Predicting gridded winter PM$_{2.5}$ concentration in the east of China

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Abstract. Exposure to high concentration levels of fine particle matter with diameter ≤ 2.5 µm (PM$_{2.5}$) can lead to great threats to human health in the east of China. Air pollution control has greatly reduced the PM$_{2.5}$ concentration and entered a crucial stage that required support like fine seasonal prediction. In this study, we analyzed the contributions of emission predictors and climate variability to seasonal prediction of PM$_{2.5}$ concentration. The socioeconomic PM$_{2.5}$, isolated by atmospheric chemical models, could well describe the gradual increasing trend of PM$_{2.5}$ during the winters of 2001–2012 and the sharp decreasing trend since 2013. The preceding climate predictors have successfully simulated the interannual variability in winter PM$_{2.5}$ concentration. Based on the year-to-year increment approach, a model for seasonal prediction of gridded winter PM$_{2.5}$ concentration (10 km × 10 km) in the east of China was trained by integrating emission and climate predictors. The area-averaged percentage of same sign was 81.4 % (relative to the winters of 2001–2019) in the leave-one-out validation. In three densely populated and heavily polluted regions, the correlation coefficients were 0.93 (North China), 0.95 (Yangtze River Delta) and 0.87 (Pearl River Delta) during 2001–2019, and the root-mean-square errors were 6.8, 4.2 and 4.7 µg m$^{-3}$. More important, the significant decrease in PM$_{2.5}$ concentration, resulting from the implementation of strict emission control measures in recent years, was also reproduced. In the recycling independent tests, the prediction model developed in this study also maintained high accuracy and robustness. Furthermore, the accurate gridded PM$_{2.5}$ prediction had the potential to support air pollution control on regional and city scales.

1 Introduction

Exposure to fine particle matter with diameter ≤ 2.5 µm (PM$_{2.5}$) can lead to severe respiratory and cardiovascular diseases (Cohen et al., 2017) and can even directly induce DNA damage (Wu et al., 2017). According to the newly recommended air quality guidelines, the level of annual mean PM$_{2.5}$ < 5 µg m$^{-3}$ has the potential to threaten human health (World Health Organization, 2021). In 2020, the average PM$_{2.5}$ concentration in cities of China was 33 µg m$^{-3}$, although the implementation of strict air quality control measures substantially reduced the emission of primary pollutants (Zhang et al., 2022). The changes in the emission of air pollutants also resulted in the shift of winter PM$_{2.5}$ trend in the east of China; that is, the winter PM$_{2.5}$ concentration gradually increased during 2000–2012 but has been decreasing since 2013 (Fig. 1a). Evident interannual variation was also to be found in the changes in PM$_{2.5}$ concentration in winter (December–January–February), which was largely at-
ttributed to climate variability (Yin et al., 2020). Given the severe impact of PM$_{2.5}$ pollution and yearly plan of control action, it is meaningful and urgent to develop prediction models to forecast PM$_{2.5}$ concentration 1–3 months in advance. Furthermore, the predicting results should have high resolution to provide valuable information on the regional and city levels.

To accurately predict climate anomalies is still a real challenge, while predicting air pollution on seasonal scale is much harder than predicting routine meteorological elements (Wang et al., 2021). In general, the methods of climate prediction included numerical climate models and statistical approaches. Despite the great advances in atmospheric chemical models in recent years, most of these models were not designed for real-time operation of seasonal predictions and lacked the coupling of the atmospheric chemical composition and the entire earth system (An et al., 2018). Additionally, statistical prediction of winter PM$_{2.5}$ concentration was limited by the short sequences of observed atmospheric composition because broad observations only started in 2014 in China. The gray prediction model performed well in dealing with small sample data and thus was used to forecast PM$_{2.5}$ concentration (Wang and Du, 2021; Wu et al., 2019; Xiong et al., 2019). Considering the strong control measures implemented to improve air quality, the buffer operators can be added to the discrete gray prediction model to reduce deviations (Dun et al., 2020). These mathematical models showed certain predictive skills but lacked underlying physical mechanisms and long-standing robustness.

