Responses to RC1

Review of Full-coverage 250 m monthly aerosol optical depth dataset (2000-2019) emended with environmental covariates by the ensemble machine learning model over the arid and semi-arid areas, NW China By Chen et al. This manuscript applies bagging trees ensemble methods to produce monthly full-coverage and high-resolution AOD product (FEC AOD). Compared with AERONET AOD, FEC AOD has good performance with an R^2 of 0.79. A good analysis of spatio-temporal variability is then presented and the interpretation of environmental covariates on FEC AOD is explored using redundancy analysis. I would like to recommend minor revisions.

Response: Many thanks for reviewing our manuscript and providing us with your recognition and valuable advice on our work, we studied your comments and responded to them point by point carefully as described below.

1. Line 33, the expression is ambiguous since the bimodal pattern usually refers to the aerosol size distribution.

Response: Thank you for your valuable suggestion. Our original intention is to express that AOD annual variation in Gansu province shows different characteristics from other provinces, where AOD has two peaks, while in other provinces it has only one. Regarding the expression of bimodal and unimodal, we also referred to the previous studies before expressing it in this way. Of course, to avoid ambiguity, we phrased it in the revision as “the AOD annual variation pattern shows a different feature, with two peaks in March and August respectively over Gansu province, but only one peak in April over other provinces." (Page 2/Lines:30-32).

2. The blank space before the reference is lacking.

Response: Thank you for your careful reading. In the revision, we carefully checked the full text to make sure there were spaces before each reference.

3. How did you get the FEC AOD at 250m resolution? Is it simply a matter of interpolating the original input data to a resolution of 250m and then inputting it into the model to get the FEC AOD?

Response: Thank you for your precious question and comment. FEC AOD is built by a downscaling method, not by simple interpolation. Actually, the basic idea for downscaling AOD with bagging trees ensemble machine learning (ML) models is to train the relationships between MAIAC AOD and the auxiliary environmental variables at coarse resolution (1 km) using ML algorithms. We then apply the trained relationships to generate a high-resolution FEC AOD product at a fine resolution (250 m). This idea of downscaling has been developed more maturely and is widely used[1-3], and it is based on a complex mathematical feature that is capable of mining the characteristics of different environmental auxiliary variables on the representation of AOD. Compared with the traditional model with poor data mining ability, low accuracy, and coarse spatial resolution, the ML approach is noise-resistant and can effectively reduce modeling variance to improve model accuracy and build robust relationships between AOD and environmental auxiliary variables. In terms of auxiliary environmental variables, we adopt a high resolution (< 250 m, i.e. 30 m or 90 m) to describe static variables, while for dynamic variables, a spatial scale of 1 km is used whenever possible. As for static variables, we only use resample to 250 m and 1 km (for LUCC, use the nearest neighbor method, and others employ the bilinear method). In terms of dynamic variables, firstly, for the ET and NDVI data below 1 km resolution, we downscaled them to 1 km using the Cubist downscaling method, not by a simple interpolation[3]. What is more, the environmental variables we have chosen are also closely related to AOD, affecting AOD production, diffusion, reaction, and sedimentation, so that the prediction of AOD can achieve better results.

[1] Duveiller, G., Filipponi, F., Walther, S., Köhler, P., Frankenberg, C., Guanter, L., and Cescatti, A.: A spatially downscaled sun-induced fluorescence global product for enhanced monitoring of vegetation productivity, Earth Syst. Sci. Data, 12, 1101–1116, https://doi.org/10.5194/essd-12-1101-2020, 2020.

[2] Yang, Q., Yuan, Q., Li, T., and Yue, L.: Mapping $PM_{2.5}$ concentration at high resolution using a cascade random forest based downscaling model: Evaluation and application, Journal of Cleaner Production, 277, 123887, https://doi.org/10.1016/j.jclepro.2020.123887, 2020.

[3] Ma, Z., Shi, Z., Zhou, Y., Xu, J., Yu, W., and Yang, Y.: A spatial data mining algorithm for downscaling TMPA 3B43 V7 data over the Qinghai–Tibet Plateau with the effects of systematic anomalies removed, Remote Sensing of Environment, 200, 378-395, https://doi.org/10.1016/j.rse.2017.08.023, 2017.

4. In Figure 3, please include a monthly comparison of MAIAC AOD with AERONET AOD for the same period.

Response: Thank you for your valuable advice. In the revision, we added the monthly comparison of MAIAC AOD with AERONET AOD for the same period. In addition, considering RC2 comments, we also added the monthly comparison of the MODIS 10 km AOD product (MOD04L2 and MYD04L2) with AERONET AOD for the same period. At the same time, we have also modified and added the relevant statements (Page 15/Lines:322-325).

