Reply to Reviewer 2:

This study by Yin et al. developed a model to predict gridded winter $PM_{2.5}$ concentrations in east of China from a climatological perspective. They integrated both emission and climate variability predictors to train the model, which could capture the trends driven by emission changes and the interannual variations contributed by climate variability. The model has good performance and such method could support air pollution control in the future. **I recommend publication after the following issues are addressed.**

Line 253-255: A plot similar to Figure 2 but for SP-EC will help the readers to understand the better performance of SP-EC more reasonably.

Reply:

According to the reviewer's suggestion, three panels (g-i) for SP-EC were added in Figure 2.

Revisions:

Lines 167-170:

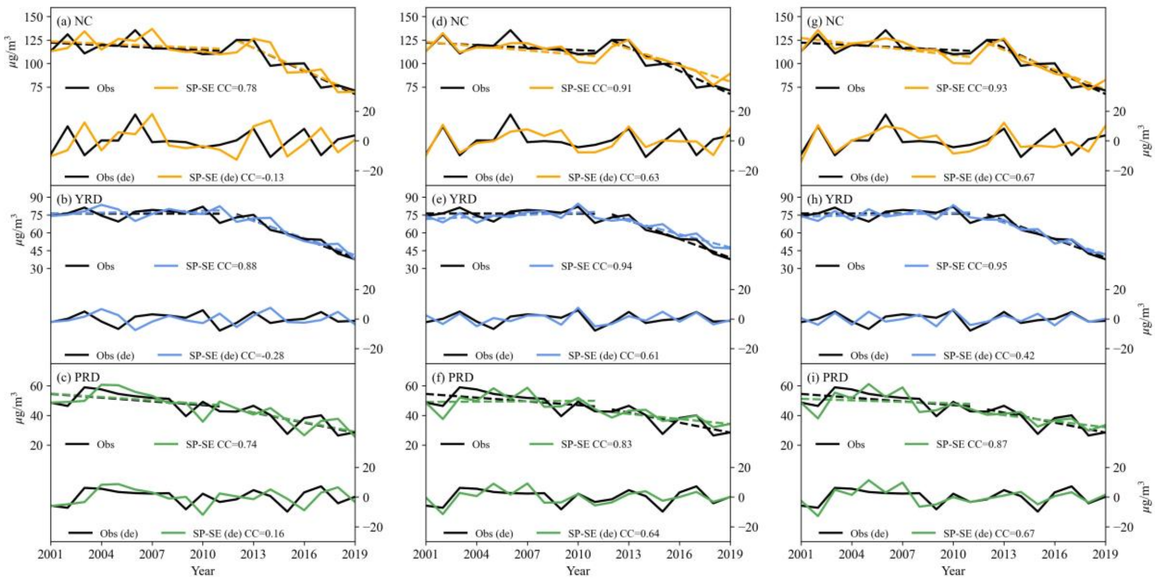

Figure 2: Variations in reanalysis (black) and SP-SE predicted winter $PM_{2.5}$ concentration in (a) NC (orange), (b) the YRD (blue), and (c) the PRD (green) from 2001 to 2019 before (upper) and after (lower) detrending. The predicted $PM_{2.5}$ is dependent on the leave-one-out validation. (d-f) are the same as (a-c), but for SP-CV. (g-i) are the same as (a-c), but for SP-EC.

Line 282-283: Figure 8f is for the year 2019, before the COVID-19 quarantine starts. This could hardly be the reason to explain the model biases in this time.

Reply:

Winter is defined as December-January-February and thus the COVID-19 happened in the winter of 2019 (i.e., January and February in 2020).

We have added the definition of winter and more information.

Revisions:

Lines 38-39: Evident interannual variation was also be found in the changes of $PM_{2.5}$ concentration in winter (**December-January-February**), which was largely attributed to climate variability (Yin et al., 2020a, 2020b).

Lines 325-327: Although the SP-EC model was proved to be skilled……were not sufficiently explained and needed further in-deep studies. As shown in Figure 8f, the SP-EC model failed to well predict the evident $PM_{2.5}$ drops in east of China caused by COVID-19 quarantines **in the winter of 2019 (especially February in 2020)** (Yin et al., 2021).

I suggest the authors to briefly discuss the uncertainties in this method.

Reply:

According to the reviewer's suggestion, the qualitative uncertainties and further studies were briefly discussed.

Revisions:

Lines 324-334: This study mainly focused on developments of seasonal $PM_{2.5}$ prediction model. **Related theories and methods are still exploratory and need further discoveries**. Although the SP-EC model was proved to be skilled, the underlying physical mechanisms of climate predictors were not sufficiently explained and needed further in-deep studies. As shown in Figure 8f, the SP-EC model failed to well predict the evident $PM_{2.5}$ drops in east of China caused by COVID-19 quarantines in the winter of 2019 (especially February in 2020) (Yin et al., 2021). Therefore, **such sudden fluctuations of $PM_{2.5}$ concentration were not involved in the established prediction model**. Furthermore, **the EOF pattern of $PM_{2.5}$ possibly changed under**

climate change and must influence the climate component of $PM_{2.5}$, which should be updated in time. Although the SP-EC model had high spatial resolution, it could only output winter-mean $PM_{2.5}$ concentration. It was meaningful to build **sub-seasonal models** to provide more detailed predictions. Modern weather and climate forecasts were heavily dependent on numerical prediction models. Thus, it is imperative to design and develop numerical models that target at routine seasonal prediction of air pollution (Yin et al., 2021).

The authors mentioned in the Abstract that the accurate PM2.5 prediction had the potential to support air pollution control on regional and city scales. This worth more discussion in the last section.

Reply:

According to the reviewer's suggestion, we have discussed more about the use of accurate $PM_{2.5}$ prediction.

Revisions:

Lines 319-323: The high-resolution $PM_{2.5}$ prediction could provide scientific supports for air pollution control at the regional and city levels. For example, real-time $PM_{2.5}$ prediction is highly demanded for determining **how to reduce anthropogenic emissions** and **how much should be reduced**; 10km×10km gridded $PM_{2.5}$ information also had **potentials to support finely and dynamically regional managements and collaborations.**

SOME TYPOS:

Line 166: 'SP-CE' should be 'SP-EC'

Reply:

Thank you. We have corrected this error.

Revisions:

Lines 161-166: Table 1: The leave-one-out validated root-mean square errors (RMSE), relative biases (absolute bias mean; %) and percentages of same sign (PSS) for three statistical models.

	RMSE (μg/m^3)			Relative Bias (%)		
	NC	YRD	PRD	NC	YRD	PRD
SP-SE	12.2	6.2	6.8	8.5	6.9	12.9
SP-CV	8.0	4.8	5.2	5.3	6.2	9.9
SP-EC	6.8	4.2	4.7	5.1	4.9	8.8

Line 271: 'pointes' should be 'points'

Reply:

Thank you. We have corrected this error.

Revisions:

Line 271−273: Figure 7: Scatter plots of the reanalysis (x axis) and predictions of (y axis) PM2.5 concentration by SP-CV (green) and SP-EC (blue) 269 in (a) east of China, (b) NC, (c) the YRD and (d) the PRD. The **points** during 2012–2019 are filled and the short lines between SP-270 CV and SP-EC points indicate the calibrations.