Many previous studies employed the long-term observed visibility, air humidity and weather phenomena to reconstruct data of haze (Xu et al., 2016; Zou et al., 2017; He et al., 2019; Yin et al., 2020). The change in winter haze days consists of long-term trend and interannual-decadal variations. The long-term trend of haze was mainly determined by human activities (i.e., primary pollutants emission and climate change), while its interannual-decadal variations had close relationships with climate variability (Yin et al., 2020; Geng et al., 2021a). Besides analysis of climate mechanisms, the number of haze days was also used as a proxy predictand of PM$_{2.5}$ pollution. Taking advantage of the memory effect in slow-varying climate forcings (e.g., sea surface temperature and sea ice), the number of haze days was successfully predicted in North China (Yin and Wang, 2016a; Yin et al., 2017), Yangtze River Delta (Dong et al., 2021) and Fenwei Plain (Zhao et al., 2021). Chang et al. (2021) used regional stratospheric warming over northeastern Asia in November to predict haze pollution in the Sichuan Basin for 5–7 weeks. Information from the preceding autumn’s El Niño was also extracted to predict winter haze days in South China (Cheng et al., 2019) and aerosol optical depth over northern India (Gao et al., 2019). In most of these studies, the predictand is the area-averaged number of haze days, which was a bit different from PM$_{2.5}$ concentration in use, and fine spatial information was missing.

The Tracking Air Pollution (TAP) database combines information from ground observations, satellite retrievals, emission inventories and chemical transport model simulations based on data fusion. A full-coverage PM$_{2.5}$ reanalysis dataset with a spatial resolution of 10 km × 10 km from 2000 until present has been released (Geng et al., 2021b). It becomes feasible to develop a statistical prediction model of PM$_{2.5}$ concentration based on this long-range dataset. Furthermore, as reviewed by Yin et al. (2022), the predictability of winter haze decreased after 2014, which was mainly attributed to the disturbances from super-strict emissions reduction in China. Rapid changes in human activities and changes in climate anomalies both should be considered and included in PM$_{2.5}$ prediction models. This is the major motivation of the present study, which is to build a climate–emission hybrid model for the prediction of gridded PM$_{2.5}$ concentration in the east of China. The findings of this study have enormous potentials to support fine designs and implementation of air pollution control in advance.

2 Datasets and method
2.1 Data

The monthly sea ice concentration (SI) and sea surface temperature (SST) dataset from 2000 to 2019, with a spatial resolution of 1° × 1°, was provided by the Met Office Hadley Centre (Rayner et al., 2003, https://www.metoffice.gov.uk/hadobs/hadisst/, last access: 19 August 2022). Monthly soil moisture (Soilw), snow depth (SD), geopotential height at 500 hPa (Z500) and 850 hPa (Z850), sea level pressure (SLP), and 10 m wind were extracted from the fifth generation reanalysis product (ERA5) produced by the European Center for Medium Range Weather Forecasts (Hersbach et al., 2020, https://cds.climate.copernicus.eu/, last access: 19 August 2022). Monthly soil moisture (Soilw), snow depth (SD), geopotential height at 500 hPa (Z500) and 850 hPa (Z850), sea level pressure (SLP), and 10 m wind were extracted from the fifth generation reanalysis product (ERA5) produced by the European Center for Medium Range Weather Forecasts (Hersbach et al., 2020, https://cds.climate.copernicus.eu/, last access: 19 August 2022). Annual emissions of ammonia, nitrogen oxide, black oxide carbon (BOC), primary PM$_{2.5}$ and sulfur dioxide in China were derived from the MEIC model (http://www.meicmodel.org/, last access: 19 August 2022; Li et al., 2017).

