovation under the I + D+i state program "Challenges Research Projects" (Ref. RTI2018-098900-B-I00).

Credit Author Statement

Marian de Blas: Investigation, Methodology, Formal Analysis, Original draft preparation; **Ana García-Rodríguez:** Formal Analysis, Validation; Reviewing and Editing; **Ignacio García:** Investigation, Methodology, Software, Visualization; Writing- Reviewing and Editing; **José Luis Torres:** Conceptualization, Writing- Reviewing and Editing Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We would like to thank those responsible for the SURFRAD network for making complete and quality weather data freely available to users. Open access funding provided by Universidad Pública de Navarra.

Appendix A. Prediction errors obtained by both the globally and locally calibrated models to estimate *PAR*

The errors obtained after validation of the globally and locally calibrated models for 1-min frequency are shown in Tables A.1 and A.2, respectively.

Table A.1

Prediction errors obtained by the globally calibrated M1 to M21 models when evaluated locally (for each SURFRAD station) and globally (all stations).

| Model | Station | R^2 | $RMSE$ (Wm^{-2}) | $RMSEr$ (%) | MPE (%) | RSD (%) |
|-------|--------------|-------|----------------------|-------------|-----------|-----------|
| M1 | BON | 0.997 | 9.798 | 4.592 | 1.297 | 5.97 |
| | DRA | 0.999 | 8.404 | 3.394 | -2.916 | 4.94 |
| | FPK | 0.997 | 8.261 | 4.113 | -2.041 | 5.571 |
| | GWN | 0.997 | 9.34 | 4.213 | 0.741 | 5.357 |
| | PSU | 0.997 | 9.514 | 4.892 | 2.305 | 6.087 |
| | SXF | 0.998 | 7.739 | 3.767 | -1.816 | 4.881 |
| | TBL | 0.998 | 7.038 | 3.338 | -0.49 | 4.477 |
| | All stations | 0.997 | 8.6 | 3.996 | -0.543 | 5.316 |
| M2 | BON | 0.997 | 9.831 | 4.607 | 1.19 | 6.002 |
| | DRA | 0.998 | 8.197 | 3.311 | -2.74 | 4.899 |
| | FPK | 0.997 | 8.284 | 4.124 | -2. | 5.578 |
| | GWN | 0.997 | 9.439 | 4.258 | 0.516 | 5.426 |
| | PSU | 0.997 | 9.641 | 4.957 | 2.299 | 6.146 |
| | SXF | 0.998 | 7.887 | 3.84 | -1.856 | 4.912 |
| | TBL | 0.998 | 7.131 | 3.382 | -0.384 | 4.502 |
| | All stations | 0.997 | 8.635 | 4.013 | -0.543 | 5.34 |
| M3 | BON | 0.997 | 9.767 | 4.577 | 1.883 | 5.95 |
| | DRA | 0.999 | 8.285 | 3.346 | -2.435 | 4.362 |
| | FPK | 0.997 | 7.986 | 3.976 | -1.353 | 4.946 |
| | GWN | 0.997 | 9.067 | 4.09 | 1.179 | 5.17 |
| | PSU | 0.997 | 9.462 | 4.865 | 2.88 | 6.307 |
| | SXF | 0.998 | 7.52 | 3.661 | -1.189 | 4.398 |
| | TBL | 0.998 | 6.895 | 3.27 | 0.158 | 4.208 |
| | All stations | 0.997 | 8.446 | 3.925 | 0.03 | 5.049 |
| M4 | BON | 0.997 | 9.782 | 4.584 | 1.775 | 5.958 |
| | DRA | 0.999 | 8.061 | 3.256 | -2.263 | 4.318 |
| | FPK | 0.997 | 8.026 | 3.996 | -1.326 | 4.958 |
| | GWN | 0.997 | 9.169 | 4.136 | 0.991 | 5.22 |
| | PSU | 0.997 | 9.555 | 4.913 | 2.873 | 6.355 |
| | SXF | 0.998 | 7.673 | 3.735 | -1.229 | 4.432 |
| | TBL | 0.998 | 6.99 | 3.315 | 0.251 | 4.236 |
| | All stations | 0.997 | 8.474 | 3.938 | 0.031 | 5.068 |
| M5 | BON | 0.997 | 10.045 | 4.707 | 1.086 | 5.964 |
| | DRA | 0.998 | 8.731 | 3.526 | -3.08 | 5.01 |
| | FPK | 0.997 | 8.635 | 4.299 | -2.252 | 5.549 |
| | GWN | 0.997 | 9.164 | 4.134 | 0.533 | 5.346 |
| | PSU | 0.997 | 9.563 | 4.917 | 2.323 | 6.17 |
| | SXF | 0.998 | 8.12 | 3.953 | -2.053 | 4.97 |
| | TBL | 0.998 | 7.407 | 3.513 | -0.598 | 4.503 |
| | All stations | 0.997 | 8.816 | 4.097 | -0.704 | 5.348 |
| M6 | BON | 0.997 | 10.024 | 4.697 | 1.101 | 6.165 |
| | DRA | 0.999 | 8.569 | 3.461 | -3.033 | 4.978 |
| | FPK | 0.997 | 8.411 | 4.187 | -2.237 | 5.672 |
| | GWN | 0.997 | 9.063 | 4.088 | 0.221 | 5.503 |
| | PSU | 0.997 | 9.516 | 4.893 | 1.57 | 6.439 |
| | SXF | 0.998 | 7.847 | 3.82 | -2.228 | 5.373 |
| | TBL | 0.998 | 7.265 | 3.446 | -0.915 | 4.986 |
| | All stations | 0.997 | 8.682 | 4.035 | -0.903 | 5.566 |
| M7 | BON | 0.996 | 10.105 | 4.735 | 0.738 | 5.991 |
| | DRA | 0.998 | 8.959 | 3.618 | -3.266 | 5.293 |
| | FPK | 0.997 | 8.908 | 4.435 | -2.569 | 5.857 |
| | GWN | 0.997 | 9.347 | 4.216 | 0.274 | 5.427 |
| | PSU | 0.997 | 9.619 | 4.945 | 2.009 | 6.063 |
| | SXF | 0.998 | 8.379 | 4.079 | -2.369 | 5.224 |
| | TBL | 0.998 | 7.551 | 3.582 | -0.869 | 4.634 |
| | All stations | 0.997 | 8.987 | 4.176 | -0.986 | 5.489 |
| M8 | BON | 0.997 | 10.009 | 4.69 | 1.084 | 6.185 |
| | DRA | 0.998 | 8.427 | 3.404 | -2.886 | 4.909 |
| | FPK | 0.997 | 8.395 | 4.179 | -2.165 | 5.646 |
| | GWN | 0.997 | 9.101 | 4.105 | 0.137 | 5.555 |

