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To cite this article: Agustín Laguarda and Gonzalo Abal 2025 *IOP Conf. Ser.: Earth Environ. Sci.* **1522** 012034

IOP Conf. Series: Earth and Environmental Science **1522** (2025) 012034 doi:10.1088/1755-1315/1522/1/012034

Power Model for Estimating UV Index from GHI and Ozone Information: Uncertainty Assessment Across Varied Conditions

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Abstract. The power model (PM) offers a simple and precise approach to estimating UV erythematic solar irradiance (UVE) from global horizontal irradiance (GHI) and total atmospheric ozone information. Its overall accuracy (RMSD) at the 10-minute level ranges from 9% to 11% of the measurement's mean with mean biases within ± 3%. This study further analyzes the performance of this PM when used with hourly atmospheric Ozone estimates from the MERRA-2 global database. Its performance is assessed under diverse environmental conditions, including variations in solar time and cloud cover, across four mid-latitude, temperate-climate sites in South and North America. The analysis reveals that the model presents higher biases during overcast conditions and tends to slightly overestimate UVE near solar noon and under clear skies, with errors reaching up to 6% when these conditions coincide, which is similar to the measurement's typical uncertainty. These findings confirm the reliability of the PM model used with MERRA-2 Ozone information, particularly in high UV index scenarios, making it a valuable tool for public health communication and UV exposure risk assessment.

1 Introduction

Solar UV radiation has a profound impact on biological tissues and human health, and its magnitude is relevant to guide good practices for for skin exposure. The UV index (IUV), is a dimenstionless quantity proportional to the Erythemically weighted UV irradiance, UVE (CIE, 1998). It is widely used to inform the public about exposure risks (Commission Internationale de l'Eclairage and World Meteorological Organization (CIE), 2014). A reliable and computationally-effective approach for UV estimation involves using measured global horizontal irradiance (GHI) and atmospheric Ozone information to estimate UVE (and thus IUV). For a broader territorial coverage, a suitable satellite-based model can be used to estimate GHI.

Several parametric models using relative air mass (m), clearness index, k_t, and total ozone column information ($[O_3]$) have been trained to ground data from several sites and used locally to convert GHI to UVE with low uncertainty (Laguarda and Abal, 2019). The most accurate model was found to be based on power functions and uses air mass, clearness index and Ozone concentration as predictor variables. This model was first introduced in Antón Martínez (2007) and a simplified version was tested with good results against data from four sites in Spain (Antón Martínez et al., 2009). More recently, a model of this kind (PM) has been locally adjusted and assessed using four years of data from four mid-latitude moderate climates in both South and North America (Laguarda et al., 2024);

$$\mathrm{UVE} = \mathrm{GHI} \times 0.705 \cdot k_t^{-0.207} \cdot m^{-1.247} \cdot \left(\frac{[O_3]}{100}\right)^{-0.950}, \tag{1}$$

where [O_3], is expressed in Dobson Units, GHI in W/m^2 and UVE in mW/m^2. The coefficients used in Eq. (1) are average values over four mid-latitude sites. As shown in (Laguarda et al., 2024) the PM model, used with MERRA-2 Ozone concentration, produces UVE estimates at 10-minute frequency with a typical uncertainty in the 9–11% range (relative RMSD) and biases within ±3% of the measurement average.

Uruguay has the highest per-capita skin cancer (melanoma and non-melanoma) rate in the Latin America (Ferlay et al., 2024) and there is a real concern in rising public awareness on the subject. Currently, the Uruguayan Meteorological Service utilizes the PM model to provide real-time public UV index information (`https://www.inumet.gub.uy`). This highlights the need for an accurate uncertainty assessment of this model to ensure that reliable public health information is being disseminated. In this work, a more detailed study of the PM model performance across several environmental conditions (including apparent solar position and cloudiness) is reported.

2 Data and Methodology

The PM model is validated using simultaneous measurements of GHI and UV-E from four subtropical sites in South and North America, as shown in Table 1. The data was integrated into 10-minute intervals, and additional variables such as relative air mass, m, and clearness index, k_t, were derived. Total ozone content ($[O_3]$) was sourced from the MERRA-2 reanalysis database (Gelaro et al., 2017), available at an hourly resolution. Each site provided four years of data, with more than ≃90% of the diurnal observations passing rigorous quality control procedures (Table 1). This dataset is identical to the one used in Laguarda et al. (2024), where further methodological details are available for reference. The typical uncertainty of the GHI data is 5% of the mean values and for UVE it is somewhat higher, about 7% of the average measurement. The Ozone estimates from Merra2 have been evaluated in Wargan et al. (2017) and have a median estimated accuracy of 12 % for mid-latitude sites.

