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Seasonal to interannual prediction of air pollution in China: Review and insight

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A R T I C L E I N F O

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A B S T R A C T

Complex air pollution problems have resulted in considerable adverse impacts on the environment, human health, and economy in China. However, owing to strict regulations since 2013, the air quality has been greatly improved. Now, the prevention of air pollution has entered a critical stage in combination with climate change mitigation in China. Accurate seasonal to interannual prediction of air pollution (haze, surface O_3, and sandstorms) could support the government in planning for air pollution control on an annual basis. Scientists from all over the world have made great progress in understanding climate change and the variability of air pollution and associated physical mechanisms in China, which has provided a scientific basis for the development of climate prediction of air pollution. This paper reviews the progress made in air-pollution climate prediction, and gives some critical insights including update of predictand, change of predictability, and development of coupled model.

摘要

复合型大气污染对中国环境, 健康和经济存在巨大的不利影响. 2013年以来的减排措施有效改善了空气质量. 目前, 我国已进入大气污染与气候变化协同治理的关键阶段. 在季节-年际尺度上, 对大气污染 (霾, 臭氧和沙尘暴) 的准确预测可以为有关部门的减排措施提供有效的科技支撑. 近年来, 全球科学家在理解中国气候变化, 大气污染变率及相关物理机制方面取得了很大进展, 为开展大气污染气候预测提供了科学基础. 本文回顾了大气污染气候预测的相关进展, 并对大气污染气候预测的—些发展方向提出了观点和判断.

1. Introduction

Regional and complex air pollution has become one of the main environmental and health issues in China. The number of haze days presented an increasing trend during 1973–2017 (Li et al., 2019b). Since 2013, the annual mean concentration of fine particles with diameters ≤ 2.5 μm ($PM_{2.5}$) has dramatically decreased due to emission reductions and energy structure optimization (Zhang et al., 2019; Zhang and Geng, 2020). However, the concentration of ground-level ozone (O_3) persistently increased from 2014 to 2019, partly because of mismatching changes in volatile organic compounds (VOCs) and nitrogen oxides (NO_x), and decreased $PM_{2.5}$ (Li et al., 2019a, 2020). In the spring of 2021, North China suffered from super sandstorms (PM_{10} > 7000 μg m^{-3}), a phenomenon that had not occurred for more than a decade (Yin et al, 2021b).

The variation in air pollution consists of long-term trend, interannual-decadal and synoptic variation, which stores various degrees of predictability. The long-term trend and its changes in air pollution are to a great extent determined by direct emissions from human activities and accompanying indirect effects from atmospheric anomalies with global warming (Fig. 1). In addition, haze and surface O_3 pollution also show significant interannual-decadal variations, which are closely related to climate anomalies (Fig. 1) and are the main forecasting objects of climate prediction (Yin and Wang, 2016, 2017; Yin et al., 2020a). For example, atmospheric anomalies were one of the main causes of the 10% rebound in $PM_{2.5}$ under intensified air pollution prevention in winter 2018 with respect to 2017 (Yin and Zhang, 2020). The meteorological conditions can change the natural emissions of precursors (Lu et al., 2019), photochemical reactions (Wang et al., 2017), and transportation (Gong et al., 2020) to influence regional concentrations of O_3 and determine shifts in the dominant spatial patterns of O_3 pollution in eastern China (Yin and Ma, 2020) (Fig. 1(b)). As for dust weather, a strong Mongolian cyclone in spring can blow and transport large amounts of sand

