Impact of modified turbulent diffusion of PM_{2.5} aerosol in WRF-Chem

simulations in Eastern China

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Abstract

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Correct description of the boundary layer mixing process of particle is an important

prerequisite to understanding the formation mechanism of pollutants, especially during

heavy pollution episodes. Turbulent mixing process of particles is usually denoted by

the turbulent diffusion of heat, which is questionable. Using mixing-length theory, a

new turbulent diffusion relationship of particle is established, embedded in the model

and verified on a long-term scale. The new turbulent diffusion coefficient is used to

represent the turbulent mixing process of pollutants separately. Simulated results of

PM_{2.5} concentration were improved by 8.3% (2013), 17% (2014), 11% (2015) and 11.7%

(2017) in Eastern China, respectively. Meanwhile, the new turbulent diffusion does not

deteriorate the simulation results of meteorological parameters. Compared with the

boundary layer height, turbulent diffusion controls the diffusion of pollutants more

significantly. However, under the influence of complex topography, the turbulent

diffusion process is insensitive to the simulation of the pollutant concentration. For mountainous area, the evolution of pollutants is more susceptible to advection transport. In addition to the PM_{2.5} concentration, CO as a primary pollutant, its concentration has also been improved, which shows that the turbulent diffusion process is extremely critical to the variation of the various aerosol pollutants.

1 Introduction

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Along with the intensive urbanization and tremendous economic development, numerous incidents of aerosol pollution have frequently occurred in China (An et al., 2019; X. Zhang et al., 2019). Aerosol pollution, characterized by PM_{2.5}, occurs primarily in the planetary boundary layer (PBL). The horizontal transportation and vertical distribution of pollutants are obviously affected by the PBL mixing process, associated with intricate turbulence eddies (Ren et al., 2018; Wang et al., 2018; Du et al., 2020). Turbulent diffusion, as a vital process, controls the exchange of momentum, heat, water vapor and pollutants through turbulence eddies within the PBL (Stull, 1988).

Moreover, the PBL height (PBLH) directly determines the effective air volume of pollutant diffusion and atmospheric environmental capacity. With the continuous development of technology, there are numerous means (e.g., radiosonde, tethered balloon, meteorological tower, aircraft, ground-based remote sensing and space-based remote sensing) and methods (e.g., based on surface fluxes, Richardson number and others diagnostic methods) to determine the PBLH, of course, the results are also different (Zhang et al., 2020). However, the PBLH is not necessarily negatively correlated with pollutant concentration (Miao et al., 2021). In particular, turbulence barrier effect can affect the vertical distribution of pollutants (Ren et al., 2021), which make the relationship between pollutant and PBLH more uncertain. The PBLH can also be diagnosed by the boundary layer parameterization schemes in the model, but the PBLH does not directly determine the effective diffusion of pollutants (Jia and Zhang, 2020; Jia et al., 2021a). Instead, the vertical diffusion and mixing of pollutants are

directly determined by the turbulent diffusion coefficient (TDC), and the diagnosis of PBLH can affect the calculation of TDC. Previous studies have analyzed some pollution cases by using process analysis methods (Xing et al., 2017; Gao et al., 2018; Chen et al., 2019). The results showed that, for a pollution event, emissions and turbulent diffusion are the two processes that contribute the most to the pollutant concentration. Meanwhile, the contributions of advection transport and chemistry cannot be ignored. The evolution of pollutants is mainly controlled by turbulent diffusion, when emissions are unchanged for a short period. Therefore, more realistic turbulent diffusion characteristics are extremely important for the simulation of pollutant concentration in the model.

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To date, there are still some problems need to be solved in the model, especially turbulent diffusion processes of all scalars (including active and passive scalars) are dealt with in a unified manner in the mesoscale model. Only a few studies have shown that pointed out the meteorological fields and pollutants can be changed by adjusting the minimum value of TDC (Savijarvi et al., 2002; Wang et al., 2018; Du et al., 2020; Liu et al., 2021), increasing turbulent kinetic energy (TKE) (Foreman and Emeis, 2012) and modifying experiment expressions (Sušelj and Sood, 2010; Huang and Peng, 2017). Recently, Jia et al. (2021b) obtained the TDC of particles by using high-resolution vertical flux data of particles based on the mixing length theory. Additionally, this relationship has been embedded into the WRF-Chem model to calculate the PBL mixing process of pollutants separately. This work has initially improved the overestimation of pollutant concentration at night in winter 2016 in Eastern China. However, a series of heavy pollution incidents have occurred and attracted much attention since 2013 (Miao et al., 2019). Therefore, we conducted a series of simulations for the heavy pollution periods in winter from 2013 to 2017 in this study. The difference between this study and previous work is that previous work focused on the analysis of observations, while this study mainly explores the influence of turbulent diffusion on pollutant concentration in the mesoscale model.