Hourly site-observed PM$_{2.5}$ concentrations during 2014–2019 were also employed in the present study (https://www.aqistudy.cn/historydata/, last access: 19 August 2022). The long-term and high-resolution TAP PM$_{2.5}$ concentration dataset during 2000–2019 can be downloaded from http://tapdata.org.cn/ (last access: 19 August 2022; Geng et al., 2021b). The PM$_{2.5}$ reanalysis data were used as training data, as well as test data, in the construction of the prediction model, and the observed PM$_{2.5}$ concentrations were also applied to verify the prediction skill of the model.

2.2 Isolation of socioeconomic PM$_{2.5}$

We employed the simulated annual mean PM$_{2.5}$ concentrations that exclude the meteorological contributions to repre-
The year-to-year increment approach is proposed to improve the skill of climate prediction (Wang et al., 2008), in which the assumption of (YS−YS−1)≈0 was no longer completely valid. Therefore, it is meaningful to consider the information of rapid emission changes and re-build the prediction model (Yin et al., 2022).

1. **Seasonal prediction model based on SE-PM$_{2.5}$ (SP-SE).** This prediction model unilaterally emphasized the impacts of human activities and was trained by DY of SE-PM$_{2.5}$ in each grid.

2. **Seasonal prediction model based on preceding climate variability (SP-CV).** This prediction model was highly focused on the impacts of climate condition and trained by DY of closely related climate factors.

3. **Seasonal prediction model based on both SE-PM$_{2.5}$ and climate (SP-EC).** The contributions of emissions and climate factors are incorporated into one prediction model, i.e., combining the PM$_{2.5}$ DY from SP-SE and SP-CV.

In the leave-one-out cross validation, root-mean-square error (RMSE), relative bias and correlation coefficient (CC) were calculated. When discussing the CC after the detrending, the linear trend was removed by stages (i.e., winters of 2001–2011 and 2012–2019). The percentage of the same sign (PSS; same sign means the mathematical sign of the fitted and observed PM$_{2.5}$ anomalies was the same) was also computed.

### 3 Relative contributions of emission and climate predictors

#### 3.1 Roles of emissions

Human activities are the major source of haze pollution in the east of China (Zhang and Geng, 2020), which im-

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**Figure 1.** Variation in (a) winter PM$_{2.5}$ concentration (black; unit: µg m$^{-3}$), (b) PM$_{2.5}$ anomalies (gray; compared to the mean of 2000–2019; unit: µg m$^{-3}$) and PM$_{2.5}$ DY (black; unit: µg m$^{-3}$). Color lines in (a) indicate relative variations in annual emissions (compared to that in 2008; unit: %) of ammonia (NH$_3$; red), nitrogen oxide (NO$_x$; purple), BOC (green), PM$_{2.5}$ (blue) and sulfur dioxide (SO$_2$; yellow) in the east of China. The black dashed line in (a) indicates the linear trend of PM$_{2.5}$ concentration.
Table 1. The leave-one-out validated root-mean-square errors (RMSEs), relative biases (absolute bias mean; %) and percentages of same sign (PSS) for three statistical models.

<table>
<thead>
<tr>
<th></th>
<th>NC</th>
<th>YRD</th>
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<th>NC</th>
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<td>RMSE (µg m⁻³)</td>
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<tr>
<td>SP-SE</td>
<td>12.2</td>
<td>6.2</td>
<td>6.8</td>
<td>8.5</td>
<td>6.9</td>
<td>12.9</td>
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<tr>
<td>SP-CV</td>
<td>8.0</td>
<td>4.8</td>
<td>5.2</td>
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<td>9.9</td>
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<tr>
<td>SP-EC</td>
<td>6.8</td>
<td>4.2</td>
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Figure 2. Variations in reanalysis (black) and SP-SE predicted winter PM₂.₅ 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 PM₂.₅ 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.