| | | | | | | |
|-----|--------------|-------|--------|-------|--------|-------|
| | PSU | 0.997 | 9.565 | 4.918 | 1.58 | 6.498 |
| | SXF | 0.998 | 7.887 | 3.84 | -2.205 | 5.379 |
| | TBL | 0.998 | 7.282 | 3.454 | -0.821 | 4.995 |
| | All stations | 0.997 | 8.672 | 4.03 | -0.863 | 5.573 |
| M9 | BON | 0.997 | 9.79 | 4.588 | 1.709 | 6.013 |
| | DRA | 0.999 | 8.072 | 3.26 | -2.324 | 4.37 |
| | FPK | 0.997 | 7.964 | 3.965 | -1.418 | 5.068 |
| | GWN | 0.997 | 9.1 | 4.104 | 0.76 | 5.157 |
| | PSU | 0.997 | 9.512 | 4.891 | 2.376 | 6.258 |
| | SXF | 0.998 | 7.549 | 3.675 | -1.421 | 4.583 |
| | TBL | 0.998 | 6.941 | 3.292 | -0.025 | 4.425 |
| | All stations | 0.997 | 8.431 | 3.918 | -0.165 | 5.117 |
| M10 | BON | 0.997 | 9.778 | 4.582 | 1.8 | 5.989 |
| | DRA | 0.999 | 8.244 | 3.33 | -2.444 | 4.392 |
| | FPK | 0.997 | 7.939 | 3.952 | -1.425 | 5.038 |
| | GWN | 0.997 | 9.034 | 4.075 | 0.934 | 5.099 |
| | PSU | 0.997 | 9.446 | 4.857 | 2.453 | 6.204 |
| | SXF | 0.998 | 7.451 | 3.627 | -1.363 | 4.513 |
| | TBL | 0.998 | 6.875 | 3.261 | -0.055 | 4.363 |
| | All stations | 0.997 | 8.416 | 3.911 | -0.137 | 5.079 |
| M11 | BON | 0.997 | 9.776 | 4.581 | 1.5 | 5.942 |
| | DRA | 0.999 | 8.345 | 3.37 | -2.725 | 4.723 |
| | FPK | 0.997 | 8.172 | 4.068 | -1.782 | 5.341 |
| | GWN | 0.997 | 9.302 | 4.196 | 0.912 | 5.287 |
| | PSU | 0.997 | 9.505 | 4.887 | 2.511 | 6.155 |
| | SXF | 0.998 | 7.68 | 3.739 | -1.574 | 4.692 |
| | TBL | 0.998 | 6.98 | 3.311 | -0.24 | 4.353 |
| | All stations | 0.997 | 8.553 | 3.975 | -0.327 | 5.205 |
| M12 | BON | 0.997 | 9.806 | 4.595 | 1.372 | 5.97 |
| | DRA | 0.998 | 8.13 | 3.284 | -2.553 | 4.698 |
| | FPK | 0.997 | 8.204 | 4.084 | -1.769 | 5.372 |
| | GWN | 0.997 | 9.4 | 4.24 | 0.671 | 5.351 |
| | PSU | 0.997 | 9.633 | 4.953 | 2.483 | 6.204 |
| | SXF | 0.998 | 7.841 | 3.817 | -1.64 | 4.741 |
| | TBL | 0.998 | 7.082 | 3.359 | -0.157 | 4.391 |
| | All stations | 0.997 | 8.591 | 3.992 | -0.346 | 5.237 |
| M13 | BON | 0.997 | 9.766 | 4.576 | 1.868 | 5.954 |
| | DRA | 0.999 | 8.282 | 3.345 | -2.401 | 4.365 |
| | FPK | 0.997 | 8.012 | 3.988 | -1.371 | 4.955 |
| | GWN | 0.997 | 9.052 | 4.083 | 1.169 | 5.172 |
| | PSU | 0.997 | 9.481 | 4.875 | 2.878 | 6.318 |
| | SXF | 0.998 | 7.538 | 3.67 | -1.195 | 4.401 |
| | TBL | 0.998 | 6.921 | 3.282 | 0.158 | 4.212 |
| | All stations | 0.997 | 8.454 | 3.929 | 0.029 | 5.055 |
| M14 | BON | 0.996 | 10.007 | 4.689 | 2.421 | 8.043 |
| | DRA | 0.998 | 9.228 | 3.727 | -1.88 | 4.734 |
| | FPK | 0.997 | 8.281 | 4.123 | 0. | 5.599 |
| | GWN | 0.997 | 8.557 | 3.86 | 1.26 | 7.155 |
| | PSU | 0.997 | 9.507 | 4.888 | 3.39 | 8.313 |
| | SXF | 0.997 | 7.907 | 3.849 | -0.337 | 6.454 |
| | TBL | 0.998 | 7.873 | 3.734 | 0.851 | 5.968 |
| | All stations | 0.997 | 8.795 | 4.087 | 0.676 | 6.622 |
| M15 | BON | 0.996 | 11.742 | 5.502 | -1.079 | 6.821 |
| | DRA | 0.997 | 11.846 | 4.785 | -4.463 | 7.004 |
| | FPK | 0.996 | 10.842 | 5.397 | -4.108 | 7.596 |
| | GWN | 0.997 | 10.307 | 4.649 | -2.105 | 6.116 |
| | PSU | 0.997 | 10.577 | 5.438 | -0.912 | 6.506 |
| | SXF | 0.997 | 10.502 | 5.112 | -4.407 | 7.212 |
| | TBL | 0.997 | 10.357 | 4.912 | -2.908 | 6.471 |
| | All stations | 0.996 | 10.93 | 5.079 | -2.939 | 6.832 |
| M16 | BON | 0.996 | 9.968 | 4.671 | 2.554 | 8.862 |
| | DRA | 0.998 | 8.302 | 3.353 | -1.417 | 5.465 |
| | FPK | 0.997 | 8.358 | 4.161 | -0.157 | 6.939 |

| | | | | | | |
|-----|--------------|-------|--------|-------|--------|--------|
| | GWN | 0.997 | 9.237 | 4.166 | 1.922 | 10.563 |
| | PSU | 0.997 | 9.644 | 4.959 | 4.041 | 11.48 |
| | SXF | 0.998 | 8.065 | 3.926 | 0.033 | 10.631 |
| | TBL | 0.998 | 7.373 | 3.497 | 1.448 | 7.777 |
| | All stations | 0.997 | 8.705 | 4.045 | 1.073 | 8.905 |
| M17 | BON | 0.996 | 9.957 | 4.666 | 2.579 | 9.189 |
| | DRA | 0.998 | 8.325 | 3.363 | -1.457 | 5.582 |
| | FPK | 0.997 | 8.361 | 4.162 | -0.153 | 7.128 |
| | GWN | 0.997 | 9.221 | 4.159 | 2.004 | 11.199 |
| | PSU | 0.997 | 9.641 | 4.957 | 4.172 | 12.04 |
| | SXF | 0.998 | 8.06 | 3.924 | 0.082 | 11.336 |
| | TBL | 0.998 | 7.358 | 3.49 | 1.466 | 8.12 |
| | All stations | 0.997 | 8.702 | 4.044 | 1.107 | 9.341 |
| M18 | BON | 0.996 | 9.939 | 4.658 | 2.74 | 9.412 |
| | DRA | 0.998 | 8.474 | 3.423 | -1.656 | 5.454 |
| | FPK | 0.997 | 8.369 | 4.166 | -0.276 | 7.028 |
| | GWN | 0.997 | 9.115 | 4.112 | 2.364 | 11.772 |
| | PSU | 0.997 | 9.569 | 4.92 | 4.173 | 11.997 |
| | SXF | 0.998 | 7.965 | 3.878 | 0.093 | 11.233 |
| | TBL | 0.998 | 7.313 | 3.469 | 1.264 | 7.689 |
| | All stations | 0.997 | 8.683 | 4.035 | 1.1 | 9.369 |
| M19 | BON | 0.997 | 9.77 | 4.578 | 2.084 | 6.021 |
| | DRA | 0.999 | 8.282 | 3.345 | -2.177 | 4.244 |
| | FPK | 0.997 | 8.002 | 3.984 | -1.077 | 4.842 |
| | GWN | 0.997 | 8.992 | 4.056 | 1.359 | 5.164 |
| | PSU | 0.997 | 9.467 | 4.868 | 3.089 | 6.495 |
| | SXF | 0.998 | 7.546 | 3.673 | -0.934 | 4.345 |
| | TBL | 0.998 | 6.925 | 3.285 | 0.44 | 4.271 |
| | All stations | 0.997 | 8.444 | 3.924 | 0.269 | 5.06 |
| M20 | BON | 0.997 | 9.765 | 4.576 | 1.989 | 6.049 |
| | DRA | 0.999 | 8.064 | 3.257 | -2.122 | 4.221 |
| | FPK | 0.997 | 7.953 | 3.959 | -1.064 | 4.884 |
| | GWN | 0.997 | 9.069 | 4.091 | 1.176 | 5.342 |
| | PSU | 0.997 | 9.5 | 4.885 | 3.011 | 6.61 |
| | SXF | 0.998 | 7.566 | 3.683 | -0.981 | 4.566 |
| | TBL | 0.998 | 6.929 | 3.286 | 0.41 | 4.303 |
| | All stations | 0.997 | 8.419 | 3.912 | 0.22 | 5.142 |
| M21 | BON | 0.996 | 10.421 | 4.884 | 3.083 | 11.237 |
| | DRA | 0.997 | 10.064 | 4.065 | -1.454 | 7.1 |
| | FPK | 0.996 | 8.969 | 4.465 | 0.919 | 9.049 |
| | GWN | 0.997 | 9.031 | 4.073 | 2.378 | 13.981 |
| | PSU | 0.997 | 9.883 | 5.082 | 5.02 | 14.882 |
| | SXF | 0.997 | 8.768 | 4.268 | 0.809 | 14.541 |
| | TBL | 0.997 | 8.66 | 4.107 | 1.941 | 10.559 |
| | All stations | 0.996 | 9.432 | 4.383 | 1.647 | 11.757 |

Table A.2

Prediction errors obtained by the locally calibrated M1 to M21 models for each SURFRAD station