2 Data and methods

2.1 Data

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In this study, the aerosol pollution level is denoted by the hourly surface PM_{2.5} concentration that is available from the official website of the China National Environmental Monitoring Center from 1 January 2013 to 31 January 2017. PM_{2.5} concentration stations increased from 35 cities in 2013(illustrated by red dots in Fig. 1b) to 78 cities in 2017(illustrated by black dots in Fig. 1b) in Eastern China. In addition to PM_{2.5} observations, the hourly concentrations of CO were acquired from the National Air Quality real-time publication platform (http://106.37.208.233:20035, last access: 20 May 2021). Meanwhile, the hourly meteorological observation data, including temperature, pressure, relative humidity, wind and visibility from the national automatic weather stations (AWS) provided by the National Meteorological Information Center of China Meteorological Administration (NMICMA) (illustrated by gray crosses in Fig. 1b). The time period of the data selected is from 1 January 2013 to 31 January 2017. In addition, the turbulent diffusion of particles is calculated using high-frequency turbulence data, and observational turbulence data are obtained from the Pingyuan County Meteorological Bureau (37.15°N, 116.47°E), Shandong Province, China from 27 December 2018 to 8 January 2019 (illustrated by orange triangle in Fig. 1b). Identical eddy-covariance systems were operated, including three-dimensional sonic anemometer-thermometer (IRGASON, Campbell Scientific, USA) and CO₂/H₂O openpath gas analyzer (LI7500, LI-COR, USA). These instruments measured three components of wind speed, potential temperature, water vapor and CO₂ concentrations with a frequency of 10 Hz. The turbulence data finally was split into 30-min segments. A continuous particle measuring instrument E-sampler (Met One) and a high-frequency sampling visibility sensor CS120A (Campbell Scientific, USA) were used to obtain PM_{2.5} mass concentration every minute and visibility of 1 Hz. The calculation of 30min vertical flux of PM_{2.5} is based on the nonlinear relationship between PM_{2.5} concentration and visibility (Ren et al., 2020). Detailed background and calculation principle of this method were presented in Ren et al. (2020), so we only describe key steps. Firstly, we separate PM_{2.5} concentration (c) and visibility datasets (V) into mean and turbulent deviations (i.e., $c=\bar{c}+c'$ and $V=\bar{V}+V'$). Secondly, we get the fitted coefficients by using exponential correlation (i.e., a and b) between the PM_{2.5} concentration and visibility (i.e., $c=a\cdot V^b$). Thirdly, combining the first two steps, we can get the turbulent fluctuations of PM_{2.5} concentration (i.e., $c'=a\cdot (\bar{V}+V')^b-\bar{c}$). Finally, we use fluctuations of vertical velocity (i.e., w') and of PM_{2.5} concentration (i.e., c') to calculate the vertical flux of PM_{2.5} (i.e., w'c').

To illustrate the influence of the PBL height (PBLH) on the PM_{2.5} pollution, soundings collected at the Fuyang site (32.54°N,115.5°E) and the Anqing site (30.37°N,116.58°E) (illustrated by yellow pluses in Fig. 1b) for the period 2013-2017 were analyzed. These two stations are equipped with L-band radiosonde systems (Jia et al., 2021c), which proved a fine resolution (1 Hz) profiles of temperature, relative humidity and wind speed two times (0800 and 2000 BJT) a day during winter. To eliminate the error caused by the difference of calculation methods of PBLH, Richardson number method is used to calculate the PBLH in both observation and simulation. The Richardson number is defined as follows:

$$Ri(z) = \frac{g(\theta_{vz} - \theta_{vs})(z - z_s)}{\theta_{vs}(u_z - u_s)^2 + (v_z - v_s)^2}$$
(1)

where z is the height above ground, g is the gravity, θ_v is the virtual potential temperature, and u and v are the component of wind. The subscript "s" denotes the surface level. The height at which the Richardson number equals 0.25 is defined as the PBLH, which is consistent with the definition of simulation.

2.2 Numerical simulation

130 Long-term three-dimensional simulation experiments are enforced using the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem version 3.9.1) (Grell et al., 2005) in this study from the winter of 2013 to 2017, when Eastern China frequently experienced severe and persistent aerosol pollution events. One month for each winter from 2013 to 2017 was selected, and a total of four months were confirmed, 135 which are January 2013, December 2014, December 2015 and January 2017, respectively. The anthropogenic emissions of BC, OC, CO, NH₃, NO_x, PM_{2.5}, PM₁₀ and volatile organic compounds (VOCs) are set based on the latest monthly Multiresolution Emission Inventory for China (MEIC) from 2013 to 2017 are provided by Tsinghua University, with a resolution of 0.25°×0.25° (http://meicmodel.org/, last access: 20 May 2021). The model domain was centered over Eastern China with a 140 horizontal resolution of 33 and 6.6 km (Fig. 1a). The model top was set to the 50 hPa level, and 48 vertical layers were configured below the top. To resolve the PBL structure, 21 vertical layers were set below 2 km (Above Ground Level, AGL). The physics parameterization schemes selected for this study included the Morrison doublemoment microphysics scheme (Morrison et al., 2009), RRTMG longwave/shortwave 145 radiation schemes (Iacono et al., 2008), MM5 similarity surface layer scheme (Jiménez et al., 2012), Noah land surface scheme (Chen and Dudhia, 2001), Singer-layer UCM scheme (Kusaka et al., 2001), CLM4.5 lake physics scheme (Subin et al., 2012; Gu et al., 2015), ACM2 planetary boundary layer scheme (Pleim, 2007), Grell-3D cumulus scheme (Grell and Devenyi, 2002). And the chemical mechanism is the RADM2-150 MADE/SORGM scheme (Ackermann et al., 1998; Schell et al., 2001). The initial and boundary conditions of meteorological fields were set up using the National Centers for Environmental Prediction (NCEP) global final (FNL) reanalysis data, with a resolution of 1°×1° (https://rda.ucar.edu/datasets/ds083.2/, last access: 20 May 2021). And the initial and boundary conditions of chemical fields were configured using the global 155

model output of Model for Ozone and Related Chemical Tracers (MOZART) (http://www/acom.ucar.edu/wrf-chem/mozart.shtml, last access: 20 May 2021).

