



# Joint retrieval of PM<sub>2.5</sub> concentration and aerosol optical depth over China using multi-task learning on Fengyun-4A Advanced Geostationary Radiation Imager data



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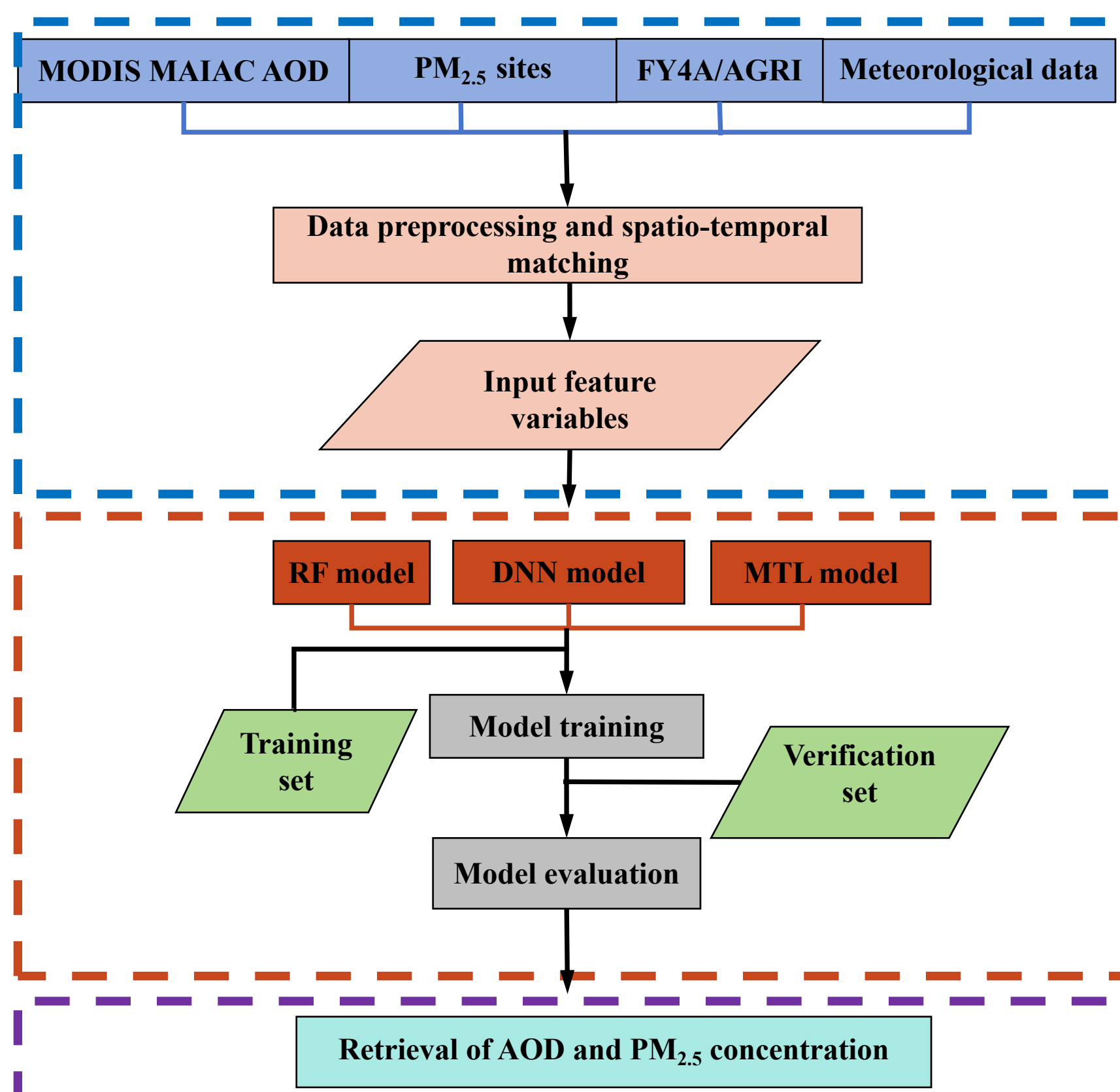
## Abstract

In this paper, a DNN-based **joint retrieval** algorithm for AOD and PM<sub>2.5</sub> is proposed using **Multi-task learning techniques** and applied on the top-of-the-atmosphere reflectance(**TOAR**) data gathered by the **Fengyun-4A** Advanced Geosynchronous Radiation Imager.

