Assessment of the Meteorological Impact on Improved PM$_{2.5}$ Air Quality Over North China During 2016–2019 Based on a Regional Joint Atmospheric Composition Reanalysis Data-Set

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Abstract In the context of China’s clean air policy, the meteorological impacts on improved particulate matter (PM$_{2.5}$) air quality during 2016–2019 are investigated based on a four-year high-resolution atmospheric composition reanalysis data-set, which has been produced by the Joint Data Assimilation System to resolve long-term fine-scale air quality variability over China. The reanalysis assimilates surface air quality observations using the Weather Research and Forecasting model coupled with Chemistry and an ensemble-based assimilation algorithm, and simultaneous assimilations of meteorological observations, chemical initial conditions (ICs) and emissions are applied to help reduce the uncertainty in meteorology, ICs and the emissions inventory. Further, objective weather classification method is applied to quantitatively explore synoptic circulation pattern changes and associated PM$_{2.5}$ variability over North China by using this unique reanalysis data-set. PM$_{2.5}$ reanalysis data are also investigated according to different circulation types, and results indicate that temporal and spatial variations of PM$_{2.5}$ are found to be closely connected with weather and circulation patterns. The northerly types correspond to the lower PM$_{2.5}$ levels, while the southerly and easterly types correspond to the higher PM$_{2.5}$ concentration due to favorable local meteorological conditions. According to the quantitative evaluation on circulation pattern changes, meteorological contribution have played a positive role in improving air quality in the context of China’s clean air policy during 2016–2019. This study serves as a basis for future retrospective assessments of air pollutant variation and emissions regulation measures.

Plain Language Summary Particulate matter (PM$_{2.5}$) concentrations depend primarily on the pollution emissions and meteorological conditions. We investigate the meteorological impact on improved PM$_{2.5}$ air quality during 2016–2019 based on a four-year high-resolution atmospheric composition reanalysis data-set. Objective weather classification method has been further used to understand the quantitative relationship between weather and air quality. The results indicate that meteorological conditions have played a positive role in improving air quality with the strict implementation of China’s clean air policy during 2016–2019.

1. Introduction

During recent decades, rapid economic development in China has resulted in huge emissions of multiple air pollutants and associated environmental issues, and Chinese governments have made great efforts to control the emissions (Silver et al., 2018; Xue et al., 2019; Zhang et al., 2018; Zheng et al., 2018). For instance, the national-scale “Atmospheric Pollution Prevention and Control Action Plan” was issued in September 2013, and China continues to implement stringent emission controls on SO$_2$ and NO$_x$ with the aim of reducing their emissions by 15% during 2016–2020 according to China’s 13th Five-Year Plan. The regulation measures have been progressively enhanced in recent years, which provide us with an opportunity to assess the impact of emissions regulations and meteorological conditions on the improvement in air quality.
Fine particulate matter smaller than 2.5 μm in diameter (PM$_{2.5}$) has received considerable attention owing to its effects on human health, public welfare, visibility, and significant climatic impacts (Goodkind et al., 2019; Hong et al., 2019). PM$_{2.5}$ concentrations depend primarily on the emissions, topography, meteorology, and physical and chemical reactions (Wang et al., 2018; X. Zhang et al., 2019). It is evident that the observed interannual and decadal variability of air pollution depends on the meteorological conditions, which affect PM$_{2.5}$ levels through a complex combination of processes, including accumulation, diffusion, and chemical processes (Liu et al., 2017; Tao et al., 2016). Consequently, if we are able to estimate the impact of meteorological conditions, then the influence of anthropogenic emissions regulations on PM$_{2.5}$ variations can be evaluated more exactly. Recent studies have reported significant air quality improvements and associated meteorological effects from 2013 to 2017 based on either observations or chemical transport models (CTMs) (Guo et al., 2019; He et al., 2017; Li et al., 2020; Liu et al., 2019; Zhai et al., 2019). Most of these studies have applied objective weather classification methods to recognize synoptic weather patterns, including the Kirchhofer method (Zhang et al., 2016), the T-mode method (Li et al., 2019), and Lamb–Jenkinson weather typing (Liao et al., 2017; Li et al., 2020; Liu et al., 2019). However, observations are rarely used in CTM simulations, even though multimodel comparison projects have shown that discrepancies and uncertainties exist between the models and observations (Chen et al., 2019).