Simulation using abovementioned configurations is referred to as the original runs. In the original PBL parameterization scheme, TDCs of heat and momentum are different (i.e., $K_h \neq K_m$). The turbulent mixing process of pollutants is considered to be similar to that of heat, which supposes the turbulent diffusions of particles and heat are identical (i.e., $K_h=K_c$). While in the improved scheme, the turbulent mixing process of pollutants is calculated by the TDC of particles (i.e., K_c), which is different from TDC of heat (i.e., $K_h \neq K_c$). These improved experiments are regarded as the new runs hereafter. All simulation included a total of eight months. The 91-h simulation is conducted beginning from 0000UTC of three days ago for each day (i.e., 248 simulation experiments), and first 64-h of each simulation is considered as the spin-up period.

2.3 Calculation principle of turbulent diffusion of particles

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Considering that the pollution is usually accompanied by the stable boundary layer (SBL), and the simulation results of pollutant concentration are poor in the SBL at night. Thus, we mainly modify the program of the stable boundary layer, while for the unstable boundary layer, we still use the default program of the original scheme.

The TDC is parameterized by the mixing length (l) and the function of Richardson number (f(Ri)) based on Mixing length theory, that is

$$K = 0.01 + \sqrt{ss} \cdot l^2 \cdot f(Ri) \tag{2}$$

where ss is the wind shear (i.e., $ss = (\partial u/\partial z)^2 + (\partial v/\partial z)^2$), 0.01 refers to the minimum value of TDC in the model. The mixing length formula (i.e., $l = \kappa z/(1 + \kappa z/\lambda)$, λ =80) proposed by Blackadar (1962), and it is widely used in the model (Louis, 1979; Lin et al., 2008; Pleim, 2016). Many previous studies have showed various functions of Richardson number, which represent the different situations of turbulence. Here, we

mainly compare the similarities and differences between the turbulent diffusion of momentum, heat and particles in the model.

(i) For the stable conditions (i.e., $Ri \ge 0$), Esau and Byrkjedal (2007) suggested:

$$f_h = (1 + 10Ri + 50Ri^2 + 5000Ri^4)^{-1} + 0.0012$$
 (3)

$$f_m = 0.8f_h + 0.00104 \tag{4}$$

where f_h and f_m denote the functions of heat and momentum, respectively, and these functions have been implemented in the original model. We added an additional function of particles into the model, that is

$$f_c = (1 + 66.6Ri)^{-1} \tag{5}$$

which is used to denote the turbulent mixing process of particles within the PBL. When Ri is greater than \sim 0.2, the TDC of particles is greater than that of heat, which may reduce pollutant concentration. With the increase of instability, the TDC of particles is gradually smaller than that of heat, which theoretically leads to the increase of pollutant concentration. For detailed analysis and comparison of functions, please refer to Jia et al. (2021b).

(ii) For the unstable conditions (Ri<0):

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$$f_h = f_c = (1 - 25Ri)^{1/2} \tag{6}$$

$$f_m = \Pr \cdot f_h \tag{7}$$

where the TDC of particles is still equal to that of heat, while the TDC of momentum is calculated by turbulent Prandtl number (i.e., Pr, Pr=0.8).

There are several important information about the TDC of particles that need to be illustrated. (1) Turbulent diffusion of particles calculated by the explicit local gradient to represent the PBL mixing process of particles, which are more suitable in the stable boundary layer (SBL) (Mahrt and Vickers, 2003). (2) The new scheme avoids the inapplicability of the Monin-Obukhov similarity theory (MOST), the deviation of the PBLH in the SBL, and higher computational efficiency (Li et al., 2010), and it is easier

to applied to the forecasting models in the future. (3) Turbulent diffusion of particles is used to evaluate the PBL mixing process of pollutants separately, which can affect the simulation results of pollutants and not influence the simulation results of meteorological parameters.

3 Evaluation of PM_{2.5} concentration simulation

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Based on the TDC relationship of particles in the previous study (Jia et al., 2021b), this study applies this relationship to a long-term scale simulation for verification. Figure 2 shows the average value of simulated and observed PM_{2.5} concentration at night from 2013 to 2017, and the simulation results can better reproduce the distribution of pollutant concentration (i.e., represented by the red dashed circle). However, the PM_{2.5} concentration was overestimated in varying degrees in Eastern China (i.e., indicated by the green dashed circle), and the mean relative bias (RB) of the region is as high as 11.8% (2013), 48% (2014), 23.8% (2015) and 20.9% (2017), respectively (Fig. 2i-l). In addition, we also found that the pollutant concentrations are underestimated in Beijing (BJ) and along the Taihang Mountains (Mt. Taihang) (i.e., indicated by the purple irregular circle), but overestimated in Tianjin (TJ) (Fig. 2i-l). What are the reasons for the pollutant concentration simulated by the same model are different in various regions? What are the different effects of turbulent diffusion in various regions? These issues will be further explained later, and this section mainly evaluates the simulation results of the pollutant concentration. Compared to the original scheme, the new scheme improves the situation where the pollutant concentration is overestimated at night in Eastern China (Fig. 3a-d). The degree of overestimation of the pollutant concentration is reduced, and the mean relative bias of the new scheme is 3.5% (2013), 31% (2014), 12.8% (2015) and 9.2% (2017), respectively (Fig. 3e-h). Moreover, the mean absolute bias is reduced by 8.3% (2013), 17% (2014), 11% (2015) and 11.7% (2017), respectively (Fig. 3i-1). In summary, compared with the original scheme, the new scheme can generally improve the overestimation of pollutant concentration in Eastern China, which is due to the improvement of turbulent diffusion. For the previously

mentioned stations where underestimated the pollutant concentration in the original scheme, the pollutant concentration will be further underestimated with the increase of turbulent diffusion. However, this underestimation cannot be avoided because there is an opposite phenomenon in the pollutant concentration of the two regions. We can only look at the differences in the two regions from other perspectives (see section 4 for details), due to there are many uncertainties in the model.