Table 1: Summary of measurement sites and data used in the analysis. The table provides the location coordinates, observation period, and the total number of 10-minute data pairs that passed the quality control process. The portion of the total data passing quality control is indicated as a percentage in parentheses. Adapted from Laguarda et al. (2024).

Site/ Location	Site Code	Lat. (°)	Lon. (°)	Alt (m)	Period Period	Number of data pairs
Salto, Uruguay	LES	-31.28	-57.92	56	01/2018 – 12/2021	59026 (95.5%)
Golden, Colorado, USA	GCO	+39.74	-105.18	1829	08/2018 – 12/2021	78901 (99.0 %)
Goodwin Creek, Mississippi, USA	GWN	+34.25	-89.87	98	07/2018 – 12/2021	77765 (96.4%)
Pilar, Córdoba, Argentina	PIL	-31.68	-63.87	330	07/2017 – 12/2021	58431 (90.0%)

To analyze the performance across varied conditions, the model is studied by categories, separating the reference UVE data in five groups, as shown in Table 2. The first category involves solar time (high sun and otherwise). The second grouping involves sky conditions, with the clearness index k_t (defined as GHI/$S_c \cdot F_n \cdot \cos(z)$, where $Sc = 1361\,\mathrm{W/m^2}$, F_n is the daily orbital factor and z the solar zenith angle) used as a proxy of cloudiness. Commonly used statistical metrics such as the Mean Bias Deviation, $\mathrm{MBD} = \sum_i d_i/N$ and the Root Mean Square Deviation, $\mathrm{RMSD} = \sqrt{\sum_i d_i^2/N}$, were obtained for each sub sub dataset. Here N is the number of samples and $d_i = \widehat{y_i} - y_i$ are the residuals between the modeled estimates $\widehat{y_i}$ and the measured UVE irradiance, y_i. Both metrics are in mW/m^2 and assess different aspects of the model's accuracy. They will be expressed in relative terms as percentages of the measurement's mean (rMBD and rRMSD) but with the reference mean values stated, so that they can be converted to absolute units.

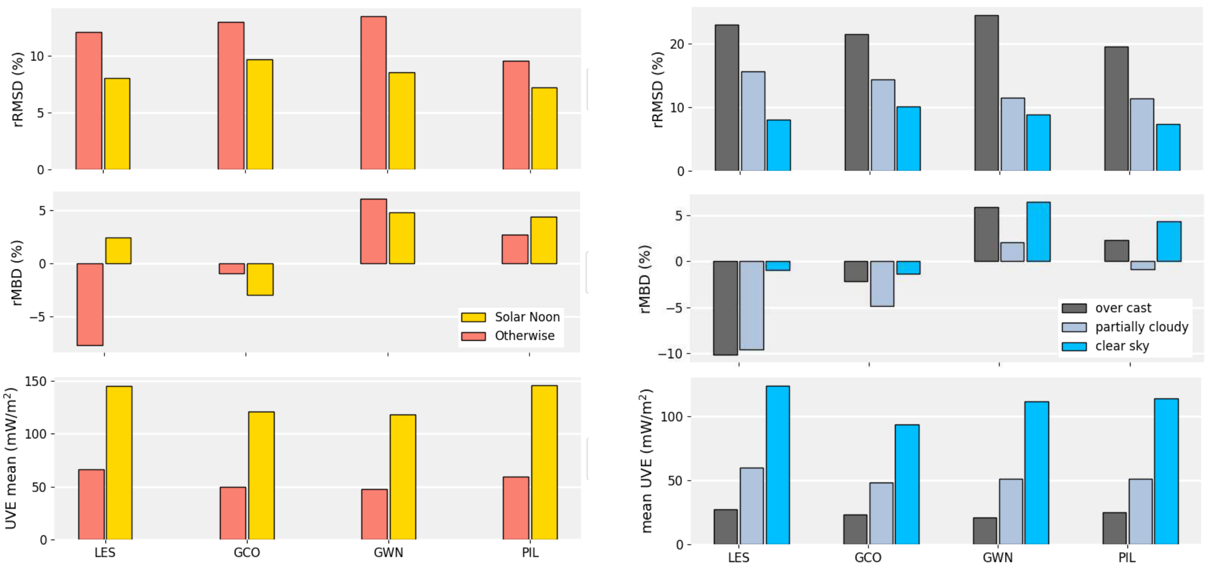
Table 2: Classification based on time from solar noon (left) and cloudiness using clearness index k_t (right).