Data assimilation (DA), which pertains to the combination of modeling and observations to produce a most probable representation of the state, is one way of overcoming these deficiencies and has been used in the context of air quality assessments. Benedetti et al. (2018) have discussed the status and future of numerical aerosol studies with a focus on data requirements. One of most valuable applications of DA is the generation of continuous, uniform, and best-estimated data products (i.e., reanalysis products). Meteorological re-analysis products, which are widely utilized for climatological studies and to drive offline CTMs, have been produced by several centers, such as the European Center for Medium-Range Weather Forecasts (ECMWF) (Dee et al., 2011), the US National Centers for Environmental Prediction (NCEP) (Kalnay et al., 1996), the Global Modeling and Assimilation office (GMAO) (Schubert et al., 1993), the Japan Meteorological Agency (JMA) (Onogi et al., 2007), and the China Meteorological Administration. However, the use of DA in atmospheric chemistry is more recent. It has been recognized that atmospheric chemistry DA is in its infancy compared to its well-matured meteorological predecessor, with a high dependence on non-operational observational data sources and wide diversity in the modeled parameters (Bocquet et al., 2015). At present, only five centers routinely assimilate aerosol data into models: the ECMWF Copernicus Atmosphere Monitoring Service (CAMS), the US Naval Research Laboratory (NRL), the GMAO, the JMA, and the UK Met Office. As an example, the CAMS reanalysis is the latest global reanalysis data-set of atmospheric composition produced by the ECMWF; it covers the period 2003–2016 and will be extended in the future by adding one year each year (Inness et al., 2019). Furthermore, the GMAO has provided an aerosol reanalysis product called the Modern-Era Retrospective analysis for Research and Applications version 2 and assimilated it concurrently with the meteorology (MERRA-2; (Buchard et al., 2017)). In addition, the NRL has developed the Navy Aerosol Analysis and Prediction System aerosol reanalysis product covering 2003–2015 (Lynch et al., 2016). Moreover, the JMA has produced a five-year Japanese aerosol reanalysis product (JRAero) for 2011–2015 (Yumimoto et al., 2017). All the above reanalysis datasets have been used in a number of studies. For example, Chen et al. (2018) used the reanalysis to characterize the long-range transport of African and Asian dust. Mukkavilli et al. (2019) assessed atmospheric aerosols over Australia from two reanalysis products. Buchard et al. (2016) evaluated the surface PM$_{2.5}$ over the United States in version 1 of the NASA MERRA aerosol reanalysis. Furthermore, Miyazaki et al. (2020) demonstrated the importance of model performance on chemical reanalysis by utilizing four different CTM frameworks and applying a common assimilation scheme.

The potential use of such air quality reanalysis data in the context of air quality regulations (e.g., evaluation of air quality exceedances, assessment of human exposure to air pollution) has been explored by Borrego et al. (2015). The European Union Air Quality Directive also suggests the application of modeling in combination with observations “to provide adequate information on the spatial distribution of the ambient air quality” (OJEU, 11 June 2008). Considering the unique characteristics of reanalysis data, further study is needed on air quality assessments based on reanalysis datasets. Ensemble-based DA approaches in combination with surface measurements have also been used for models, such as Community Multiscale Air...
Quality, WRF-Chem (Weather Research and Forecasting model coupled with Chemistry), Chinese Unified Atmospheric Chemistry Environment for dust, and Nested Air Quality Prediction Modeling System in China (Lin et al., 2008; Kou et al., 2017; Peng et al., 2017; Tang et al., 2016). For instance, Candiani et al. applied the ensemble Kalman filter (EnKF) to integrate a CTM and ground-level measurements and produced PM$_{10}$ reanalysis fields for northern Italy (Candiani et al., 2013). However, there are still few atmospheric species reanalysis data available in China. With increasing attention being given to air pollution control, there is a strong impetus to develop an atmospheric composition reanalysis data-set and evaluate the recent air quality in China.

Previous studies have highlighted that the assimilation of atmospheric chemistry observations can improve air quality forecasts by reduce the uncertainties of both the initial conditions (ICs) and the emissions (Miyazaki et al., 2012). Recently, Peng et al. (2018) improved air quality forecasts and emissions estimations over China by developing an ensemble-based data assimilation system, which jointly adjusts the chemical ICs and emissions of the species influencing the concentrations of PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$, O$_3$, and CO by using surface measurements. Moreover, meteorological observations were assimilated concurrently to reduce the uncertainty in meteorological fields (Peng et al., 2020). As an extension to this work, the Joint Data Assimilation System (JDAS) has produced a regional atmospheric composition reanalysis product as well as an updated emission inventory over China for 2016–2019 by applying this DA system. To our knowledge, the JDAS reanalysis is one of the latest Chinese reanalysis datasets of atmospheric composition, including surface concentration fields of all six conventional air pollutants (PM$_{2.5}$, PM$_{10}$, O$_3$, NO$_2$, SO$_2$, and CO) and an updated emissions inventory. It will be of great value in retrospective analyses of air quality, model evaluation, and satellite data calibration, as well as the assessment of health and environmental impacts at fine scales.

In this paper, we focus on the assessment of PM$_{2.5}$ concentration during 2016–2019 when stringent emissions regulations were implemented. Using this unique reanalysis data-set, we address the following questions:

1. What is the PM$_{2.5}$ variability in North China during 2016–2019?
2. What is the impact of meteorological variations and emissions reduction on the improvement of air quality?

2. Material and Methods

2.1. Joint Data Assimilation System Reanalysis Data-Set Description

The Chinese reanalysis data-set of atmospheric composition in this study was produced by the JDAS. In the joint assimilation system, chemical ICs, emissions, and meteorological data can be simultaneously analyzed, which implies that concentrations and emissions are both model state variables, and any useful observation information used in the current assimilation cycle can be utilized effectively in the following assimilation cycle with the lowest uncertainty of meteorological influence. A brief summary of the joint assimilation framework, the three-dimensional CTM, and observations is given below.

