Supplement of
The role of aerosol layer height in quantifying aerosol absorption from ultraviolet satellite observations

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Part A: OMI-AERONET joint data set (based on global data from 1 January 2005 to 31 December 2017).

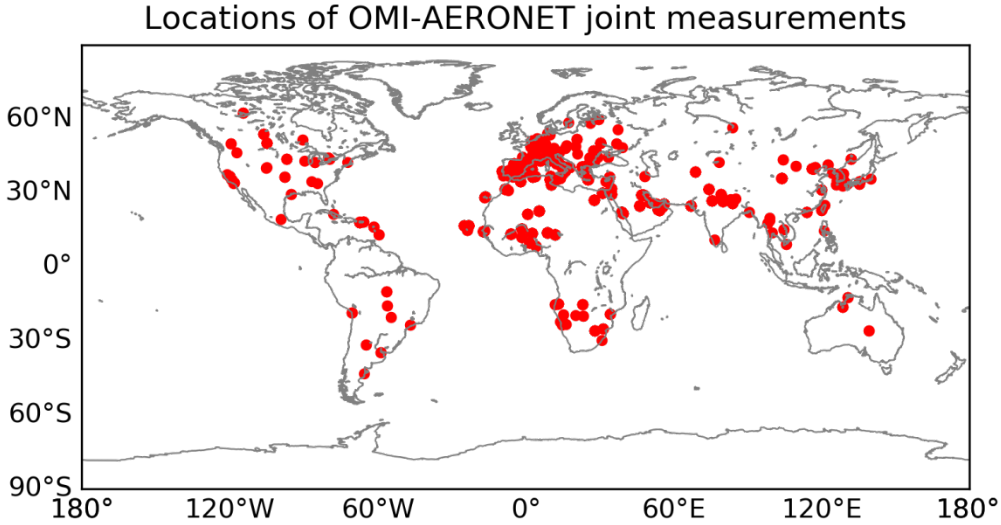

Figure A1: Global distribution of OMI-AERONET joint data set. Note that all aerosol types are included.