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235 To better evaluate the model performance, Figure 4 shows the Taylor diagram of hourly PM_{2.5} concentration, and the black (red) dots indicate original (new) simulation results at all stations from 2013 to 2017. The statistical results present a consistent feature, that is, the worse the simulation results of the original scheme are, the more obvious improvement of the new scheme becomes (arrows indicate improved stations in the Fig. 240 4). The results indicate that the pollutant concentrations at all stations are not improved to the same extent. When the simulation of pollutant concentration is overestimated by the original scheme, the new scheme will significantly reduce the degree of overestimation. While the simulation of pollutant concentration is underestimated by the original scheme, the new scheme will not further underestimate with the previous changing and the degree of re-underestimate is not obvious (Fig. 4). And the standard 245 deviation (normalized) of the mean value is decreased by 0.2 (2013), 0.28 (2014), 0.14 (2015) and 0.16 (2017) (Fig. 4). As a whole, the new scheme can significantly improve the common phenomenon of overestimated pollutant concentration in the SBL in Eastern China (Fig. 4).

With the increase of turbulent diffusion, the pollutant concentration decreases gradually. Where do the reduced pollutants go? Did it spread to the surrounding area in the horizontal direction or to the upper level in the vertical direction? This question deserves further discussion. It can be seen from Figure 3 that the reduction of pollutant concentration is a regional synchronous change, and there is no regular concentration gradient in the horizontal direction. Therefore, we should also pay more attention to the changes in the vertical direction. Theoretically, increasing turbulent diffusion will

reduce the pollutant concentrations near the surface-layer, and the pollutants will be more fully mixing in the vertical direction, which results in lower concentrations of pollutants in the near surface-layer and higher concentrations of pollutants in the upper layer. As we expected, the pollutant concentration is reduced in the surface-layer and it is increased in the upper layer at night (Fig. 5), which is consistent with the theory.

4 Uncertainty analysis

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4.1 Meteorological parameters

Depending on high-frequency particle flux, the TDC of particles has been added in the model to calculate the turbulent mixing process of particles separately. Compared with previous studies on the improvement of parameterization scheme, the greatest strengths of the new scheme are that not only improves the simulation results of pollutant concentration, but also does not deteriorate the simulation results of other parameters. To verify the new scheme does not affect the simulation results of the meteorological parameters, the simulation results of the near-surface meteorological elements (i.e., 2m temperature, 2-m relative humidity and 10-m wind speed) between original and new schemes have been compared and analyzed. It can be seen from Figure S1-S3 that the correlation coefficients of meteorological parameters by two schemes are greater than 0.99, noting that the new scheme does not alter the performance of meteorological fields, which is an advantage of the new scheme. As mentioned earlier, modifying the turbulent diffusion coefficient of heat not only affects the simulation of temperature (Savijarvi and Kauhanen, 2002), but also influences the results of pollutants (Liu et al., 2021). Improving the parameterization scheme is a long and tough process, making it difficult to improve the simulation results of all parameters at once. When the simulation results of one parameter are improved, we should first seek to ensure that the simulation results of other parameters are not deteriorated. Then, we are going to look at improving other parameters. Although the aerosol-radiation two-way feedback process has been considered in the WRF-Chem model, the change of PM_{2.5} concentration caused by

radiation feedback is only a few percentage (Li et al., 2017; Wu et al., 2019; Gao et al., 2020). We should focus more on the feedback process between turbulence and aerosol, and hopefully develop a turbulence-aerosol two-way feedback module. Some turbulent characteristics (e.g., turbulence barrier effect) can be taken into consideration during HPEs, reflecting a more realistic evolution process of pollutant concentration. We will further clarify the relationship between particles, momentum and heat transport through observational data, so as to lay the foundation for the improvement of the model.

4.2 PBL height

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Although PBL height (PBLH) is widely used to determine the effective air volume and atmospheric environmental capacity for pollutant diffusion, various methods diagnose different PBLH, which reinforces uncertainty about the PBLH as a criterion. When there is a transport stage with a high wind speed during HPEs, the mechanical turbulence is strong, and the PBLH and pollutant concentration increase simultaneously (Jia et al., 2021c; Miao et al. 2021). Therefore, the relationship between PBLH and PM_{2.5} pollution is intricate. The impact of PBLH is ultimately represented through the TDC in the model, because the PBLH is used to calculate TDC (Jia et al., 2021b), and artificial changing PBLH can also affect the simulation of pollutant concentration. If the simulation error of pollutant concentration is caused by the PBLH, that is the pollutant concentration is overestimated and the PBLH should be underestimated. However, the PBLH is reproduced well by the model, and the model does not underestimate the PBLH (Fig. 6). Anqing is located in the mountain corridor, the simulation results of PBLH (Index of agreement, IOA=0.49~0.81) is slightly worse than that in Fuyang (IOA=0.63~0.85). Therefore, various factors will influence the calculation of PBLH. A more accurate PBLH can indeed reduce some uncertainty of the model, but how to apply the accurate PBLH through observation to the model is a thorny problem. For example, the turbulence barrier effect changes the mixing height of pollutants (Ren et al., 2021), which cannot be reflected in the model and can lead to deviation in the simulation of pollutant concentration. The new scheme does not disturb

the simulation results of meteorological fields, thus, does not affect the simulation results of PBLH (Fig. S4). The simulation results of pollutant concentrations are improved under the similar PBLH, which further demonstrates that the simulation of pollutant concentration is not only controlled by the PBLH, but also influenced by turbulent diffusion. In the final analysis, turbulent diffusion controls the diffusion of pollutant concentration and the evolution of meteorological parameters.