### Motivation:

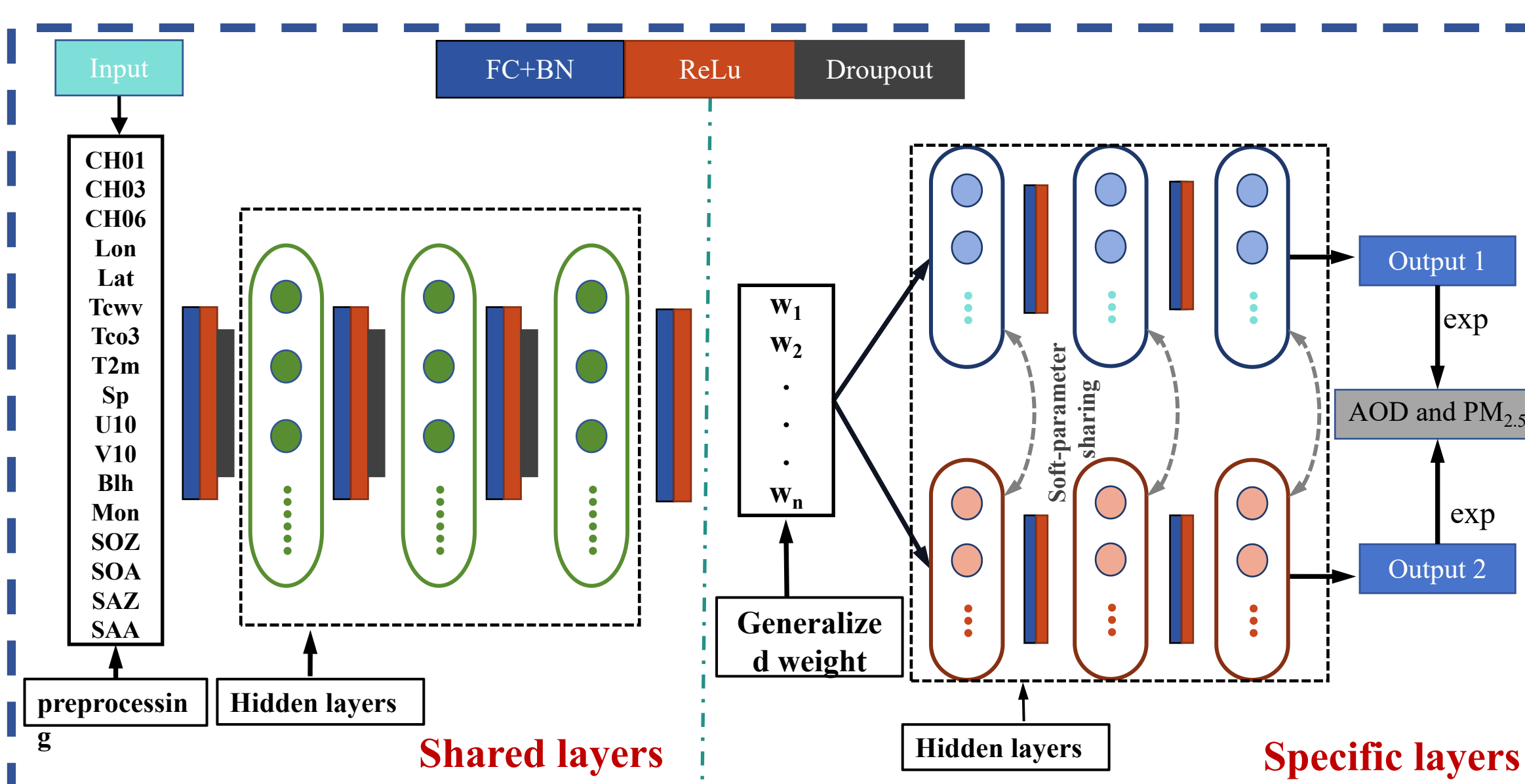
- ◆ Overcoming the challenges of AOD and PM<sub>2.5</sub> retrieval;
- ◆ Simultaneous high-precision retrieval of AOD and PM<sub>2.5</sub>;
- ◆ Provides a new perspective for efficient aerosol monitoring.

