Response to Referee #3

First High-Resolution Surface Spectral Clear-Sky Ultraviolet Radiation Dataset across China (1981–2023): Development, Validation, and Variability

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Dear editor and reviewers,

We would like to thank the editor for handling our manuscript and the reviewers for their careful evaluation of our work and the valuable comments, suggestions, and questions. Our point by point response to the comments made by Reviewers are given below, we have also marked changes in the manuscript. Please find a detailed point-by-point response to each comment.

Yours sincerely,
Wenmin Qin, Qinghai Qi and co-authors

General Comment:

The development of a reliable Solar Ultraviolet (UV) radiation dataset is undeniably crucial, underpinning a wide range of applications from biophysical modeling to public health assessments. The dataset presented by Qi et al., covering mainland China from 1982 to 2023 and generated using the SMARTS (Simple Model of the Atmospheric Radiative Transfer of Sunshine) spectral model, represents a significant and valuable contribution to the community. The validation results against ground observations, which show a strong performance, are commendable.

Response:

We would like to express our sincere gratitude to you for the precious time and effort you have dedicated to reviewing our manuscript. We are truly appreciative of your insightful comments and constructive suggestions, which have been invaluable in helping us to improve the quality and clarity of our work.

Major Comment 1:

However, two major points regarding the methodology and presentation of results require clarification and revision, as detailed below.

Precision and significance of reported digital numbers

The study frequently employs an excessive number of digital numbers (e.g., reporting the correlation coefficient R as 0.919). While precision is generally desirable, the number of significant digits must be meaningful and justified by the data quality and the inherent uncertainty of the model and observations.

Please review the entire manuscript and uniformly apply a statistically meaningful number of significant figures to all reported metrics (e.g., R, RMSE, bias, and model parameters). For instance, given typical measurement and model uncertainties, reporting R to three decimal places may imply a false level of precision where R=0.919 is not meaningfully distinct from R=0.923. The chosen precision should reflect the uncertainty of the estimated value.

Response:

We agree with the reviewer that the previously reported precision, such as R = 0.919, could create a misleading impression of accuracy beyond the capability of our data and model. The revision to R = 0.92 is not a loss of information but a more honest representation of the statistical confidence in our results. It removes the 'false precision' and ensures that the significant digits we report are truly meaningful and justified by the underlying uncertainty in our estimates. We have systematically standardized the numerical precision to two decimal places for all key statistical metrics, including correlation coefficients, root mean square error, mean bias error, and model-derived trends. This principled adjustment was applied consistently to the text, tables, and figures to ensure uniformity and to eliminate any false precision.

Major Comment 2:

Rationale for linear regression methodology

The linear regression analysis, as displayed in Figures 4(a), 5(a), 6(a)(b), and 7(a)(b), appears to be conducted directly on the entire scatter plot of data points. When dealing with large sample sizes, this approach can lead to a regression bias that is unduly influenced by the density distribution of the samples, particularly at the extremes.

I recommend considering an alternative or supplementary approach: first compute the conditional mean (i.e., bin the observed data along the x-axis and calculate the mean of the modeled data for each bin) and then perform the linear fit on these conditional mean values. This technique can effectively suppress the sampling bias and provide a more robust characterization of the central tendency relationship between the modeled and observed values, especially when the sample size is large. A discussion on the impact of this methodological choice should be included.

Response:

We sincerely thank the reviewer for the insightful suggestion regarding potential biases in linear regression with large sample sizes and the recommendation to perform a binned analysis. This is an excellent point for ensuring a robust evaluation. We have performed the suggested binned analysis by calculating conditional means, and the results have been added to the revised manuscript. To address the concern regarding regression bias, we performed a quantile binning analysis. The relevant binned regression results are as follows:

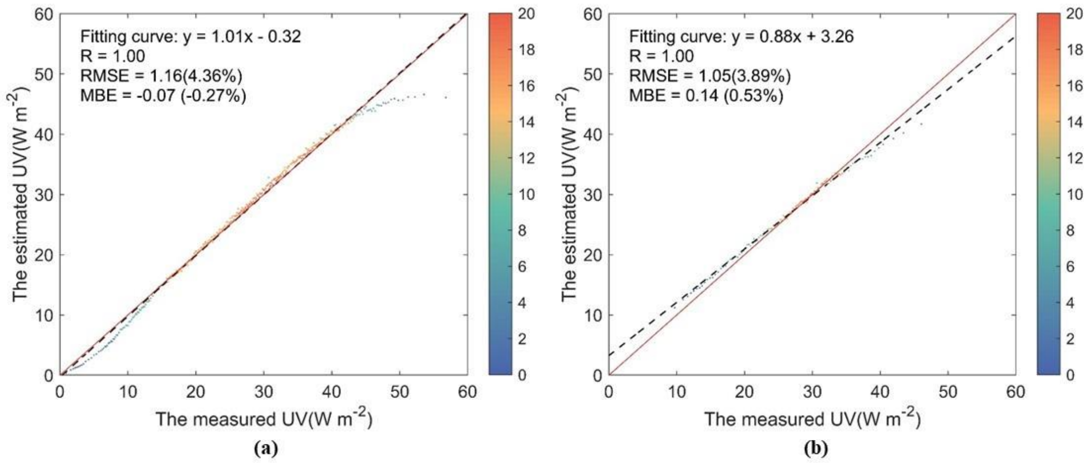

Figure A2. Binning scatter validation results of the estimated clear-sky UV dataset against observations at 37 CERN stations from 2005-2013. (a) Density scatter plot between the hourly estimated dataset and observations;(b) same as (a) but for daily results.