| Model | Station | R^2 | $RMSE$ (Wm^{-2}) | $RMSEr$ (%) | MPE (%) | RSD (%) |
|-------|---------|-------|----------------------|-------------|-----------|-----------|
| M1 | BON | 0.997 | 8.422 | 3.947 | -0.38 | 5.679 |
| | DRA | 0.999 | 5.777 | 2.333 | -0.546 | 3.917 |
| | FPK | 0.997 | 7.93 | 3.948 | -0.701 | 5.155 |
| | GWN | 0.997 | 8.255 | 3.723 | -0.548 | 5.091 |
| | PSU | 0.998 | 7.712 | 3.966 | -0.253 | 5.658 |
| | SXF | 0.998 | 7.209 | 3.51 | -0.516 | 4.561 |
| | TBL | 0.998 | 6.954 | 3.298 | -0.501 | 4.473 |
| M2 | BON | 0.997 | 8.798 | 4.123 | -0.44 | 5.825 |
| | DRA | 0.999 | 6.408 | 2.588 | -0.58 | 4.138 |
| | FPK | 0.997 | 7.991 | 3.978 | -0.698 | 5.186 |
| | GWN | 0.997 | 8.907 | 4.017 | -0.67 | 5.428 |
| | PSU | 0.997 | 8.15 | 4.191 | -0.31 | 5.775 |
| | SXF | 0.998 | 7.346 | 3.576 | -0.516 | 4.604 |
| | TBL | 0.998 | 7.095 | 3.365 | -0.539 | 4.519 |
| M3 | BON | 0.997 | 8.347 | 3.912 | 0.13 | 5.49 |
| | DRA | 0.999 | 5.573 | 2.251 | 0.122 | 3.57 |
| | FPK | 0.997 | 7.674 | 3.82 | 0.076 | 4.767 |
| | GWN | 0.997 | 8.063 | 3.636 | -0.015 | 4.797 |
| | PSU | 0.998 | 7.603 | 3.91 | 0.192 | 5.576 |
| | SXF | 0.998 | 7.008 | 3.412 | 0.11 | 4.302 |
| | TBL | 0.998 | 6.823 | 3.236 | 0.101 | 4.207 |
| M4 | BON | 0.997 | 8.748 | 4.099 | 0.054 | 5.603 |
| | DRA | 0.999 | 6.205 | 2.506 | 0.151 | 3.738 |
| | FPK | 0.997 | 7.745 | 3.855 | 0.058 | 4.789 |
| | GWN | 0.997 | 8.797 | 3.968 | -0.167 | 5.206 |
| | PSU | 0.997 | 8.064 | 4.147 | 0.123 | 5.676 |
| | SXF | 0.998 | 7.155 | 3.483 | 0.084 | 4.325 |
| | TBL | 0.998 | 6.965 | 3.303 | 0.049 | 4.224 |
| M5 | BON | 0.996 | 8.991 | 4.213 | -0.6 | 5.8 |
| | DRA | 0.998 | 6.849 | 2.766 | -0.504 | 4.026 |
| | FPK | 0.997 | 8.323 | 4.143 | -0.985 | 5.234 |
| | GWN | 0.997 | 8.832 | 3.984 | -0.394 | 5.308 |
| | PSU | 0.997 | 8.1 | 4.165 | -0.14 | 5.711 |
| | SXF | 0.998 | 7.561 | 3.681 | -0.714 | 4.66 |
| | TBL | 0.998 | 7.398 | 3.509 | -0.758 | 4.519 |
| M6 | BON | 0.997 | 8.87 | 4.157 | -0.731 | 6.004 |
| | DRA | 0.999 | 6.4 | 2.585 | -0.543 | 4.483 |
| | FPK | 0.997 | 8.131 | 4.048 | -1.111 | 5.47 |
| | GWN | 0.997 | 8.666 | 3.908 | -0.659 | 5.42 |
| | PSU | 0.997 | 8.018 | 4.123 | -0.43 | 5.784 |
| | SXF | 0.998 | 7.36 | 3.583 | -1.018 | 5.244 |
| | TBL | 0.998 | 7.263 | 3.445 | -0.923 | 4.863 |
| M7 | BON | 0.996 | 9.095 | 4.262 | -0.88 | 5.922 |
| | DRA | 0.998 | 7.259 | 2.932 | -0.958 | 4.268 |
| | FPK | 0.997 | 8.594 | 4.278 | -1.402 | 5.513 |
| | GWN | 0.997 | 8.929 | 4.027 | -0.713 | 5.371 |
| | PSU | 0.997 | 8.185 | 4.209 | -0.397 | 5.738 |
| | SXF | 0.998 | 7.78 | 3.788 | -1.059 | 4.819 |
| | TBL | 0.998 | 7.534 | 3.573 | -0.998 | 4.658 |
| M8 | BON | 0.997 | 8.766 | 4.108 | -0.877 | 5.983 |
| | DRA | 0.999 | 6.187 | 2.499 | -0.656 | 4.363 |
| | FPK | 0.997 | 8.13 | 4.047 | -1.099 | 5.467 |
| | GWN | 0.997 | 8.243 | 3.718 | -0.906 | 5.304 |
| | PSU | 0.998 | 7.741 | 3.981 | -0.65 | 5.734 |
| | SXF | 0.998 | 7.36 | 3.583 | -1.026 | 5.244 |
| | TBL | 0.998 | 7.261 | 3.444 | -0.942 | 4.868 |
| M9 | BON | 0.997 | 8.696 | 4.075 | -0.116 | 5.685 |
| | DRA | 0.999 | 6.084 | 2.457 | -0.018 | 3.864 |
| | FPK | 0.997 | 7.698 | 3.832 | -0.104 | 4.874 |
| | GWN | 0.997 | 8.659 | 3.906 | -0.543 | 5.331 |

| | | | | | | |
|-----|-----|-------|--------|-------|--------|--------|
| | PSU | 0.997 | 8.001 | 4.114 | -0.216 | 5.721 |
| | SXF | 0.998 | 7.062 | 3.438 | -0.223 | 4.595 |
| | TBL | 0.998 | 6.928 | 3.286 | -0.108 | 4.328 |
| M10 | BON | 0.997 | 8.336 | 3.907 | 0.05 | 5.495 |
| | DRA | 0.999 | 5.547 | 2.24 | 0.046 | 3.56 |
| | FPK | 0.997 | 7.64 | 3.803 | -0.064 | 4.826 |
| | GWN | 0.997 | 8.012 | 3.614 | -0.243 | 4.775 |
| | PSU | 0.998 | 7.58 | 3.898 | -0.015 | 5.554 |
| | SXF | 0.998 | 6.951 | 3.384 | -0.136 | 4.448 |
| | TBL | 0.998 | 6.805 | 3.227 | -0.014 | 4.255 |
| M11 | BON | 0.997 | 8.388 | 3.931 | -0.159 | 5.588 |
| | DRA | 0.999 | 5.712 | 2.307 | -0.318 | 3.778 |
| | FPK | 0.997 | 7.849 | 3.907 | -0.378 | 4.984 |
| | GWN | 0.997 | 8.219 | 3.707 | -0.355 | 4.958 |
| | PSU | 0.998 | 7.7 | 3.96 | -0.102 | 5.623 |
| | SXF | 0.998 | 7.149 | 3.48 | -0.262 | 4.437 |
| | TBL | 0.998 | 6.891 | 3.268 | -0.256 | 4.353 |
| M12 | BON | 0.997 | 8.775 | 4.112 | -0.289 | 5.752 |
| | DRA | 0.999 | 6.349 | 2.564 | -0.389 | 4.005 |
| | FPK | 0.997 | 7.916 | 3.941 | -0.401 | 5.027 |
| | GWN | 0.997 | 8.888 | 4.009 | -0.57 | 5.351 |
| | PSU | 0.997 | 8.142 | 4.187 | -0.234 | 5.752 |
| | SXF | 0.998 | 7.299 | 3.553 | -0.31 | 4.495 |
| | TBL | 0.998 | 7.044 | 3.341 | -0.335 | 4.407 |
| M13 | BON | 0.997 | 8.38 | 3.927 | 0.115 | 5.503 |
| | DRA | 0.999 | 5.592 | 2.258 | 0.107 | 3.575 |
| | FPK | 0.997 | 7.678 | 3.822 | 0.077 | 4.773 |
| | GWN | 0.997 | 8.089 | 3.648 | -0.036 | 4.813 |
| | PSU | 0.998 | 7.611 | 3.914 | 0.17 | 5.584 |
| | SXF | 0.998 | 6.999 | 3.407 | 0.106 | 4.292 |
| | TBL | 0.998 | 6.825 | 3.237 | 0.095 | 4.202 |
| M14 | BON | 0.996 | 8.912 | 4.176 | 0.625 | 8.221 |
| | DRA | 0.998 | 7.141 | 2.884 | 0.673 | 5.688 |
| | FPK | 0.997 | 8.216 | 4.09 | 0.565 | 6.301 |
| | GWN | 0.997 | 8.376 | 3.778 | 0.373 | 6.418 |
| | PSU | 0.997 | 7.969 | 4.098 | 0.523 | 7.267 |
| | SXF | 0.997 | 7.603 | 3.701 | 0.646 | 7.472 |
| | TBL | 0.998 | 7.867 | 3.731 | 0.793 | 5.893 |
| M15 | BON | 0.996 | 10.961 | 5.137 | -2.798 | 7.185 |
| | DRA | 0.997 | 11.167 | 4.51 | -3.061 | 6.268 |
| | FPK | 0.996 | 10.749 | 5.351 | -3.49 | 7.318 |
| | GWN | 0.997 | 10.214 | 4.607 | -2.645 | 6.296 |
| | PSU | 0.997 | 9.582 | 4.927 | -2.847 | 7.071 |
| | SXF | 0.997 | 10.03 | 4.883 | -3.106 | 6.568 |
| | TBL | 0.997 | 10.344 | 4.906 | -3.121 | 6.558 |
| M16 | BON | 0.996 | 9.062 | 4.247 | 0.946 | 8.677 |
| | DRA | 0.998 | 7.015 | 2.833 | 0.987 | 7.033 |
| | FPK | 0.997 | 8.111 | 4.038 | 1.119 | 7.758 |
| | GWN | 0.997 | 9.064 | 4.088 | 0.966 | 9.719 |
| | PSU | 0.997 | 8.405 | 4.322 | 1.058 | 9.035 |
| | SXF | 0.998 | 7.48 | 3.642 | 1.162 | 10.326 |
| | TBL | 0.998 | 7.332 | 3.478 | 1.057 | 7.577 |
| M17 | BON | 0.996 | 9.013 | 4.224 | 1.048 | 10.402 |
| | DRA | 0.998 | 6.996 | 2.826 | 1.069 | 7.828 |
| | FPK | 0.997 | 8.109 | 4.037 | 1.139 | 7.974 |
| | GWN | 0.997 | 8.983 | 4.052 | 1.144 | 12.878 |
| | PSU | 0.997 | 8.299 | 4.268 | 1.246 | 11.284 |
| | SXF | 0.998 | 7.474 | 3.639 | 1.228 | 11.275 |
| | TBL | 0.998 | 7.316 | 3.47 | 1.134 | 8.337 |
| M18 | BON | 0.997 | 8.781 | 4.115 | 1.061 | 10.565 |
| | DRA | 0.998 | 6.511 | 2.63 | 1. | 7.869 |
| | FPK | 0.997 | 8.08 | 4.022 | 1.146 | 8.2 |
| | GWN | 0.997 | 8.439 | 3.806 | 1.152 | 12.53 |