## Data and method



Two single-task learning (STL) models: **DNN and RF**.

- ◆ 17 features as inputs to the models.
- ◆ Soft and hard sharing of parameters.
- ◆ Comparison of MTL and STL performance.



### Input:

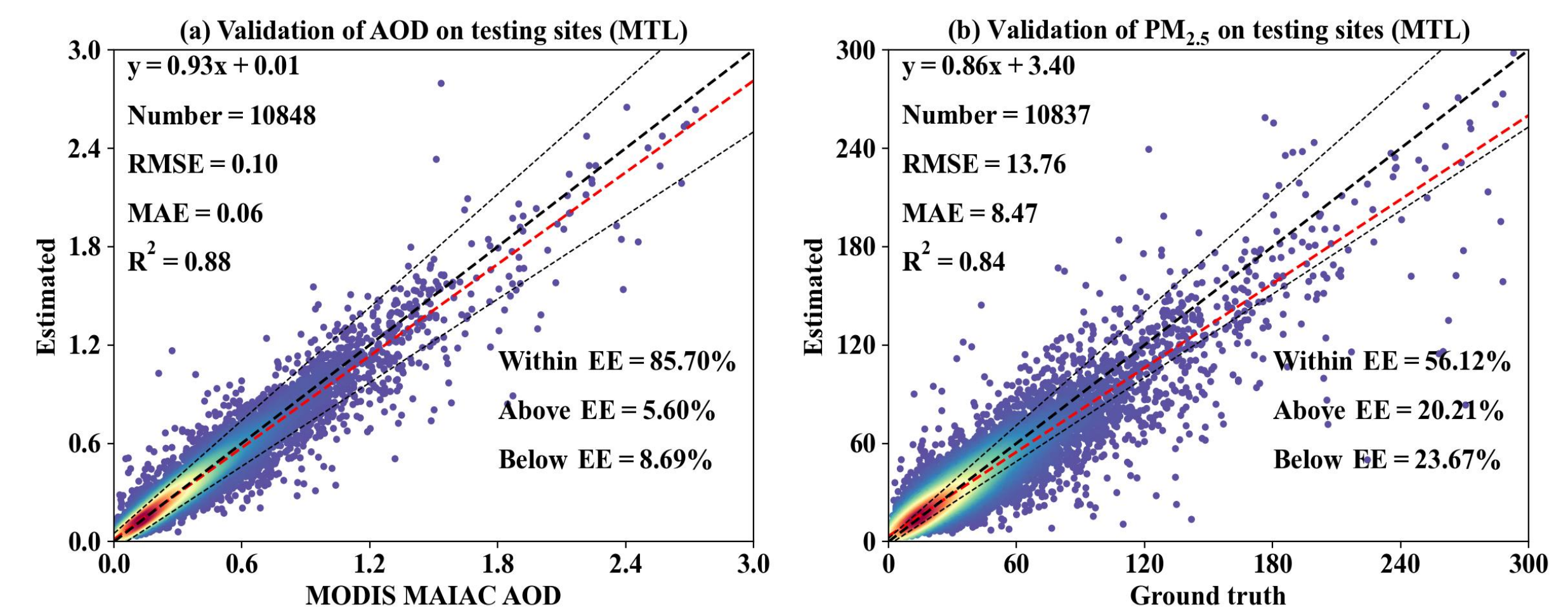
- Meteorological data
- Satellite data

$$L(w, \sigma_1, \sigma_2) = \frac{1}{2\sigma_1^2} L_1(w) + \frac{1}{2\sigma_2^2} L_2(w) + \log \sigma_1 \sigma_2$$

In the above equation, the larger  $\sigma$  is, the greater the **uncertainty** of the task, the smaller the weight of the task is, i.e., noisy and difficult to learn tasks will have a smaller weight.