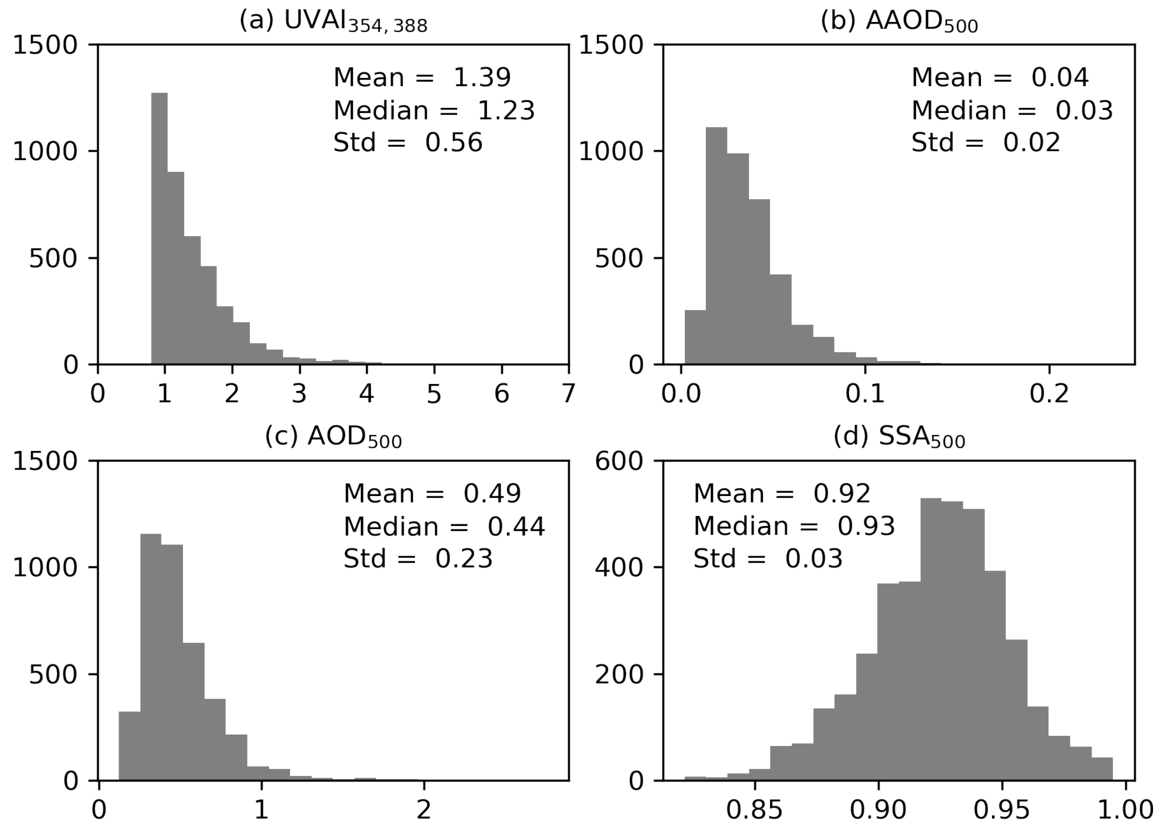

Figure A2: Statistics of the OMI-AERONET joint data set: (a) OMI UVAI calculated from reflectance at 354 and 388 nm; (b) AERONET AAOD at 500 nm; (c) AERONET AOD at 500 nm; (d) AERONET SSA at 500 nm.

Part B: Determining SVR hyper-parameters.

Fig.B1-B3 show the tuning procedure SVR hyper-parameters, i.e. the regularization constant C, the width of insensitive zone ε and the kernel parameter σ^2. According to Cherkassky and Ma (2004), C and ε can be determined from the training data.

$$C = \max(|\overline{y} + 3\sigma_y|, |\overline{y} - 3\sigma_y|) \tag{B1}$$

$$\varepsilon = 3\sigma\sqrt{\frac{\ln(n)}{n}} \tag{B2}$$

, where $\overline{y}$ and σ_y are the mean and standard deviation of the output parameter in the training data set, σ is the input noise level and $\boldsymbol{n}$ is the number of training samples. The choice of C and ε used in this paper are indicated by the cross marker in Fig.B1-B3. The choice of σ^2 is explained as follows.

We present RMSE of the training data set and that of the test data set as a function of SVR parameters, respectively. The RMSE in the training process should be relatively low (high model accuracy) meanwhile the RMSE in test process should be at the similar magnitude to that in the training process (prevent overfitting, i.e. high model generalization capability). For ALH prediction, the RMSE in both training and test process are at the same magnitude, indicating the high generalization capability of the model within the selected range of parameters (Fig.B1a-f). Both RMSEs slightly decrease with C while increase with σ^2. The influence of ε on RMSEs is limited. As we are aimed to improve the relationship between UVAI and ALH in OMAERUV, we also provided the correlation coefficient between UVAI and predicted ALH ($\rho_{UVAI,ALH}$; Fig.B1g-i) as a function of SVR model parameters. $\rho_{UVAI,ALH}$ decreased with C and σ^2. Therefore, the choice of parameters of SVR for ALH prediction is a trade-off between a relatively high model accuracy, and a relatively significant correlation between UVAI and ALH. The parameter C (4.2571) and ε (0.0013) selected based on Cherkassky and Ma (2004) (indicated by the cross marker in Fig.B1) with the kernel parameter σ^2 equaling 0.25 meets this requirement.

For both SVR models with the original and adjusted training data set (Fig.B2 and B3, respectively), a similar behavior of RMSE is found. σ^2 equaling 1 is sufficient to obtain a relatively high accuracy, meanwhile prevents overfitting on the training data set. In other words, compared with σ^2 equaling 0.5, the difference between RMSE of the training data set and that of the test data set is smaller when σ^2 equaling 1. The corresponding C and ε determined by Cherkassky and Ma (2004) for both SVR models are 0.1010 and 0.0002, respectively.