| | | | | | | |
|-----|-----|-------|-------|-------|-------|--------|
| | PSU | 0.997 | 7.982 | 4.104 | 1.253 | 12.001 |
| | SXF | 0.998 | 7.405 | 3.605 | 1.226 | 11.36 |
| | TBL | 0.998 | 7.261 | 3.444 | 1.136 | 8.322 |
| M19 | BON | 0.997 | 8.405 | 3.939 | 0.343 | 5.538 |
| | DRA | 0.999 | 5.655 | 2.284 | 0.356 | 3.702 |
| | FPK | 0.997 | 7.676 | 3.821 | 0.408 | 4.852 |
| | GWN | 0.997 | 8.06 | 3.635 | 0.211 | 4.758 |
| | PSU | 0.998 | 7.617 | 3.917 | 0.327 | 5.622 |
| | SXF | 0.998 | 7.006 | 3.411 | 0.366 | 4.349 |
| | TBL | 0.998 | 6.839 | 3.244 | 0.351 | 4.27 |
| M20 | BON | 0.997 | 8.69 | 4.072 | 0.148 | 5.586 |
| | DRA | 0.999 | 6.1 | 2.464 | 0.015 | 3.688 |
| | FPK | 0.997 | 7.688 | 3.827 | 0.166 | 4.799 |
| | GWN | 0.997 | 8.652 | 3.903 | 0.33 | 5.834 |
| | PSU | 0.997 | 7.981 | 4.104 | 0.2 | 5.724 |
| | SXF | 0.998 | 7.066 | 3.44 | 0.095 | 4.275 |
| | TBL | 0.998 | 6.912 | 3.278 | 0.105 | 4.217 |
| M21 | BON | 0.996 | 9.491 | 4.448 | 1.435 | 11.097 |
| | DRA | 0.997 | 8.564 | 3.459 | 1.593 | 9.784 |
| | FPK | 0.996 | 8.932 | 4.446 | 1.571 | 9.782 |
| | GWN | 0.997 | 8.945 | 4.034 | 1.538 | 12.704 |
| | PSU | 0.997 | 8.468 | 4.354 | 1.579 | 11.47 |
| | SXF | 0.997 | 8.383 | 4.081 | 1.824 | 14.474 |
| | TBL | 0.997 | 8.642 | 4.099 | 1.731 | 10.556 |

Appendix B. Calibration coefficients of the models fitted from 1-min input data from each SURFRAD station

Tables B.1 to B.7 show the calibration coefficients for models M1 to M21, fitted for each station and all sky types together.

Table B.1

Calibrated models for PAR using 1-min input data from Bondville station (BON) and obtained determination coefficients (R^2).

| Model | Calibrated expression | R^2 |
|-------|---|--------|
| M1 | $PAR = G(-0.0259244 \cos^2 \theta_z - 0.0260871 \ln \Delta - 0.0273576 \ln \varepsilon + 0.000523075 T_d + 0.421399)$ | 0.9988 |
| M2 | $PAR = G(-0.016265 \cos^2 \theta_z - 0.0270273 \ln \Delta - 0.0302163 \ln \varepsilon + 0.423116)$ | 0.9986 |
| M3 | $PAR = G(-0.0359644 \cos \theta_z - 0.0290155 \ln k_T + 0.000527191 T_d + 0.43095)$ | 0.9988 |
| M4 | $PAR = G(-0.0222549 \cos \theta_z - 0.034567 \ln k_T + 0.423968)$ | 0.9987 |
| M5 | $PAR = G(0.406094 - 0.0388095 \ln k_T)$ | 0.9986 |
| M6 | $PAR = G(-0.0357595 (\ln k_T)^2 - 0.0799766 \ln k_T + 0.397569)$ | 0.9986 |
| M7 | $PAR = G(0.0344183 \ln k_d - 0.0322647 \ln \Delta + 0.411185)$ | 0.9985 |
| M8 | $PAR = G(-0.0339204 (\ln k_T)^2 - 0.0764894 \ln k_T + 0.000245817 T_d + 0.396128)$ | 0.9986 |
| M9 | $PAR = G(-0.0194519 \cos \theta_z - 0.0237968 (\ln k_T)^2 - 0.0624967 \ln k_T + 0.416044)$ | 0.9987 |
| M10 | $PAR = G(-0.0342295 \cos \theta_z - 0.0108944 (\ln k_T)^2 - 0.0419848 \ln k_T + 0.000509824 T_d + 0.427092)$ | 0.9988 |
| M11 | $PAR = G(-0.0361981 \cos \theta_z - 0.0262882 \ln \Delta - 0.0274304 \ln \varepsilon + 0.00788274 \ln w + 0.432731)$ | 0.9988 |
| M12 | $PAR = G(-0.0231224 \cos \theta_z - 0.0271304 \ln \Delta - 0.0302421 \ln \varepsilon + 0.430717)$ | 0.9986 |
| M13 | $PAR = G(-0.0337806 \cos \theta_z - 0.0293596 \ln k_T + 0.00395218 w + 0.425031)$ | 0.9988 |
| M14 | $PAR = (\cos \theta_z)^{0.932509} (-180.122 k_T^3 + 216.937 k_T^2 + 462.983 k_T + 19.9528)$ | 0.9986 |
| M15 | $PAR = 564.298 k_T \cos \theta_z$ | 0.9979 |
| M16 | $PAR = 0.405545 G + 8.66282$ | 0.9927 |
| M17 | $PAR = 0.409719 G - 8.91491 k_T + 12.1406$ | 0.9928 |
| M18 | $PAR = 0.284018 e + 0.40531 G - 1.99409 k_T + 6.35328$ | 0.9931 |
| M19 | $PAR = G(0.000622256 e - 0.0292528 \ln k_T + 0.0205566 \ln m + 0.393739)$ | 0.9988 |
| M20 | $PAR = 0.472062 G - 0.0171748 G \cos \theta_z - 0.0576354 G k_T + 1.01416$ | 0.9933 |
| M21 | $PAR = 539.478 k_T \cos \theta_z + 11.8191$ | 0.992 |

Table B.2

Calibrated models for *PAR* using 1-min input data from Desert Rock station (DRA) and obtained determination coefficients (R^2).

| Model | Calibrated expression | R^2 |
|-------|--|--------|
| M1 | $PAR = G(-0.0261923 \cos^2 \theta_z - 0.0288812 \ln \Delta - 0.0315234 \ln \varepsilon + 0.000726564T_d + 0.446473)$ | 0.9996 |
| M2 | $PAR = G(-0.020241 \cos^2 \theta_z - 0.0386956 \ln \Delta - 0.0416245 \ln \varepsilon + 0.438563)$ | 0.9995 |
| M3 | $PAR = G(-0.036648 \cos \theta_z - 0.0412194 \ln k_T + 0.000712762T_d + 0.450721)$ | 0.9996 |
| M4 | $PAR = G(-0.0290814 \cos \theta_z - 0.05102 \ln k_T + 0.440383)$ | 0.9995 |
| M5 | $PAR = G(0.414445 - 0.0671817 \ln k_T)$ | 0.9994 |
| M6 | $PAR = G(-0.0873278(\ln k_T)^2 - 0.154097 \ln k_T + 0.399142)$ | 0.9995 |
| M7 | $PAR = G(0.0557939 \ln k_d - 0.0528724 \ln \Delta + 0.423928)$ | 0.9993 |
| M8 | $PAR = G(-0.0819571(\ln k_T)^2 - 0.145498 \ln k_T + 0.000414549T_d + 0.402171)$ | 0.9995 |
| M9 | $PAR = G(-0.0225632 \cos \theta_z - 0.0494384(\ln k_T)^2 - 0.103847 \ln k_T + 0.425906)$ | 0.9995 |
| M10 | $PAR = G(-0.0332541 \cos \theta_z - 0.0227353(\ln k_T)^2 - 0.0660267 \ln k_T + 0.00067542T_d + 0.443522)$ | 0.9996 |
| M11 | $PAR = G(-0.036849 \cos \theta_z - 0.0301012 \ln \Delta - 0.0324425 \ln \varepsilon + 0.00992457 \ln w + 0.457635)$ | 0.9996 |
| M12 | $PAR = G(-0.0292137 \cos \theta_z - 0.0393187 \ln \Delta - 0.0420293 \ln \varepsilon + 0.447881)$ | 0.9995 |
| M13 | $PAR = G(-0.0353215 \cos \theta_z - 0.0411073 \ln k_T + 0.00995549w + 0.438687)$ | 0.9996 |
| M14 | $PAR = (\cos \theta_z)^{0.933089} (-478.987k_T^3 + 669.882k_T^2 + 270.083k_T + 55.0193)$ | 0.9993 |
| M15 | $PAR = 582.699k_T \cos \theta_z$ | 0.9983 |
| M16 | $PAR = 0.415534G + 11.5006$ | 0.9963 |
| M17 | $PAR = 0.41783G - 6.02535k_T + 14.4017$ | 0.9964 |
| M18 | $PAR = 0.922787e + 0.414496G + 2.68309k_T + 5.24025$ | 0.9969 |
| M19 | $PAR = G(0.00161196e - 0.0408081 \ln k_T + 0.0221729 \ln m + 0.405402)$ | 0.9996 |
| M20 | $PAR = 0.522273G - 0.0265693G \cos \theta_z - 0.0896594Gk_T - 0.627671$ | 0.9972 |
| M21 | $PAR = 552.111k_T \cos \theta_z + 16.0335$ | 0.9946 |