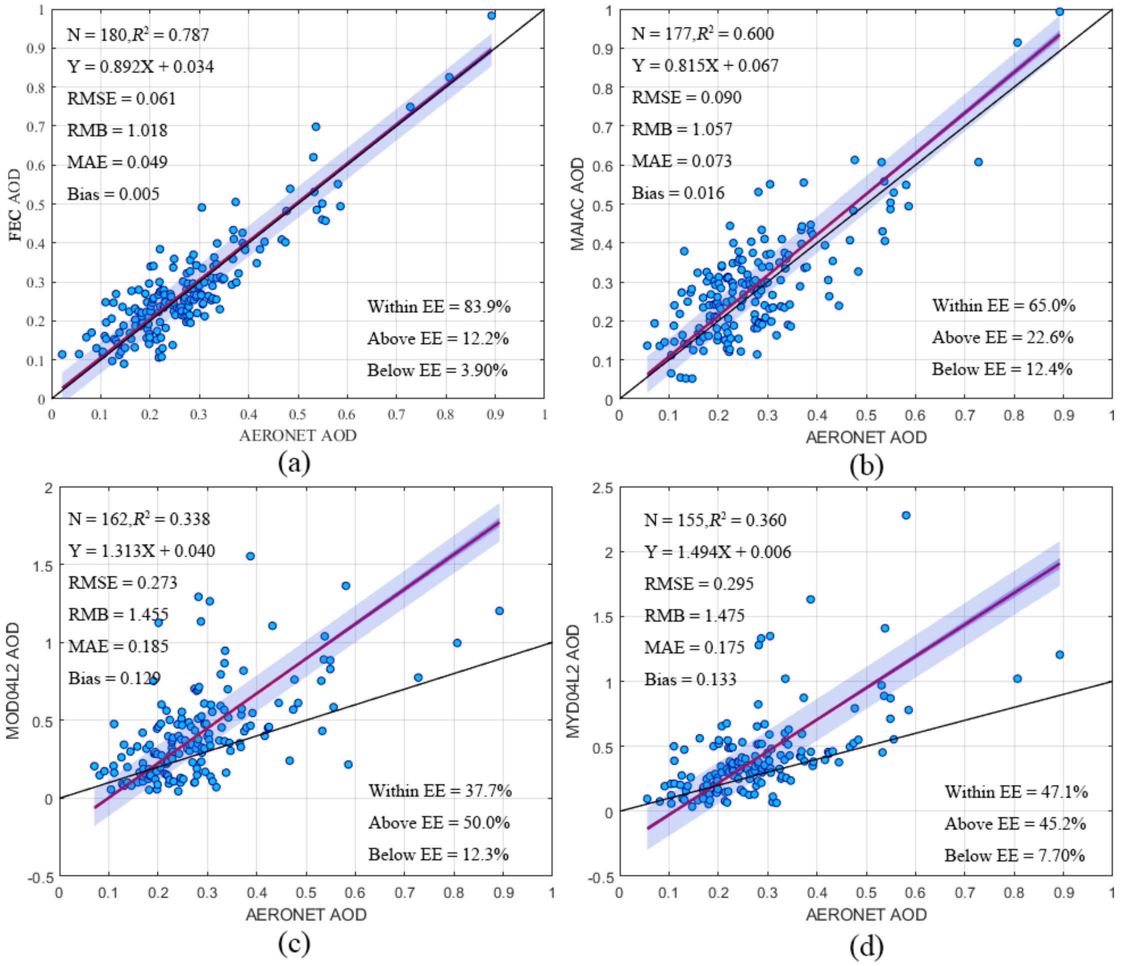

Figure 3. Comparison with AERONET AOD. (a) FEC AOD, (b) MAIAC AOD, (c) MOD04L2 AOD, (d) MYD04L2 AOD. The red line denotes the regression line, the black line shows the 1:1 line, and the blue area indicates the 95% prediction interval.

5. In Line 351-352, the author concludes that FEC AOD products demonstrate a reliable accuracy and ability to capture local information, even superior to MAIAC and MxD08 AOD products. However, the loess-based seasonal trend decomposition procedure (STL) in Figure 5 does not show the advantage of FEC AOD over MAIAC AOD. If the advantage is only the spatial resolution, as described in the third point, wouldn't we be able to get any resolution with interpolation?

Response: Thank you for your precious advice. Firstly, in Section 3.1, we intend to verify the performance of FEC AOD based on in-situ and satellite respectively. In terms of the loess-based seasonal trend decomposition procedure (STL) in Figure 5, our starting point is to use SLT to compare the temporal consistency of the FEC AOD with other AOD products to demonstrate FEC AOD's ability to characterize aerosol temporal variations. Actually, the FEC AOD has a good consistency with other AOD products. What is more, based on RC2 comments, we make MOD08 and MYD08 transfer to MOD04 and MYD04 and find the accuracy advantage still remains. This again also supports the reliability of FEC AOD.