4.3 Influence of other processes

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Overestimating of pollutant concentrations has been improved in Eastern China, but there are also some sites in northern China where pollutant concentrations are underestimated (Fig. 2i-1). These sites (i.e., Hebei and Beijing) are mostly located in the east of the Taihang Mountains and the south of the Yan Mountains (Fig. 7). For example, in December 2016, the pollutant concentrations of all sites in Beijing were not underestimated. Jia et al. (2021b) have found that the pollutant concentrations of two sites located in the south of Beijing (i.e., blue dots in Fig. S2 in Jia et al., 2021b) are well reproduced by the model. This phenomenon also occurred in 2013-2017 (Fig. 7), and the pollutant concentrations were significantly underestimated at some sites, which are close to the mountainous area. The boundaries of overestimated and underestimated sites are pronounced in Beijing-Tianjin-Hebei region (white dashed in Fig. 7), and the pollutant concentration is overestimated at some sites, which are away from the mountainous area (i.e., Tianjin and southeast of Hebei). Meanwhile, the TDC of the new scheme is greater than that of the original scheme in Eastern China (i.e., red dashed circle in Fig. 8i-l), that is, the increased turbulent diffusion reduces the overestimation of pollutant concentration in this area. Furthermore, we found that the TDC of the new scheme is significantly smaller than that of the original scheme in the mountainous area (i.e., green irregular circle in Fig. 8). Theoretically, the reduced TDC should increase the pollutant concentration, and improve the underestimation of pollutant concentration in the original scheme. Disappointingly, the change of TDC does not improve the underestimation of pollutant concentration in the mountainous

area (Fig. 7, 8i-l), which indicates that the change of turbulent diffusion is not sensitive to the pollutant concentration in the mountainous area.

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In addition to the two main influencing factors of emission and turbulent diffusion, advection transport and chemistry processes can also affect the simulation of pollutant concentration. Since we use the latest emissions source inventory, there is no way to use other more elaborate inventories to quantify the uncertainty caused by emissions. Advection process, is highly related to wind and PM_{2.5} concentration gradients from upwind areas to downwind areas (Gao et al., 2018). Figure 9 shows that the simulation results of wind speed, and we found that the wind speed is overestimated in the whole simulation area, which is also the systematic deviation of the model (Jia and Zhang, 2020). However, there are regional differences in the overestimation of wind speed, which is more obvious in areas with complex terrain (framed by purple lines in Fig. 9). Jimenez and Dudhia (2012) indicated that the overestimation of wind speed may be caused by the incorrect describe sub-grid surface roughness. For the purple rectangle region, although the wind speed is overestimated, there is no obvious wind speed gradient and pollutant concentration gradient (Fig. 2a-d, 9a-d). Thus, the effect of advection is not significant. While for the irregular purple region, we can see that the obvious wind speed gradient and pollutant concentration gradient (Fig. 2a-d, 9a-d). In the northwest of the irregular purple area, clean air will pass through this area under the control of stronger northwesterly wind. Therefore, this area is extremely likely to be affected by advection transport, so that the pollutant concentration has been underestimated in this area. We should pay more attention to the improvement of wind field simulation on complex terrain and we expect that the simulation of wind field will be improved and the pollutant concentration in this area will also be improved.

Chemistry process, i.e., the $PM_{2.5}$ concentration contribution caused by secondary transformation, was negligible in this study, and is not mentioned further in this paper. Whether the simulation of chemical components has been improved, it cannot be well verified due to lack of observational data. Although the simulation results of $PM_{2.5}$

components are not capable of being evaluated, CO, as a representative of primary pollutants, can be compared to the observations. Results from new scheme with TDC of particles are more consistent with the observations than the original scheme (Fig. S5), which supports the improvement of $PM_{2.5}$ concentration (Fig. 4 and S5). In addition, the dry deposition process of particles is also extremely important (Zhang et al., 2001; Farmer et al., 2021). The turbulent mixing and dry deposition processes belong to the same main program in the mesoscale model. However, with increasing particle size, particle inertia and gravity cannot be neglected, but these inertia and gravity effects are neglected for particles smaller than $10~\mu m$ in diameter (Fratini et al., 2007). Therefore, we did not involve the influence of gravity on pollutant concentration in this study. In the future, we should use long-term simulation results to verify the difference of aerosol process decomposition in detail.

Conclusions and prospects

At present, mesoscale model is facing numerous challenges, especially during heavy pollution episodes. One of these challenges is the correct describe the turbulent mixing process of pollutants. Although the model can reproduce the evolution of pollutants, the simulation of diurnal variation of pollutants is fundamentally flawed, especially at night. Errors in estimation of pollutant concentration are primarily caused by defects in the turbulent mixing of pollutants in the model. Actually, there is a difference between the turbulent transport of heat and particles. This result inspires us to deal with the turbulent diffusion of heat and particles separately. Therefore, based on the turbulent diffusion expression of particles proposed by Jia et al., 2021b, we again demonstrated the improvement of pollutant concentration in winter from 2013 to 2017, and the uncertainty factors are also analyzed in the model.