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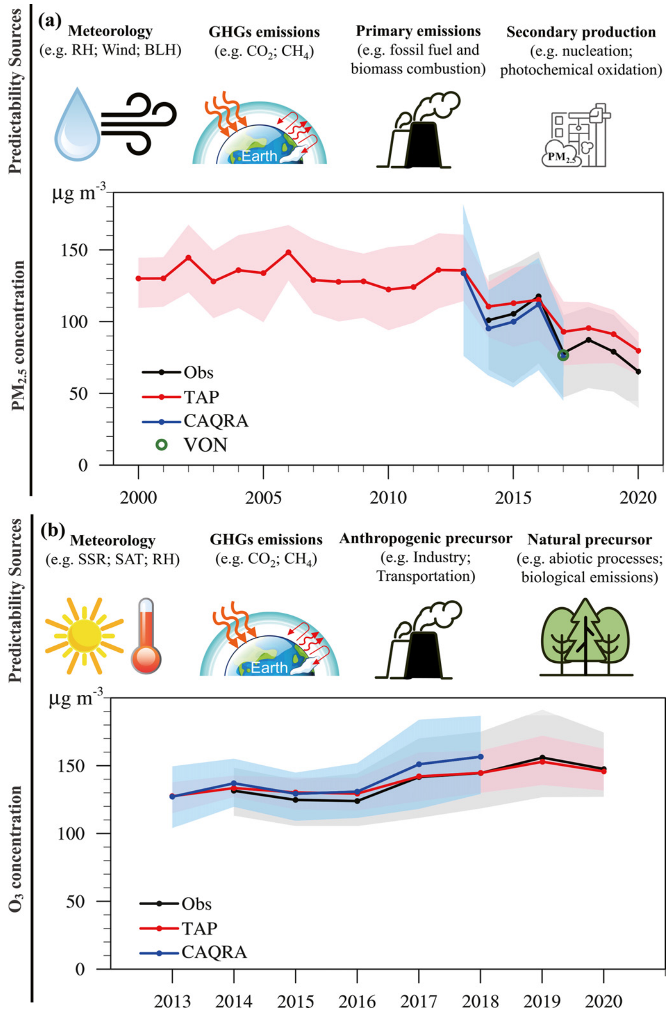

Fig. 1. Variation in (a) winter mean $PM_{2.5}$ and (b) summer mean O_3 concentrations in North China and possible sources of climate predictability. The reanalysis data for the $PM_{2.5}$ and O_3 were from site observations (black; https://www.aqistudy.cn/historydata/), CAQRA (blue; Chinese Air Quality Reanalysis dataset, https://doi.org/10.11922/sciencedb.00053), TAP (red; Tracking Air Pollution in China dataset, http://tapdata.org.cn), and a virtual $PM_{2.5}$ observation network (green). Factors that influence the interannual-decadal variation and long-term trend of (a) $PM_{2.5}$ and (b) O_3 pollution and an indication of the potential sources of predictability are summarized in the upper half of each panel.

particles from the bare and loose ground into North China (Huang et al., 2008).

Atmospheric chemical processes play critical roles in the occurrence of heavy-pollution events, and yet their impacts on the interannual-decadal variation of air pollution have not been thoroughly assessed. During the COVID-19 quarantines in February 2020, the chemical formation of secondary pollutants partly offset the reduction in primary emissions and contributed to several severe $PM_{2.5}$ and O_3 pollution episodes in North China (Hu et al., 2021; Tang et al., 2021; Zhang et al., 2021). In addition, interactions such as those between the meteorology and emissions, $PM_{2.5}$ and O_3, and short- and long-life particles, are important in determining monthly and seasonal levels of air pollution.

It is well documented that preceding external forcings have significant impacts on the interannual-decadal variability of winter haze, summer O_3, and spring dust (Fig. 2). Arctic sea ice (Wang et al., 2015), Eurasian snow and soil moisture (Zou et al., 2017), the sea surface temperature (SST) in the Pacific (He et al., 2019) and Atlantic (Xiao et al., 2015), and the forcing of the Tibetan Plateau (Ma et al., 2020) can solely and jointly influence the variations of haze days in North China (HD_{NC}) (Yin et al., 2020b) (Fig. 2(a)). When most of these preceding factors are in-phase, large anomalies of the number of HD_{NC}. The phenomenon of the in-phase has happened a lot in these years, accompanied by large anomalies of HD_{NC}. To the best of our knowledge, there have been fewer studies on the climate factors influencing surface O_3 in China than those of haze. Anomalies of late-spring Arctic sea ice and Eurasian snow could stimulate Rossby-wave-like trains to influence the variability of O_3 pollution in North China (Yin et al., 2019, 2021a). The southern Indian Ocean dipole could store its thermodynamic signals in the subsurface and influence the dipole pattern of O_3 pollution in the east of China (Ma and Yin, 2021) (Fig. 2(b)). Anomalies of sea-ice shift in the Barents and Kara seas and the SSTs in the eastern Pacific and northwestern Atlantic have been identified to induce tremendous dust sources around Mongolia, which is an essential material basis of spring dust (Yin et al., 2021b).