2.1.1. Joint Assimilation Framework

The ensemble square-root filter (EnSRF) (Whitaker and Hamill, 2002) is used to assimilate the meteorological and chemical observations to update the meteorological and chemical fields, respectively (Peng et al., 2018, 2020). It is noted that the chemical ICs and emissions are jointly assimilated in this work. Following (Peng et al., 2018), the forecast model includes two parts: the WRF-Chem model (Grell et al., 2005), which is used to forecast the transport of atmospheric chemical species, and a persistence forecasting operator of emissions, which was used to prepare the background fields of the emissions scaling factors. The Regional Atmospheric Chemistry Mechanism Scheme and the Goddard Chemistry Aerosol Radiation and Transport were utilized to simulate the gaseous chemical species and aerosols, respectively. The state vector $x$ includes the mass concentration $C$ and the emission scaling factor $f$, i.e., $x = [C, f]^T$. Here, the state variables of mass concentration $C$ are the 16 WRF-Chem/GOCART aerosol variables and chemical species, such as SO$_2$, NO$_2$, O$_3$, and CO. The ensemble forecast chemical fields of PM$_{2.5}$, PM$_{10}$, NO, SO$_2$, NH$_3$, and CO are respectively used to calculate the emission scaling factors $f = [\lambda^f_{PM_{2.5}}, \lambda^f_{PM_{10}}, \lambda^f_{NO}, \lambda^f_{SO_2}, \lambda^f_{NH_3}, \lambda^f_{CO}]$, where the superscript $f$ denotes priors. The ensemble members of chemical fields $C^f$ are forecasted using...
WRF-Chem, forced by the forecast emissions $E^f$, the ICs of which are previously analyzed concentration fields. Then, the background of the joint vector, $x^b = \begin{bmatrix} C^b \end{bmatrix}^T$, is produced. Then, the analyzed state vector, $x^a = \begin{bmatrix} C^a \end{bmatrix}^T$, is optimized by applying the EnSRF. The configuration of the EnSRF settings followed previous studies (Peng et al., 2018, 2020; Whitaker and Hamill, 2002). The observation operator of PM$_{2.5}$ and PM$_{10}$ was expressed as in (Schwartz et al., 2012). To ameliorate the spurious multivariate correlations due to the limited ensemble members and errors in both the measurements and CTM, a cross-variable update is not applied in this DA system, which is similar to other weak-coupling DAs in order to avoid the influence of (Miyazaki et al., 2012).

In this study, the ensemble size was chosen as 50 to maintain a balance between the computational cost and the filter performance. Furthermore, the horizontal covariance localization radius was set as 675 km to localize the impact of observations and mitigate the spurious error correlations between observations and state variables. An inflation technique was also used to dynamically inflate the background error to prevent the underestimation of true background error covariance. The posterior (i.e., after assimilation) multiplicative inflation with coefficients 1.12 for all meteorological and chemical variables is applied to enlarge the ensemble spread, which brings about favorable assimilation results by enlarging the ensemble spread due to a limited ensemble size following Peng, et al. (2017, 2018, 2020). To keep the ensemble spread of the emission scaling factors, the inflation factor was set as 1.2, 1.5, 1.2, 1.2, 0.9, and 2.5 for the ensemble concentration ratios of PM$_{2.5}$, PM$_{10}$, SO$_2$, NO, NH$_3$, and CO, respectively.

The model domain for WRF-Chem 3.6.1 was $8,100 \times 7,650$ km$^2$, with a grid resolution of $45 \times 45$ km$^2$ on a Lambert conformal map projection centered at $24.0^\circ$N, $106.0^\circ$E, which covers most of East Asia (as shown in Figure 1). In this study, we focus on the assimilation over China due to the available observations. The model has 57 vertical layers unequally spaced from the ground to approximately 10 hPa, with nearly half of them concentrated in the lowest 2 km to resolve the planetary boundary layer (PBL). The output time step is one hour. The hourly and constantly prescribed anthropogenic emissions are obtained from the Emission

![Figure 1](image_url)
Database for Global Atmospheric Research for Hemispheric Transport of Air Pollution v2.2, Janssens-Maenhout et al., 2015 inventory, in which the Chinese emissions are derived from the Multiresolution Emission Inventory (MEIC, www.meicmodel.org) in 2010 (Li et al., 2014). Time variation was not added to preserve objectivity in the prior anthropogenic emissions.

2.1.2. Observations

The 6 h meteorological observations, including all in situ observations and cloud motion vectors from the NCEP Global Data Assimilation System, were assimilated in JDAS every 6 h. The hourly surface conventional air pollutant observations (i.e., PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$, O$_3$ and CO) were from the Ministry of Ecology and Environment of China (MEE; http://106.37.208.233:20035/). The network was launched in 2013 as part of the Clean Air Action Plan and by 2019 the number of monitoring stations had increased to ∼1,500 stations. In most cases, one measurement was chosen randomly for assimilation on a 45 × 45 km grid. Figure 1 shows the assimilated chemical observation network, which has 560 randomly chosen stations from 1,576 stations in total. The thinning of observations is applied to avoid correlated errors of observations (Peng et al., 2017). The observation priors are computed by the “observer” portion of the Grid-point Statistical Interpolation system (Kleist et al., 2009). In addition, concentrations were reported by the MEE in units of μg m$^{-3}$ under standard conditions (273 K, 1,013 hPa) until August 31, 2018. This reference state was changed on September 1, 2018 (to 298 K, 1,013 hPa) for gases and the local ambient state for PM$_{2.5}$ and PM$_{10}$ (Ministry of Ecology and Environment, 2018). We rescaled post-August 2018 gas, PM$_{2.5}$, and PM$_{10}$ concentrations to standard conditions to be consistent with the previous data. Moreover, quality control of the observations was performed before DA to ensure data reliability. Here, either data values or observations leading to innovations exceeding a certain threshold were detected and removed. The observation error, including the measurement error and representation error, were defined following Elbern et al. (2007). Then, the JDAS executed assimilation for each year from 2016 to 2019 separately, starting at 00:00 UTC on December 26 of the previous year as a 6 days spin up. This reanalysis data set will be extended in the future by adding one year each year.