The original scheme overestimates the surface $PM_{2.5}$ concentration by 11.8% (2013), 48% (2014), 23.8% (2015) and 20.9% (2017) at night, respectively. The new scheme has improved the overestimation of the surface $PM_{2.5}$ concentration in eastern China at

night, and the mean absolute bias of the region can be reduced by 8.3% (2013), 17% (2014), 11% (2015) and 11.7% (2017), respectively. In the horizontal direction, the pollutant concentration showed regional synchronous changes. Therefore, the pollutant concentration is reduced near the surface and better mixed in the whole layer, increasing the pollutant concentration in the upper level. Moreover, the new scheme not only improves the simulation of pollutant concentration, but also does not deteriorate the simulation of other meteorological parameters. Although the PBLH affects the diffusion of pollutants, the simulation of pollutant concentration is not specifically controlled by the PBLH, but effected by TDC. It is worth noting that TDC has a negligible impact on the simulation of pollutant concentration at some sites with complex topography. Meanwhile, advection transport may dominate the evolution of pollutant concentration in mountainous area. The simulation results of PM_{2.5} components cannot be evaluated, due to lack of observational data. CO, however, as a representative of primary pollutants, can be compared to observations. Results from new scheme are more consistent with the observations than the original scheme, which supports the improvement of PM_{2.5} concentration.

The new scheme could provide promising guidance during heavy pollution episodes. The turbulent transport mechanism and turbulent parameterization is a complex topic (Lemon et al., 2019; Couvreux et al., 2020; Edwards et al., 2020), and beyond that, other processes (or other parameters) also need in-depth understanding and exploration (Zhang et al., 2001; Seinfeld et al., 2016; Shao et al., 2019; Emerson et al., 2020). Therefore, more research during the heavy pollution episodes, especially on the experimental side (e.g., carry out extensive measurement campaigns), might shed more light on the turbulent mixing process and transport mechanisms of pollutants.

Data availability

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The surface $PM_{2.5}$ concentration, meteorological data, turbulent datasets and turbulent flux data of $PM_{2.5}$ are available by request (xiaoye@cma.gov.cn).

Author contributions

Development of the ideas and concepts behind this work was performed by all the authors. Model execution, data analysis and paper preparation were performed by WJ and XZ with feedback and advice.

Competing interests

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The authors declare that they have no conflict of interest.

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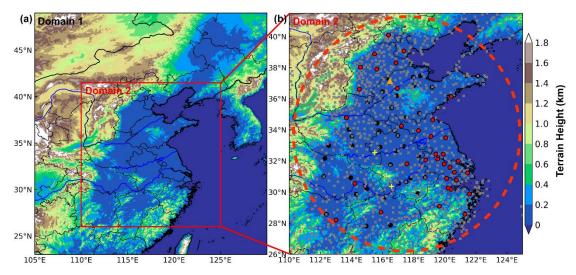


Figure 1. (a) Map of terrain height in the two nested model domains. (b) The locations of surface meteorological stations, air quality monitoring stations and sounding stations are marked by the gray crosses, red(black) dots and yellow pluses, respectively. The turbulence data site is denoted by the orange triangle. The red dashed circle indicates the areas of our primary concern.

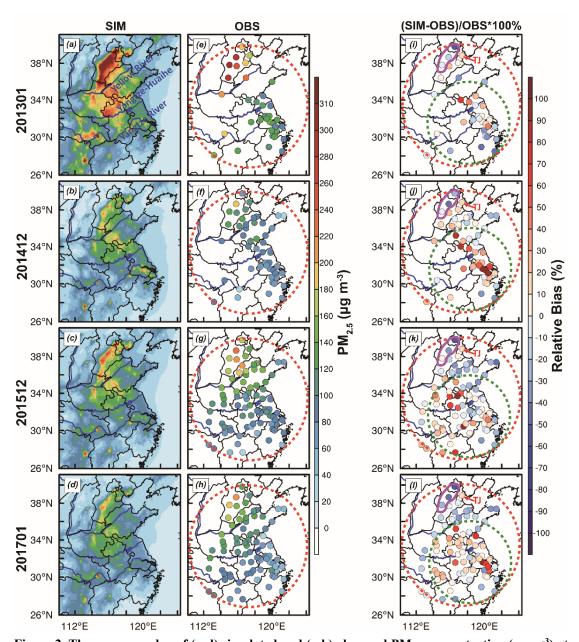


Figure 2. The average value of (a-d) simulated and (e-h) observed PM2.5 concentration ($\mu g \ m^3$) at night, (i-l) the relative bias (RB, %) between simulation and observation, and the calculation formula of relative bias is $RB = \left(\overline{X_{sim}} - \overline{X_{obs}}\right) / \overline{X_{obs}} \times 100\%$, where $\overline{X_{sim}}$ and $\overline{X_{obs}}$ represent the average value of simulation and observation, respectively. The locations of three rivers (i.e., Yellow River, Yangtze-Huaihe and Yangtze River) are marked by blue lines. The red and green dashed circles represent the whole simulation area and Eastern China, respectively. The

purple solid irregular circle indicates mountainous areas, and the red text TJ indicates Tianjin.