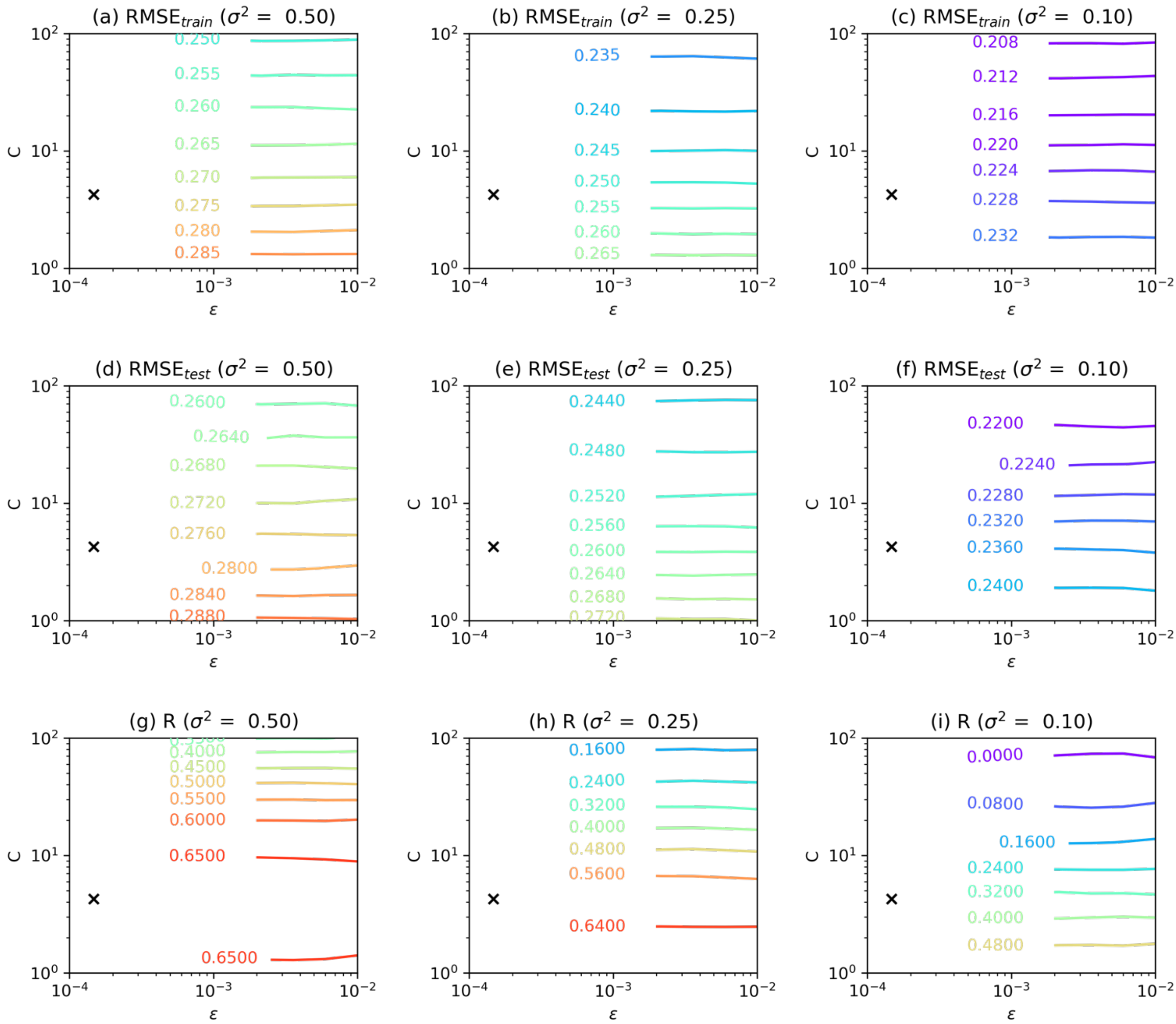

Figure B1: The accuracy of ALH prediction (the RMSE between the SVR predicted ALH and the TROPOMI ALH) and correlation coefficients ($\rho_{UVAI,ALH}$) between OMAERUV UVAI and the SVR predicted ALH as a function of SVR parameters (C, ε and σ^2). The cross marker represents the choice of C and ε according to Cherkassky and Ma (2004), i.e. the settings used in our study to generate the final results. The final selected σ^2 is 0.25.