2.2. Lamb–Jenkinson Weather Typing Technique

The Lamb–Jenkinson weather type method is applied to categorize the synoptic circulation patterns. This method is advantageous over experience based subjective and computer-based objective techniques because it was based on a clear physical understanding of the weather climatology and also could be calculated objectively with great efficiency. The meteorological data used in this study are gridded sea-level pressure (SLP) data on a 16-point movable grid and is therefore easily applicable with the available data (Jenkinson and Collison, 1977; Lamb, 1972). Using a group of circulation indices that recognize the direction and vorticity of the geostrophic flow (i.e., total flow, westerly flow, southerly flow, total shear vorticity, westerly shear vorticity, and southerly shear vorticity), the weather type for a given time is described as one of these 27 weather types. This weather typing classification approach has been used throughout the world, including in northern and southern China (Liao et al., 2017; Li et al., 2020; Liu et al., 2019; Yu et al., 2017; Zhang et al., 2016).

In this study, the weather types are developed using the SLP data from the JDAS reanalysis data-set with a central point (31°N, 120°E) in the North China Plain (NCP) during 2016–2019. Considering the frequent restructuring of the synoptic circulation pattern, hourly SLP is utilized instead of the daily averaged data as in previous studies (Liao et al., 2017; Liu et al., 2019). Then, several empirical rules contrived previously (Jones et al., 1993) are applied to categorize as one of these 27 weather types per hour, including eight directional types (easterly, E; southerly, S; westerly, W; northerly, N; northeasterly, NE; southeasterly, SE; southwesterly, SW; northwesterly, NW), two vorticity types (cyclonic, C; anticyclonic A), 16 hybrid types (AE, AS, AW, AN, ANE, ASE, ASW, ANW, CE, CS, CW, CN, CNE, CSE, CSW, CNW), and an undefined type (UD). The detailed description of this weather typing technique can be referred to (Trigo & Dacamara, 2000).
In order to evaluate the interannual variability caused by variations in circulation patterns, Comrie and Yamal (1992) proposed an algorithm to separate synoptic and non-synoptic variability in atmospheric environmental data. Moreover, many studies have indicated that both frequency and intensity changes constitute the variation in synoptic circulation patterns. Therefore, a reconstruction of PM$_{2.5}$ concentration can be defined as follows:

$$\overline{PM_{2.5}}(\text{fre}) = \sum_{k=1}^{27} PM_{2.5k}F_{km}$$  \hspace{1cm} (1)

$$\overline{PM_{2.5}}(\text{fre + int}) = \sum_{k=1}^{27} \left( PM_{2.5k} + \Delta PM_{2.5k} \right)F_{km}$$  \hspace{1cm} (2)

where $\overline{PM_{2.5}}(\text{fre + int})$ is the reconstructed mean PM$_{2.5}$ concentration influenced by the changes in frequency and intensity of the circulations in year $m$, $PM_{2.5k}$ is the four-year mean PM$_{2.5}$ for weather type $k$, and $F_{km}$ represents the occurrence frequency of weather type $k$ in year $m$. $\Delta PM_{2.5km}$ refers to the annual reanalysis PM$_{2.5}$ oscillation caused by the intensity changes, and it can be calculated by a linear fitting of PM$_{2.5}$ annual anomalies based on the annual reanalysis values and the circulation intensity index (CII) of weather type $k$ in year $m$. Domain-averaged SLP is the most universal metric that can be applied readily to all weather types; thus, we use the domain-averaged SLP (32°N−42°N, 110°E−120°E) to represent the CII following (Hegarty et al., 2007). In this way, the interannual oscillation in PM$_{2.5}$ levels influenced by the circulation pattern variability is quantified, and the residual variability could be attributed to emissions regulation measures.