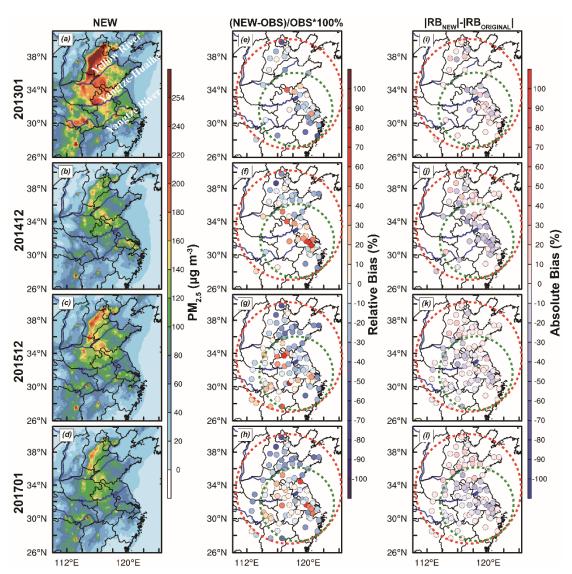


Figure 3. The average value of (a-d) simulated PM_{2.5} concentration (μ g m⁻³) by new schemes, (e-h) the relative bias (RB, %) of PM_{2.5} concentration between simulation of new scheme and observation, (i-l) the absolute bias (AB, %) between new and original schemes, and the calculation formula of absolute bias is $AB = \left|RB_{new}\right| - \left|RB_{original}\right|$, where $\left|RB_{new}\right|$ and $\left|RB_{original}\right|$ represent the relative bias of new and original schemes, respectively. The red and green dashed circles represent the whole simulation area and Eastern China, respectively.

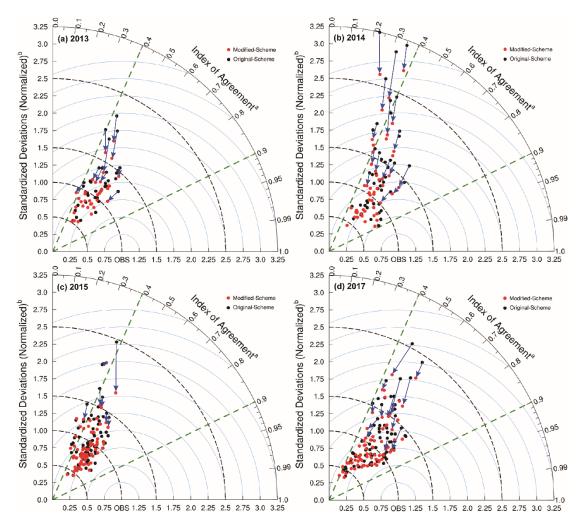


Figure 4. Taylor diagram of simulation by original scheme and modified scheme. XY axes and arc represent the normalized standardized deviations (NSTD,

$$NSTD = \frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{n}\left(X_{sim,i} - \overline{X}_{sim}\right)^{2}}}{\sqrt{\frac{1}{N-1}\sum_{i=1}^{n}\left(X_{obs,i} - \overline{X}_{obs}\right)^{2}}} \ , \ \overline{X}_{sim} \quad \text{and} \quad \overline{X}_{obs} \quad \text{represent the average value of}$$

640 simulation and observation, respectively) and index of agreement (IOA,

$$IOA = 1 - \frac{\left[\sum_{i=1}^{n} |X_{sim,i} - X_{obs,i}|^2\right]}{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}, \quad X_{sim,i} \quad and \quad X_{obs,i} \quad represent \quad the \quad value \quad of \quad A_{obs,i} = 1 - \frac{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}, \quad X_{sim,i} \quad and \quad X_{obs,i} = 1 - \frac{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}, \quad X_{sim,i} \quad and \quad X_{obs,i} = 1 - \frac{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}, \quad X_{sim,i} = 1 - \frac{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}, \quad X_{sim,i} = 1 - \frac{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}, \quad X_{sim,i} = 1 - \frac{\left[\sum_{i=1}^{n} (|X_{sim,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs}}|)^2\right]}{\left[\sum_{i=1}^{n} (|X_{obs,i} - \overline{X_{obs}}| + |X_{obs,i} - \overline{X_{obs,i}}|)^2\right]}, \quad X_{sim,i} = 1 - \frac{\left[\sum_{i=1}^{n} (|X_{obs,i} - \overline{X_{obs,i}}| + |X_{obs,i} - \overline{X_{obs,i}}|)^2\right]}{\left[\sum_{i=1}^{n} (|X_{obs,i} - \overline{X_{obs,i}}| + |X_{obs,i} - \overline{X_{obs,i}}|)^2\right]}, \quad X_{sim,i} = 1 - \frac{\left[\sum_{i=1}^{n} (|X_{obs,i} - \overline{X_{obs,i}}| + |X_{obs,i} - \overline{X_{obs,i}}|)^2\right]}{\left[\sum_{i=1}^{n} (|X_{obs,i} - \overline{X_{obs,i}}| + |X_{obs,i} - \overline{X_{obs,i}}|)^2\right]}$$

simulated and observed, respectively. i refers to time and n is the total number of time series), respectively. All cities (a total of 35 cities in 2013 and 78 cities in 2014, 2015 and 2017) are shown through dots, and black (red) represents original (new) scheme. The root mean square (RMS) is denoted by blue dashed line and the arrow indicates the change of the new scheme compared to the original scheme at the same station.

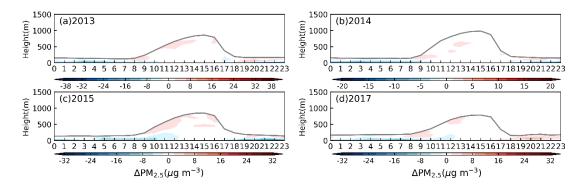


Figure 5. Time-height cross sections for the difference of PM_{2.5} concentration between original and new schemes (i.e., the new scheme minus the original scheme) within the PBL. The gray line indicates the PBLH.