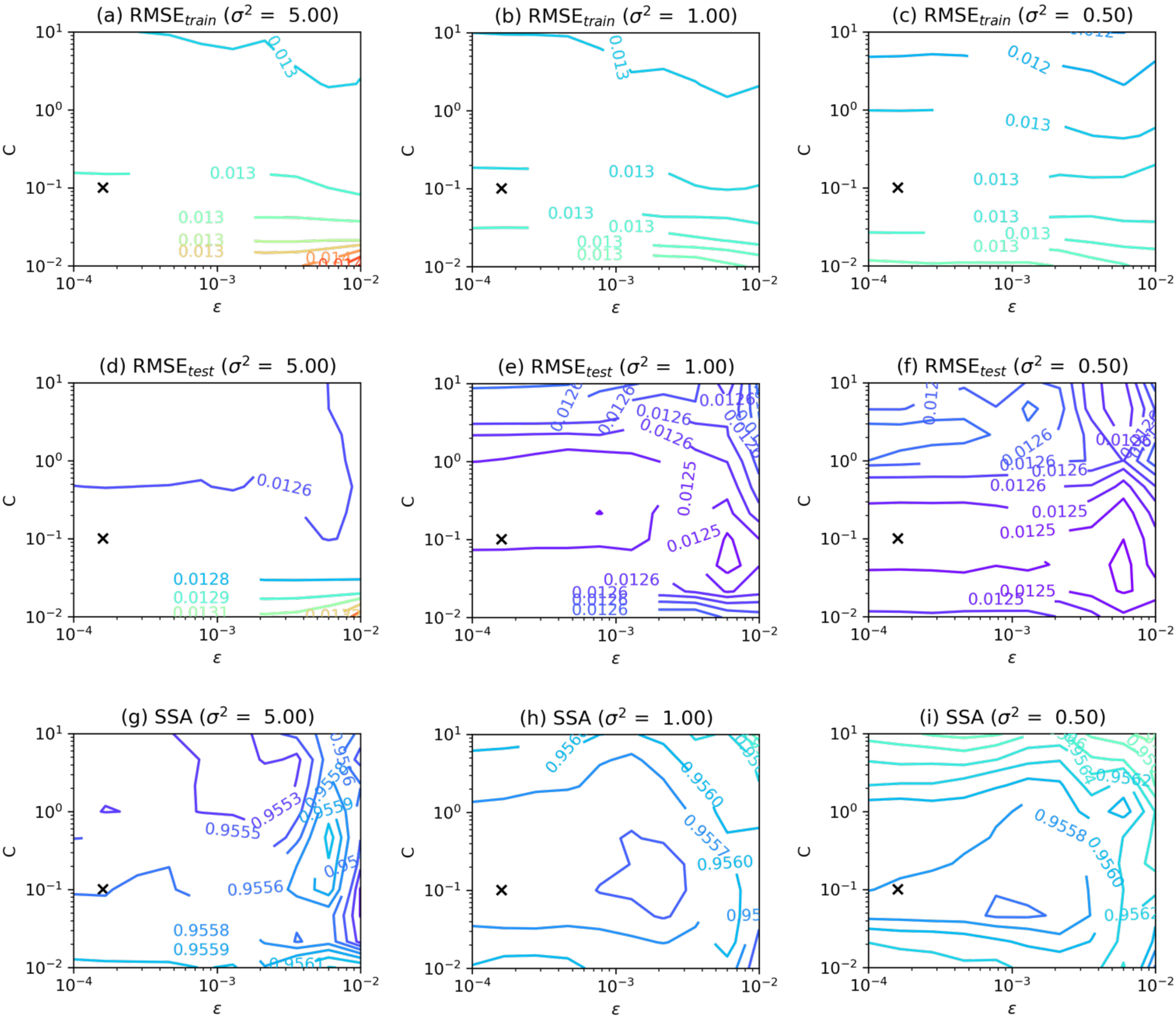

Figure B2: The accuracy of SSA prediction (the RMSE between the SVR predicted SSA and the AERONET SSA) and the retrieved SSA based on the original training data set as a function of SVR parameters (C, ε and σ^2). The cross marker represents the choice of C and ε according to Cherkassky and Ma (2004), i.e. the settings used in this study to generate the final results. σ^2 equaling 1 is sufficient to obtain a relatively high accuracy, and meanwhile prevents overfitting on the training data set.