plies that a large proportion of PM₂.₅ concentration is predictable. Particularly, the large reduction of anthropogenic emissions since 2013 has determined the decreasing trend of winter PM₂.₅ concentration (Fig. 1a). As mentioned above, the socioeconomic PM₂.₅ (i.e., SE-PM₂.₅) isolated by CMAQ could well reflect the impacts of human activities and was a potentially effective predictor for seasonal prediction of PM₂.₅ concentration. As expected, the one-variable linear regression model based on anomalies of SE-PM₂.₅ successfully reproduced different slopes of trend during 2001–2007, 2008–2013 and 2014–2019, but the predicted PM₂.₅ concentration varied too smoothly (Fig. S1a in the Supplement). Furthermore, the quantities were underestimated when observed PM₂.₅ concentration increased and overestimated when PM₂.₅ concentration rapidly decreased. To eliminate the influence of trend shift, we calculated DY of PM₂.₅ and SE-PM₂.₅. Compared with its anomalies, PM₂.₅ DY did not show a significant trend but displayed regularly oscillating characteristics (Fig. 1b), and its predictability was much better (Wang et al., 2008). The SP-SE model was trained by DY of SE-PM₂.₅ in each grid to predict PM₂.₅ DY. After adding the predicted PM₂.₅ DY to observed PM₂.₅ in the previous year, the final PM₂.₅ concentration was obtained. The CC between predicted and observed PM₂.₅ was 0.87 during 2001–2019 in the east of China. The underestimated (2001–2007) and overestimated (2014–2019) values in Fig. S1a were largely corrected, and interannual variation also appeared in the results of SP-SE prediction (Fig. S1b). The staged trends from the SP-SE model almost overlapped with the observed trends, indicating the model performed well in capturing the changes in trend (Fig. S2).

North China (NC; 34–42° N, 114–120° E), the Yangtze River Delta (YRD; 27–34° N, 117–122° E) and the Pearl River Delta (PRD; 21.5–25° N, 112–116° E) are three regions that have been experiencing severe PM₂.₅ pollution (Yin et al., 2015). Thus, the performance of the SP-SE model in NC, the YRD and the PRD was validated separately (Table 1, Fig. 2a–c). The RMSEs were 12.2, 6.2 and 6.8 µg m⁻³ in NC, the YRD and the PRD, respectively (Ta-
Figure 3. Spatial patterns (a–d) and corresponding PCs (e–h) of the first four EOF modes for winter PM$_{2.5}$ DY in the east of China during 2000–2019. The variance accounted for by each EOF mode is given in the panel.

3.2 Impacts of climate variability

Decomposition and prediction of dominant modes of climate conditions were applied in short-term prediction of precipitation (Huang et al., 2022) and surface air temperature (Hsu et al., 2020) in the east of China. In this study, we decompose the first four leading modes of PM$_{2.5}$ DY during 2001–2019 (accumulated variance contribution = 81 %) produced by empirical orthogonal function (EOF) analysis, built a prediction model for each respective principal component, recalculated the predicted PM$_{2.5}$ DY by projecting the predicted PCs onto the observed EOF spatial patterns and finally added the predicted PM$_{2.5}$ DY to the observation in the previous year to finish the development of SP-CV (Fig. S3, Table S1 in the Supplement). The interannual–decadal variation in haze pollution could be explained well by meteorological condition and preceding climate forcings (Yin et al., 2020) such as the Arctic sea ice extent (Wang et al., 2015; Yin et al., 2019), Eurasia snow (Zou et al., 2017) and soil moisture (Yin and Wang, 2018), and SST in the Pacific (Yin and Wang, 2018) and Atlantic (Yin and Zhang, 2020). Prediction signals from these climate anomalies could be observed before winter and had specific physical implications.

The first EOF mode of PM$_{2.5}$ DY illustrated the heavily haze-polluted status in NC (Fig. 3a, e). According to the correlation analysis, the September SST DY in the southwest Pacific (CC with PC1 = −0.73; Fig. 4a) and October SST DY in the Sargasso Sea (CC = −0.73; Fig. 4b) were selected to be the two predictors for PC1 of PM$_{2.5}$ DY (Table S1). Both of the predictors had close relationships with the dipole pattern of Eurasian cyclonic and northeast Asian anti-cyclonic circulations (Fig. S4b, c), which were identical to those associated with PC1 (Fig. S4a) and could restrain the invasion of cold air from high latitude into NC.