3. Results and Discussion

3.1. Evaluation of Reanalysis Particulate Matter 2.5 Concentrations

We begin by further assessing the reanalysis data performance in this study. The locations of the observation stations are given in Figure 1, and Figure 2 shows a comparison between ground-based measurements, simulated background concentration, and reanalysis of PM$_{2.5}$ from January to December of 2016 in Beijing, Tianjin and Hebei Province; 36°N−41°N, 114°E−118°E (BTH), with the rightmost lines representing the annual average. The monthly means were calculated from the daily means based on hourly outputs. For instance, the monthly averages in January and February of 2016 for reanalysis were 88.53 and 61.29 μg m$^{-3}$; for observation were 91.92 and 62.64 μg m$^{-3}$; for background simulation were 86.04 and 61.10 μg m$^{-3}$. Thus, the magnitude of the observations, background, and reanalysis were close to each other with the analysis value between the observed and background value. As shown in Figure 2, the observations, background,
and reanalyzes were generally in good agreement, suggesting that the reanalysis data-set is well calibrated and has an acceptable performance. Moreover, the JDAS performed well for both major meteorological variables and chemical variables, and particularly in reproducing the ridge and trough of PM$_{2.5}$ concentrations during both polluted and clean episodes (Chu et al., 2018; Peng et al., 2018). In general, comprehensive evaluation indicates that the JDAS provides a reasonable representation of the current atmosphere, making it suitable for retrospective multi-year analyses.

3.2. Improved Particulate Matter 2.5 Air Quality From 2016 to 2019

In this section, we investigate the variation in the trends of PM$_{2.5}$ concentration during 2016–2019. Using Beijing as a reference (Figure 3), the percentage of exceedance ratios (the proportion of days when daily-averaged PM$_{2.5}$ larger than 75 μg m$^{-3}$ according to the National Ambient Air Quality standard of Grade 2) decreased from 27.40% in 2016 to 7.95% in 2019, representing an ∼19% reduction in the year-round statistics. Seasonal changes in Beijing are also summarized in Figure 3. Significant seasonal variation of PM$_{2.5}$ levels occurred, with the most frequent pollution episodes in winter and the least in summer, which is not only associated with the increased energy consumption to meet the electricity demands for heating but also with more frequent unfavorable meteorological conditions in winter (Li et al., 2014; Wang et al., 2018). According to Figure 3, substantial improvement in PM$_{2.5}$ levels occurred across Beijing as a result of a considerable reduction in the emissions of major pollutants, with the greatest decrease in the BTH region, which is consistent with previous studies indicating the intensity of emissions reduction (Q. Zhang et al., 2019; Zheng et al., 2018). In general, the much-refined description in the reanalysis data-set allows for a more detailed characterization of the spatial-temporal distribution of PM$_{2.5}$ and can further facilitate an interpretation of sparse observational data in a regional context over China. Next, we discuss the role of meteorological conditions in shaping the spatial patterns and variation of PM$_{2.5}$.

3.3. Meteorological Impact on Particulate Matter 2.5 Concentration Variation

3.3.1. Weather Circulation Pattern Variation From 2016 to 2019

Synoptic weather patterns turn out to be closely related to regional pollution (Zhai et al., 2019; Zhang et al., 2016; X. Zhang et al., 2019). In this study, the automated Lamb–Jenkinson weather typing technique (discussed in Section 2.2) provides 27 circulation types affecting northern China, including two vorticity types, eight directional types, 16 hybrids of vorticity and directional types, and a UD type. Most previous studies have utilized a simplified strategy in which only vorticity and directional types are retained; however, hybrid types and UD account for about 37%–40% in all weather categories, which become a non-negligible part in the north of China. The interannual variation of occurrence frequency and associated SLP fields per year indicates that all the synoptic weather types vary not only in frequency but also in intensity. These mean SLP patterns are deemed to adjust diffusion, transport conditions and local atmospheric pollution in the NCP.

According to Figure 4, vorticity types, pure directional types, and UD together account for 83.83%, 86.53%, 84.88%, and 85.50% during 2016, 2017, 2018, and 2019, respectively. In general, types A, C, UD, W, E, NW, SW, AW, AE, and CW are the dominant weather types throughout the year, with an occurrence ratio greater than 2.0%. Type UD follows type A and turns out to be the second largest category during 2016–2019, which is characterized as low geostrophic wind and vorticity, indicating stagnant air conditions. Figure 4 also shows the seasonal effect of occurrence frequency of the 27 weather types. As anticipated, the synoptic circulation patterns displays a high degree of seasonality, which is mainly driven by the seasonal variation of key synoptic systems affecting the circulation and meteorological conditions in the north of China. Usually, cyclones are located in the north of China and dominate in summer and spring, and the Western Pacific Subtropical High is crucial in summer. In contrast, northern China is deeply affected by the Siberian High in autumn, winter, and spring. For instance, type A occurs most frequently in autumn, winter, and spring when a cold high occurs and is blocked in northern China. Accordingly, the BTH area is in the influence of anticyclonic systems (e.g., type A). Rather, northern China is affected by cyclonic systems (e.g., type C) when the Western Pacific Subtropical High or the cyclones dominate (Liao et al., 2017; Li et al., 2019; Liu et al., 2019). Furthermore, the predominant types in winter are type A (>52%), UD (>9%), and others (>20%; E, AE, W, AW C, NE, and ANE). With the lowest frequency of type A (∼10%) but highest proportion...
of type C (∼22%) during 2016–2019, summer has a distinctly different circulation pattern as cyclones occur frequently, and types UD, CW, CNE, and CNW are also more common during this season. Types W and E is the highest frequency of occurrence in spring and autumn (i.e., transitional seasons). Types AS, AN, CS, and CN display low frequency in almost all seasons.