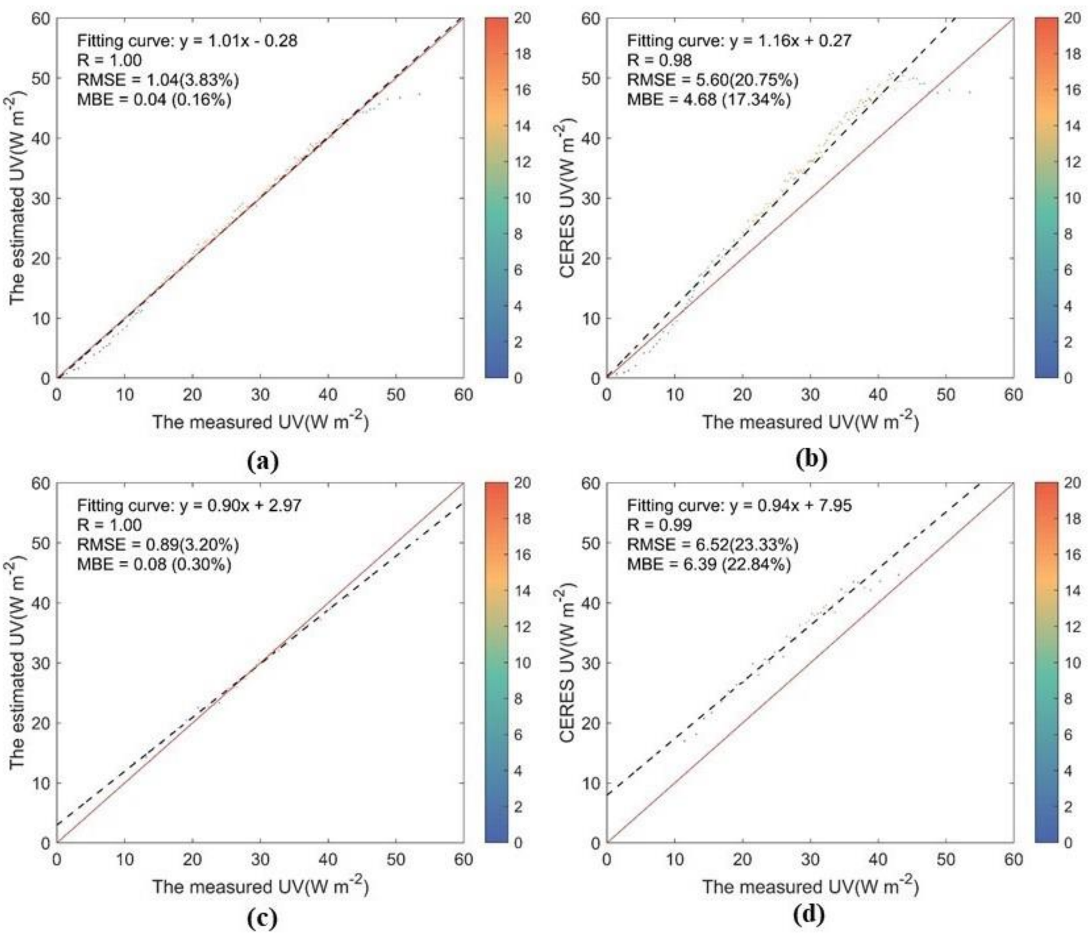

Figure A3. Binning scatterplot of assessment results for two clear-sky UV radiation products. (a) Density scatterplot between the hourly clear-sky SMARTS-derived UV irradiance estimates and CERN observations. (b) Same as (a) but for the CERES SYN1deg estimates. (d) and (e) same as (a) (b) but for daily results.

The binned regression excellently characterizes the average functional relationship between the model and observations. However, the regression on the entire dataset provides a unique and statistically valid estimate of the overall, aggregate error structure across the entire population of time steps. This is a crucial metric for many practical applications, such as assessing the model's suitability for generating large-scale radiation budgets.

Minor Comments

1) *Line 145: The physical significance and unit of the parameter z should be explicitly stated in the text where it is first introduced or used.*

Response:

We thank the reviewer for your careful reading of the manuscript. The parameter 'Z' is indeed a key variable in our methodology, and it is defined and described in detail in the Line 146. For clarity, it represents the solar zenith angle.

2) *Figure 13: The interpretation of trends, particularly in long-term, non-stationary time series, is highly sensitive to the chosen data range and the trend methodology. The authors should acknowledge this sensitivity and briefly discuss the potential impact of their chosen methods, perhaps referencing relevant literature. (e.g., Zhao et al., On the trend, detrending, and variability of nonlinear and nonstationary time series, PNAS, 2007, 104 (38) 14889-14894).*

Response:

We thank the reviewer for raising this critical point regarding the sensitivity of long-term trend analysis in non-stationary time series. We fully agree that the robustness of trends must be scrutinized.

In our study, we specifically designed the trend analysis to address this very issue. The division of the full period (1981-2023) into three sub-periods (1981-1994, 1995-2009, and 2010-2023) was not arbitrary but was physically and policy-based. This segmentation is grounded in distinct phases of both global climate evolution and China's domestic environmental governance. For instance, the post-2010 period aligns with the implementation of China's most stringent and comprehensive air pollution control policies, while the earlier segments correspond to different stages of economic development and climate variability.

We have revised the manuscript to explicitly acknowledge this methodological sensitivity. In the section 4.4.3, we have added a paragraph: "*The analysis of trends in long-term environmental time series is recognized as being sensitive to the selected data range and to methodology of detrending (Wu et al., 2007).*" at Line 436; "*Finally, while the identified trend is statistically significant and physically consistent, it should be noted that its quantitative value is methodology- and period-dependent, a common consideration in non-stationary time series analysis.*" at Line 456.

Wu, Z., Huang, N. E., Long, S. R., and Peng, C. K.: On the trend, detrending, and variability of nonlinear and nonstationary time series. *Proc. Natl. Acad. Sci. U. S. A.* **104**, 14889–14894, https://doi.org/10.1073/pnas.0701020104, (2007).

3) *Code Sharing: To maximize the utility and reproducibility of this valuable work, the authors are strongly encouraged to convert the SMARTS model implementation used for this study into a Python-based package and share the code with the community. Python facilitates easy integration with modern data science and AI/Machine Learning models, significantly enhancing the model's accessibility and impact.*

Response:

We thank the reviewer for the interest in the SMARTS model code used in our study. We fully support the principles of open science and research reproducibility. The SMARTS model are not novel and have long been publicly available at https://www.solarconsultingservices.com/. The specific implementation in this work was based on this established, open-source Fortran version. Recognizing the value of modern, accessible tools, we are currently developing a new, user-friendly Python implementation of the model. This new version, which will include enhanced features and greater modularity, is planned for public release upon the completion of our ongoing follow-up study.