Response to Reviewer #1:

This is a good paper which provides valuable UV dataset for epidemiological studies. In this study, they performed very strict validations using spatial, temporal, as well as by-year cross validation methods, indicating the high accuracy of their reconstructed UV dataset. I believe this dataset is valuable for environmental health studies of UV in China. I have some comments for the authors to improve the manuscript.

Response: Thank you for the positive comments and constructive suggestions to help improve our manuscript. We have fully responded to the comments below point-to-point and revised the manuscript accordingly. The line numbers referred to in this response document corresponded to those in the revised manuscript with tracked changes.

1. It is not clear why missing values of OMI EDD data have been greatly increased since 2008. Please explain it.

Response: Thank you for the suggestion. We added the explanation in lines 48-51 in the revision as “However, missing values of the OMI EDD data were non-random. Especially since 2008, the field of view of the instrument has been partially obstructed by the peeling of the spacecraft's protective film, leading to data loss in the center-right section of each observational swath. This has greatly increased the missing rate of OMI EDD data, posing a challenge to the accuracy of exposure assessments in epidemiological studies (Mcpeters et al., 2015)”.

References:

McPeters, R. D., Frith, S., and Labow, G. J.: OMI total column ozone: extending the long-term data record, Atmospheric Measurement Techniques, 8, 4845-4850, https://doi.org/10.5194/amt-8-4845-2015, 2015.

2. The method using to fill the missing OMI EDD values is not clear. Specifically, what is the three-day moving average method? Does this method have enough accuracy to fill the missing values? If there are many consecutive days with missing values, how to address this?

Response: Thanks for the suggestions.

First, we added explanation of the three-day moving average method as suggested in lines 144-148 in the revision as “We employed the three-day moving average method to fill the OMI EDD values on grid-days with missing data by calculating the mean of the OMI EDD values from the two preceding days if they were available for those grid cells. In the case of grid cells with missing data on consecutive days (more than 1 day), the missing OMI EDD data were not filled in this study. With this method, the missing rate of OMI EDD significantly decreased from 23.04% to 0.62% on average in 2005-2020 (Table A2)".

Second, we utilized 10-fold cross-validation (CV) to assess the accuracy of the three-day moving average method and added relevant descriptions and results in the revision in lines 148-153 as "10-fold CV was employed to assess the accuracy of the three-day moving average method for filling the gap of OMI EDD data. In each iteration, 10% of the original OMI EDD data in the dataset were randomly dropped, and the three-day moving average method was applied to fill the missing values. This process was repeated ten times, and the gap-filled OMI EDD values were compared to the corresponding original OMI EDD values. The results of the 10-fold CV are presented in Table A2 in Appendix, with R^2 ranging from 0.85 to 0.90 in 2005-2020, indicating the relatively high accuracy of the gap-filling method".

Table A2 in Appendix was modified accordingly and was displayed here for your convenient reference.

Table A2. Missing rate of erythemal daily dose (EDD) retrieved from the Ozone Monitoring Instrument (OMI) before and after gap-filling and the results of 10-fold cross-validation of the three-day moving average method from 2005 to 2020 in China.

Year	Missing rate before gap-filling	Missing rate after gap-filling	R^2 of 10-fold cross-validation
2005	3.03%	0.00%	0.90
2006	3.53%	0.27%	0.90
2007	3.38%	0.00%	0.90
2008	5.69%	0.57%	0.89

2009	20.33%	0.21%	0.88
2010	30.28%	0.40%	0.88
2011	33.59%	0.53%	0.88
2012	21.80%	0.17%	0.90
2013	24.24%	0.28%	0.88
2014	28.20%	0.37%	0.90
2015	31.95%	0.50%	0.88
2016	35.29%	4.19%	0.87
2017	32.78%	1.52%	0.86
2018	32.19%	0.55%	0.85
2019	32.12%	0.42%	0.85
2020	30.34%	0.00%	0.86
2005-2020	23.04%	0.62%	0.88

3. For the method of comparing the long-term trend of UV radiation and air pollution, they should use an independent section. They should not include it in the section of 2.1.4 Other predictor variables.