### 3.3.2. Typical Weather Types and Associated Particulate Matter 2.5 Levels

Figures 5 and 6 show the horizontal distributions of mean PM$_{2.5}$ levels and wind fields over northern China in 2016 and 2019, respectively, under typical weather types, including the above-mentioned predominant
types of A, C, UD, W, E, and AW (>82%) as well as the pollution-related types of S, AS, CS, SE, CSE, and ASE. As shown in Figure 5, surface wind fields tends to be strict with the principle of gradient wind. Type A is particularly different from type C due to opposite pressure patterns in NCP. Very small wind speeds over the domain are found in type UD. Overall, the lowest PM$_{2.5}$ concentration occurs when the wind direction diverts from north to south. The pollution-related types have predominantly southerly winds throughout the region, and exhibit high PM$_{2.5}$ levels together with the prevailing wind, indicating that the meteorological conditions are favorable for PM$_{2.5}$ formation and accumulation. SE-related types (SE, ASE and CSE) correspond to the highest PM$_{2.5}$ concentrations (>120 μg m$^{-3}$) with a diminishing PM$_{2.5}$ level (from 120 to 30 μg m$^{-3}$) from central (Shandong Province and southern Hebei Province) to northeast NCP. As discussed above and

Figure 4. Interannual variation of occurrence frequency of the 27 weather types in each of the four seasons and whole year in 2016–2019. The dark blue, blue, yellow, and maroon bars represent 2016, 2017, 2018, and 2019, respectively.
Figure 5. Spatial distribution of average particulate matter 2.5 concentration (μg m$^{-3}$) and wind fields over the North China Plain region (30°N–43°N, 107°E–122°E; the green frames in Figure 1) in 2016 under typical weather conditions, including the six predominant types of A, C, UD, W, E, and AW (with occurrence frequency above 82% in 2016–2019) as well as the pollution-related types of S, AS, CS, SE, CSE, and ASE.
Figure 6. As in Figure 5 but for 2019.
Based on findings from previous studies (Hegarty et al., 2007; Pope et al., 2016; Zhang et al., 2016), several possible mechanisms are suggested to explain the relationship between the synoptic type and PM$_{2.5}$ level. The southeastward transport and the effect of terrain on meteorological conditions could well explain the spatial pattern of pollutants, with accumulation in Hebei Province and Shandong Province. Thus, transport and diffusion affected by surface winds have a more significant influence on regional PM$_{2.5}$ levels.

Under similar circulation patterns (e.g., types C, UD, W, E, AW, AS, SE, ASE), the PM$_{2.5}$ spatial distribution decreases from 2016 to 2019, indicating the contribution from emissions control. For instance, PM$_{2.5}$ levels of type E in 2016 reach 120 μg m$^{-3}$ in the south of Hebei, but continuously decline to 80 μg m$^{-3}$ by 2018 (Figures 5 and 6). A similar phenomenon appears in type ASE, with high PM$_{2.5}$ levels (~140 μg m$^{-3}$) found over Beijing, Tianjin, Hebei, and Shandong in 2016, while clean conditions (<70 μg m$^{-3}$) dominated in 2019. In contrast, S-, CS-, and CSE-related PM$_{2.5}$ patterns show an increasing tendency over North China from 2016 to 2019, with little pollution in 2016 but heavier pollution in the following years. This difference could be attributed to the seasonal variation of PM$_{2.5}$ levels, as S, CS, and CSE occur more frequently during summer and transitional seasons in 2016 with a higher frequency of 0.17%, 0.13%, and 0.57%, whereas they are more commonly seen in winter in 2019 with a lower frequency of 0.07%, 0.10%, and 0.05%, respectively.

Compared with the annual average PM$_{2.5}$ levels, higher values appear more frequently in winter for most of the weather types, consistent with previous studies. The BTH domain-averaged PM$_{2.5}$ concentration and meteorological conditions for the 27 synoptic weather types during winter in 2016–2019 are summarized in Table 1. Some crucial meteorological variables, including wind speed, PBL height, precipitation, and temperature, show significant regularities in the variability of PM$_{2.5}$ levels and need to be considered. As has been discussed, prevailing southerly or easterly winds (e.g., types S, SE, ASE, CE, and CSE) could contribute to transportation and accumulation of pollutants from the south plain with meteorological characteristics of moderate temperature, low PBL height (200–440m), weak winds (3.3–4.7 m s$^{-1}$), sporadic rain, strong downward flow in the lower troposphere, and higher atmospheric moisture carried by the southern or eastern circulation, which leads to heavy pollution episodes with PM$_{2.5}$ concentrations >115 μg m$^{-3}$ (Li et al., 2020; Wang et al., 2018; Zhang et al., 2019b). Moderate pollution categories (75–115 μg m$^{-3}$; e.g., C, UD, W, E, SW, AS, ASW, AW, CNE, CS, CSW, CW, and CNW) are typically associated with the meteorological conditions [i.e., warm and humid air, a small amount of precipitation, low PBL height (240–630 m), and weak or moderate wind speed (3.3–6.2 m s$^{-1}$)] that are conducive to the formation and accumulation of PM$_{2.5}$. Briefly, northerly wind and A categories are usually directly related to cool air, high wind speed (4.9–7.1 m s$^{-1}$), high PBL height (660–920 m), moderate rain, and clean air masses from Inner Mongolia; these conditions are disadvantageous to aerosol formation. Hence, the corresponding area-averaged concentrations are below 40 μg m$^{-3}$. This is consistent with the findings of previous studies (Li et al., 2020; Zhang et al., 2016; Zheng et al., 2018). Thus, southerly wind makes PM$_{2.5}$ prone to reaching high levels, whereas PM$_{2.5}$ levels tend to decline influenced by northerly winds. As introduced earlier, type UD, with low wind speed (~3.8 m s$^{-1}$), PBL height (~400 m), and rainfall, tends to form static and stable conditions, which are unfavorable to the diffusion of pollutants. Moreover, although high pressure has been related to the removal process due to the dominant northerly winds, the low wind speed that sometimes occurs in type A could contribute to regional pollution. Thus, the wind direction, wind speed, and PBL height is directly related to weather types and changes accordingly, which can be distinguished as the key meteorological factors.