Table B.3

Calibrated models for *PAR* using 1-min input data from Fort Peck station (FPK) and obtained determination coefficients (R^2).

| Model | Calibrated expression | R^2 |
|-------|--|--------|
| M1 | $PAR = G(-0.0336945 \cos^2 \theta_z - 0.02636 \ln \Delta - 0.0274589 \ln \varepsilon + 0.000257494T_d + 0.439355)$ | 0.9988 |
| M2 | $PAR = G(-0.0300909 \cos^2 \theta_z - 0.0290494 \ln \Delta - 0.0297221 \ln \varepsilon + 0.436958)$ | 0.9988 |
| M3 | $PAR = G(-0.0425077 \cos \theta_z - 0.0330176 \ln k_T + 0.00027324T_d + 0.448656)$ | 0.9989 |
| M4 | $PAR = G(-0.0375712 \cos \theta_z - 0.034241 \ln k_T + 0.445954)$ | 0.9988 |
| M5 | $PAR = G(0.416632 - 0.0432368 \ln k_T)$ | 0.9987 |
| M6 | $PAR = G(-0.0470733(\ln k_T)^2 - 0.0987647 \ln k_T + 0.404925)$ | 0.9987 |
| M7 | $PAR = G(0.0368049 \ln k_d - 0.0356874 \ln \Delta + 0.420645)$ | 0.9986 |
| M8 | $PAR = G(-0.0470845(\ln k_T)^2 - 0.0987823 \ln k_T - 0.0000287484T_d + 0.405043)$ | 0.9987 |
| M9 | $PAR = G(-0.0340508 \cos \theta_z - 0.0237318(\ln k_T)^2 - 0.063078 \ln k_T + 0.437304)$ | 0.9989 |
| M10 | $PAR = G(-0.0390583 \cos \theta_z - 0.0202025(\ln k_T)^2 - 0.0576783 \ln k_T + 0.000248194T_d + 0.441045)$ | 0.9989 |
| M11 | $PAR = G(-0.0453089 \cos \theta_z - 0.0269816 \ln \Delta - 0.0278478 \ln \varepsilon + 0.00387382 \ln w + 0.452978)$ | 0.9988 |
| M12 | $PAR = G(-0.0406329 \cos \theta_z - 0.0296938 \ln \Delta - 0.0301463 \ln \varepsilon + 0.449311)$ | 0.9988 |
| M13 | $PAR = G(-0.041594 \cos \theta_z - 0.0331143 \ln k_T + 0.00279824w + 0.444784)$ | 0.9989 |
| M14 | $PAR = (\cos \theta_z)^{0.926626} (-293.565k_T^3 + 373.445k_T^2 + 409.399k_T + 27.6677)$ | 0.9987 |
| M15 | $PAR = 577.976k_T \cos \theta_z$ | 0.9978 |
| M16 | $PAR = 0.415314G + 9.42583$ | 0.9941 |
| M17 | $PAR = 0.416205G - 1.84007k_T + 10.1584$ | 0.9941 |
| M18 | $PAR = 0.158742e + 0.414881G - 0.340784k_T + 8.49953$ | 0.9941 |
| M19 | $PAR = G(0.000448402e - 0.0326234 \ln k_T + 0.0242581 \ln m + 0.406583)$ | 0.9989 |
| M20 | $PAR = 0.493898G - 0.0315763G \cos \theta_z - 0.0582316Gk_T + 0.955542$ | 0.9947 |
| M21 | $PAR = 550.626k_T \cos \theta_z + 12.2792$ | 0.9928 |

Table B.4

Calibrated models for *PAR* using 1-min input data from Goodwin Creek station (GWN) and obtained determination coefficients (R^2).

| Model | Calibrated expression | R^2 |
|-------|--|--------|
| M1 | $PAR = G(-0.0187438 \cos^2 \theta_z - 0.0253306 \ln \Delta - 0.0250879 \ln \varepsilon + 0.000758056T_d + 0.414868)$ | 0.9989 |
| M2 | $PAR = G(-0.00630393 \cos^2 \theta_z - 0.0213583 \ln \Delta - 0.0262149 \ln \varepsilon + 0.425841)$ | 0.9987 |
| M3 | $PAR = G(-0.0281131 \cos \theta_z - 0.0272605 \ln k_T + 0.000733611T_d + 0.425694)$ | 0.9989 |
| M4 | $PAR = G(-0.00832906 \cos \theta_z - 0.0342831 \ln k_T + 0.417691)$ | 0.9987 |
| M5 | $PAR = G(0.410867 - 0.0356833 \ln k_T)$ | 0.9987 |
| M6 | $PAR = G(-0.033815(\ln k_T)^2 - 0.0785134 \ln k_T + 0.401537)$ | 0.9988 |
| M7 | $PAR = G(0.0298569 \ln k_d - 0.0264207 \ln \Delta + 0.41872)$ | 0.9987 |
| M8 | $PAR = G(-0.0323216(\ln k_T)^2 - 0.0741496 \ln k_T + 0.000490602T_d + 0.396461)$ | 0.9989 |
| M9 | $PAR = G(-0.00371422 \cos \theta_z - 0.0318378(\ln k_T)^2 - 0.0753847 \ln k_T + 0.405126)$ | 0.9988 |
| M10 | $PAR = G(-0.0244533 \cos \theta_z - 0.0186725(\ln k_T)^2 - 0.0517045 \ln k_T + 0.000698264T_d + 0.417939)$ | 0.999 |
| M11 | $PAR = G(-0.0282613 \cos \theta_z - 0.0249653 \ln \Delta - 0.0247003 \ln \varepsilon + 0.0115315 \ln w + 0.42468)$ | 0.9989 |
| M12 | $PAR = G(-0.0108586 \cos \theta_z - 0.0208078 \ln \Delta - 0.025743 \ln \varepsilon + 0.430597)$ | 0.9987 |
| M13 | $PAR = G(-0.0265596 \cos \theta_z - 0.0271722 \ln k_T + 0.00506549w + 0.419701)$ | 0.9989 |
| M14 | $PAR = (\cos \theta_z)^{0.947929} (-210.208k_T^3 + 232.516k_T^2 + 485.752k_T + 14.6498)$ | 0.9989 |
| M15 | $PAR = 571.122k_T \cos \theta_z$ | 0.9983 |
| M16 | $PAR = 0.411303G + 7.71913$ | 0.9935 |
| M17 | $PAR = 0.416971G - 10.9468k_T + 11.4661$ | 0.9936 |
| M18 | $PAR = 0.398187e + 0.410254G + 0.14252k_T + 1.71339$ | 0.9943 |
| M19 | $PAR = G(0.000818772e - 0.0267586 \ln k_T + 0.018002 \ln m + 0.394531)$ | 0.9989 |
| M20 | $PAR = 0.456942G + 0.00166113G \cos \theta_z - 0.0545554Gk_T + 2.81898$ | 0.9941 |
| M21 | $PAR = 549.744k_T \cos \theta_z + 10.5202$ | 0.9937 |

Table B.5

Calibrated models for *PAR* using 1-min input data from Penn. State University station (PSU) and obtained determination coefficients (R^2).