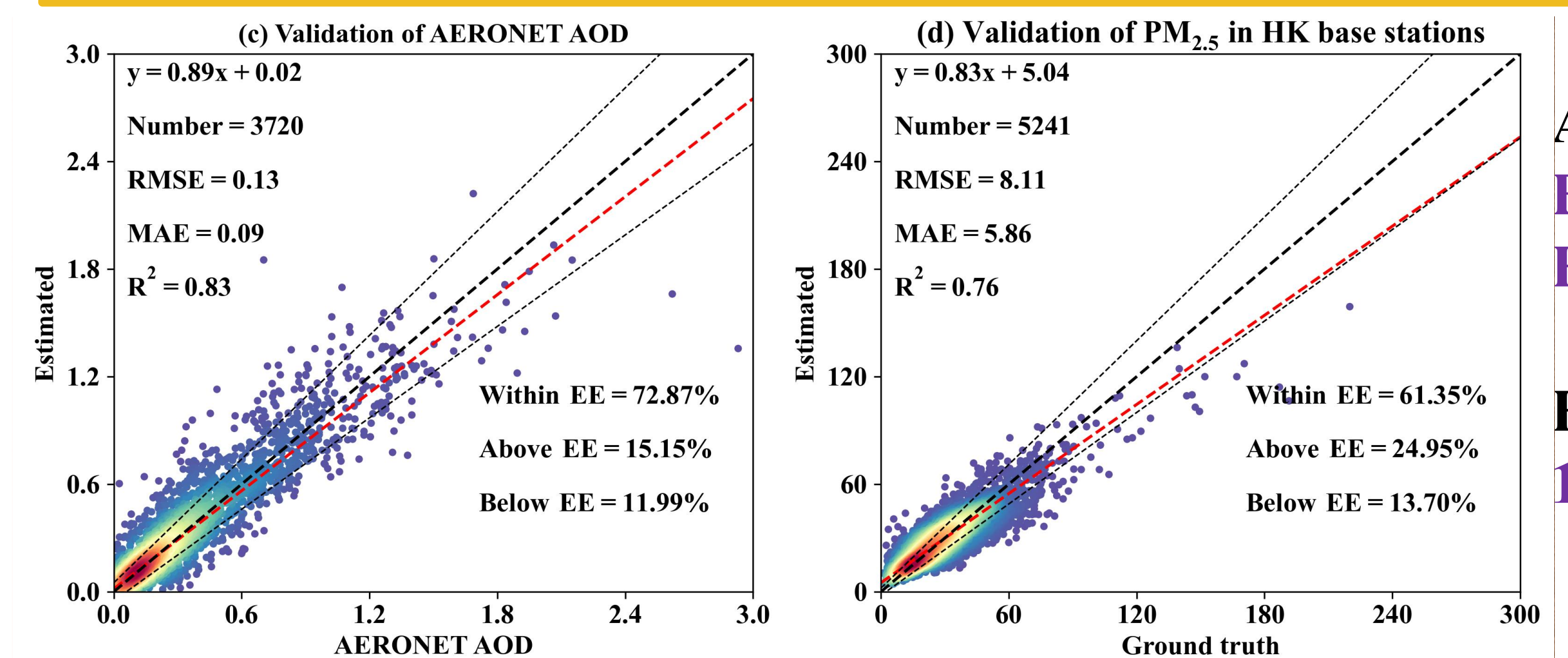
## Results and discussion

Comparing with DNN STL model, the R<sup>2</sup> of the MTL model for estimating AOD and PM<sub>2.5</sub> increased by 0.01 and 0.05, respectively. This indicates that the MTL model is better optimized for PM<sub>2.5</sub>.