Figure 7 shows the BTH domain-averaged PM$_{2.5}$ concentration and frequency of weather categories per year from 2016 to 2019 for winter, which is when most pollution episodes occur. In general, PM$_{2.5}$ levels in 2019 decreased distinctively compared with 2016 under similar weather conditions, including C, UD, W, E, SE, S, ASE, AW, CE, and CSE. For instance, one of the dominant weather types, UD (easily polluted), has the second highest frequency during winter in 2016–2019, with a ratio of 11%, 13%, 9%, and 12%, respectively. Simultaneously, type UD-related PM$_{2.5}$ concentration decreases from ~110 μg m$^{-3}$ in 2016, to ~100 μg m$^{-3}$ in 2017, to ~75 μg m$^{-3}$ in 2018, to ~60 μg m$^{-3}$ in 2019. Similarly, the mean PM$_{2.5}$ concentration of type S slightly decreases from 100 μg m$^{-3}$ in 2016 to 75 μg m$^{-3}$ in 2019. Also, type SE-related concentration declines from ~150 μg m$^{-3}$ in 2017 to ~70 μg m$^{-3}$ in 2019, while the frequency increases from 0.05% to 0.46%. In addition, the frequency of NE, E, C, CE, AN, and ASW gradually decrease in winter, and SE, S, W, NW, AS, and AW gradually increase. Therefore, this indicates that not only the frequency of weather types but also the intensity of the related meteorological factors are linked to pollution events.
It is necessary and important to assess the effects of meteorological variation on the interannual PM$_{2.5}$ variability, as PM$_{2.5}$ levels are closely linked with synoptic weather patterns. Favorable weather conditions could facilitate the diffusion of pollutants, while unfavorable atmospheric patterns could further worsen air pollution levels under the same emissions background (Hegarty et al., 2007; Liao et al., 2017; Wang et al., 2018). As discussed earlier, all synoptic circulation patterns differs in both frequency and intensity, including the occurrence ratio, the center pressure, the location of the dominant system, and the area-averaged SLP. Based on this reanalysis data-set, we first reconstructed PM$_{2.5}$ levels in several typical cities in Beijing, Tianjin and Hebei Province during winter in 2016–2019.
Figure 7. The Beijing, Tianjin and Hebei Province domain-averaged (the cyan frames in Figure 1) particulate matter (PM\textsubscript{2.5}) concentration (black) and occurrence frequency of 27 weather types (red) during winter in 2016, 2017, 2018, and 2019, with standard deviation (±) of PM\textsubscript{2.5} concentration provided.
the NCP from 2016 to 2019 based on Equations 1 and 2 to distinguish the meteorological contribution on PM$_{2.5}$ interannual variability. Both frequency-only variation (referred to as PM$_{2.5m}$ (fre)) and frequency and intensity variation (referred to as PM$_{2.5m}$ (fre + int)) in circulation are taken into account. The differences between the maximum and minimum annual averaged reconstructed PM$_{2.5}$ are noted as ΔPM$_{2.5m}$ (fre) and ΔPM$_{2.5m}$ (fre + int). Then ΔPM$_{2.5}$ refers to the difference between the maximum and minimum annual averaged reanalysis PM$_{2.5}$ concentration. Finally, the meteorological contribution of interannual variability in PM$_{2.5}$ influenced by both frequency only and frequency and intensity variations can be approximated as the ratio of ΔPM$_{2.5m}$ (fre) / ΔPM$_{2.5}$ and ΔPM$_{2.5m}$ (fre + int) / ΔPM$_{2.5}$, respectively. In this way, the interannual oscillation in PM$_{2.5}$ levels influenced by the circulation pattern variability is quantified.