| Model | Calibrated expression | R^2 |
|-------|--|--------|
| M1 | $PAR = G(-0.0166701 \cos^2 \theta_z - 0.0250514 \ln \Delta - 0.0252981 \ln \varepsilon + 0.000556096T_d + 0.414047)$ | 0.9988 |
| M2 | $PAR = G(-0.00673068 \cos^2 \theta_z - 0.0238131 \ln \Delta - 0.0264715 \ln \varepsilon + 0.416307)$ | 0.9987 |
| M3 | $PAR = G(-0.0229097 \cos \theta_z - 0.0264228 \ln k_T + 0.000550073T_d + 0.421451)$ | 0.9988 |
| M4 | $PAR = G(-0.00890567 \cos \theta_z - 0.0299549 \ln k_T + 0.414148)$ | 0.9987 |
| M5 | $PAR = G(0.407185 - 0.0310584 \ln k_T)$ | 0.9987 |
| M6 | $PAR = G(-0.0201476(\ln k_T)^2 - 0.0575878 \ln k_T + 0.401414)$ | 0.9987 |
| M7 | $PAR = G(0.027987 \ln k_d - 0.0260995 \ln \Delta + 0.411151)$ | 0.9986 |
| M8 | $PAR = G(-0.0185985(\ln k_T)^2 - 0.0542781 \ln k_T + 0.000388764T_d + 0.39928)$ | 0.9988 |
| M9 | $PAR = G(-0.00621358 \cos \theta_z - 0.0180068(\ln k_T)^2 - 0.0539991 \ln k_T + 0.406885)$ | 0.9987 |
| M10 | $PAR = G(-0.0208019 \cos \theta_z - 0.0108647(\ln k_T)^2 - 0.0410521 \ln k_T + 0.000531084T_d + 0.416817)$ | 0.9988 |
| M11 | $PAR = G(-0.0232898 \cos \theta_z - 0.0249902 \ln \Delta - 0.0251929 \ln \varepsilon + 0.00811827 \ln w + 0.42153)$ | 0.9988 |
| M12 | $PAR = G(-0.00996949 \cos \theta_z - 0.02376 \ln \Delta - 0.0263967 \ln \varepsilon + 0.419806)$ | 0.9987 |
| M13 | $PAR = G(-0.0214083 \cos \theta_z - 0.0264027 \ln k_T + 0.0049105w + 0.414311)$ | 0.9988 |
| M14 | $PAR = (\cos \theta_z)^{0.954153} (-194.753k_T^3 + 222.936k_T^2 + 474.176k_T + 16.2113)$ | 0.9987 |
| M15 | $PAR = 563.059k_T \cos \theta_z$ | 0.9981 |
| M16 | $PAR = 0.407821G + 6.43092$ | 0.9941 |
| M17 | $PAR = 0.414188G - 10.7777k_T + 9.67382$ | 0.9942 |
| M18 | $PAR = 0.34763e + 0.409569G - 5.06873k_T + 4.50106$ | 0.9946 |
| M19 | $PAR = G(0.000792017e - 0.0263632 \ln k_T + 0.0131349 \ln m + 0.394484)$ | 0.9988 |
| M20 | $PAR = 0.457128G - 0.00352162G \cos \theta_z - 0.052867Gk_T + 0.992148$ | 0.9946 |
| M21 | $PAR = 543.701k_T \cos \theta_z + 8.87978$ | 0.994 |

Table B.6

Calibrated models for PAR using 1-min input data from Sioux Falls station (SXF) and obtained determination coefficients (R^2).

| Model | Calibrated expression | R^2 |
|-------|--|--------|
| M1 | $PAR = G(-0.0270748 \cos^2 \theta_z - 0.0233918 \ln \Delta - 0.0244928 \ln \varepsilon + 0.000301957T_d + 0.437978)$ | 0.999 |
| M2 | $PAR = G(-0.0208262 \cos^2 \theta_z - 0.0263429 \ln \Delta - 0.0274028 \ln \varepsilon + 0.435804)$ | 0.999 |
| M3 | $PAR = G(-0.0359149 \cos \theta_z - 0.0290881 \ln k_T + 0.000307922T_d + 0.446052)$ | 0.9991 |
| M4 | $PAR = G(-0.0274843 \cos \theta_z - 0.031694 \ln k_T + 0.441531)$ | 0.999 |
| M5 | $PAR = G(0.419954 - 0.0372785 \ln k_T)$ | 0.9989 |
| M6 | $PAR = G(-0.0408875 (\ln k_T)^2 - 0.0870585 \ln k_T + 0.409132)$ | 0.999 |
| M7 | $PAR = G(0.0319198 \ln k_d - 0.0311002 \ln \Delta + 0.423177)$ | 0.9989 |
| M8 | $PAR = G(-0.0408183 (\ln k_T)^2 - 0.0869378 \ln k_T + 0.0000125502T_d + 0.409064)$ | 0.999 |
| M9 | $PAR = G(-0.0240868 \cos \theta_z - 0.0280449 (\ln k_T)^2 - 0.0665285 \ln k_T + 0.431441)$ | 0.9991 |
| M10 | $PAR = G(-0.0322136 \cos \theta_z - 0.0222174 (\ln k_T)^2 - 0.0569965 \ln k_T + 0.000271039T_d + 0.437517)$ | 0.9991 |
| M11 | $PAR = G(-0.0374632 \cos \theta_z - 0.0237178 \ln \Delta - 0.0246503 \ln \varepsilon + 0.00465075 \ln w + 0.449544)$ | 0.9991 |
| M12 | $PAR = G(-0.0289148 \cos \theta_z - 0.0267004 \ln \Delta - 0.0276172 \ln \varepsilon + 0.444885)$ | 0.999 |
| M13 | $PAR = G(-0.0348077 \cos \theta_z - 0.0291257 \ln k_T + 0.0026568w + 0.442077)$ | 0.9991 |
| M14 | $PAR = (\cos \theta_z)^{0.929967} (-291.019k_T^3 + 364.55k_T^2 + 426.772k_T + 22.5131)$ | 0.9989 |
| M15 | $PAR = 582.089k_T \cos \theta_z$ | 0.9981 |
| M16 | $PAR = 0.419434G + 8.05983$ | 0.9952 |
| M17 | $PAR = 0.420718G - 2.61838k_T + 9.06978$ | 0.9952 |
| M18 | $PAR = 0.154547e + 0.418294G + 0.383924k_T + 6.65462$ | 0.9953 |
| M19 | $PAR = G(0.000421147e - 0.0287839 \ln k_T + 0.0207711 \ln m + 0.409903)$ | 0.9991 |
| M20 | $PAR = 0.490487G - 0.0238271G \cos \theta_z - 0.0574915Gk_T + 0.434208$ | 0.9957 |
| M21 | $PAR = 557.054k_T \cos \theta_z + 11.3821$ | 0.9939 |

Table B.7

Calibrated models for PAR using 1-min input data from Table Mountain station (TBL) and obtained determination coefficients (R^2).

| Model | Calibrated expression | R^2 |
|-------|---|--------|
| M1 | $PAR = G(-0.023619 \cos^2 \theta_z - 0.0276188 \ln \Delta - 0.0277975 \ln \varepsilon + 0.00035631T_d + 0.428664)$ | 0.9992 |
| M2 | $PAR = G(-0.0183781 \cos^2 \theta_z - 0.0287877 \ln \Delta - 0.0292228 \ln \varepsilon + 0.426524)$ | 0.9991 |
| M3 | $PAR = G(-0.0325096 \cos \theta_z - 0.0287528 \ln k_T + 0.000351184T_d + 0.439248)$ | 0.9992 |
| M4 | $PAR = G(-0.0256534 \cos \theta_z - 0.030557 \ln k_T + 0.434464)$ | 0.9991 |
| M5 | $PAR = G(0.414619 - 0.0348299 \ln k_T)$ | 0.999 |
| M6 | $PAR = G(-0.0303389 (\ln k_T)^2 - 0.0713085 \ln k_T + 0.407652)$ | 0.9991 |
| M7 | $PAR = G(0.0334245 \ln k_d - 0.0336848 \ln \Delta + 0.414363)$ | 0.999 |
| M8 | $PAR = G(-0.0303117 (\ln k_T)^2 - 0.0712003 \ln k_T + 0.0000400073T_d + 0.407599)$ | 0.9991 |
| M9 | $PAR = G(-0.0234503 \cos \theta_z - 0.0159809 (\ln k_T)^2 - 0.0501389 \ln k_T + 0.42909)$ | 0.9992 |
| M10 | $PAR = G(-0.0305593 \cos \theta_z - 0.0114026 (\ln k_T)^2 - 0.0428243 \ln k_T + 0.000331802T_d + 0.43515)$ | 0.9992 |
| M11 | $PAR = G(-0.0330803 \cos \theta_z - 0.0281437 \ln \Delta - 0.028116 \ln \varepsilon + 0.00517464 \ln w + 0.438895)$ | 0.9992 |
| M12 | $PAR = G(-0.0261265 \cos \theta_z - 0.029134 \ln \Delta - 0.0294361 \ln \varepsilon + 0.434904)$ | 0.9991 |
| M13 | $PAR = G(-0.0317435 \cos \theta_z - 0.0288389 \ln k_T + 0.00401612w + 0.433972)$ | 0.9992 |
| M14 | $PAR = (\cos \theta_z)^{0.929085} (-142.691k_T^3 + 166.044k_T^2 + 494.632k_T + 15.9574)$ | 0.9989 |
| M15 | $PAR = 573.024k_T \cos \theta_z$ | 0.9981 |
| M16 | $PAR = 0.412172G + 8.21022$ | 0.9958 |
| M17 | $PAR = 0.414113G - 3.93812k_T + 9.77532$ | 0.9958 |
| M18 | $PAR = 0.236214e + 0.412381G - 1.72243k_T + 7.49131$ | 0.9958 |
| M19 | $PAR = G(0.000623222e - 0.0285695 \ln k_T + 0.0191117 \ln m + 0.404614)$ | 0.9992 |
| M20 | $PAR = 0.478529G - 0.0213716G \cos \theta_z - 0.0519381Gk_T + 0.729894$ | 0.9962 |
| M21 | $PAR = 548.87k_T \cos \theta_z + 11.5596$ | 0.9941 |