The second EOF mode of PM$_{2.5}$ DY showed a “north–south” dipole pattern (Fig. 3b, f). The variations in PM$_{2.5}$ DY in Huanghuai and the YRD accounted for a large proportion. The October soil moisture DY in the Indo-China Peninsula (CC with PC2 = 0.73; Fig. 4c) and June–August SST DY in the Gulf of Alaska (CC = −0.69; Fig. 4d) were selected to build the prediction model of PC2 (Table S1). The anomalous atmospheric circulation associated with PC2 and its predictors
could enhance cold air invasion to NC (strong northerlies) but prevented the cold air from moving further south (weak 10 m winds in Fig. S4d–f).

The third EOF mode indicated a triple pattern with centers located in the east of Inner Mongolia, the Fenwei Plain and South China (Fig. 3c, g). The Fenwei Plain was highly polluted and gained great attention in recent years, while the other two centers have relatively better air quality (Zhao et al., 2021). The October snow depth DY in eastern Siberia (CC with PC3 = −0.65; Fig. 4e), October sea ice DY in the north to Barents Sea (CC = −0.60; Fig. 4f) and September–October soil moisture DY in the Indian Penin-
both the trend of and the interannual variation in PM$_{2.5}$ concentration (Fig. 2d–f). Thus, the SP-CV model simulated well the observed and predicted PM$_{2.5}$ concentration before (after) detrending by stages was 0.91 (0.63) in NC, 0.94 (0.61) in the YRD and 0.83 (0.64) in the PRD in the leave-one-out validation (Fig. 2d–f). The predicted biases were the smallest in the PRD, while those in the YRD were in between. These results were consistent with different intensities of pollution control in the three regions (Fig. 2e, f), which further indicated the importance of fully taking into account the impacts of climate variability and anthropogenic emissions.

4 PM$_{2.5}$ prediction with integrated factors

As mentioned above, the SP-SE model trained by the SE-PM$_{2.5}$ DY considered the impacts of emission changes unilaterally and could simulate well the values and staged trends. However, it completely failed to reproduce the interannual variation in winter PM$_{2.5}$ concentration in the east of China (Fig. 2a–c). Differently, the predictors of climate variability and the yearly increment approach had the ability to bring the sharp downward trend after 2013 in NC and YRD, the RMSEs of the SP-CV simulations for the period 2015–2019 increased up to 11.6, 6.5 and 5.3 µg m$^{-3}$ in NC, the YRD and the PRD compared to that of the SP-SE simulations. Obvious positive biases were found in the predictions of PM$_{2.5}$ concentration after 2014 (Fig. 2d–f) because the SP-CV model was short of information about the super-strict emission regulations (Fig. S2). Based on different levels of haze pollution, various degrees of air pollution control were carried out in NC, the YRD and the PRD (Zhang and Geng, 2020). In NC, where anthropogenic emissions were most prominently restricted, the predicted biases were also the largest (Fig. 2d). The predicted biases were the smallest in the PRD, while those in the YRD were in between. These results were consistent with different intensities of pollution control in the three regions (Fig. 2e, f), which further indicated the importance of fully taking into account the impacts of climate variability and anthropogenic emissions.
of China; the RMSE was 2.7 µg m\(^{-3}\), which was 43.8 % (32.5 %) smaller than the RMSE of SP-SE (SP-CV) in the leave-one-out validation. That is, the trend simulated by the SP-EC model almost overlapped with the trend of observations (similar to results of SP-SE), and the interannual variation was also reproduced (similar to results of SP-CV). The CCs between observed and SP-EC-predicted PM\(_{2.5}\) concentrations before (after) detrending were 0.93 (0.67) in NC, 0.95 (0.42) in the YRD and 0.87 (0.67) in the PRD (Fig. 2g–i). The RMSEs were 6.8 in NC, 4.2 in YRD and 4.7 µg m\(^{-3}\) in PRD, which were 44.3 % (15.0 %), 32.3 % (12.5 %) and 30.9 % (9.6 %) lower than that of SP-SE (SP-CV), indicating greater improvements in NC than in the other two regions (Table 1). According to the relative biases, the SP-EC model
also demonstrated a better skill in NC (5.1 %) than that in the YRD (4.9 %) and the PRD (8.8 %) in the leave-one-out validation. As shown in Fig. 7, the decreases in PM$_{2.5}$ resulting from the implementation of strict emission control measures in recent years were also reproduced by the SP-EC model. The evident and positive biases in the SP-CV results were largely corrected in the east of China, NC, the YRD and the PRD (Fig. 7).