The JDAS reanalysis and reconstructed interannual PM$_{2.5}$ concentrations during 2016–2019 in 20 cities (including Beijing, Tianjin, Hebei, Shandong, Shanxi, and Henan Province) are shown in Figure 8, and Table 2.
summarizes the contribution of weather condition changes in each of the four seasons. In general, meteorological contribution to PM$_{2.5}$ interannual variability is affected by the frequency and intensity of circulation, which ranges from 68% to 88% in the year-round statistics in these cities, and the contribution from frequency changes ranges from 5% to 13%. According to the quantitative evaluation on circulation pattern changes, the meteorological contribution have played a positive role in improving air quality in the context of China's clean air policy during 2016–2019. The interannual fluctuations in the PM$_{2.5}$ levels are mainly attributed to weather-type intensity variation in North China. The contribution of circulation variations calculated here (60%–80%) in most cities are larger than those assessed by (Li et al., 2020) in all four seasons. The discrepancy can be because our study relies on: (a) Synoptic circulation patterns classified based on hourly SLP due to the frequent restructuring of synoptic circulation pattern; (b) more synoptic weather types with UD included especially; (c) the JDAS reanalysis data-set with area-averaged concentration; and (d) during 2016–2019 rather than 2013–2017. It should be noted that type UD is especially considered in this study with low wind speed, PBL height, and rainfall which are unfavorable to the diffusion of pollutants. The variation in frequency and intensity of type UD could lead to higher circulation contribution. In addition, higher meteorological contributions and decreasing reconstructed PM$_{2.5}$ levels imply that synoptic patterns play a crucial role in the PM$_{2.5}$ variation in the north of China during 2016–2019, compared with that of 2013–2017. The meteorological contribution to the reduction in PM$_{2.5}$ concentration was 65%, 62%, 80%, and 42% in spring, summer, autumn, and winter, respectively. And the difference of meteorological contribution in four seasons can be attributed to the variation of frequency and intensity of circulation pattern in different seasons, as well as the variation of emission regulation in different seasons. The residual variability could be attributed to emissions regulation measures in the north of China. The results also illustrate that the meteorological contribution is lower in winter than in summer. Most of the haze pollution episodes occur in winter, and the contribution of emission
regulation measures turns out to be greater than that of other seasons. Haze pollution rarely occurs in summer, and meteorology tends to contribute more to the PM$_{2.5}$ variation than that of other seasons. Nevertheless, the winter contribution from meteorology in most cities is lower than that evaluated by (Li et al., 2020), which indicates that the decreasing trend of PM$_{2.5}$ levels from 2016 to 2019 in North China is greatly associated with the impact of its emissions reduction measures.

4. Summary and Conclusions

PM$_{2.5}$ concentrations depend primarily on the pollution emissions and meteorological conditions. In this study, the meteorological impact on improved PM$_{2.5}$ air quality is investigated. We use a regional high-resolution reanalysis data-set of atmospheric composition over China for 2016–2019 that has been produced by the JDAS, with joint assimilation that includes meteorological observations, chemical ICs, and emissions at high spatial (45 km) and temporal (1 h) resolution. Comprehensive evaluation indicates that the JDAS provides a reasonable representation of the current atmosphere, making it suitable for retrospective multi-year analyses.

A significant reduction in PM$_{2.5}$ concentrations occurred across Beijing from 2016 to 2019 as a result of the considerable reduction in the emissions of major pollutants, with the greatest decrease in the BTH region, which is consistent with previous studies indicating the intensity of emissions reduction. According to the JDAS reanalysis data-set, the percentage of exceedance ratios has decreased from 27.40% in 2016% to 7.95% in 2019, representing an ~19% reduction in the year-round statistics. Winter shows the most obvious decline in PM$_{2.5}$ compared with spring, summer, and autumn during 2016–2019.

The contribution of meteorological conditions and emissions control to regulation of the spatiotemporal distribution and seasonal patterns of PM$_{2.5}$ over the NCP was further assessed. Most pollution episodes are usually related to the presence of unfavorable meteorological conditions. Twenty seven synoptic circulation types were objectively categorized using the Lamb–Jenkinson method. Temporal and spatial variations of PM$_{2.5}$ in the NCP were found to be closely connected with weather and circulation patterns. The heavy pollution categories are mainly related to S, SE, ASE, CE, and and CSE, with mean PM$_{2.5}$ concentrations greater than 115 μg m$^{-3}$ and an occurrence frequency of about ~3%, and moderate pollution categories include C, UD, W, E, SW, AS, ASW, AW, CNE, CS, CSE, CW, and CNW, with mean PM$_{2.5}$ concentrations of about 75–100 μg m$^{-3}$. PM$_{2.5}$ levels in 2019 decreased distinctly compared with 2016 under similar weather conditions, including C, UD, W, E, SE, S, ASE, AW, CE, and CSE. However, unfavorable meteorological conditions should not be ignored when assess the influence of regulation measures and developing further policies. In general, the meteorological contribution to PM$_{2.5}$ variability ranged from 60% to 80% in most cities in the NCP, and domain-averaged PM$_{2.5}$ reduction from meteorological contribution were 65%, 62%, 80%, and 42% in spring, summer, autumn, and winter, respectively. The results illustrate that the emissions control influence to the PM$_{2.5}$ reduction was higher in winter than in summer. According to the quantitative evaluation on circulation pattern changes, the meteorological contribution have played a positive role in improving air quality in the context of China’s clean air policy during 2016–2019. This study serves as a basis for future retrospective analyses of emissions and air pollutant variations using the reanalysis data-set produced by JDAS (which will be extended in the future by adding one year each year).

Data Availability Statement

The data used in this study from JDAS reanalysis data-set are available online (https://meso.nju.edu.cn/xwdt/20210408/i191929.html).

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