References

- Aguiar, L.J.G., Fischer, G.R., Ladle, R.J., Malhado, A.C.M., Justino, F. B., Aguiar, R.G., da Costa, J.M.N., 2012. Modeling the photosynthetically active radiation in South West Amazonia under all sky conditions. *Theoret. Appl. Climatol.* 108, 631–640. <https://doi.org/10.1007/s00704-011-0556-z>.
- Akitsu, T., Kume, A., Hirose, Y., Ijima, O., Nasahara, K.N., 2015. On the stability of radiometric ratios of photosynthetically active radiation to global solar radiation in Tsukuba, Japan. *Agric. For. Meteorol.* 209, 59–68. <https://doi.org/10.1016/j.agrformet.2015.04.026>.
- Alados, I., Foyo-Moreno, I., Alados-Arboledas, L., 1996. Photosynthetically active radiation: measurements and modelling. *Agric. For. Meteorol.* 78, 121–131. [https://doi.org/10.1016/0168-1923\(95\)02245-7](https://doi.org/10.1016/0168-1923(95)02245-7).
- Awal, M., Koshi, H., Ikeda, T., 2006. Radiation interception and use by maize/peanut intercrop canopy. *Agric. For. Meteorol.* 139, 74–83. <https://doi.org/10.1016/j.agrformet.2006.06.001>.
- Beck, H.E., Zimmermann, N.E., McVicar, T.R., Vergopolan, N., Berg, A., Wood, E.F., 2018. Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data* 5, 180214. <https://doi.org/10.1038/sdata.2018.214>.
- Bhattacharya, A., 2019. Radiation-Use Efficiency Under Different Climatic Conditions. In: *Changing Climate and Resource Use Efficiency in Plants*, Elsevier, 2019, pp. 51–109. <https://doi.org/10.1016/B978-0-12-816209-5.00002-7>. URL: <https://linkinghub.elsevier.com/retrieve/pii/B9780128162095000027>.
- Bredmose, N., Costes, E., 2017. Axillary Bud Growth. In: *Reference Module in Life Sciences*, Elsevier, 2017. <https://doi.org/10.1016/B978-0-12-809633-8.05056-1>. URL: <https://www.sciencedirect.com/science/article/pii/B9780128096338050561>, <https://linkinghub.elsevier.com/retrieve/pii/B9780128096338050561>.
- Campillo, C., Fortes, R., del Hénar Prieto, M., 2012. Solar Radiation Effect on Crop Production. In: *Solar Radiation*, figure 1, InTech, <https://doi.org/10.5772/34796>. URL: <http://www.intechopen.com/books/solar-radiation/solar-radiation-effect-on-crop-production>.
- Dauzat, J., Eroy, M., 1997. Simulating light regime and intercrop yields in coconut based farming systems. In: *Developments in Crop Science*, vol. 25, Elsevier, 1997, pp. 87–98. [https://doi.org/10.1016/S0378-519X\(97\)80011-6](https://doi.org/10.1016/S0378-519X(97)80011-6). URL: <https://www.sciencedirect.com/science/article/pii/S0378519X97800116>, <https://linkinghub.elsevier.com/retrieve/pii/S0378519X97800116>.
- Ferrera-Cobos, F., Vindel, J., Valenzuela, R., González, J., 2020. Models for estimating daily photosynthetically active radiation in oceanic and mediterranean climates and their improvement by site adaptation techniques. *Adv. Space Res.* 65, 1894–1909. <https://doi.org/10.1016/j.asr.2020.01.018>.
- Foyo-Moreno, I., Alados, I., Alados-Arboledas, L., 2017. A new conventional regression model to estimate hourly photosynthetic photon flux density under all sky conditions. *Int. J. Climatol.* 37, 1067–1075. <https://doi.org/10.1002/joc.5063>.
- García-Rodríguez, A., García-Rodríguez, S., Díez-Mediavilla, M., Alonso-Tristán, C., 2020. Photosynthetic active radiation, solar irradiance and the cie standard sky classification. *Appl. Sci. (Switzerland)* 10, 1–14. <https://doi.org/10.3390/app10228007>.
- García-Rodríguez, A., Granados-López, D., García-Rodríguez, S., Díez-Mediavilla, M., Alonso-Tristán, C., 2021. Agricultural and Forest Meteorology Modelling Photosynthetic Active Radiation (PAR) through meteorological indices under all sky conditions. *Agric. For. Meteorol.* 310. <https://doi.org/10.1016/j.agrformet.2021.108627>.
- Ge, S., Smith, R.G., Jacovides, C.P., Kramer, M.G., Carruthers, R.I., 2011. Dynamics of photosynthetic photon flux density (PPFD) and estimates in coastal northern California. *Theoret. Appl. Climatol.* 105, 107–118. <https://doi.org/10.1007/s00704-010-0368-6>.
- Gueymard, C.A., 2018. A reevaluation of the solar constant based on a 42-year total solar irradiance time series and a reconciliation of spaceborne observations. *Sol. Energy* 168, 2–9. <https://doi.org/10.1016/j.solener.2018.04.001>.
- Gueymard, C., Myers, D., Emery, K., 2002. Proposed reference irradiance spectra for solar energy systems testing. *Sol. Energy* 73, 443–467. [https://doi.org/10.1016/S0038-092X\(03\)00005-7](https://doi.org/10.1016/S0038-092X(03)00005-7).
- Hao, D., Asrar, G.R., Zeng, Y., Zhu, Q., Wen, J., Xiao, Q., Chen, M., 2020. DSCOVER/EPIC-derived global hourly and daily downward shortwave and photosynthetically active radiation data at 0.1° x 0.1° resolution. *Earth Syst. Sci. Data* 12, 2209–2221. <https://doi.org/10.5194/essd-12-2209-2020>.
- Hu, B., Wang, Y., Liu, G., 2007. Measurements and estimations of photosynthetically active radiation in Beijing. *Atmos. Res.* 85, 361–371. <https://doi.org/10.1016/j.atmosres.2007.02.005>.
- IEC, 2019. IEC 60904-3: 2019. Photovoltaic devices - Part 3: Measurement principles for terrestrial photovoltaic (PV) solar devices with reference spectral irradiance data, Technical Report, International Electrotechnical Commission.
- Igawa, N., 2014. Improving the All Sky Model for the luminance and radiance distributions of the sky. *Sol. Energy* 105, 354–372. <https://doi.org/10.1016/j.solener.2014.03.020>.
- Jacovides, C., Tymvios, F., Assimakopoulos, V., Kaltsounides, N., 2007. The dependence of global and diffuse PAR radiation components on sky conditions at Athens, Greece. *Agric. For. Meteorol.* 143, 277–287. <https://doi.org/10.1016/j.agrformet.2007.01.004>.
- Jacovides, C., Tymvios, F., Boland, J., Tsitouri, M., 2015. Artificial Neural Network models for estimating daily solar global UV, PAR and broadband radiant fluxes in an eastern Mediterranean site. *Atmos. Res.* 152, 138–145. <https://doi.org/10.1016/j.atmosres.2013.11.004>.
- Jajoo, A., Ladle, R.J., Zivcak, M., Łukasik, I., Goltsev, V., Brestic, M., Oukarroum, A., Dbrowski, P., Ahmad, P., Samborska, I.A., Cetner, M.D., Kalaji, H.M., 2014. The Use of Chlorophyll Fluorescence Kinetics Analysis to Study the Performance of Photosynthetic Machinery in Plants. In: *Emerging Technologies and Management of Crop Stress Tolerance*, Academic Press, pp. 347–384. <https://doi.org/10.1016/b978-0-12-800875-1.00015-6>. URL: <https://www.sciencedirect.com/science/article/pii/B9780128008751000156>.
- Janjai, S., Wattan, R., Sripradit, A., 2015. Modeling the ratio of photosynthetically active radiation to broadband global solar radiation using ground and satellite-based data in the tropics. *Adv. Space Res.* 56, 2356–2364. <https://doi.org/10.1016/j.asr.2015.09.020>.
- Kasten, F., Young, A.T., 1989. Revised optical air mass tables and approximation formula. *Appl. Opt.* 28, 4735. <https://doi.org/10.1364/AO.28.004735>.
- Leckner, B., 1978. The spectral distribution of solar radiation at the earth's surface—elements of a model. *Sol. Energy* 20, 143–150. [https://doi.org/10.1016/0038-092X\(78\)90187-1](https://doi.org/10.1016/0038-092X(78)90187-1).
- Li, R., Zhao, L., Ding, Y., Wang, S., Ji, G., Xiao, Y., Liu, G., Sun, L., 2010. Monthly ratios of PAR to global solar radiation measured at northern Tibetan Plateau, China. *Sol. Energy* 84, 964–973. <https://doi.org/10.1016/j.solener.2010.03.005>.
- Li, L., Xin, X., Zhang, H., Yu, J., Liu, Q., Yu, S., Wen, J., 2015. A method for estimating hourly photosynthetically active radiation (PAR) in China by combining geostationary and polar-orbiting satellite data. *Remote Sens. Environ.* 165, 14–26. <https://doi.org/10.1016/j.rse.2015.03.034>.
- Liu, X., Rahman, T., Song, C., Yang, F., Su, B., Cui, L., Bu, W., Yang, W., 2018. Relationships among light distribution, radiation use efficiency and land equivalent ratio in maize-soybean strip intercropping. *Field Crops Res.* 224, 91–101. <https://doi.org/10.1016/j.FCR.2018.05.010>.
- Long, C., Dutton, E., 2002. BSRN Global Network Recommended QC Tests, v2.0. In: Report No 1–3, Baseline Surface Radiation Network.
- McCree, K., 1972. Test of current definitions of photosynthetically active radiation against leaf photosynthesis data. *Agric. Meteorol.* 10, 443–453. [https://doi.org/10.1016/0002-1571\(72\)90045-3](https://doi.org/10.1016/0002-1571(72)90045-3).
- Mizoguchi, Y., Ohtani, Y., Aoshima, T., Hirakata, A., Yuta, S., Takanashi, S., Iwata, H., Nakai, Y., 2010. Comparison of the characteristics of five quantum sensors. *Bull. FFPRI* 9, 113–120.
- Mizoguchi, Y., Yasuda, Y., Ohtani, Y., Watanabe, T., Kominami, Y., Yamanoi, K., 2014. A practical model to estimate photosynthetically