High spatial resolution was one of the advantages of the seasonal prediction model developed in this study. That is, the SP-EC model could predict winter PM$_{2.5}$ concentration at each 10 km $\times$ 10 km grid in the east of China. When only considering emission predictors (i.e., SP-SE), RMSEs $>$ 12 $\mu$g m$^{-3}$ were found in the middle part of the study region, and the PSS was lower than 60 % in South China and Inner Mongolia (Fig. 6a). When only considering climate predictors (i.e., SP-CV), RMSEs $>$ 12 $\mu$g m$^{-3}$ existed in Beijing and its surrounding areas, and PSS significantly increased compared to the result of SP-SE (Fig. 6b). When integrating both of the emission predictors and climate predictors (i.e., SP-EC), the RMSE in each grid further decreased, and the PSS also increased (Fig. 6c). In the middle part of the study region, the PSS was higher than 80 %. In view of gaps between site observations and model simulations, the SP-EC-predicted PM$_{2.5}$ concentrations were compared with site observations (Fig. 8). NC was the most severely polluted area, and the SP-EC model could capture the PM$_{2.5}$ values and interannual differences. Particularly, the SP-EC model reproduced the sudden rebound of PM$_{2.5}$ pollution in 2018 (Fig. 8e) that was mainly the result of climate anomalies (Yin and Zhang, 2020).

Due to the limitation of the short sequence of data, recycling independent tests (RITs) were designed to further verify the performance of the SP-EC model. In the RIT predictions, the prediction model was trained by samples from 2001 to the expiration year of training data, and the PM$_{2.5}$ anomalies from the next year to 2019 were independently predicted. For example, the prediction model trained by the data from 2001 to 2014 can produce independent predictions from 2015 to 2019. The expiration year of the training data

Figure 7. Scatter plots of the reanalysis (x axis) and predictions of (y axis) PM$_{2.5}$ concentration by SP-CV (green) and SP-EC (blue) in (a) the 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-CV and SP-EC points indicate the calibrations.
moved forward from 2015 to 2019, so there were 15 independent predictions. The PM$_{2.5}$ concentration was independently predicted five times for 2019, four times for 2018, and so on. The PSS of PM$_{2.5}$ anomalies was 100%, not only relative to winters of 2001–2019 but also 2015–2019, indicating a high accuracy of prediction in the east of China. The predicted values for each year did not vary much (Fig. 6d), indicating a high reliability and robustness of the model. For example, when the SP-EC model was trained by the samples only from 2000 to 2014, the predicted PM$_{2.5}$ anomalies for 2018 and 2019 were also close to the results of leave-one-out validations and the measurements.