The prevention of air pollution has entered a critical stage in China and requires better support from the perspective of climate prediction. Accurate real-time climate prediction of air pollution could support the government in planning for air pollution control on an annual basis; that is, to determine whether extra emission reductions are required to counteract the adverse climate effects in advance. However, theories and methods related to the prediction of air pollution are still in an exploratory stage and in need of further research and discoveries.

2. Progress

2.1. Prediction of haze

Because of the "memory" effect in slow-varying external forcings, preceding climate factors influence the HD_{NC} and store efficient predictive information (Table S1; Yin and Wang, 2016). Yin and Wang (2016) issued a seasonal prediction model of winter haze in North China. In this model, the predictand and predictors were the year-to-year difference (DY) instead of climate anomalies. The root-mean-square error (RMSE) and explained variance of the multi-linear regression (MLR) prediction model was 3.39 days and 53%, respectively. Furthermore, the changing trend and the extrema were successfully reproduced. To some extent, the nonlinear relationships are also important for climate predictions. The preceding DY of SST around Gulf of Alaska and the sea ice of the Beaufort Sea, which nonlinearly contribute to the variation of HD_{NC}, were addressed by the generalized additive model approach to predict HD_{NC}. The long-term trend and turning points were simulated well and the percentage of the same sign (PSS) was quite high during recycling independent tests (Yin and Wang, 2017).

With regards to Yangtze River Delta (YRD), a seasonal nonlinear grey Bernoulli model was developed to provide skillful forecasts for the $PM_{2.5}$ concentrations in Shanghai, Hangzhou, Nanjing, and Hefei (Zhou et al., 2020). The level of accuracy was high in both training and testing periods and one possible reason could be that this model grasps the seasonality during its initial design. Based on this verified model, the air quality of four cities was predicted to be better than before. The DY approach was also applied to predict the number of haze days in the YRD (HD_{YRD}) in each month of winter (Dong et al., 2021). The RMSE, PSS, and explained variance were 2.76 days, 97.3%, and 79.04%, respectively, indicating good predictive skill. Chang et al. (2021) found that regional stratospheric warming over northeastern Asia in November influenced haze pollution in the Sichuan Basin in 5–7 weeks and developed a prediction model with a correlation coefficient (CC) of 0.57 in the hindcast of early-winter haze. Similarly, August–October mean Niño3.4 index and three other identified predictors were used to predict winter haze days in South China and could explain 90% of the total variance (Cheng et al., 2019). $PM_{2.5}$ in Fuzhou was forecasted by the Auto Regressive Integrated Moving Average model 1–24 months in advance (Zhang et al., 2018). Gao et al. (2019) found the preceding autumn El