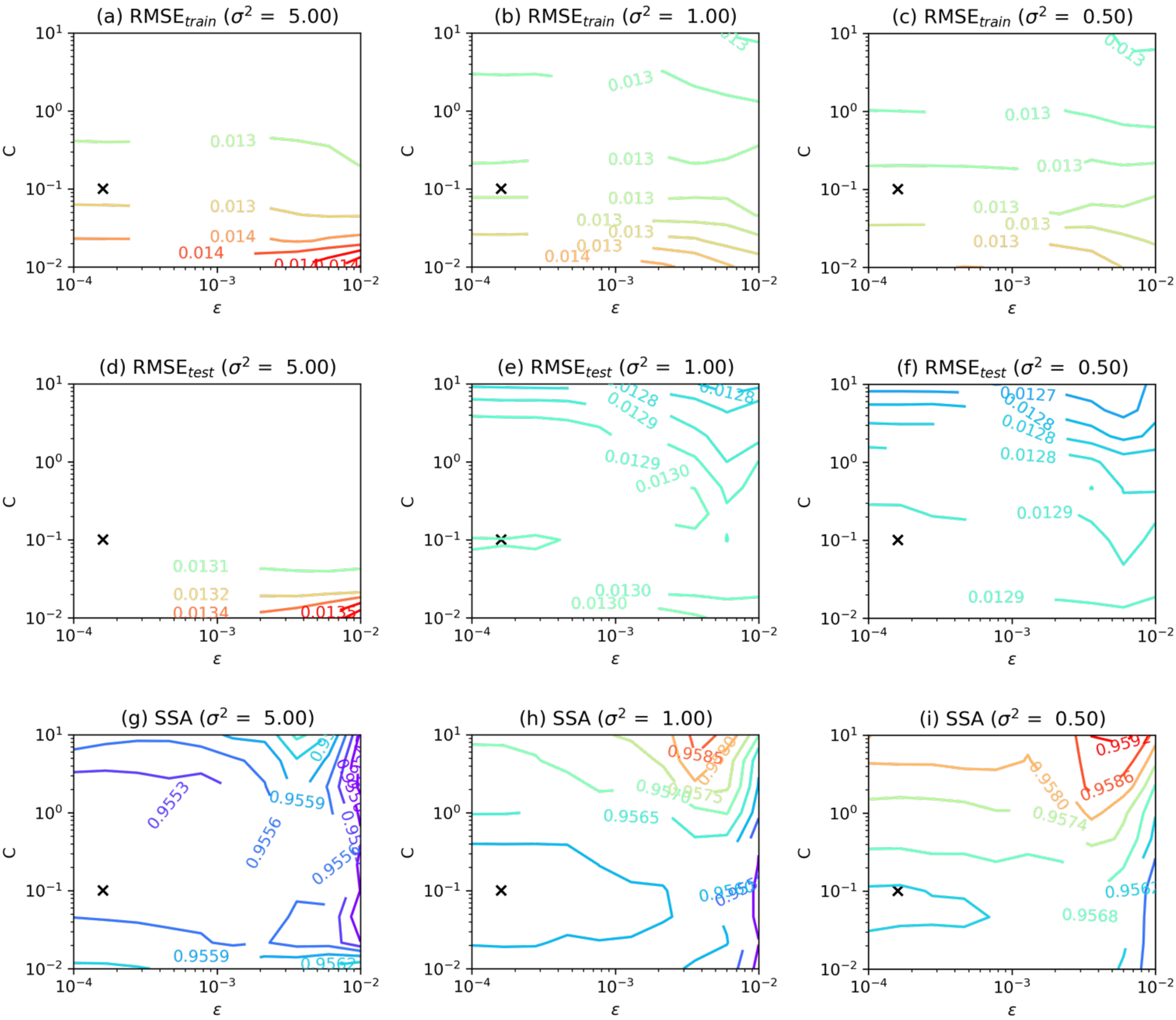

Figure B3: The accuracy of SSA prediction (the RMSE between the SVR predicted SSA and the AERONET SSA) and the retrieved SSA based on the adjusted training data set as a function of SVR parameters (C, ε and σ^2). The cross marker represents the choice of C and ε according to Cherkassky and Ma (2004), i.e. the settings used in this study to generate the final results. σ^2 equaling 1 is sufficient to obtain a relatively high accuracy, meanwhile prevents overfitting on the training data set.