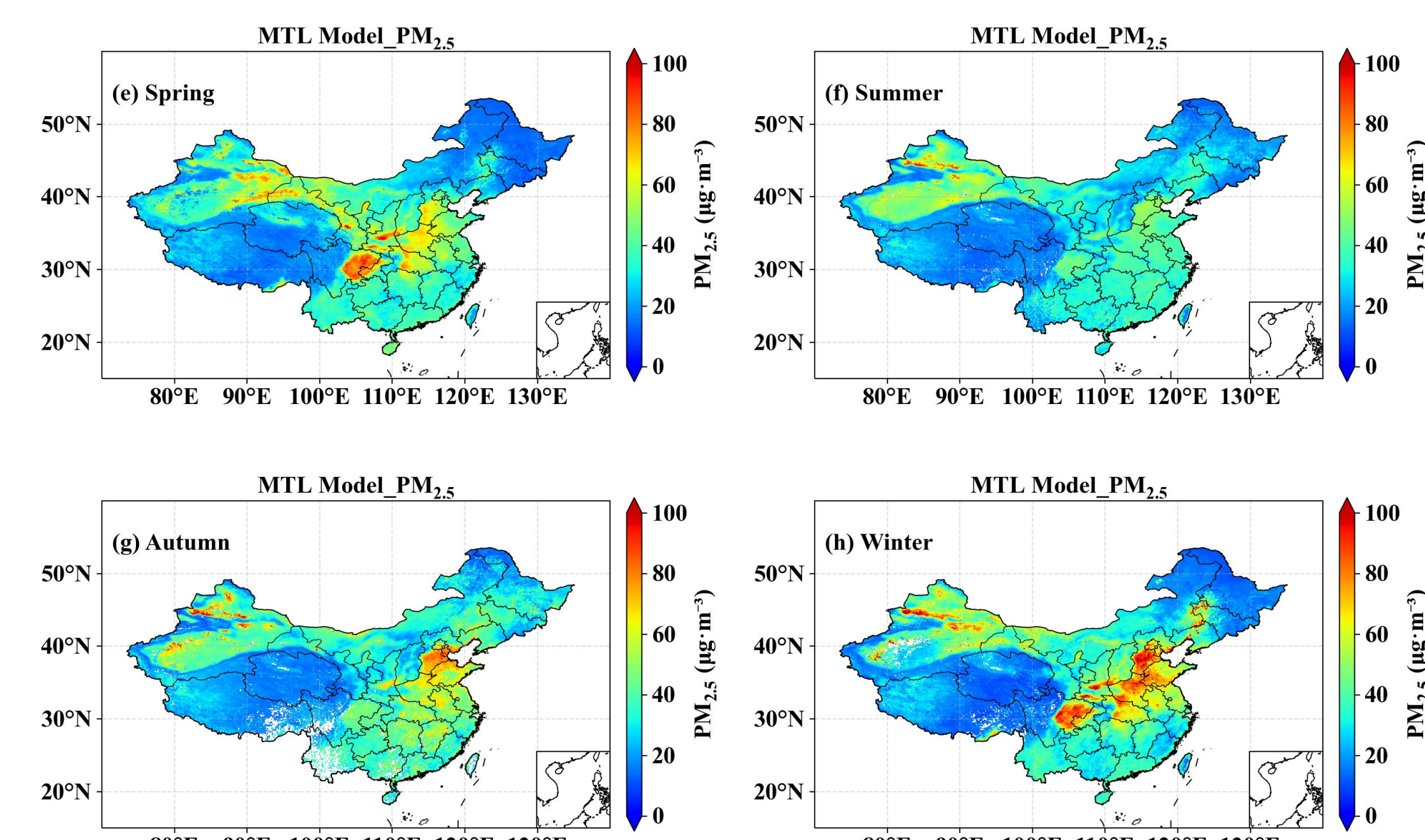
**Validation results on 159 testing sites.**

Independently verified by AERONET AOD and HK PM<sub>2.5</sub>. This proves that MTL model has good **generalization ability**.