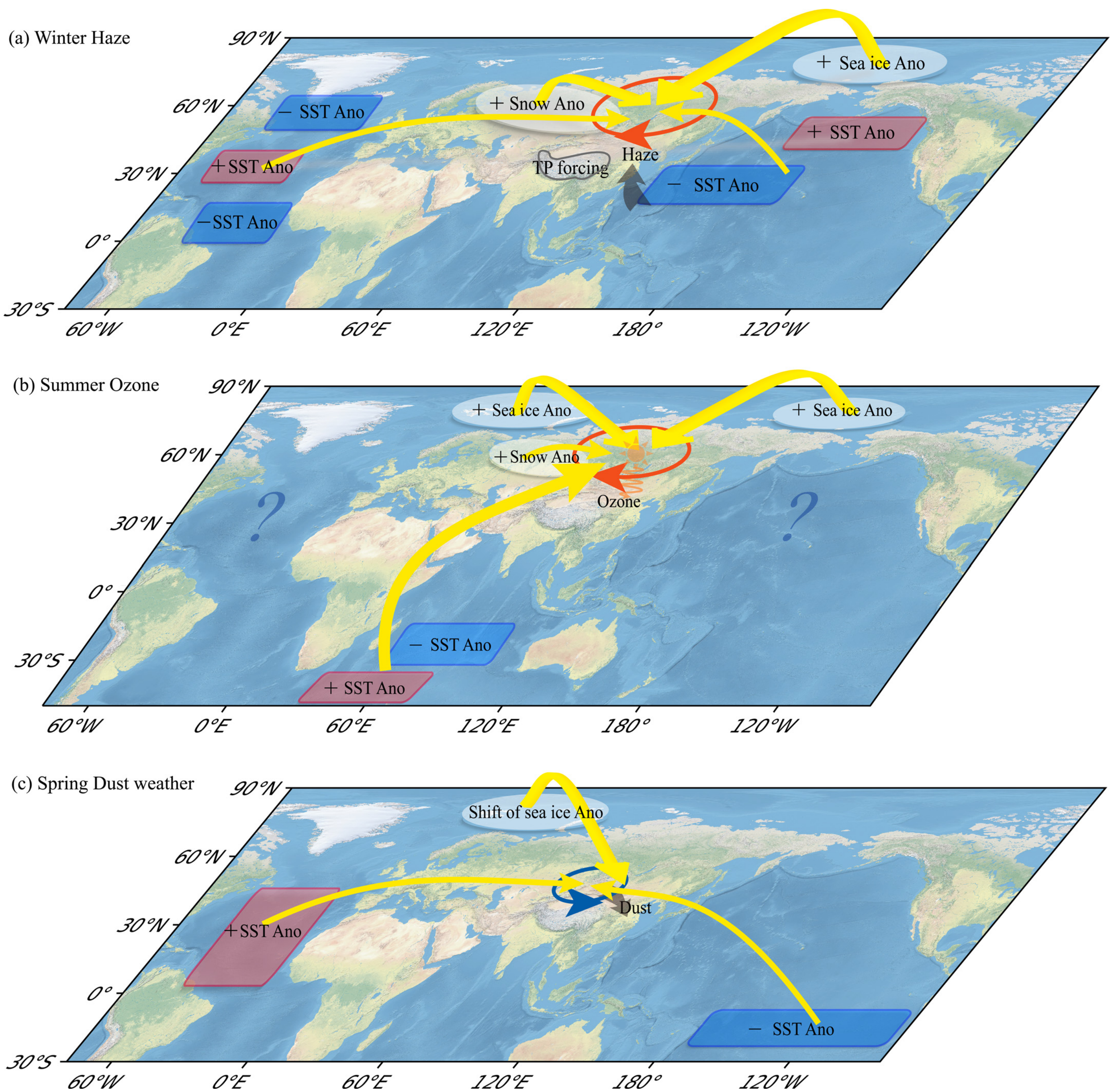

Fig. 2. Schematic diagram of the impacts of preceding climate factors on (a) winter haze pollution, (b) summer surface O_3 pollution, and (c) spring dust weather in North China.

Niño and Antarctic Oscillation could predict the aerosol optical depth over northern India (CC = 0.78).

2.2. Prediction of surface O_3

Surface O_3 concentrations have been observed since 1980 in the eastern United States and the sequence length possibly supports climate prediction. High summer O_3 is correlated with previous-spring positive SST anomalies in the tropical Atlantic and negative SST anomalies in the northeastern Pacific, as well as higher sea level pressure over Hawaii and lower sea level pressure anomalies over the Atlantic and North America. Based on these climate anomalies, a statistical model was developed to predict summer-mean daily maximum 8-h average O_3 concentrations (MDA8 O_3) in the eastern United States, which successfully explained ~45% of the variability (Shen and Mickley, 2017).

Ground-level O_3 concentrations have been extensively observed since 2014 in China, but this time scale cannot support climate prediction of O_3 pollution. As mentioned, climate factors could significantly modulate the O_3 concentrations in summer. The O_3 weather index, an optimized proxy dataset, was predicted by Yin et al. (2019). Higher O_3 weather index indicated the climate conditions were beneficial for the production of surface O_3. Based on the DY approach, observed preceding predictors were used to establish the MLR prediction model (Table S1; Yin et al., 2020b). Further absorbing information from the NCEP Climate Forecast System (CFS), the PSS of this statistical–dynamical hybrid model was 93.9% and the CC between the observation and predicted values was 0.84. With improving performances in the most recent decade, this model has considerable potential to execute real-time seasonal predictions of O_3 pollution.

2.3. Prediction of dust weather

Based on the previous summer's vegetation in North China, the winter Antarctic Oscillation and sea ice over the Barents Sea, the frequency of spring dust weather has been successfully predicted. Further deriving a spring 850-hPa geopotential height index from CFS, a dynamical–statistical hybrid prediction model produced a hindcast correlation of 0.82 and successfully reproduced the trend of spring dust frequency (Table S1; Ji and Fan, 2019). The winter and spring climate, especially the air temperature and precipitation, was predicted and used for forecasting the frequency and intensity of dust weather in spring (Wang et al., 2003). Some mathematical models, such as support vector machines, the vector autoregressive moving average, autoregressive integrated moving average (Garcia Nieto et al., 2017), and gray model (Wu et al., 2019; Zhou et al. 2020) have also been used to forecast the average PM_{10} concentration. However, seasonal forecasting of PM_{10} is still in a relatively preliminary stage.