5 Conclusions and discussion

The change in haze pollution consisted of long-term trends, interannual–decadal variations, synoptic disturbances and so on. Seasonal prediction focused on predicting long-term trends and interannual–decadal variations 1–3 months in advance (Wang et al., 2021). Because of the limitation of short observational period, many previous studies employed the number of haze days as a proxy of PM$_{2.5}$ pollution to build statistical prediction models (Yin and Wang, 2016a; Yin et al., 2017; Dong et al., 2021; Zhao et al., 2021; Chang et al., 2021). Since 2020, several high-resolution PM$_{2.5}$ reanalysis datasets have been successively released, which greatly increased the possibility for direct seasonal prediction of PM$_{2.5}$ concentration that is more familiar to decision makers and the public (Yin et al., 2021).

In this study, two seasonal prediction models were separately trained by emission factor (i.e., SP-SE) or preceding climate predictors (i.e., SP-CV) to discuss their relative contributions. The SP-SE model could simulate the slow rising trend of PM$_{2.5}$ concentration before 2012 and the strong downward trend after 2012. However, it was incapable of importing the interannual component. The SP-CV model benefited from the year-to-year increment approach and could introduce a large portion of the linear trend except the sharp
decrease in winter PM$_{2.5}$ concentration from 2013. Furthermore, the SP-CV model performed well in predicting the obvious interannual variation in PM$_{2.5}$ concentration. We integrated the emission and climate factors to establish the final prediction model (i.e., SP-EC), which could reproduce well both the trend of and the interannual variation in PM$_{2.5}$ concentration. The area-averaged PSS was 81.4% in the east of China and CC between observed and predicted PM$_{2.5}$ concentrations before (after) the detrending was 0.96 (0.74). The RMSEs were 6.8 in NC, 4.2 in the YRD and 4.7 µg m$^{-3}$ in the PRD, which were 44.3% (15.0%), 32.3% (12.5%) and 30.9% (9.6%) lower than the results of SP-SE (SP-CV). Due to the implementation of the super-strict emission control measures, the air quality has been substantially improved, and this improvement was also perfectly predicted by the SP-EC model. During recycling independent tests, the PSS of PM$_{2.5}$ anomalies was 100%, demonstrating high accuracy and robustness. The high-resolution PM$_{2.5}$ prediction could provide scientific support 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; 10 km × 10 km gridded PM$_{2.5}$ information also had the potential to support finely and dynamically regional management and collaborations.

This study mainly focused on developments of a seasonal PM$_{2.5}$ prediction model. Related theories and methods are still exploratory and need further discoveries. Although the SP-EC model was proven to be skilled, the underlying physical mechanisms of climate predictors were not sufficiently explained and needed further in-depth studies. As shown in Fig. 8f, the SP-EC model failed to predict well the evident PM$_{2.5}$ drops in the 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 routine seasonal prediction of air pollution (Yin et al., 2021).

**Data availability.** The monthly sea ice concentration and sea surface temperature (SST) dataset was provided by the Met Office Hadley Centre: https://www.metoffice.gov.uk/hadobs/hadisst/ (last access: 19 August 2022) (Met Office Hadley Centre, 2022). Monthly soil moisture, snow depth, geopotential height at 500 and 850 hPa, sea level pressure, and 10 m wind were extracted from the fifth generation reanalysis product (ERA5) produced by the European Center for Medium Range Weather Forecasts: https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset (last access: 19 August 2022; ERA5, 2022). Annual emissions of ammonia, nitrogen oxide, black oxide carbon (BOC), primary PM$_{2.5}$ and sulfur dioxide in China were derived from the MEIC model: http://www.meicmodel.org/ (last access: 19 August 2022; MEIC, 2022). Hourly site-observed PM$_{2.5}$ concentrations during 2014–2019 were acquired from the China National Environmental Monitoring Center: https://www.aqistudy.cn/historydata/ (last access: 19 August 2022, CENEMC, 2022). The long-term and high-resolution TAP PM$_{2.5}$ concentration dataset during 2000–2019 can be downloaded from http://tapdata.org.cn/ (last access: 19 August 2022; TAP, 2022).

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**Author contributions.** HW and ZY designed this research. YL, TX and MD performed analyses and trained prediction models. ZY prepared the manuscript with contributions from all co-authors.

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