About "FEC AOD products demonstrate a reliable accuracy and ability to capture local information, even superior to MAIAC and MxD08 AOD products", which is a conclusion about section 3.1, that is, it is a general summary. Of course, we have also made corresponding modifications in the revision to avoid misunderstandings (Page 18/Lines:371-373).

In this paper, our advantage mainly lies in the improvement on spatial resolution with an effective downscaling method, but also filling the gap in no data areas. As we all know, the scale effect is a classical issue in remote sensing, and many fine features still need to be revealed by high-resolution data[1,2]. So a high-resolution and accurate dataset is crucial to future research, especially in the data scarcity zone. If only from the perspective of interpolation, we can get any spatial resolution AOD in theory, but its accuracy and spatiotemporal consistency are difficult to guarantee, and the most important point is that interpolation ignores multi-environmental variables inter-relationship and intrinsic association constraints, but ML makes up for these deficiencies well. In addition, in terms of AOD, not the higher spatial resolution is better, some studies have shown that it is appropriate to study at a scale of 250-500 m[3,4]. Actually, with higher resolution of relevant environmental variables, by the effective downscaling model, we can theoretically obtain higher performance AOD, which not only advances the discipline but also fills the data gaps and narrows the knowledge gap. This study does a good trial following the above guidelines.

[1] Atkinson, Peter M., A. Stein, and C. Jeganathan.: Spatial sampling, data models, spatial scale and ontologies: Interpreting spatial statistics and machine learning applied to satellite optical remote sensing, Spatial Statistics, 50, 100646, https://doi.org/10.1016/j.spasta.2022.100646, 2022.

[2] Yu, Ying, Yan Pan, Xiguang Yang, and Wenyi Fan.: Spatial Scale Effect and Correction of Forest Aboveground Biomass Estimation Using Remote Sensing, Remote sensing, 14, 2828, https://doi.org/10.3390/rs14122828, 2022.

[3] Wang, Z., Deng, R., Ma, P., Zhang, Y., Liang, Y., Chen, H., Zhao, S., and Chen, L.: 250-m Aerosol Retrieval from FY-3 Satellite in Guangzhou, Remote Sensing, 13, 920, https://doi.org/10.3390/rs13050920, 2021.

[4] Chen, X., Ding, J., Wang, J., Ge, X., Raxidin, M., Liang, J., Chen, X., Zhang, Z., Cao, X., and Ding, Y.: Retrieval of Fine-Resolution Aerosol Optical Depth (AOD) in Semiarid Urban Areas Using Landsat Data: A Case Study in Urumqi, NW China, Remote Sensing, 12, 467, https://doi.org/10.3390/rs12030467, 2020.

6. Please describe in detail the calculation of AOD uncertainty (lines 498-503).

Response: Thank you for your valuable comment and careful reading. In terms of Section 4.1 Model uncertainty, we randomly select a month to check the model reliability and stability. Specifically, firstly, we do 100 repetitions of the experiment. Then, we calculate model uncertainty by the standard deviation, upper and lower limits 95% confidence interval to realize (The specific calculation formula we have added in the Support Information Text S1).

Text S1. Calculation of model uncertainty

To ensure the reliability and reasonability of the FEC AOD, we performed 100 modelings and predictions for August 2010, that is, 100 times of prediction for each pixel, and the final prediction result is the average of 100 times.

$$AOD_{mean}\,(j) = \frac{1}{n}\sum_{i=1}^{n} AOD_i\,(j)$$

Where n is the number of modeling and predictions (n = 100), $AOD_i(j)$ is the AOD predicted value of the jth pixel and ith modeling, $AOD_{mean}\,(j)$ is the predicted AOD mean of the jth pixel.

The model uncertainty is calculated as follows:

$$\mathrm{CI}_{upper}\,(j) = \mu + 1.96 \times \frac{\sigma}{\sqrt{n}}$$

$$\mathrm{CI}_{lower}\,(j) = \mu - 1.96 \times \frac{\sigma}{\sqrt{n}}$$

$$AOD_{uncertainty}\,(j) = \frac{\left[\mathrm{CI}_{upper}\,(j) - \mathrm{CI}_{lower}\,(j)\right]}{\mathrm{AOD}_{\mathrm{mean}}\,(j)}$$

Where $\mathrm{CI}_{upper}\,(j)\ and\ \mathrm{CI}_{lower}\,(j)$ are the upper and lower limits of the 95% confidence interval (CI) of the jth pixel respectively, μ is the jth pixel AOD mean at 100 predictions, σ is the jth pixel AOD standard deviation predictions, and n is the number of samples, $AOD_{uncertainty}\,(j)$ is the uncertainty of the jth pixel prediction.