3. Insights

3.1. Changing predictand

Closely related to record-breaking haze pollution in winter 2012, an observation network of atmospheric compositions was constructed in China and has been taking shape since 2014. The pollutant concentration is the major monitoring and weather-forecasting variable that is familiar to decision makers and the public. However, the length of concentration data is insufficient for establishing long-term standing prediction models, and thus most of previous studies have attempted to predict the number of polluted days. Since 2020, some high-resolution reanalysis datasets of air pollution have been successively released. These reanalysis data try to combine information from multiple sources, including ground observations, satellite retrievals, emission inventories, air quality simulations from chemical transport models, and so on (Geng et al., 2021; Kong et al., 2021; Gui et al., 2020). More importantly, some publicly downloadable datasets (e.g., the Tracking Air Pollution in China dataset, TAP) provide long-term records of the $PM_{2.5}$ concentration (>20 yr) and increase the possibility to directly predict pollutant concentrations on the climatological time scale. However, the ground-level O_3 concentration has only been recorded since 2013. As shown in Fig. 1 and Fig. S1, the spatiotemporal resolution and data quality vary regionally and differ among different kinds of reanalysis datasets. These reanalysis datasets have higher uncertainties before the construction of the China national monitoring network (i.e., before 2013). Furthermore, little is known about the quality of the derived $PM_{2.5}$ data during 2000–2013 due to a lack of direct site observations, although machine learning approaches could fit optimal results to a great certain extent. It is emergent to assess the availability of the developing air pollution reanalysis datasets and the possibility to incorporate pollutant concentrations into the predictand of climate prediction.

3.2. Predictability

In most of seasonal to interannual predictions, meteorological conditions are essential predictors to forecast air pollution in China. These documented relationships could simulate the number of haze days from 1979–2012 well; however, Yin et al. (2020b) illustrated the same MLR failed to reproduce the variations during 1979–2018. On the daily time scale, the CCs between MLR-fitted and observed $PM_{2.5}$ concentrations were around 0.7 in each year (Fig. 3(a)) and illustrated robust impacts of meteorology on winter $PM_{2.5}$ concentrations from 2014 to 2019. The contradiction between the interannual and synoptic relationships might be caused by the intensified air pollution management since 2013. When the MLR model was trained by daily data in a specific year, the emissions baseline of this year was implicitly expressed in the coefficients of meteorological factors. To verify this speculation, a fixed model was fitted that only depended on data in 2014, and was then used to simulate daily $PM_{2.5}$ concentrations with meteorological elements from 2014 to 2019. In Fig. 3(b), the simulated winter mean $PM_{2.5}$ is quite close to the observation in 2014 and the difference becomes larger along with time. A percentage value, defined as (observed − simulated) / observed $PM_{2.5}$, was used to simply represent the impact of emission changes, which also linearly increased and was independent of the specific training year (Fig. 3(c)). This is because anthropogenic emissions significantly reduced after the implementation of China's Air Pollution Prevention and Control Action Plan. However, this information cannot be contained in the coefficients of a fixed statistical model.

As for the O_3 concentrations, the CCs with daily meteorological changes were also robust from 2014 to 2020 and even higher than those of haze (Fig. 3(d)). In Fig. 3(e, f), the differences and percentages shift from negative to positive. In the early stages, the reductions in primary pollutants (particularly NO_x) induced improvement in the surface O_3 conditions. However, along with sustained emissions reduction, the mismatched changes of NO_x and VOCs and the decreased $PM_{2.5}$ both enhanced the O_3 concentrations in North China (Li et al., 2021). The reduction of $PM_{2.5}$ is conducive to the production of O_3 by scavenging hydroperoxy and NO_x radicals, which then cause the increase in O_3 concentrations (Li et al., 2019a, 2020). Furthermore, the changes in O_3 were also closely related to the formaldehyde concentration (Ling et al., 2017). Although the varied range of O_3 was smaller than that of $PM_{2.5}$, it must influence the climate predictability of O_3 pollution, which needs urgent and further research. As for dust weather, its frequency in northern China featured two high-frequency periods (1966–1979 and 2000–2014) during the period 1966–2014 (Fan et al., 2016). After an absence of sandstorms for more than 10 years, strong sandstorms reoccurred in spring of 2021 (Yin et al., 2021b). These decadal changes of dust variability must have substantial influences on the predictability of dust weather or sandstorms. Therefore, information on rapid changes in human activities and decadal changes of climate should be considered and contained in air pollution prediction models in later work.