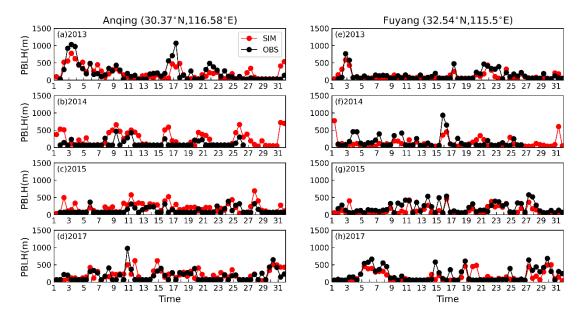


Figure 6. Time series of the observed (black) and simulated (red) PBLH at 0800 and 2000 (BJT) in the (a-d) Anqing and (e-h) Fuyang from 2013 to 2017.

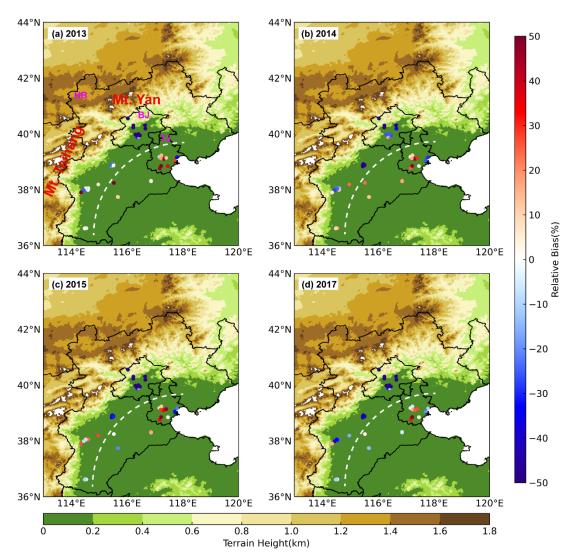


Figure 7. The relative bias (%) between simulation and observation at all environment monitoring stations and terrain height in Beijing-Tianjin-Hebei in (a) 2013, (b) 2014, (c) 2015 and (d) 2017. Taihang Mountain (Mt. Taihang) and Yanshan Mountain (Mt. Yan) are indicated by red text, Beijing (BJ), Tianjin (TJ) and Hebei (HB) are represented by purple abbreviation and the dividing line between overestimated and underestimated areas is indicated by a white dashed line.

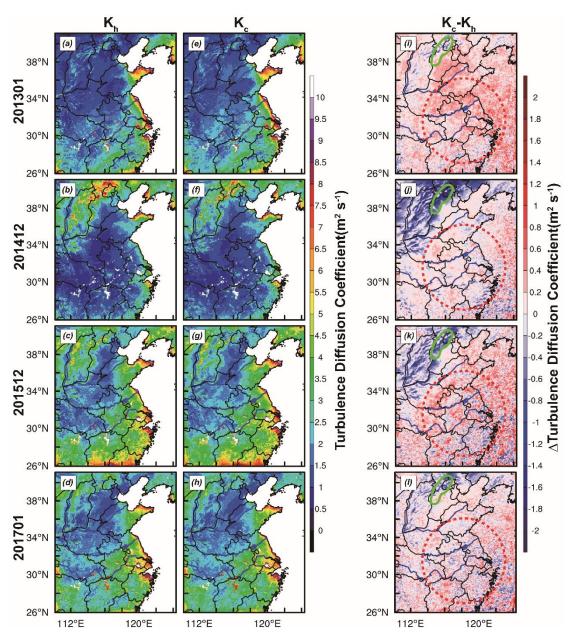


Figure 8. Turbulent diffusion coefficient of (a-d) heat and (e-h) particles, and (i-l) the difference between two turbulent diffusion coefficients. The red dashed and green solid irregular circles represent Eastern China and mountainous areas, respectively.

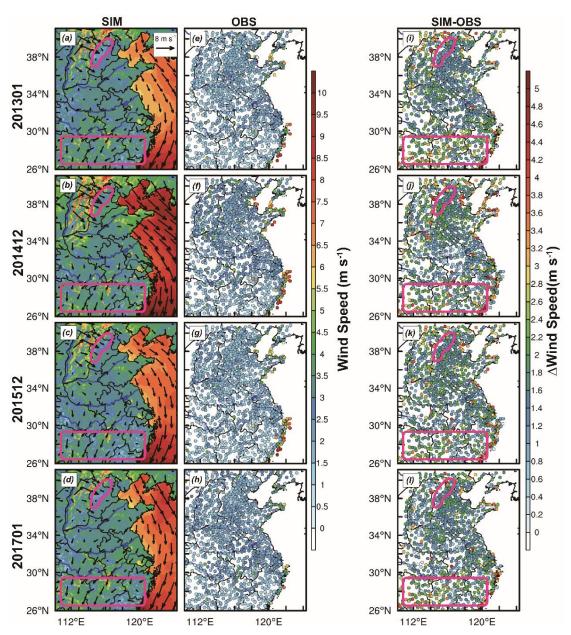


Figure 9. (a-d) Simulated and (e-h) observed wind speed at 10 m above ground level (AGL), and (i-l) the difference of simulated and observed. The purple rectangle indicates the area where the observed wind speed is significantly overestimated.