- active radiation using general meteorological elements in a temperate humid area and comparison among models. *Theoret. Appl. Climatol.* 115, 583–589. <https://doi.org/10.1007/s00704-013-0912-2>.
- Mottus, M., Sulev, M., Baret, F., Lopez-Lozano, R., Reinart, A., 2012. Photosynthetically Active Radiation: Measurement photosynthesis/photosynthetic(ally) active radiation (PAR) measurement and Modeling photosynthesis/photosynthetic(ally) active radiation (PAR) modeling. In: Meyers, R.A. (Ed.), *Encyclopedia of Sustainability Science and Technology*, Springer, New York, New York, NY, 2012, pp. 7902–7932. https://doi.org/10.1007/978-1-4419-0851-3_451. URL: http://link.springer.com/10.1007/978-1-4419-0851-3_451.
- Nwokolo, S., Amadi, S., 2018. A Global Review of Empirical Models for Estimating Photosynthetically Active Radiation. *Trends Renew. Energy* 4, 236–327. <https://doi.org/10.17737/tre.2018.4.2.0079>.
- Ogburn, R.M., Edwards, E.J., 2010. The Ecological Water-Use Strategies of Succulent Plants. In: *Advances in Botanical Research*, vol. 55, Academic Press, pp. 179–225. <https://doi.org/10.1016/B978-0-12-380868-4.00004-1>. URL: <https://www.sciencedirect.com/science/article/pii/B9780123808684000041>, <https://linkinghub.elsevier.com/retrieve/pii/B9780123808684000041>.
- O’Gorman, E.J., Pichler, D.E., Adams, G., Benstead, J.P., Cohen, H., Craig, N., Cross, W.F., Demars, B.O., Friberg, N., Gíslason, G.M., Gudmundsdóttir, R., Hawczak, A., Hood, J.M., Hudson, L.N., Johansson, L., Johansson, M.P., Junker, J.R., Laurila, A., Manson, J.R., Mavromati, E., Nelson, D., Ólafsson, J.S., Perkins, D.M., Petchev, O.L., Plebani, M., Reuman, D.C., Rall, B.C., Stewart, R., Thompson, M.S., Woodward, G., 2012. Impacts of Warming on the Structure and Functioning of Aquatic Communities. In: Woodward, G., Jacob, U., O’Gorman, E.J.B.T.A.I.E.R. (Eds.), *Advances in Ecological Research*, vol. 47, Academic Press. <https://doi.org/10.1016/B978-0-12-398315-2.00002-8>, URL: <https://www.sciencedirect.com/science/article/pii/B9780123983152000028>, <https://linkinghub.elsevier.com/retrieve/pii/B9780123983152000028>.
- Peng, S., 2000. Single-leaf and canopy photosynthesis of rice. Citation: Sheehy JE, Mitchell PL, Hardy B, editors. 2000. Redesigning rice photosynthesis to increase yield. *Proceedings of the Workshop on The Quest to Reduce Hunger: Redesigning Rice Photosynthesis*, 30 Nov. In: *Studies in Plant Science*, vol. 7, Elsevier, 2000, pp. 213–228. URL: <https://www.sciencedirect.com/science/article/pii/S0928342000800178>, <https://linkinghub.elsevier.com/retrieve/pii/S0928342000800178>. [https://doi.org/10.1016/S0928-3420\(00\)80017-8](https://doi.org/10.1016/S0928-3420(00)80017-8).
- Perez, R., Ineichen, P., Seals, R., Michalsky, J.J., Stewart, R., 1990. Modeling daylight availability and irradiance components from direct and global irradiance. *Sol. Energy* 44, 271–289. [https://doi.org/10.1016/0038-092X\(90\)90055-H](https://doi.org/10.1016/0038-092X(90)90055-H).
- Rahman, M.M., Stanley, J.N., Lamb, D.W., Trotter, M.G., 2014. Methodology for measuring fAPAR in crops using a combination of active optical and linear irradiance sensors: a case study in Triticale (X Triticosecale Wittmack). *Precision Agric.* 15, 532–542. <https://doi.org/10.1007/s11119-014-9349-6>.
- Ross, J., Sulev, M., 2000. Sources of errors in measurements of PAR. *Agric. For. Meteorol.* 100, 103–125. [https://doi.org/10.1016/S0168-1923\(99\)00144-6](https://doi.org/10.1016/S0168-1923(99)00144-6).
- Sun, Z., Liang, H., Liu, J., Shi, G., 2017. Estimation of photosynthetically active radiation using solar radiation in the UV–visible spectral band. *Sol. Energy* 153, 611–622. <https://doi.org/10.1016/j.solener.2017.06.007>.
- Tang, W., Qin, J., Yang, K., Niu, X., Min, M., Liang, S., 2017. An efficient algorithm for calculating photosynthetically active radiation with MODIS products. *Remote Sens. Environ.* 194, 146–154. <https://doi.org/10.1016/j.rse.2017.03.028>.
- Torres, A.P., Lopez, R.G., 2012. Measuring Daily Light Integral in a Greenhouse Commercial Greenhouse Production Purdue extension HO-238-W, URL: www.hort.purdue.edu.
- Vindel, J.M., Valenzuela, R.X., Navarro, A.A., Zarzalejo, L.F., Paz-Gallardo, A., Souto, J.A., Méndez-Gómez, R., Cartelle, D., Casares, J. J., 2018. Modeling photosynthetically active radiation from satellite-derived estimations over mainland Spain. *Remote Sens.* 10, 1–13. <https://doi.org/10.3390/rs10060849>.
- Vindel, J., Valenzuela, R., Navarro, A., Zarzalejo, L., 2018. Methodology for optimizing a photosynthetically active radiation monitoring network from satellite-derived estimations: A case study over mainland Spain. *Atmos. Res.* 212, 227–239. <https://doi.org/10.1016/j.atmosres.2018.05.010>.
- Wandji Nyamsi, W., Espinar, B., Blanc, P., Wald, L., 2015. Estimating the photosynthetically active radiation under clear skies by means of a new approach. *Adv. Sci. Res.* 12, 5–10. <https://doi.org/10.5194/asr-12-5-2015>.
- Wandji Nyamsi, W., Blanc, P., Augustine, J.A., Arola, A., Wald, L., 2019. A New Clear-Sky Method for Assessing Photosynthetically Active Radiation at the Surface Level. *Atmosphere* 10, 219. <https://doi.org/10.3390/atmos10040219>.
- Wang, L., Gong, W., Li, C., Lin, A., Hu, B., Ma, Y., 1961. Measurement and estimation of photosynthetically active radiation from 1961 to 2011 in Central China. *Appl. Energy* 111 (2013), 1010–1017. <https://doi.org/10.1016/j.apenergy.2013.07.001>.
- Wang, L., Kisi, O., Zounemat-Kermani, M., Hu, B., Gong, W., 2016. Modeling and comparison of hourly photosynthetically active radiation in different ecosystems. *Renew. Sustain. Energy Rev.* 56, 436–453. <https://doi.org/10.1016/j.rser.2015.11.068>.
- Yu, X., Wu, Z., Jiang, W., Guo, X., 2015. Predicting daily photosynthetically active radiation from global solar radiation in the Contiguous United States. *Energy Convers. Manage.* 89, 71–82. <https://doi.org/10.1016/j.enconman.2014.09.038>.
- Zempila, M.M., Taylor, M., Bais, A., Kazadzis, S., 2016. Modeling the relationship between photosynthetically active radiation and global horizontal irradiance using singular spectrum analysis. *J. Quant. Spectrosc. Radiat. Transfer* 182, 240–263. <https://doi.org/10.1016/j.jqsrt.2016.06.003>.
- Zhang, L., van der Werf, W., Bastiaans, L., Zhang, S., Li, B., Spiertz, J., 2008. Light interception and utilization in relay intercrops of wheat and cotton. *Field Crops Res.* 107, 29–42. <https://doi.org/10.1016/j.fcr.2007.12.014>.