3.3. Coupled climate model targeted at routine predictions of air pollution

Modern weather forecasting and climate prediction are almost completely reliant on high-performance computing of atmospheric physical equations with accurate descriptions of initial conditions (WMO, 2021). Numerical climate models need to manage the complex spheres of the earth system and integrate for days, months, and years. In recent years, atmospheric chemical models advanced greatly, but most of them were not designed for climate prediction. Thus, it is necessary to design and construct a coupled numerical model targeted at routine seasonal to interannual predictions of air pollution. Such a climate–chemical coupled model must reasonably describe the sources and sinks of atmospheric chemical compositions as well as complex processes of the earth system and further successfully treat the multi-source uncertainties (An et al., 2018). Alternatively, another possible way is to utilize a regional climate–chemical model that re-predicts and downscales the concentrations of air pollution from a global model.

Critical issues must be solved or improved, as follows: (i) Traditional numerical models elaborate the strong convection process, but little consideration is given to the stable boundary layer that closely relates to air pollution (Zhang et al., 2012). Thus, the parameterization scheme for the stable boundary layer must be improved in both the climate and chemical modules. (ii) Data assimilation of atmospheric composition (using reanalysis, vertical Lidar observations and remote sensing satellite data) is very likely to be a powerful tool to provide bet-

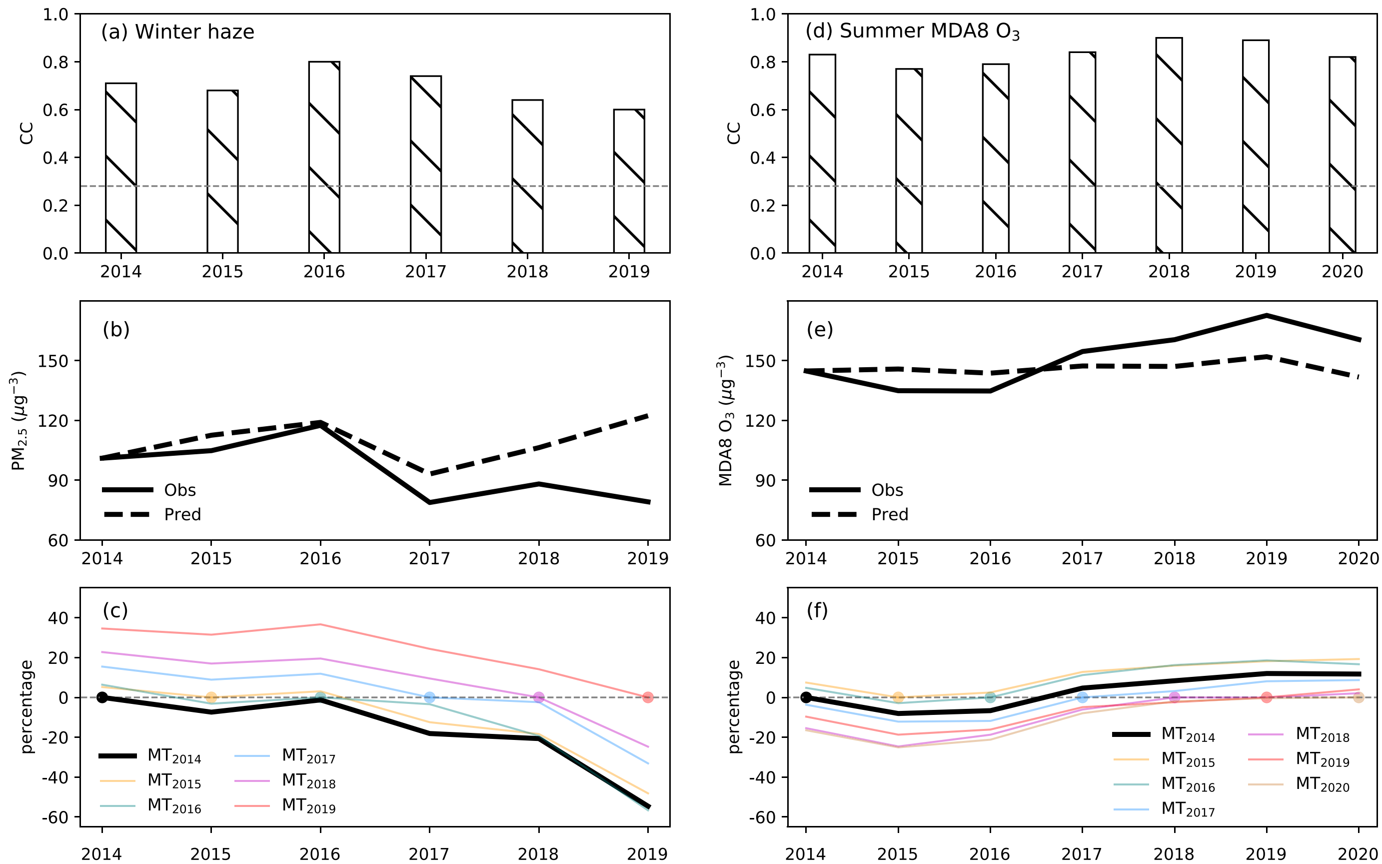

Fig. 3. (a) Correlation coefficients (CCs) between daily observed $PM_{2.5}$ and values fitted with closely related meteorology in North China in winter, and (d) CCs between daily observed MDA8 O_3 and fitted values in summer. (b) The winter-mean observed (solid) and predicted (dashed) $PM_{2.5}$ from 2014 to 2019, and (e) observed (solid) and predicted (dashed) summer-mean MDA8 O_3 from 2014 to 2020. The seasonal mean predicted value was calculated from daily predictions. The daily simulations dependent on a fixed MLR model trained with data in 2014 (MT2014) but calculated with real meteorology in each year. The percentage, defined as (observed – predicted) / observed (c) $PM_{2.5}$, (f) MDA8 O_3. The predictions were from the MT2014 model (black) and other MT_{year} models (colors), and the solid dots mark the year when the fixed model is based on. Daily atmospheric reanalysis data (1° × 1°) were downloaded from the fifth generation European Center for Medium Range Weather Forecasts (Copernicus Climate Change Service) dataset.