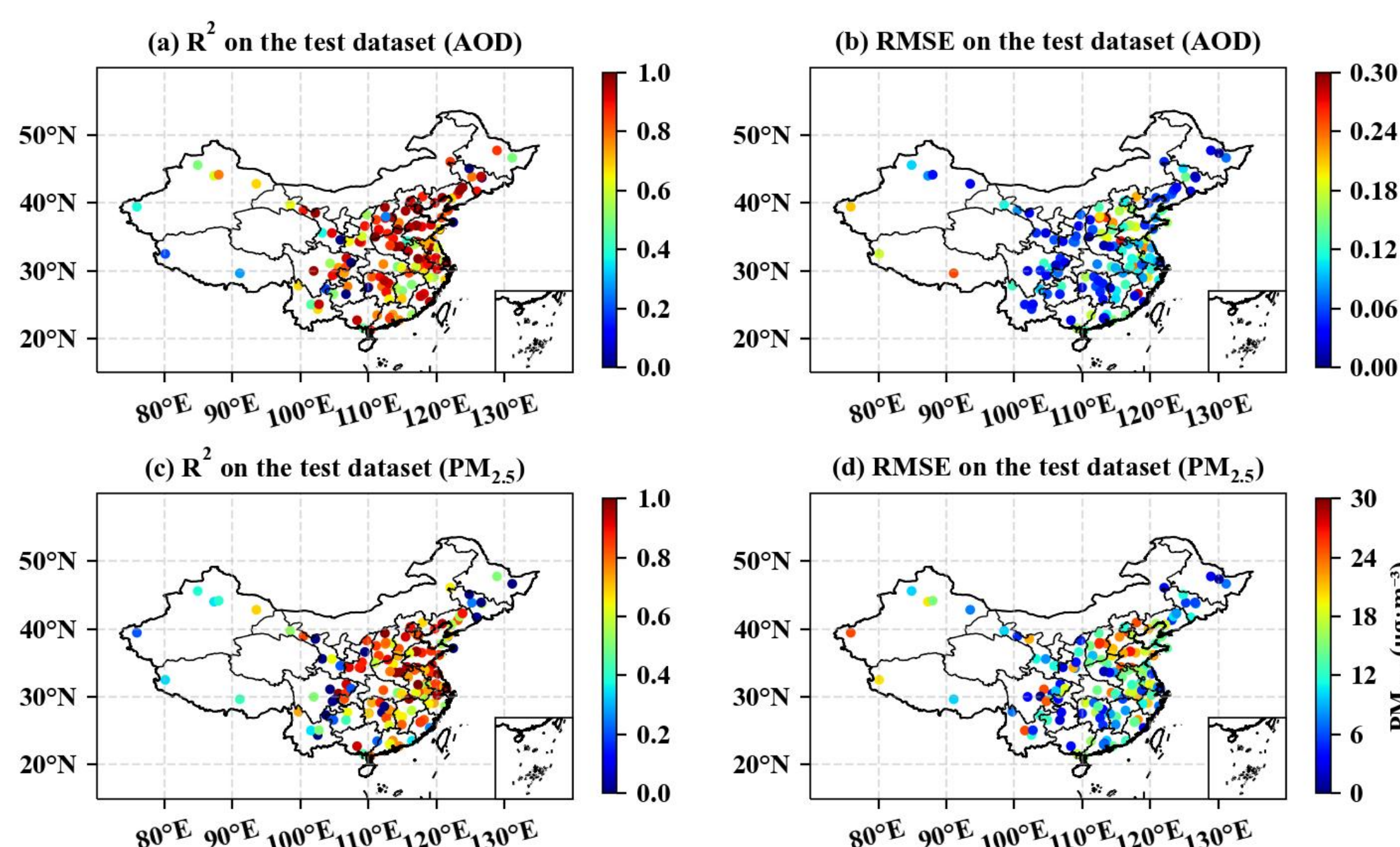


**AERONET : Beijing-Tianjin-Hebei;**

**HK: 15 PM<sub>2.5</sub> sites**



**Seasonal average of PM<sub>2.5</sub> (μg·m<sup>-3</sup>):**  
➤ spring (37.67)  
➤ summer (26.45)  
➤ autumn (30.81)  
➤ winter (41.51)



The performance of the MTL model is affected by the unevenness and scarcity of ground stations.

## Conclusions

- ◆ The MTL model achieves joint retrieval of two tasks (AOD and PM<sub>2.5</sub>) with correlation, and the results outperform the STL model.
- ◆ The problem of insufficient training samples and model overfitting can be solved to a certain extent, and it is applicable to places with fewer ground monitoring stations.
- ◆ The seasonally averaged distributions of AOD and PM<sub>2.5</sub> are similar to previous findings and provide new insights for efficient monitoring of aerosol properties.