Response: Thanks for the suggestion. An independent section was added in the " 2.1 Data " Section:

[lines 125-129] “2.1.5 Air pollution data

For comparing the long-term trends of UV radiation and air pollution, fine particulate matter

($PM_{2.5}$) and O_3 data were included. $PM_{2.5}$ data were predicted using a random forest model at a daily level and a spatial resolution of 1 × 1 km in China (Meng et al., 2021; Shi et al., 2023a; Shi et al., 2023b). The source and spatiotemporal resolution of the O_3 data were the same as those in Section 2.1.4 Other predictor variables".

4. More analyses about the relationship between PM2.5/O3 and UV should be conducted. Although they show the importance for predictor variables, which shows AOD and O3 are important variables. They should perform SHAP analysis to show the impact directions of AOD/O3 on the UV. This could further demonstrate the impacts of PM2.5/O3 on UV increase.

Response: Thanks for the constructive comment. We have conducted SHAP analysis to further elucidate the impact direction of predictors on UV radiation predictions as suggested, and added relevant descriptions in Method and Results sections, which were also summarized below for your convenient reference.

Descriptions of the methods were added in the " 2.2 Methods " Section in lines 178-188 as:

"2.2.3 Impacts of predictors on UV predictions

Two methods were applied to evaluate the impacts of all predictors on UV radiation levels. First, random forest model itself could produce importance rankings of all predictors to evaluate the contribution of each predictor to UV radiation predictions, and this is also one of the advantages of the random forest model. The importance of a predictor was measured by randomly permuting its values and comparing the decrease in predicting accuracy between the predictions before and after the permutation. Second, SHapley Additive exPlanations (SHAP) method can be used to evaluate both contributions and directions of predictors on final predictions (Lundberg and Lee, 2017). SHAP method employs the classic game theory concept of Shapley values to compute the feature importance for a specific machine learning model (Strumbelj and Kononenko, 2010). Aggregating the SHAP values across multiple data points provides a global explanation of the model. In this study, we utilized the SHAP library in Python to interpret impacts of predictors on UV radiation predictions based on a random forest model (Lundberg et al., 2020)."

Relevant results of SHAP method were added in lines 222-233 as:

"3.3. Impacts of predictors on UV radiation predictions

Fig. A2 shows the importance ranking of all predictors produced by the random forest model itself that ERA-5 UV, OMI EDD, and MAIAC AOD were the most important predictors of UV radiation. Fig. 4 shows the SHAP summary plot and feature importance, which were the same with that from the random forest method. SHAP method also provided evaluation on the impact directions of predictors on UV radiation predictions. In Fig. 4a, each point represents a sample from the dataset. The color of each point indicates the magnitude of the predictor, with redder values indicating higher values and bluer indicating lower values. For example, ERA-5 UV and OMI EDD exerted the most substantial impact and similar impact directions on UV radiation predictions. High values of ERA-5 UV and OMI EDD increased the predicted UV radiation predictions, whereas low values decreased UV radiation predictions. Ambient aerosols (MAIAC AOD) and O_3 levels showed opposite effects on UV radiation predictions based on SHAP method. Higher MAIAC AOD values displayed higher negative SHAP values, meaning that higher MAIAC AOD values tended to associate with decreased UV radiation levels. Conversely, High O_3 levels corresponded to positive SHAP values, indicating that high O_3 levels were associated with high UV radiation predictions."