ter initial conditions (Zhu et al., 2018). (iii) The formation and growth of new atmospheric particles and secondary aerosols are important error sources in synoptic chemistry models, let alone climate prediction, so it is necessary to make clear associated change mechanisms and describe them in numerical models. Machine learning methods are probably helpful for the initialization of climate models, improvement of parameterization, utilization of fuzzy understanding, and so on. (iv) More concerns should be given to the interactions among multi-time-scale climate variabilities and multi-scale dynamics, as this will certainly contribute to the seamless prediction of basic meteorological variables and also to rational simulations of short- and long-life aerosols. (v) In most current routine seasonal-to-interannual climate forecast models, the human activities are set as fixed parameters and cannot respond in a timely manner to rapid changes in emissions that happened during the COVID-19 quarantines and are about to happen under carbon neutrality. Near-real-time emissions inventories and modules of carbon and nitrogen cycles will greatly favor the real-time prediction of $PM_{2.5}$ and O_3 pollution.

To the best of our knowledge, routine predictions of air pollution are considerably lacking in China. The Center for Climate System Prediction Research (CCSP, supported by the National Natural Science Foundation of China) direct predict the number of haze days in China and have provided the advice to relevant government departments since 2016 (Wang et al., 2020). The Beijing Climate Center also operate a Climate Prediction System of Atmospheric Pollution Potential to monitor and predict meteorological dispersion conditions, and have reported the prediction results jointly with the China National Environmental Monitoring Centre of the Ministry of Ecology and Environment since 2018 (http://cmdp.ncc-cma.net/climate/disaster.php). According to this review, literature related to the climate prediction of air pollution is also scarce and restricted in the development of prediction models. Therefore, it is meaningful and urgent to boost collaborative innovations to study the scientific issues posed in this study and to develop prediction approaches. Furthermore, the associated health effects and impacts should be considered holistically in the future, and thus scientific support to governments will be immediately useful and enduringly strong.

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Authors' contribution

Wang H. J. designed this research and revised the manuscript. Yin Z. C. and the remaining co-authors performed associated calculations and prepared the manuscript.

Declaration of Competing Interest

The authors declare no conflict of interest.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.aosl.2021.100131.

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