Solar Time	Description
A	noon, ± 1.5 hours from solar noon
B	otherwise

Clearness Index	Description
I	overcast, $k_t \leq 0.3$
II	partially cloudy, $0.3 < k_t \leq 0.6$
III	mostly clear sky, $k_t > 0.6$

3 Results and Discussion

Figure 1a shows the results of the PM model separated by solar time categories. The mean values used to normalize the metrics for each case are included at the bottom. When segregating the data according to solar time, approximately 30% of the data falls within the high Sun category (A) and the remaining 70% is in category B. The rRMSD values are consistently lower around solar noon (A), ranging from 7% to 10%, compared to 10 - 13% for the low Sun group (B). On the other hand, mean biases exhibit a variable behavior across sites, as expected from a quasi-universal model for which the coefficients are not trained to the particular sites. There is a general trend of overestimation near solar noon, except for GCO, whereas mean bias for low Sun conditions shows variable signs depending on the site.



(a) Solar time (b) Cloudiness

Figure 1: Relative MBD and RMSD. The percenages are referred to the measurements mean, showed in the bottom panel.

Figure 1b, categorized by clearness index, shows that the relative dispersion (rRMSD) consistently decreases as k_t increases, with values above 20% for group I (overcast conditions) and dropping to 9-10% for group III (mostly clear sky conditions). The mean bias for overcast conditions (group I) shows a high variability across sites, with large magnitudes and changing signs. A similar pattern is observed in group II, though with smaller amplitude. Finally, in group III, the biases tend to be smaller, with values being slightly positive or negative, reaching an extreme of 5% for the GWN site.

Figure 2 illustrates the model's performance for different cloudiness conditions with scatter plots for the LES site, as an example. In this case, the mean bias indicates under-estimation under cloudy conditions which gradually shifts to over-estimation under clear sky and low air mass (near solar noon) conditions. Relative RMSD (dispersion) is lower for mostly clear skies (III) or near noon (A). When the two conditions are satisfied simultaneously (A and III), it reaches its lowest value at 6%, which is similar to the typical uncertainty of the ground-based UV measurements. These findings highlight the PM model's robustness, particularly during high IUV periods that are critical for the public health applications currently underway.

4 Conclusion

This study evaluated the performance of a simple model based on power functions of the clearness index (cloudiness), the air mass (solar altitude) and Ozone concentration (atmospheric Ozone) for estimating the erythematic UV irradiance (UVE) under varied environmental conditions. Ozone information was obtained the reanalysis (MERRA-2) database. The model was evaluated using data from four mid-latitude sites with temperate climates.

The results indicate that the model tends to present high biases for overcast conditions, and there it is still challenging to estimate accurately UV irradiance under significant cloud cover. Conversely, a shift toward overestimation was observed in mostly clear sky conditions and low air mass, particularly near solar noon. This period,

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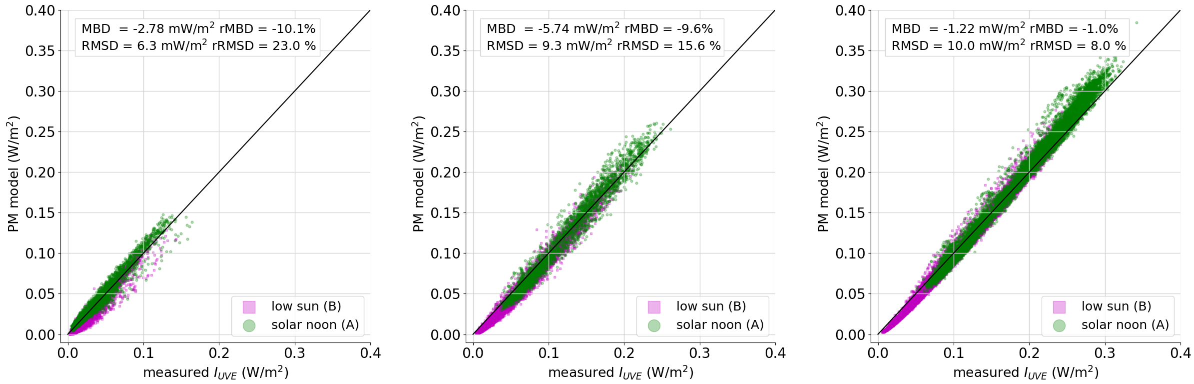

(a) Cloudy (I) (b) Partially cloudy (II) (c) Mostly clear sky (III)

Figure 2: Scatter plots for different k_t categories at the LES site, with colors representing groups A (High Sun) and B (Low Sun) in each plot.

which accounts for 30% of the data, exhibits the lowest rRMSD (6%), which is similar to the typical uncertainty levels of the UV ground measurements.

The study confirms the reliability of the PM model under high UV index scenarios, with accuracy improving notably during clear skies and near solar noon, the most relevant conditions for health related applications. These findings reinforce the model's suitability for public communication and UV exposure risk assessments, particularly during the summer months in regions with limited UV measurement infrastructure. However, other factors can also play a relevant role, such as surface albedo and aerosol type and concentration. Their effects on UVE may be different than their impact in GHI and there is room for improvement in these aspects.

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