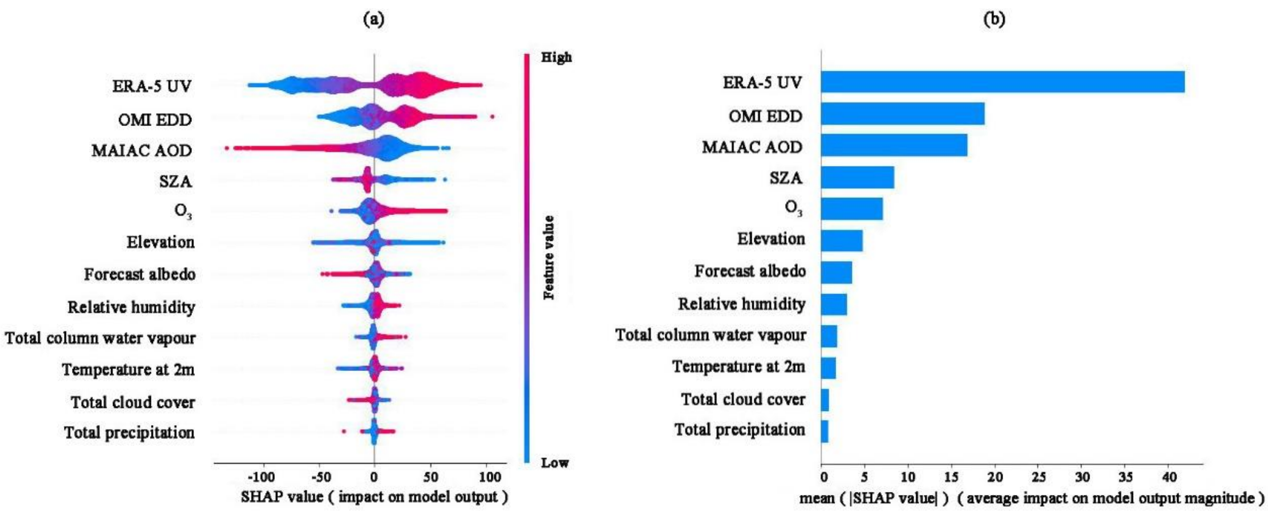

Figure 4. Impacts of predictors on UV radiation predictions based on SHAP method (a); importance ranking of predictors for predicting UV radiation levels, calculated by taking the average of the absolute SHAP values (b).

Relevant discussions were added in " 4 Discussion " Section in lines 343-345 as:

“Additionally, the results of the SHAP analysis were consistent with the long-term trend analysis, which indicated that ambient aerosols levels were negatively associated with UV radiation predictions while O_3 concentrations positively related with UV radiation levels.”

5. Table 1 is not necessary in main text. I recommend combine Table 1 into Table A1.

Response: Thanks for the suggestion. We have combined Table 1 into Table A1 in the Appendix. We also displayed Table A1 here for your convenient reference.

Table A1 Statistical descriptions of UV radiation measurements from ground monitoring stations in CERN in China from 2005–2020

Year	Mean (W m^{-2})	Standard deviation (W m^{-2})	P25 (W m^{-2})	Median (W m^{-2})	P75 (W m^{-2})
2005	160.62	81.07	94.35	153.57	160.62
2006	158.34	80.56	94.20	149.90	214.90
2007	159.54	82.99	91.81	150.41	220.21
2008	162.39	83.09	93.49	153.60	223.16
2009	159.64	82.65	91.46	152.20	222.60
2010	155.46	81.73	88.56	144.91	215.80
2011	160.95	84.37	90.11	152.60	223.50

2012	159.65	85.38	88.75	153.60	221.80
2013	160.21	82.87	92.00	149.93	221.50
2014	160.87	82.41	94.06	152.90	221.50
2015	170.96	91.32	96.66	162.70	238.20
2016	175.66	96.84	97.72	162.75	248.00
2017	180.90	109.28	100.90	168.40	254.60
2018	187.00	103.48	102.00	176.30	262.00
2019	189.80	104.63	103.90	178.60	265.70
2020	190.10	105.01	104.10	177.20	266.90
2005–2020	168.40	91.39	94.80	158.10	232.80